Should English Majors Take Computer Science Courses? Labor Market Benefits of the Occupational Specificity of Major and Nonmajor College Credits

Audrey Light
Department of Economics
Ohio State University
light.20@osu.edu

Sydney Schreiner Wertz
Office of Economic Policy
U.S. Department of the Treasury
sydney.wertz@treasury.gov

July 2021

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, and nondisciplinary components. We define the occupational specificity of each college field as the exogenous likelihood that a student majoring in that field subsequently works in an occupation requiring field-specific skills. We find that occupationally-specific, non-disciplinary courses are strongly associated with earnings; *e.g.*, an eight-credit 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.

Acknowledgement: 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. 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 The Ohio State University's Center for Human Resource Research (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.

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 and 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 and Pisacreta 2019). 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 (or other "non-vocational" fields), are labor market outcomes positively associated with completed credits 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 *exogenous* likelihood that a student majoring in the given field subsequently works in an occupation requiring the specific skills acquired in that field. Among the 60 fields that we consider, 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 that closely match the skills acquired in college history courses. History majors might be productively

[1]All statistics in this paragraph are computed from numbers reported in table 322.10 of the 2017 Digest of Education Statistics (https://nces.ed.gov/programs/digest/d17/tables/dt17_322.10.asp).

employed in journalism, sales, elementary education and any number of other occupations on the basis of their *general* skills, but because no occupation forms a direct pipeline for this field of study it is judged to lack occupational specificity.

We combine our field-specific, occupational specificity measure with college transcript data for over 90,000 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 general education or major-specific credit requirements that might be used to contend with potential correlations between individual ability (or college quality) and the occupational specificity indexes. Instead, we control for graduation year fixed effects, university fixed effects, first-semester grade point average, first-semester percent of attempted credits that are completed, college transfer patterns, enrollment duration, and other factors to account for heterogeneity in pre-college student ability, institutional quality, and labor market conditions. In a series of robustness checks, we take further steps to net out individual ability and institutional quality, including reducing the sample to a single institution and eliminating students who transfer between colleges or earn double majors.

Our analytic strategy enables us to estimate marginal effects of various credit-related interventions that alter the distribution of total credits between major and nonmajor courses. We use these computations to answer such questions as: Can individuals with occupationally specific majors potentially enhance their labor market outcomes by amassing additional credits in their majors? How do their "returns" to increased within-major credit concentration compare to analogous estimates for less occupationally specific majors? Can individuals with less

[2]We use the term "discipline" to refer to groupings of related college fields. For example, the humanities discipline includes such fields as English, philosophy, history, and foreign languages, while the natural sciences discipline includes chemistry, zoology, and computer science. At U.S. colleges and universities, fields of study often correspond to departments, especially within the humanities, social sciences, and natural sciences disciplines; outside the core "arts and sciences," disciplines often correspond to professional schools or colleges within the university (*e.g.*, business, education, health sciences).

occupationally specific majors benefit from choosing occupationally specific courses outside their major? Do *these* benefits differ with the occupational specificity of the major? Do they 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 and Eide 1995; Hamermesh and Donald 2008; Kirkeboen *et al*. 2016; Webber 2016), but is most closely aligned with the strand of this literature that asks whether wages differences among majors are attributable to differences in skill specificity (Blom *et al.* 2015; Bridet and Leighton 2015; Leighton and Speer 2020; Malamud 2011, 2012; Silos and 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 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 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 our efforts to control for "ability bias" via observables and reliance on within-institution variation, we suspect that these substantial, estimated marginal effects might be partially attributable to a positive relationship between unobserved ability and credit distributions outside the major. Even if our findings represent an upper bound on a positive, causal effect of increasing the occupational specificity of courses taken outside the major, the message is clear: *all* college students—including those who choose majors with low occupational specificity—can potentially improve their post-college earnings prospects by augmenting their degree requirements with occupationally specific, nonmajor courses.

2. Background

To clarify our contributions, we briefly discuss three strands of the literature that are particularly relevant to our analysis: (1) studies that assess wage returns to the skill specificity of college majors; (2) studies that consider the *ex post* match between college major and occupational skill requirements as a determinant wages; and (3) studies that consider broader aspects of students' college curriculum than simply the major.

A number of analysts have asked whether the widely-studied wage gaps among college graduates with different majors (Altonji *et al*. 2012; Berger 1988; Grogger and Eide 1995; Hamermesh and 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 and Leighton (2015) use transcript data in the Baccalaureate and Beyond (B&B) Longitudinal Study to track, term-by-term, college students' within-major credit concentration; when this concentration reaches a certain threshold, they determine that specialization has begun. Rakitan and Artz (2015) and Silos and Smith (2015) ignore intra-term variation in credit concentrations, and instead use completed credit distributions across several 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.[3]

Another set of studies considers the vocational orientation of college training or, more generally, the 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 broad dichotomy, vocationally-oriented training can be

[3]Dolton and Vignoles (2002) Malamud (2012) apply a similar approach in identifying the "depth vs. breadth" of U.K. high school students' training.

measured directly. When using U.S. data, the more common approach is to construct exogenous measures of the extent to which college graduates in each major are concentrated among occupations (Altonji *et al*. 2012; Blom *et al.* 2015). Whereas the use of occupational concentration as a proxy for skill specificity stems from the view that workers with degrees in highly specific fields of study will be tightly clustered within a relatively small number of occupations, Leighton and Speer (2020) argue that the dispersion of wages, rather than the dispersion of occupations, is the more relevant measure. They 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.

While we agree with Leighton and Speer (2020) that wage inequality is ideal for capturing the transferability (specificity) of skills, we opt not to base our measure of occupational specificity on realized occupational *or* wage dispersions because our goal is to focus on the strength of each field's occupational pipeline. In section 3.C, we compare our occupational specificity measure to occupational concentration measures to highlight the fact that the latter do not distinguish between concentrations within occupations that are unrelated to the major and concentrations within occupations that comprise (exogenous) pipelines for the major. Isolating the latter is our current goal, although we believe our analysis might be fruitfully extended to incorporate alternative specificity measures in the future.

Roksa and Levey (2010) use a regressor that is conceptually similar to ours in their analysis of early-career attainment of occupational status. They define occupational specificity as the proportion of students in each field who work in occupations related to their majors. To construct their empirical measure, Roksa and Levey rely on a table in NCES (2001) showing how workers who hold bachelor's degrees in 12 broadly-defined majors (corresponding, roughly, to our disciplines) are distributed among 11 select, broadly-defined occupational categories; they define each of the 12 fields as having low, medium, or high occupational specificity based on the percentage of workers employed in a similar occupational category. In contrast, we (a) consider 60 distinct fields of study and the entire Census taxonomy of occupations; (b) identify matches based on careful consideration of whether the specific skills taught in each field of study are required by each occupation; and (c) construct a continuous measure of occupational specificity to capture fully the variation between fields.

Our strategy of matching college fields of study with occupations has commonality with the job matching sub-literature in which the "closeness" (or lack thereof) of each worker's college major and occupation has been found to be a key determinant of post-college earnings (Abel and 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.[4]

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. Instead, we consider each individual's entire credit distribution across 60 fields of study—one of which, of course, is the student's major. We form an index of the credit-weighted occupational specificity of *all* completed courses, which we decompose into within-major, within-discipline, and non-discipline components. Our use of the entire credit distribution has as its genesis Rakitan and Artz (2015), Silos and Smith (2015) and other studies that assess the depth vs. breadth of each student's college coursework. It also borrows from Hamermesh and Donald (2008), Joy (2003), and Light and Schreiner (2019), all of which use wage models that control for college coursework in addition to dummy variables identifying college major. While Hamermesh and Donald (2008) and Joy (2003) control for courses in a limited way (*e.g.*, Hamermesh and Donald (2008) include a single measure of the number of credits completed in upper-division science and math courses), Light and Schreiner (2019) use transcript data in the 1997 National Longitudinal Survey of Youth to estimate log-wage models with controls for 13 college majors *and* the percent of credits in each of those 13 fields. Despite differences in methodology, each of these prior studies finds a substantial relationship between college coursework and post-college wages, 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

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

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; details on our use of ACS data are deferred to section 3.C.

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 data were 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.[5] The large sample size enables us to define detailed college majors and eliminate unobserved, institution-specific factors (average student ability, course offerings, average course difficulty, credit requirements, *etc*.) 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 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 are not required to participate in the Ohio UI system.[6] As a result, we lack information for out-of-state employment, for employees of the federal government, and for some self-employed workers. As described below, our sample selection rules are designed to contend with these data shortcomings.

3.A. Sample selection

We assess the relationship between the occupational specificity of college graduates' credit distributions and two alternative outcomes: employment, and log-earnings. We proceed to

[5] The 13 institutions are Bowling Green State University, Central State University, Cleveland State University, Kent State University, Miami University, Ohio State University, Ohio University, Shawnee State University, University of Akron, University of Cincinnati, University of Toledo, Wright State University and Youngstown State University.

[6] Employers are required to file unemployment insurance if they employ at least one person for some portion of the day for at least 20 weeks during the year, or if they pay at least $1,500 in wages to employees in any quarter.

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 impose a number of selection rules to eliminate individuals with notably atypical credit accumulations, majors, or paths to a bachelor's degree. Each criterion is designed to minimize the probability of retaining sample members with incomplete transcripts or highly irregular credit distributions. First, we drop from the sample 25,883 individuals (15% of 168,870) who are younger than 20 or older than 26 when they receive their bachelor's degree.[7] We then eliminate fewer than 10 individuals who are incarcerated between high school graduation and the receipt of a bachelor's degree. 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 represented 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 3,216 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 three fields) 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

[7]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.

employment and earnings samples.

In constructing a sample used to model the probability of employment, we must contend with our inability to distinguish between individuals who are nonemployed and individuals who are employed outside Ohio. To do so, we eliminate 25,364 individuals (19% of 130,902) whose UI record lacks at least one "valid" earnings report (defined in section 3.B) 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 awaiting the start of a 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.

While the employment sample is necessarily restricted to outcomes observed approximately one year after college graduation, the log-wage sample includes wages earned during the entire post-graduation observation period (which extends up to seven years), conditional on the individual remaining nonenrolled. To construct this 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 a "valid" 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; this one-quarter delay is imposed because we lack precise college graduation dates (see footnote 7) and do not want to model earnings associated with student jobs. The earnings window ends with the earlier of two dates: (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. By defining the early-career observation window in this fashion, we ensure that we are modelling earnings outcomes only for individuals who hold a bachelor's degree and have no additional degrees or enrollment.[8] Each remaining sample member contributes one observation for every

[8] Among the 36,096 individuals dropped because they lack a valid wage during the relevant post-college observation window, fewer than 1,900 are excluded solely because they lack a wage within

quarter in which he or she has "valid" 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). We include graduation year fixed effects in our log-earnings models to address any unobserved differences across cohorts.

Among the 94,806 individual who contribute quarterly observations to the earnings sample, 90,444 (95%) also appear in our employment sample. Most of the remaining individuals (4,097 of 4,362) belong to the earnings sample but not the employment sample, which indicates that they earn a wage and then reenroll within the first year of receiving their bachelor's degree. The remaining 265 individuals appear in the employment sample but not 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.B. Dependent variables

To construct the dependent variable for our earnings model, we begin by defining a "valid" earnings report. UI records include total earnings and total weeks worked for as many as five employers per quarter. A small but nontrivial number of employer-specific records entail positive earnings and either zero or missing weeks worked. To contend with this issue, we first drop any such record if weeks worked associated with other employer-specific records in the same quarter sum to 11 or more. Next, if the same employer reports positive earnings and weeks in an adjacent or "nearby" quarter, we replace the zero or 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 then adjusted to fall between 1 and 13. We then define a valid earnings report as one with positive values for both reported earnings and either reported *or* imputed weeks.

Having identified "valid" earnings, we construct our log-earnings variable by summing valid earnings reports across all employers for the quarter and dividing by total weeks worked for all employers (capped at 13). We deflate this "average quarterly earnings" variable by the quarterly

---

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. Among the robustness tests reported in section 5.C, we further restrict the sample to individuals observed four years after receiving their bachelor's degree (with no intervening enrollment) to ensure that we focus on "terminal" college graduates.

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 binary, "any" employment outcome if his/her quarterly UI record (one year after college graduation) contains a valid earnings report 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—which, we assume, is not typically the early-career outcome that drives college curriculum decisions—we define an alternative measure of full-time employment. Individuals are deemed to be employed full-time 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 as well as the regressors described in sections 3.C-D.

3.C. Credit-related regressors

We model each outcome described in section 3.B as a highly flexible function of four credit-related variables. In this subsection we define these variables, provide key details on their construction, and briefly summarize the data.

Each student i takes C_i courses to complete his or her bachelor's degree, with each course contributing $CREDIT_{ic}$ credit hours. After all courses and majors are aggregated into one of 60 fields, we determine that each student takes courses in $F_i < C_i$ unique fields, with each field contributing $CREDIT_{if}$ credit hours.

By combining each student's credit distribution across F_i fields with our exogenous measure of the occupational specificity of each field (OS_f), we construct a credit-weighted occupational specificity index for each student:

$$PCOS_i = 100 \cdot \sum_1^{F_i}(CREDIT_{if} \cdot OS_f) / \sum_1^{F_i} CREDIT_{if} = \sum_1^{F_i} PC_{if} \cdot OS_f. \quad (1)$$

We refer to this index as $PCOS_i$ to highlight the fact that the occupational specificity of field f is weighted by the percent of total credits allocated to that field (PC_{if}).

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

$$PCOS_i = PCOS_{im} + PCOS_{id} + PCOS_{io} \quad (2a)$$

$$= 100 \cdot [CREDIT_{i1} \cdot OS_m + \textstyle\sum_2^{D_i}(CREDIT_{if} \cdot OS_f)$$

$$+ \textstyle\sum_{D_i+1}^{F_i}(CREDIT_{if} \cdot OS_f)] / \textstyle\sum_1^{F_i} CREDIT_{if} \qquad (2b)$$

$$= PC_{im} \cdot OS_{im} + \textstyle\sum_2^{D_i}(PC_{if} \cdot OS_f) + \textstyle\sum_{D_i+1}^{F_i}(PC_{if} \cdot OS_f), \qquad (2c)$$

where PC_{im} is the percent of total credits taken in the major and OS_{im} is the occupational specificity of that major field (*f*=1=*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 Census data to define the occupational specificity of each field. 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.C.1. Defining fields

HEI transcript data include the number of credits earned in each course, the title (subject matter) 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 the nature of the data and the research goals.[9] We begin by aggregating most six-digit CIP codes to their broader CIP "subject field." This leaves us with 144 fields that are typically associated with college majors; for example, 10 six-digit codes identifying such detailed subjects as environmental

[9]For example, Kinsler and Pavan (2015) use three majors (business, science and other) to estimate a structural model; Hamermesh and Donald (2008) use 10 majors and Altonji *et al*. (2012) use 171 majors to identify major-specific parameters; and Altonji *et al*. (2016) and Leighton and Speer (2020) map 51 majors to skill-specificity measures.

architecture, interior architecture, and landscape architecture are aggregated to "architecture." To aggregate further to the 60 fields listed in table 1, we rely on the 51-field taxonomy used by Altonji *et al*. (2016) and Leighton and Speer (2020) while simultaneously looking ahead to subsequent data construction steps to determine what level of aggregation best suits our needs.

Those subsequent steps entail (a) mapping each field to one of 191 Census degree fields used by the 2010-18 ACS; (b) matching ACS/OLDA fields to 2010 Census Occupational Classification codes based on our assessment of whether the skills associated with the major closely match the skills required by the occupation; and (c) defining occupational specificity as the percentage of ACS respondents with completed majors in each field who are employed in "matched" occupations. This process 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 vs. 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). Otherwise, we would have to choose between treating "miscellaneous" as "all" (astronomy *and* geology *and* physics, *etc.*) or "none" and, in turn, assigning each miscellaneous field either a higher or lower level of occupational specificity than its related subfields.

3.C.2. Defining the occupational specificity of each field

To define OS_f we must determine which occupations listed in the 2010 Census Occupational Classification use skills that are directly related to the skills acquired in field of study f. For all but the most familiar fields, 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 several 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.

Virtually 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 teaching majors (elementary education, special education, *etc*.) 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," the field of sports and recreation matches to "lifeguards and other recreational workers," and the field of forestry, wildlife and environmental resources matches to "fishing and hunting workers." Although a college degree is not required for many jobs within these occupations, the matched fields of study unquestionably prepare individuals to work in the occupation and to hold a relatively high-skill job.

We experimented with alternative OS_f definitions based on different degrees of "closeness" of the field-occupation matches.[10] 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," "financial examiners" and a few additional occupations. Our reason for avoiding the narrowest matches is two-fold. First, the availability of the most direct field-occupational matches (accounting-accountants, *etc.*) depends as much on the nature of the occupational taxonomy as on the specificity of each college field and is, therefore, somewhat arbitrary. Second, relatively few fields substantially change their rank within the OS_f distribution when we switch from the broadest matches to the narrowest. One field that *does* substantially change rank is special education, which 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") and a value of only 32% when matched solely (and most directly) with "special education teachers." This example illustrates the fact that some college fields are more narrowly-defined than others, and would be assigned a misleadingly low level of

[10]Appendix table A3 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.

occupational specificity if we relied on the narrowest field-occupation links.[11]

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. This gives us the occupational specificity of each field (OS_f).

3.C.3. Credit variable summary statistics

Table 1 summarizes the credit-related variables for each of the 60 fields of study, sorted by occupational specificity (OS_f). The first column of numbers reveals that nursing has the highest level of occupational specificity (91.3), followed by special 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 science field (international relations) with $OS_f = 0$. Overall, the occupational specificity ranking conforms quite well 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.* (2015) 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 illustration to highlight the difference between our measure and concentration-based measures (including the wage inequality measure used by Leighton and Speer (2020)). Out of 60 fields, journalism ranks as 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

[11]Because relatively few fields see their OS_f level change dramatically when we narrow our definition of a field-occupation link, the findings presented in section 5 are robust to which definition we use.

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. None of the 11 occupations that we match with journalism (including announcers; news analysts/reporters/correspondents; and editors) accounts for more than 4% of workers with journalism degrees, yet the matched occupations combine to account for 13.2% of journalism majors. 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 or diffusion.

The remaining statistics in table 1 are based on a sample of 95,071 individuals who appear in our employment and/or earnings samples. We see that the average percent of total credits taken within the major 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). As noted in section 1, we find 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, and *not* solely the major field, to characterize skills sets.

Turning to the $PCOS_d$ and $PCOS_o$ columns in table 1 (and dropping individual subscripts), three patterns are evident. First, $PCOS_d$ tends to be relatively high, unsurprisingly, for fields with low within-major credit concentrations; *e.g.*, the highest mean value (1857.7) is seen among education administration majors, who have one of the lowest means for PC_m. Second, mean levels of $PCOS_d$ are lowest among those fields with only one or two majors within the discipline (agriculture, sports and recreation, *etc.*) but also among health-related majors where a broad, disciplinary curriculum is not the norm. Third, although there is considerably less variation in $PCOS_o$ than in $PCOS_d$, the "outliers" in this dimension tend to be fields within the natural sciences; *e.g.*, chemistry, zoology, other biological sciences, and physical sciences, which account for the four lowest mean levels of $PCOS_o$.[12]

[12]We reestimated our earnings model after alternately dropping (a) fields with PC_m<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.

3.D. 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) to 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" (either non-Black, non-Asian and non-white, or unknown); white is the omitted racial category. We lack a pre-college measure of academic ability or performance (*e.g*. college admissions test scores or 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 to distinguish between (presumably, high ability) students who take no such credits or a single course in personal finance, wellness, *etc*. and those who take multiple remedial and/or vocational courses.[13]

Our in-college, baseline 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's 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.

Because the earnings model uses multiple observations for each sample member, we augment

[13]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. These and other robustness tests are discussed in section 5.C.

the uniform set of baseline controls for this model by adding a measure of work experience and its square. We define actual experience as cumulative quarters with positive earnings between receipt of the bachelor's degree and the quarter in which the wage is earned, divided by four for conversion to years.

4. Analytic strategy

4.A. Model specification and identification

We use 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.D, including institution and graduation year fixed effects, as well as a flexible function of occupational specificity of the major (OS_m) and the credit-weighted occupational specificity indexes for courses taken within the major ($PCOS_m$), outside the major but within the discipline ($PCOS_d$), and outside the discipline ($PCOS_o$). To select that flexible function, we began with a specification that includes the four credit variables and their squares plus pair-wise interactions between each of these eight variables, for a total of 36 credit-related regressors. We opted to drop all 10 cubic and quadratic-quadratic interaction terms after determining that estimates are similar for the 26- and 36-parameter versions except at the extreme tails of the OS_m distribution. Table A2 lists the regressors as well as the OLS parameter estimates.

Before discussing the marginal effects that we rely on to draw inferences, we offer a few additional details on our overall strategy. 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 and 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 preferences and ability influence both credit distributions and labor market outcomes. Unfortunately, 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.[14] On the positive side, however, given our baseline controls and focus on the marginal effects of PC_m, $PCOS_d$, and $PCOS_o$ *conditional* on OS_m, the only confounding factors that prevent us from interpreting our estimates as causal effects are those that (a) vary within institution; (b) are not "netted out" by first-semester GPA, enrollment duration, *etc.*; and (c) are not subsumed by the choice of college major. In a series of robustness checks presented in section 5.C, we attempt to reduce further these factors by, *e.g.*, focusing on a single institution and eliminating students who transfer between colleges or earn double majors. Sources of endogeneity invariably remain despite our efforts to eliminate or control for them, so we interpret our findings as upper bounds on the causal effects of interest, based on both the fact that our estimated payoffs are often surprisingly large and the assumption that productivity-enhancing, unobserved factors are likely to be *positively* correlated with occupational-specificity indexes.

4.B. 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, using values corresponding to the 25th, 50th and 75th percentiles in the OS_m 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_m distribution and setting OS_m equal to, alternatively, its p25, p50 and p75 values. In contrast to the partial effect, which introduces no offsetting reduction in credits, we then compute the "total" marginal effect of the same increment to PC_m by simultaneously removing five percentage points worth of credits from the course(s) outside the discipline with, alternatively, the lowest and highest occupational

[14]In the fall of 2021, for example, Ohio State University, which accounts for 25% of the observations in our log-wage sample, will launch the first substantial change in its general education requirements in 30 years (https://news.osu.edu/senate-approves-overhauled-gen-ed-program-to-begin-autumn-2021/).

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 $PCOS_o$, and using the sample mean of those increments ($\overline{\Delta PCOS_o}$) as part of the intervention, along with ΔPC_m=5. We 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_m and PC_m 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.[15]

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 specificity to computer science, compute the resulting $\overline{\Delta PCOS_o}$ for English majors, and set OS_m, $PCOS_d$ and the starting value for $PCOS_o$ to the mean (or, in the case of OS_m, the fixed value) among English majors. For comparison, we compute analogous marginal effects for physical sciences ("physics") and accounting majors. Both English and physics have low occupational specificity (8.3 and 6.2, respectively) but, unlike English, physics shares a discipline with computer science. Computer science is outside the discipline of both English and accounting majors, but in contrast to English and physics, accounting has a high level of specificity (63.4) that is comparable to computer science (62.2).

5. Findings

5.A. Estimated effects of increased occupational specificity

Table 2 presents the first set of marginal effects described in section 4, 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_m 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

[15]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.

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. We find that the 14-point increment in OS_m 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_m 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 earning high wages. Nonetheless, it is reassuring to find that increased occupational specificity is positively associated with each outcome—and interesting to learn that the estimated marginal effect of occupational specificity increases with OS_m (to a point) when the outcome is employment, but *decreases* with log-earnings.

5.B. Estimated effects of credit shifts conditional on occupational specificity

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 designed to achieve this goal (described in section 4) are presented in tables 3-6. In each table, we confine our attention to the full-time employment and log-earnings outcomes, given that estimates for "any" employment are always smaller in magnitude than those for full-time employment. Estimates for full-time employment tend to be small and imprecise in their own right, so our discussion focuses on log-earnings effects.

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. Setting the starting level of within-major credit concentration (PC_m) at, alternatively, the 25th, 50th, or 75th percentile value, the estimated marginal effect increases substantially as the occupational specificity of the major increases; *e.g.,* from 0.011 to 0.027 to 0.042 when PC_m is set at its p25 value. Moreover, table 3 reveals (by reading across each row) that estimated marginal effects diminish slightly as PC_m 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.

While the "partial" estimates in table 3 consider the costless addition of five percentage points worth of credits to PC_m, "total" estimates in the middle panel are computed by 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 credits are substantially more valuable in an occupationally-specific course that is, in many instances, far afield from the major field than in a course within the major—especially when the major has a low level of occupational specificity and/or the student already 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_m and PC_m while increasing the within-discipline occupational specificity index ($PCOS_d$) 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. Holding OS_m constant, however, we see decreasing "returns" to $PCOS_d$ that are more pronounced than the patterns seen in table 3. For example, among individuals with OS_m at the p75 level, the estimated payoff to increased occupational specificity of within-discipline courses is 0.044 at a low (p25) level of $PCOS_d$ and only 0.027 at p75. These patterns suggest that, regardless of major, students can potentially boost their future earnings by completing several occupationally-specific, nonmajor courses within their discipline, although the "return" to doing so decreases in $PCOS_d$.

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 ($PCOS_o$) 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 3-4, although even the largest point estimate (0.024, at the p25 value for both OS_m and $PCOS_o$) 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_m 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.C. Robustness checks

To assess further the finding that the occupational specificity of courses taken outside the major *and* the discipline are strongly, positively associated with log-earnings, we undertake a series of robustness tests. 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_m. Using these "full sample" estimates as the benchmark, we assess 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 a poor proxy for pre-college ability, this variable should absorb much of the "ability effect" on log-earnings and result in lower estimated marginal effects if, as conjectured, our estimates suffer from upward ability bias. Table 6 reveals the inclusion of final GPA has no effect on the estimates.

Next, we eliminate earnings observations contributed by graduates 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 exceed the benchmark estimates slightly (by 7% or less). The differences are not enough to cast doubt on our findings, nor do they indicate that upward "ability bias" is reduced when we impose this sample restriction. Our third, related experiment involves redefining the credit-related variables (OS_m, $PCOS_o$, *etc.*) 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 credit, and general education requirements play a prominent role in many students' curriculum choices. Table 6 reveals that this sample restriction has no effect on the estimated marginal effects.

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 of Ohio State University, which is typically considered to be the highest-quality institution in our sample. The estimated marginal effects for both experiments are very close to the benchmark estimates in all cases but one: among Ohio State graduates with $PCOS_o$ 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 in the Ohio State subsample, versus 0.053 in the full sample. It appears that Ohio State students with a relatively high level of occupational specificity among "outside" credits differ from other students in our sample, but careful inspection of the data did not reveal to us precisely what explains this somewhat anomalous discrepancy.

In our final set of experiments, we confine the sample to individuals whose observed, post-college earnings histories last at least three years and, alternatively, to earnings reported approximately four years after graduation. All samples used throughout our analysis are confined to individuals with no post-college enrollment, but by imposing these additional restrictions we eliminate individuals who enroll in graduate school (or re-locate to another state) within 3-4 years of completing college; in the full sample, those individuals contribute earnings observations until they reenroll or re-locate. As with most of the preceding robustness tests, table 6 reveals that these sample restrictions have very small effects on the estimates. Estimates based on the "employed for ≥3 years" subsample are consistently smaller in magnitude than the benchmark estimates, which is consistent with the notion that the benchmarks reflect a slight upward ability bias due to the presence of "soon to be" graduate students. The subsample based on earnings reported four years after graduation is an alternative method of eliminating those potentially "high ability" individuals, yet it does not yield the same pattern.

The experiments summarized in table 6 as well as those reported in footnotes 11-13 demonstrate that the strong, positive relationship between log-earnings and $PCOS_o$ is highly robust. Moreover, they fail to produce evidence that the estimates in tables 5 are dominated by a strong, positive correlation between student ability and the decision to take non-disciplinary courses with high occupational specificity. In particular, they reveal that neither the inclusion of final GPA among the controls nor the elimination of high-ability students who will soon enroll in graduate school result in lower estimated marginal effects. Despite our failure to find evidence of "ability bias," we suspect that some form of unobserved ability accounts for a portion of the relationships we identify. Therefore, we interpret all our estimates—and not just those in table 5—as upper bounds on causal effects, while relying on our experiments to infer that a nontrivial portion of these relationships *are* causal.

5.D. 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 revise the intervention underlying tables 4-6 as follows: First, we set OS_m to the actual level for, alternately, physics, English and accounting majors, rather than to a percentile value. Second, for physics majors, we (a) hold $PCOS_o$ at the sample mean among physics majors; (b) use the physics-specific mean level of $PCOS_d$ as the starting value; and (c) compute a major-specific, mean increment in $PCOS_d$ after assigning each physics major a five percentage point credit shift from his/her least occupationally specific, within-discipline course(s) to computer science courses. Third, we repeat the computation for English and accounting majors after reversing the role of $PCOS_d$ and $PCOS_o$. In short, we revise the table 4 estimates for physics majors, given that physics and computer science are both in the natural sciences discipline, while revising table 5 for English and accounting. As noted in section 4, we focus on English and physics because they both have low occupational specificity, but differ with respect to their "relationship" to computer science; we focus on accounting because its occupational specificity is similar to that for computer science.

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. Interestingly, the increment to $PCOS_d$ 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.[16] Accounting majors are predicted to receive a substantially larger "return" to the intervention than

[16]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.

English majors because they start at a lower level of $PCOS_o$, and because they have a higher level of OS_m and $PCOS_d$. Assuming a nontrivial portion of these table 7 estimates represent causal effects, we conclude that individuals in these representative majors can substantially enhance their post-college earnings by completing several credits in computer science or other occupationally specific, nonmajor courses.

6. Conclusions

In this study, we combine unemployment insurance records with college transcript data for over 90,000 recent graduates of Ohio 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 (exogenous) 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, 26-parameter function to allow each key regressor's relationship with the outcome to be nonlinear and dependent on all other factors. 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 occupationally specific course to the most occupational 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 highly robust to changes in model specification, variable definition and sample restrictions. 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%; if a physics major makes the same shift, the expected earnings boost is 6.4%. Even if these estimated marginal effects are partially due to unobserved ability, there appears to be considerable scope for students in *all* majors to enhance their labor market outcomes by increasing the occupational specificity of courses taken outside the major.

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 makers advocate for concentrating educational resources into fields that offer direct pipelines to “in demand” occupations and others defend the liberal arts and 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.

References

Abel, Jaison R. and Richard Deitz. "Agglomeration and Job Matching Among College Graduates." *Regional Science and Urban Economics* 51 (March 2015): 14-24.

Adamuti-Trache, Maria, Colleen Hawkey, Hans G. Schuetze and Victor Glickman. "The Labour Market Value of Liberal Arts and Applied Education Programs: Evidence from British Columbia." *Canadian Journal of Higher Education* 36 (August 2006): 49-74.

Altonji, Joseph G., Erica Blom and Costa Meghir. "Heterogeneity in Human Capital Investments: High School Curriculum, College Major, and Careers." *Annual Review of Economics* 4 (September 2012): 185-223.

Arcidiacono, Peter. "Ability Sorting and the Returns to College Major." *Journal of Econometrics* 121 (July-August 2004): 343-75.

Berger, Mark C. "Predicted Future Earnings and Choice of College Major." *Industrial and Labor Relations Review* 41(April 1988): 418-29.

Blom, Erica, Brian C. Cadena and Benjamin J. Keys. "Investment Over the Business Cycle: Insights from College Major Choice." IZA Discussion Paper No. 9167, July 2015.

Bridet, Luc and Margaret Leighton. "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 2015.

Dolton, P.J. and A. Vignoles. "Is a Broader Curriculum Better"? *Economics of Education Review* 21 (October 2002): 415-429.

Grogger Jeffrey and Eric Eide. "Changes in College Skills and the Rise in the College Wage Premium." *Journal of Human Resources* 30 (Spring 1995): 280-310.

Hamermesh, Daniel S. and Stephen G. Donald. "The Effect of College Curriculum on Earnings: An Affinity Identifier for Non-Ignorable Non-Response Bias." *Journal of Econometrics* 144 (June 2008): 479-91.

Hanushek, Eric A., Guido Schwerdt, Ludger Woessmann, and Lei Zhang. "General Education, Vocational Education, and Labor-Market Outcomes Over the Lifecycle." *Journal of Human Resources* 52 (Winter 2017): 48-87.

Hill, Catharine B. and Elizabeth Davidson Pisacreta. "The Economic Benefits and Costs of a Liberal Arts Education." The Andrew W. Mellon Foundation research report, 2019.

Joy, Lois. "Salaries of Recent Male and Female College Graduates: Educational and Labor Market Effects." *Industrial and Labor Relations Review* 56 (July 2003): 606-21.

Kirkeboen, Lars, Edwin Lueven and Magne Mostad. "Field of Study, Earnings and Self-Selection." *Quarterly Journal of Economics* 131 (August 2016): 1057-1111.

Leighton, Margaret, and Jamin Speer. "Labor Market Returns to College Major Specificity." *European Economic Review* 128 (September 2020). Available online at

https://doi.org/10.1016/j.euroecorev.2020.103489

Lemieux, Thomas. "Occupations, Fields of Study and Returns to Education." *Canadian Journal of Economics* 47, no. 4 (November 2014): 1047-77.

Light, Audrey and Sydney Schreiner. "College Major, College Coursework, and Post-College Wages." *Economics of Education Review* 73 (December 2019).

Malamud, Ofer. "Breadth Versus Depth: The Timing of Specialization in Higher Education." *Labour 2*4 (December 2010): 359-390.

Malamud, Ofer. "Discovering One's Talent: Learning from Academic Specialization." *Industrial and Labor Relations Review* 64 (January 2011): 375-405.

Malamud, Ofer. "The Effect of Curriculum Breadth and General Skills on Unemployment." University of Chicago working paper, April 2012.

Montt, Guillermo. "Field-of-Study Mismatch and Overqualificiation: Labour Market Correlates and their Wage Penalty." *IZA Journal of Labor Economics* 6 (2017).

National Center for Education Statistics. "From Bachelor's Degree to Work: Major Field of Study and Employment Outcomes of 1992-93 Bachelor's Degree Recipients Who Did Not Enroll in Graduate Education by 1997." Statistical Analysis Report, NCES 2001-165. Washington DC: U.S. Department of Education, 2001.

Ost, Ben, Weixiang Pan and Douglas Webber. "The Returns to College Persistence for Marginal Students: Regression Discontinuity Evidence from University Dismissal Policies." *Journal of Labor* Economics 36 (July 2018): 779-805.

Rakitan, T.J. and Georgeanne M. Artz. "What Good Are Skills, Anyway? Estimating the Returns to Specific Skills in a College Education." Iowa State University working paper, 2015.

Robst, John. "Education, College Major, and Job Match: Gender Differences in Reasons for Mismatch." *Education Economics* 15 (June 2007a): 159-75.

Robst, John. "Education and Job Match: The Relatedness of College Major and Work." *Economics of Education Review* 26 (August 2007b): 397-407.

Roksa, Josipa and Tania Levey. "What Can You Do with That Degree? College Major and Occupational Status of College Graduates Over Time." *Social Forces* 89 (March 2010): 389-415.

Silos, Pedro, and Eric Smith. "Human Capital Portfolios." *Review of Economic Dynamics* 18 (July 2015): 635-52.

Webber, Douglas A. "Are College Costs Worth it? How Ability, Major, and Debt Affect the Returns to Schooling." *Economics of Education Review* 53 (August 2016): 296-310.

Wiswall, Matthew and Basit Zafar. "Determinants of College Major Choice: Identification Using an Information Experiment." *Review of Economic Studies* 82 (April 2015): 791-824.

Table 1: Summary Statistics for Credit-Related Variables, by Field of Study
(ranked by occupational specificity)

		PC_m		$PCOS_d$		$PCOS_o$		
Field of study [Discipline]	OS_f	Mean	SD	Mean	SD	Mean	SD	N
Nursing [Health]	91.3	50.6	7.6	33.3	62.0	762.6	168.5	4,815
Special education [Education]	86.1	31.7	12.5	1270.3	789.8	527.9	193.0	1,319
Elementary/early education [Education]	78.0	25.3	15.6	1711.9	886.4	588.0	212.6	2,592
Junior/senior high education [Education]	70.8	25.0	11.2	374.6	291.5	814.2	347.4	5,033
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	2,055
Accounting [Business]	63.4	22.1	5.0	904.2	310.6	644.7	265.4	3,130
Environmental/geo. engineering [Enginr.]	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	1,522
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	1,014
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	1,698
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	2,517
Finance [Business]	40.0	15.9	4.1	1324.1	315.6	609.8	210.0	2,910
Sales and marketing [Business]	37.5	19.3	6.4	1004.2	400.0	728.0	344.2	5,361
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	1,033
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	4,576
Other business [Business]	24.0	9.0	7.0	1255.4	404.3	669.4	293.8	1,362
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	2,790
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	3,421
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	4,924

Continued.

Table 1 (continued)

Field of study	OS_f	PC_m Mean	PC_m SD	$PCOS_d$ Mean	$PCOS_d$ SD	$PCOS_o$ Mean	$PCOS_o$ SD	N
Journalism [Communications]	13.2	33.2	8.2	35.9	56.1	821.1	342.9	7,051
Sports/recreation [Sports and recreation]	12.9	30.4	10.7	0.0	0.0	1463.4	547.5	2,777
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	1,124
Family/consumer studies [Social sciences]	12.2	26.5	10.6	171.3	122.8	1308.6	505.4	3,551
English [Humanities]	8.3	33.8	10.2	14.9	18.7	835.3	585.2	2,701
Engineering technology [Engineering]	7.8	30.7	20.6	998.7	910.1	873.0	557.8	1,224
Political science [Social sciences]	7.7	27.2	8.2	167.6	188.1	533.2	335.7	1,872
Other social sciences [Social sciences]	7.3	25.3	14.6	150.8	173.0	827.5	552.3	1,526
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	1,009
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	1,072
History [Humanities]	0.0	31.7	7.1	68.5	42.7	667.3	350.5	1,231
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	1,218
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 based on ACS data. The remaining columns show statistics computed for the N HEI respondents majoring in the field: PC_m is the percent of credits in the major and $PCOS_d$ and $PCOS_o$ are the credit-weighted occupational specificity indexes for nonmajor courses within the field's discipline and outside the discipline, respectively.

Table 2: Estimated Marginal Effects of a 14 Percentage Point Increase in Occupational Specificity of Major (OS_m) at Different Points in the OS_m Distribution

OS_m starting value	P(employment)[a] Any	Full time	Log-earnings[b]
10.2 (p25)	.009**	.019***	.091***
	(.004)	(.004)	(.001)
25.2 (p50)	.014***	.029***	.098***
	(.003)	(.003)	(.001)
51.1 (p75)	.025***	.026***	.037***
	(.003)	(.003)	(.001)

[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.

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

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

Table 3: Estimated Marginal Effects of a Five Percentage Point Increase in Major Concentration (PC_m) at Different Points in the Major Occupational Specificity (OS_m) and PC_m Distributions

	P(full-time employment)[a]			Log-earnings[b]		
OS_m	Major concentration (PC_m) starting value					
starting value	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***
	(.001)	(.001)	(.001)	(.000)	(.000)	(.000)
25.2 (p50)	.004**	.002	.000	.027***	.023***	.021***
	(.002)	(.002)	(.002)	(.001)	(.001)	(.001)
51.1 (p75)	.003	.001	-.001	.042***	.040***	.038***
	(.002)	(.002)	(.003)	(.001)	(.001)	(.001)
Total effects (reduce credits in lowest-OS non-discipline course)[c]						
p25 (10.2)	.001	.001	.000	.009***	.008***	.007***
	(.001)	(.001)	(.001)	(.001)	(.000)	(.000)
p50 (25.2)	.004**	.002	-.000	.025***	.021***	.018***
	(.002)	(.002)	(.002)	(.001)	(.001)	(.001)
p75 (51.1)	.003	.001	-.001	.040***	.038***	.036***
	(.002)	(.002)	(.003)	(.001)	(.001)	(.001)
Total effects (reduce credits in highest-OS non-discipline course)[c]						
p25 (10.2)	-.017***	-.019***	-.020***	-.054***	-.057***	-.059***
	(.003)	(.003)	(.003)	(.001)	(.001)	(.001)
p50 (25.2)	-.006**	-.011***	-.016***	-.035***	-.044***	-.052***
	(.003)	(.003)	(.003)	(.001)	(.001)	(.001)
p75 (51.1)	.004	-.005	-.012***	-.014***	-.031***	-.048***
	(.004)	(.003)	(.003)	(.001)	(.001)	(.001)

[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 $PCOS_o$ 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.

Note: Based on estimated regression coefficients reported in appendix table A2. Marginal effects are computed at the given percentile values of OS_m and PC_m and mean values (using the employment sample) of other credit-related variables. A five point increase in PC_m 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.

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_m) and $PCOS_d$ Distributions

	P(full-time employment)[a]			Log-earnings[b]		
OS_m	$PCOS_d$ starting value					
starting value	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***
	(.002)	(.001)	(.001)	(.001)	(.001)	(.000)
p50 (25.2)	.006***	.006***	.005***	.046***	.041***	.031***
	(.002)	(.001)	(.001)	(.001)	(.001)	(.000)
p75 (51.1)	.003*	.003*	.002	.044***	.038***	.027***
	(.002)	(.002)	(.002)	(.001)	(.001)	(.001)

[ab]See notes a and b in table 2.

Note: Based on estimated regression coefficients reported in appendix table A2. Marginal effects are computed at the given percentile values of OS_m and $PCOS_d$ and mean values (using the employment sample) of other credit-related variables. $PCOS_d$ 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 1% level; remaining estimates have significance levels above 10%.

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_m) and $PCOS_o$ Distributions

	P(full-time employment)[a]			Log-earnings[b]		
OS_m	$PCOS_o$ starting value					
starting value	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***
	(.004)	(.003)	(.003)	(.001)	(.001)	(.001)
p50 (25.2)	.014***	.012***	.009***	.080***	.069***	.053***
	(.003)	(.003)	(.003)	(.001)	(.001)	(.001)
p75 (51.1)	.004	.003	.003	.079***	.068***	.053***
	(.005)	(.003)	(.004)	(.001)	(.001)	(.001)

[ab]See notes a and b in table 2.

Note: Based on estimated regression coefficients reported in appendix table A2. Marginal effects are computed at the given percentile values of OS_m and $PCOS_o$ and mean values (using the employment sample) of other credit-related variables. $PCOS_o$ 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.

***Statistically significant at the 1% level; remaining estimates have significance levels above 10%.

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 $PCOS_o$ Distribution and Using Alternative Samples
(Dependent variable is log-earnings; OS_m starting value is the sample median)

	$PCOS_o$ starting value		
	500.2	731.1	1068.2
Sample/Specification description	(p25)	(p50)	(p75)
Full sample (from table 5)	.080***	.069***	.053***
n=1,527,187	(.001)	(.001)	(.001)
Add "final" GPA to ability controls	.080***	.068***	.052***
n=1,527,187	(.001)	(.001)	(.001)
Drop transfer students and double majors	.086***	.074***	.055***
n=1,129,955	(.001)	(.001)	(.001)
Credit variables based on last 2 years of coursework	.081***	.069***	.053***
n=1,527,187	(.001)	(.001)	(.001)
Graduates of six highest quality universities only[a]	.082***	.070***	.053***
n=1,118,176	(.001)	(.001)	(.001)
Graduates of Ohio State University only	.084***	.064***	.035***
n=393,575	(.003)	(.002)	(.003)
Employed for ≥3 years after college graduation	.072***	.063***	.050***
n=882,590	(.001)	(.001)	(.001)
Earnings in 4th year after college graduation	.084***	.071***	.052***
n=59,895	(.005)	(.004)	(.005)

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

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_m	6.2	8.3	63.4
PC_m	37.5	33.8	22.1
$PCOS_d$	491.5	14.9	904.2
$PCOS_o$	438.2	835.3	644.7
Increments:			
$PCOS_d$	247.6	—	—
$PCOS_o$	—	283.2	310.2
Marginal effects			
Full-time employment[a]	.013***	.019***	-.001
Log earnings[b]	.062***	.055***	.084***

[a,b]See notes a and b in table 2.

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 $PCOS_d$ or $PCOS_o$; 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).

***Statistically significant at the 1% level; the remaining estimate has a significance level about 10%.

Table A1: Means and Standard Deviations for Select Regression Variables (weighted and unweighted samples)

	Employment		Log-Earnings	
Regressor	Unwtd.	Wtd.[a]	Unwtd.	Wtd.[a]
Dependent variables				
1 if employment=1	.79	.77	—	—
1 if full-time employment=1	.71	.70	—	—
Log-earnings	—	—	5.77	5.79
			(.68)	(.69)
Credit-related regressors				
Occupational specificity of major	33.74	31.49	35.31	31.49
(OS_m)	(26.61)	(24.79)	(26.97)	(24.79)
Credit-weighted occupational specificity indexes:				
Within-major ($PCOS_m$)/100	10.26	8.61	10.74	8.61
	(11.80)	(9.83)	(12.13)	(9.81)
Within-discipline ($PCOS_d$)/100	4.75	5.09	4.96	5.12
	(5.76)	(6.13)	(5.88)	(6.15)
Outside discipline ($PCOS_o$)/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
	(.91)	(.93)	(.90)	(.92)
1st term percent completed credits	.854	.833	.863	.840
	(.37)	(.35)	(.36)	(.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's 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		1,527,187	

[a]Observations are weighted by the inverse of the size of the individual's major to give equal weight to all majors.

Note: See table A2 for additional regressors.

Table A2: Estimated OLS Coefficients for Alternative Outcomes

Regressor	P(employ-ment)	P(full-time employment)	Log-earnings
OS_m	.0038**	.0031*	.0015**
$OS_m^2/100$	.0016	.0037*	.0100***
$PCOS_m/100$	.0014	.0007	.0020
$PCOS_m^2/10^4$	-.0003**	-.0006***	-.0009***
$PCOS_d/100$	.0061*	.0042	.0160***
$PCOS_d^2/10^5$	.0004	.0008	- .0011*
$PCOS_o/10$	.0014***	.0016***	.0033***
$PCOS_o^2/10^4$	-.0004***	-.0004***	-.0007***
$OS_m \cdot PCOS_m/10^4$	-.0021	.0170*	.0490***
$OS_m \cdot PCOS_m^2/10^6$	.0004***	.0008***	.0015***
$OS_m \cdot PCOS_d/10^4$	-.0028	.0120	-.0068**
$OS_m \cdot PCOS_d^2/10^6$	-.0001	-.0028	.0043***
$OS_m \cdot PCOS_o/1000$	-.0067***	-.0073***	-.0046***
$OS_m \cdot PCOS_o^2/10^6$	.0016***	.0017***	.0014***
$OS_m^2 \cdot PCOS_m/10^4$	-.0001	-.0004***	-.0010***
$OS_m^2 \cdot PCOS_d/10^6$	.0002	-.0170*	-.0500***
$OS_m^2 \cdot PCOS_o/10^5$	.0023*	.0025*	-.0008
$PCOS_m \cdot PCOS_d/10^4$	-.0005**	-.0007**	.0019***
$PCOS_m \cdot PCOS_d^2/10^8$	.0002	.0008	-.0034***
$PCOS_m \cdot PCOS_o/10^4$	.0009**	.0012***	.0012***
$PCOS_m \cdot PCOS_o^2/10^8$	-.0028**	-.0040***	-.0044***
$PCOS_m^2 \cdot PCOS_d/10^8$	.0016***	.0020***	-.0020***
$PCOS_m^2 \cdot PCOS_o/10^8$	-.0003	-.0001	.0024***
$PCOS_d \cdot PCOS_o /10^5$	.0003	.0028	.0270***
$PCOS_d \cdot PCOS_o^2/10^8$	.0012	.0008	-.0056***
$PCOS_d^2 \cdot PCOS_o/10^8$	-.0015	-.0014	-.0072***
Constant	.330***	.290***	5.150***
1 if male	-.012**	-.023***	-.180***
1 if Hispanic[c]	-.033	-.028	-.040***
1 if race=Black[bc]	-.020**	-.026**	-.063***
Asian	-.060***	-.065***	-.022***
other	-.027***	-.036***	.003
1st term grade point average	-.002	-.004**	.011***
1st term pct. completed credits	.044***	.048***	-.051***
1 if basic skills credits ≤ 3	.004	-.000	-.047***
1 if single 2-4 college transfer[c]	.009	.014	-.011**
1 if single 4-4 college transfer[bc]	.027***	.032***	-.014***
1 if multiple college transfers[ab]	.028***	.028**	.032***
1 if earns Associate's degree[bc]	.039***	.009	-.065***
1 if attends multiple campuses[bc]	.031***	.019***	-.033***
Age at bachelor's degree[c]	.012***	.010***	-.022***

Continued.

Table A2 (continued)

Regressor	P(employ-ment)	P(full-time employment)	Log-earnings
Years of work experience	—	—	.270 ***
Work experience squared[c]	—	—	-.021 ***
Adjusted R^2	.027	.033	.280
No. observations	90,709	90,709	1,527,187

[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.

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

Note: The four credit-related variables are occupational specificity of the major (OS_m) and credit-weighted occupational specificity indexes for courses taken within-major ($PCOS_m$),within-discipline ($PCOS_d$) and outside the discipline ($PCOS_o$). 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.

Table A3: OLDA Majors Mapped to Census Fields of Degrees Mapped to Closely Related 2010 Census Occupations

Discipline	OLDA major	Census field of degree	Code	Census Occupation	Code
Agriculture	Agriculture	General agriculture +	1100	*Farmers, ranchers and other agricultural managers*	0205
		Miscellaneous agriculture	1109	Biomedical and agricultural engineers	1340
				Agricultural and food scientists	1600
				Agricultural and food science technicians	1900
				Agricultural inspectors	6010
				Graders and sorters, agricultural products	6040
				Miscellaneous agricultural workers, including animal breeders	6050
	Agriculture	Ag. production/management	1102	Same occupations as General ag. (only *0205 is italicized*)	
	Agriculture	Animal science +	1103	Same occupations as General ag. (only *1600, 1900 are italicized*)	
		Food science +	1104		
		Plant science/agronomy +	1105		
		Soil science +	1106		
Agriculture	Forestry, wildlife, and natural resources	Environmental science	1301	Environmental engineers	1420
				Biological scientists	1610
				Conservation scientists and foresters	1640
				Environmental scientists and geoscientists	1740
				First-line supervisors of farming, fishing, and forestry workers	6005
				Fishing and hunting workers	6100
				Forest and conservation workers	6120
				Logging workers	6130
	Forestry, wildlife, and natural resources	Forestry +	1302	Environmental engineers	1420
		Natural resource management	1303	*Conservation scientists and foresters*	1640
				Environmental scientists and geoscientists	1740
				First-line supervisors of farming, fishing, and forestry workers	6005
				Fishing and hunting workers	6100
				Forest and conservation workers	6120
				Logging workers	6130
Arts	Design	Commercial art/graphic design +	6004	Archivists, curators, and museum technicians	2400
		Video game design/development	6008	*Artists and related workers*	2600
				Designers	2630
				Photographers	2910
Arts	Performing, visual, and fine arts	Drama and theater arts	6001	Artists and related workers	2600
				Actors	2700
				Producers and directors	2710
				Dancers and choreographers	2740

Continued.

Table A3 (continued)

Discipline	OLDA major	Census field of degree	Code	Census Occupation	Code
Arts (cont.)	Performing, visual (cont.)			Musicians, singers, and related workers	2750
				Television, video, and movie camera operators/editors	2920
	Performing, visual, and fine arts	Music	6002	Artists and related workers	2600
				Actors	2700
				Producers and directors	2710
				Dancers and choreographers	2740
				Musicians, singers, and related workers	2750
	Performing, visual, and fine arts	Visual and performing arts	6003	*Artists and related workers*	2600
				Designers	2630
				Actors	2700
				Producers and directors	2710
				Dancers and choreographers	2740
				Musicians, singers, and related workers	2750
				Photographers	2910
				Television, video, and movie camera operators and editors	2920
	Performing, visual, and fine arts	Film, video and photographic arts	6005	Archivists, curators, and museum technicians	2400
				Artists and related workers	2600
				Designers	2630
				Producers and directors	2710
				Photographers	2910
				Television, video, and movie camera operators and editors	2920
	Performing, visual, and fine arts	Fine Arts +	6000	Archivists, curators, and museum technicians	2400
		Art history and criticism +	6006	*Artists and related workers*	2600
		Studio arts +	6007	*Designers*	2630
		Miscellaneous fine arts	6099	*Photographers*	2910
Business	Accounting	Accounting	6201	Financial managers	0120
				Accountants and auditors	0800
				Budget analysts	0820
				Credit analysts	0830
				Financial analysts	0840
				Personal financial advisors	0850
				Financial examiners	0900
				Credit counselors and loan officers	0910
				Tax examiners and collectors, and revenue agents	0930

Continued.

Table A3 (continued)

Discipline	OLDA major	Census field of degree	Code	Census Occupation	Code
Business (cont.)	Accounting (cont.)			*Tax preparers*	0940
				Financial specialists, all other	0950
				Actuaries	1200
	Accounting	Actuarial science	6203	Financial managers	0120
				Accountants and auditors	0800
				Budget analysts	0820
				Credit analysts	0830
				Financial analysts	0840
				Personal financial advisors	0850
				Insurance underwriters	0860
				Financial examiners	0900
				Credit counselors and loan officers	0910
				Tax examiners and collectors, and revenue agents	0930
				Tax preparers	0940
				Financial specialists, all other	0950
				Actuaries	1200
Business	Computer and quantitative business	Management information systems	6212	*Computer and information systems managers*	0110
				Computer and information research scientists	1005
				Computer systems analysts	1006
				Information security analysts	1007
				Computer programmers	1010
				Software developers, applications and systems software	1020
				Computer support specialists	1050
				Database administrators	1060
				Network and computer systems administrators	1105
				Computer occupations, all other	1107
Business	Finance	Finance	6207	*Financial managers*	0120
				Compensation and benefits managers	0135
				Accountants and auditors	0800
				Appraisers and assessors of real estate	0810
				Budget analysts	0820
				Credit analysts	0830
				Financial analysts	0840
				Personal financial advisors	0850

Continued.

Table A3 (continued)

Discipline	OLDA major	Census field of degree	Code	Census Occupation	Code
Business (cont.)	Finance (cont.)			*Insurance underwriters*	0860
				Financial examiners	0900
				Credit counselors and loan officers	0910
				Tax examiners and collectors, and revenue agents	0930
				Tax preparers	0940
				Financial specialists, all other	0950
				Actuaries	1200
Business	Management	Bus. management/administration+	6203	*General and operations managers*	0020
		Operations logistics/e-comm.+	6204	*Advertising and promotions managers*	0040
		HR/personnel management +	6209	Marketing and sales managers	0050
		Hospitality management	6211	*Public relations and fundraising managers*	0060
				Administrative services managers	0100
				Compensation and benefits managers	0135
				Human resources managers	0136
				Training and development managers	0137
				Industrial production managers	0140
				Purchasing managers	0150
				Transportation, storage, and distribution managers	0160
				Farmers, ranchers, and other agricultural managers	0205
				Food service managers	0310
				Gaming managers	0330
				Lodging managers	0340
				Medical and health services managers	0350
				Natural sciences managers	0360
				Property, real estate, and community association managers	0410
				Social and community service managers	0420
				Emergency management directors	0425
				Miscellaneous managers, including funeral service managers	0430
				HR workers	0630
				Management analysts	0710
				First-line supervisors of retail sales workers	4700
				First-line supervisors of non-retail sales workers	4710
Business	Sales and marketing	Marketing +	6206	*Marketing and sales managers*	0050
		Marketing research	6208	Wholesale and retail buyers, except farm products	0520

Continued.

Table A3 (continued)

Discipline	OLDA major	Census field of degree	Code	Census Occupation	Code
Business (cont.)	Sales and marketing (cont.)			Purchasing agents, except wholesale, retail, and farm products	0530
				Market research analysts and marketing specialists	0735
				First-line supervisors of retail sales workers	4700
				First-line supervisors of non-retail sales workers	4710
				Advertising sales agents	4800
				Insurance sales agents	4810
				Securities, commodities, and financial services sales agents	4820
				Travel agents	4830
				Sales representatives, services, all other	4840
				Sales representatives, wholesale and manufacturing	4850
				Models, demonstrators, and product promoters	4900
				Real estate brokers and sales agents	4920
				Sales engineers	4930
				Sales and related workers, all other	4965
Business	Other business	General business +	6200	Same occupations as sales/marketing +	
		Business economics +	6205	*General and operations managers*	0020
		International business +	6210	*Financial managers*	0120
		Miscellaneous business	6299	*Business operations specialists, all other*	0740
Communi- cations	Journalism	Communications +	1902	*Announcers*	2800
		Journalism +	1902	*News analysts, reporters and correspondents*	2810
		Mass media	1903	Public relations specialists	2825
				Editors	2830
				Technical writers	2840
				Writers and authors	2850
				Miscellaneous media and communication workers	2860
				Broadcast/sound engineering technicians and radio operators	2900
				Photographers	2910
				Television, video, and motion picture camera operators/editors	2920
				Misc. office/admin. support workers, incl. desktop publishers	5940
Comm.	Public relations, advertising	Advertising/public relations	1904	*Advertising and promotions managers*	0040
				Marketing and sales managers	0050
				Public relations and fundraising managers	0060
				Public relations specialists	2825
				Editors	2830

Continued.

Table A3 (continued)

Discipline	OLDA major	Census field of degree	Code	Census Occupation	Code
Comm. (cont.)	Public relations, advertising (cont.)			Technical writers	2840
				Writers and authors	2850
				Miscellaneous media and communication workers	2860
				Broadcast/sound engineering technicians and radio operators	2900
				Advertising sales agents	4800
				Misc. office/admin. support workers, incl. desktop publishers	5940
Education	Education admin.	Educ. administration/supervision+	2301	*Education administrators*	0230
		Miscellaneous education	2399	Postsecondary teachers	2200
				Preschool and kindergarten teachers	2300
				Elementary and middle school teachers	2310
				Secondary school teachers	2320
				Special education teachers	2330
				Other teachers and instructors	2340
				Librarians	2430
				Library technicians	2440
				Teacher assistants	2540
				Other education, A/V specialists, training, and library workers	2550
Education	Elementary education	Elementary education +	2304	Same occupations as education administration	
		Early childhood education	2307	(*only 2300, 2310 are italicized*)	
Education	Junior and senior education	General education +	2300	Same occupations as education administration	
		Counseling +	2303	(*only 2320, 2340, 2430 are italicized*)	
		Physical/health education +	2306		
		Computer teacher education +	2302		
		Math teacher education +	2305		
		Science teacher education +	2308		
		Secondary education +	2309		
		Social science education +	2311		
		Multiple levels education +	2312		
		Language/drama education +	2313		
		Art and music education	2314		
Education	Special ed.	Special needs education	2310	Same occupations as education administration (*2330*)	
Engineering	Architecture	Architecture	1401	Architectural and engineering managers	0300
				Architects, except naval	1300
				Surveyors, cartographers and photogrametrists	1310

Continued.

Table A3 (continued)

Discipline	OLDA major	Census field of degree	Code	Census Occupation	Code
Engineering (cont.)	Architecture (cont.)			Drafters	1540
				Surveying and mapping technicians	1560
				Designers	2630
Engineering	Aerospace engineering		2401	Architectural and engineering managers	0300
				Aerospace engineers	1320
				Biomedical and agricultural engineers	1340
				Chemical engineers	1350
				Civil engineers	1360
				Computer hardware engineers	1400
				Electrical and electronics engineers	1410
				Environmental engineers	1420
				Industrial engineers, including health and safety	1430
				Marine engineers and naval architects	1440
				Materials engineers	1450
				Mechanical engineers	1460
				Petroleum, mining and geological engineers	1520
				Miscellaneous engineers, including nuclear engineers	1530
				Engineering technicians, except drafters	1550
Engineering	Biological engineering	Biological engineering + Biomedical engineering	2402 2404	Same occupations as aerospace engineering (*only 1340 is italicized*)	
Engineering	Chem. eng.	Chemical engineering	2405	Same occupations as aerospace engineering (*1350*)	
Engineering	Civil eng.	Civil engineering	2406	Same occupations as aerospace engineering (*1360*)	
Engineering	Comp. eng.	Computer engineering	2407	Same occupations as aerospace engineering (*1400*) +	
				Computer systems analysts	1006
				Computer programmers	1010
				Software developers, applications and systems software	1020
				Computer support specialists	1050
Engineering	Elec. eng.	Electrical engineering	2408	Same occupations as aerospace engineering (*1410*)	
Engineering	Indus. eng.	Industrial/manufacturing eng.	2412	Same occupations as aerospace engineering (*1430*)	
Engineering	Mech. eng.	Mechanical engineering + Engineering mechanics/physics	2414 2409	Same occupations as aerospace engineering (*1460*)	
Engineering	Envir. eng.	Environmental engineering + Geological engineering	2410 2411	Same occupations as aerospace engineering (*1420*)	
Engineering	Mater. eng.	Materials engineering and science	2413	Same occupations as aerospace engineering (*1450*)	

Continued.

Table A3 (continued)

Discipline	OLDA major	Census field of degree	Code	Census Occupation	Code
Engineering	Other eng.	General engineering +	2400	Same occupations as aerospace engineering (*1320,1340,1350,*	
		Architectural engineers +	2403	*1360,1400,1410,1420,1430,1440,1450,1460,1520,1530 are*	
		Miscellaneous engineering	2499	*Italicized)*	
Engineering	Engineering technology	Engineering technologies +	2500	*Architectural and engineering managers*	0300
		Engineering/industrial mgmt.+	2501	*Logisticians*	0700
		Electrical engineering tech. +	2502	Miscellaneous engineers, including nuclear engineers	1530
		Industrial production tech. +	2503	*Engineering technicians, except drafters*	1550
		Mechanical engineering tech. +	2504	Surveying and mapping technicians	1560
		Misc. engineering technology	2599	Geological and petroleum technicians, and nuclear technicians	1930
				Miscellaneous life, physical, and social science technicians	1965
				Avionics technicians	7030
				Aircraft mechanics and service technicians	7140
Health	Commun. disorders	Communication disorders	6102	*Special education teachers*	2330
				Audiologists	3140
				Speech-language pathologists	3230
Health	General and public health	Community and public health	6110	*Medical and health services managers*	0350
				Counselors	2000
				Social workers	2010
				Miscellaneous community and social service specialists	2025
				Other healthcare practitioners and technical occupations	3540
				Nursing, psychiatric, and home health aides	3600
				Healthcare support workers, all other	3655
Health	Health admin.	General medical and health svcs.+	6100	*Medical and health services managers*	0350
		Medical office administration +	6101	*Medical records and health information technicians*	3510
		Health and medical admin. svcs.	6103		
Health	Nursing	Nursing	6107	*Medical and health services managers*	0350
				Dietitians and nutritionists	3030
				Physician assistants	3110
				Registered nurses	3255
				Nurse anesthetists	3256
				Nurse practitioners and nurse midwives	3258
				Licensed practical and licensed vocational nurses	3500
				Nursing, psychiatric, and home health aides	3600
Health	Diet/nutrition	Nutrition sciences	4002	*Dietitians and nutritionists*	3030

Continued.

Table A3 (continued)

Discipline	OLDA major	Census field of degree	Code	Census Occupation	Code
Health (cont.)	Dietetics, nutrition (cont.)			Licensed practical and licensed vocational nurses	3500
				Miscellaneous health technologists and technicians	3535
				Other healthcare practitioners and technical occupations	3540
Health	Medical technology	Nuclear/radiation technologies +	5102	*Clinical laboratory technologists and technicians*	3300
		Medical assisting services +	6104	*Diagnostic related technologists and technicians*	3320
		Medical technologies	6105	*Emergency medical technicians and paramedics*	3400
				Health practitioner support technologists and technicians	3420
				Medical records and health information technicians	3510
				Miscellaneous health technologists and technicians	3535
				Other healthcare practitioners and technical occupations	3540
				Phlebotomists	3649
				Healthcare support workers, all other,	3655
Health	Health therapy	Treatment therapy professions +	6109	Counselors	2000
		Energy/bio. based therapy	6111	Social workers	2010
				Occupational therapists	3150
				Physical therapists	3160
				Radiation therapists	3200
				Recreational therapists	3210
				Respiratory therapists	3220
				Other therapists, including exercise physiologists	3245
Health	Pharmacy	Pharmacy	6108	*Pharmacists*	3050
				Health diagnosing and treating practitioners, all other	3260
				Health practitioner support technologists and technicians	3420
				Other healthcare practitioners and technical occupations	3540
				Healthcare support workers, all other	3655
Health	Professional medicine	Health/medical preparatory +	6106	*Chiropractors*	3000
		Misc. health medical professions	6108	*Dentists*	3010
				Optometrists	3040
				Physicians and surgeons	3060
				Physician assistants	3110
				Podiatrists	3120
				Radiation therapists	3200
				Health diagnosing and treating practitioners, all other	3260
				Dental hygienists	3310

Continued.

Table A3 (continued)

Discipline	OLDA major	Census field of degree	Code	Census Occupation	Code
Health (cont.)	Professional medicine (cont.)			*Opticians, dispensing*	3520
				Other healthcare practitioners and technical occupations	3540
				Nursing, psychiatric, and home health aides	3600
				Healthcare support workers, all other	3655
Humanities	Area/ethnic	Area/ethnic/civilization studies	1501	None	
Humanities	English	English language and literature +	3301	*Editors*	2830
		Composition and rhetoric	3302	*Technical writers*	2840
				Writers and authors	2850
				Miscellaneous office workers, including desktop publishers	5940
Humanities	Foreign languages	Linguistics +	2601	None	
		French, German, Latin	2602		
		Other foreign languages	2603		
Humanities	History	History +	6402	None	
		United States history	6403		
Humanities	Liberal and general stud.	Liberal arts +	3401	None	
		Humanities	3402		
Humanities	Philosophy	Philosophy and religious studies	4801	Clergy	2040
				Directors, religious activities and education	2050
				Religious workers, all other	2060
Natural sciences	Chemistry	Chemistry	5003	Natural sciences managers	0360
				Agricultural and food scientists	1600
				Biological scientists	1610
				Medical scientists, and life scientists, all other	1650
				Chemists and materials scientists	1720
				Physical scientists, all other	1760
				Agricultural and food science technicians	1900
				Biological technicians	1910
				Chemical technicians	1920
				Miscellaneous life, physical, and social science technicians	1965
Natural sciences	Other biology	Biology +	3600	Natural sciences managers	0360
		Biochemistry +	3601	Agricultural and food scientists	1600
		Botany +	3602	*Biological scientists*	1610
		Molecular biology +	3603	Medical scientists, and life scientists, all other	1650
		Ecology +	3604	Chemists and materials scientists	1720

Continued.

Table A3 (continued)

Discipline	OLDA major	Census field of degree	Code	Census Occupation	Code
Natural sciences (cont.)	Other biology (cont.)	Genetics +	3605	Agricultural and food science technicians	1900
		Microbiology +	3606	*Biological technicians*	1910
		Neuroscience +	3611	Chemical technicians	1920
		Miscellaneous biology	3699	Miscellaneous life, physical, and social science technicians	1965
				Clinical laboratory technologists and technicians	3300
Natural sciences	Zoology	Physiology +	3608	Natural sciences managers	0360
		Zoology	3609	Agricultural and food scientists	1600
				Biological scientists	1610
				Conservation scientists and foresters	1640
				Medical scientists, and life scientists, all other	1650
				Environmental scientists and geoscientists	1740
				Agricultural and food science technicians	1900
				Biological technicians	1910
				Chemical technicians	1920
				Miscellaneous life, physical, and social science technicians	1965
				Clinical laboratory technologists and technicians	3300
				Animal trainers	4340
				Nonfarm animal caretakers	4350
Natural sciences	Physical sciences	Physical sciences +	5000	Natural sciences managers	0360
		Astronomy and astrophysics +	5001	*Astronomers and physicists*	1700
		Atmospheric sciences +	5002	*Atmospheric and space scientists*	1710
		Geology and earth sciences +	5004	*Chemists and materials scientists*	1720
		Geoscience +	5005	*Environmental scientists and geoscientists*	1740
		Physics +	5007	*Physical scientists, all other*	1760
		Materials science +	5008	Chemical technicians	1920
		Multi-disciplinary science +	5098	*Geological and petroleum technicians, and nuclear technicians*	1930
		Misc. physical science	5099	Miscellaneous life, physical, and social science technicians	1965
Natural sciences	Computer sciences	Computer and info. systems +	2100	*Computer and information systems managers*	0110
		Computer programming +	2101	*Computer and information research scientists*	1005
		Computer sciences +	2102	*Computer systems analysts*	1006
		Computer systems analysis +	2103	*Information security analysts*	1007
		Data processing +	2104	*Computer programmers*	1010
		Information sciences +	2105	*Software developers, applications and systems software*	1020
		Computer admin./mgmt. +	2106	*Web developers*	1030

Continued.

Table A3 (continued)

Discipline	OLDA major	Census field of degree	Code	Census Occupation	Code
Natural sciences (cont.)	Computer sciences (cont.)	Computer networking +	2107	*Computer support specialists*	1050
		Misc. computer sciences	2199	*Database administrators*	1060
				Network and computer systems administrators	1105
				Computer network architects	1106
				Computer occupations, all other	1107
				Miscellaneous mathematical science occupations	1240
Natural sciences	Mathematics, statistics	Mathematics +	3700	Financial analyst	0840
		Applied mathematics +	3701	Computer systems analyst	1006
		Statistics +	3702	*Actuary*	1200
		Decision science +	3705	*Operations research analysts*	1220
		Miscellaneous mathematics	3799	*Misc. math. Science occupations, including mathematicians*	1240
Social sciences	Criminal justice	Criminal justice/fire protection	5301	*First-line supervisors of correctional officers*	3700
				First-line supervisors of police and detectives	3710
				First-line supervisors of firefighting and prevention workers	3720
				First-line supervisors of protective service workers, all other	3730
				Firefighters	3740
				Fire inspectors	3750
				Bailiffs, correctional officers, and jailers	3800
				Detectives and criminal investigators	3820
				Police officers	3850
				Private detectives and investigators	3910
				Security guards and gaming surveillance officers	3930
				Transportation security screeners	3945
Social sciences	Economics	Agricultural economics +	1102	*Economists*	1800
		Economics	5501	*Urban and regional planners*	1840
				Miscellaneous social scientists, including survey researchers	1860
				Misc. social science technicians, incl. research assistants	1965
Social sciences	Family and consumer studies	Family and consumer sciences	2901	Social and community service managers	0420
				Miscellaneous social scientists, including survey researchers	1860
				Misc. social science technicians, incl. research assistants	1965
				Social and human service assistants	2016
				Social workers	2010
Social sciences	International relations	International relations	5501	*Miscellaneous social scientists, incl. survey researchers*	1860
				Misc. social science technicians, including research assistants	1965

Continued.

Table A3 (continued)

Discipline	OLDA major	Census field of degree	Code	Census Occupation	Code
Social sciences	International relations	International relations	5501	*Miscellaneous social scientists, incl. survey researchers*	1860
				Misc. social science technicians, including research assistants	1965
Social sciences	Other social sciences	Interdisciplinary Social Sciences +	4007	Social and community service managers	1840
		Public Administration +	5401	Urban and regional planners	1860
		Public Policy +	5402	*Miscellaneous social scientists, including survey researchers*	1965
		General Social Sciences +	5500	*Misc. social science technicians, including research assistants*	2105
		Anthropology +	5502	Social workers	2145
		Geography +	5504	Social and human service assistants	2160
		Miscellaneous Social Sciences	5599		
Social sciences	Political science	Pre-law and legal studies +	3202	Urban and regional planners	1840
		Political science and government	5506	*Miscellaneous social scientists, including survey researchers*	1860
				Misc. social science technicians, including research assistants	1965
				Judicial law clerks	2105
				Paralegals and legal assistants	2145
				Miscellaneous legal support workers	2160
Social sciences	Psychology	Psychology +	5200	Social and community service managers	0420
		Educational Psychology +	5201	*Psychologists*	1820
		Clinical Psychology +	5202	Miscellaneous social scientists, including survey researchers	1860
		Counseling Psychology +	5203	Misc. social science technicians, including research assistants	1965
		Experimental Psychology +	5204	*Counselors*	2000
		Industrial/Org Psychology +	5205	Social workers	2010
		Social Psychology +	5206	Social and human service assistants	2016
		Miscellaneous Psychology	5299		
Social sciences	Social Work	Social Work	5404	*Social and community service managers*	0420
				Miscellaneous social scientists, including survey researchers	1860
				Misc. social science technicians, including research assistants	1965
				Counselors	2000
				Social workers	2010
				Social and human service assistants	2016
Social sciences	Sociology	Sociology	5507	Social and community service managers	0420
		Criminology	5503	*Miscellaneous social scientists, including survey researchers*	1860
				Misc. social science technicians, including research assistants	1965
				Social workers	2010
				Social and human service assistants	2016

Continued.

Table A3 (continued)

Discipline	OLDA major	Census field of degree	Code	Census Occupation	Code
Sports and recreation	Sports and recreation	Physical fitness, parks/recreation and leisure	4101	Athletes, coaches, umpires, and related workers	0420
				Entertainers and performers, sports and related workers	1860
				Physical therapists	1965
				Lifeguards and other recreational workers	2010
				Recreation and fitness workers	2016

Note: For panels defined by *solid* horizontal lines, all Census degree fields map to the given OLDA field and to *all* listed Census occupations. For example, Census fields Sociology (5507) and Criminology (5503) both map to OLDA field Sociology and to the five listed Census occupations. For panels defined by *dotted* lines, multiple Census fields map to the same OLDA major. In the arts discipline, for example, five Census fields (drama/theater arts; music; visual/performing arts; film, video/photographic arts; and the aggregate of fine arts, *etc.*) are each matched to different occupations, and then aggregated to form a single OLDA major (performing, visual and fine arts). For each OLDA field, occupational specificity (OS_f) is defined as the percent of ACS workers with the given Census degree(s) who work in any of the given occupations. Occupations indicated by italics form an alternative, narrow occupational specificity variable. See section 3.C and table 1 for details.