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College major, college coursework, and post-college wages

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ABSTRACT

We ask whether estimated wage payoffs to college majors change when we account for skills acquired in college by including college major dummies and detailed coursework measures in log-wage models. Using data from the 1997 National Longitudinal Survey of Youth, we find that students in all majors differ considerably in the percentage of credits taken within-major, as well as in their overall credit distributions. When credit distributions are taken into account in modeling log-wages, estimated coefficients for college majors often fall by 50% or more. Moreover, estimated log-wage gaps between select pairs of majors often change by orders of magnitude depending on whether we compare individuals whose overall credit distributions correspond to obtaining a low, medium, or high level of credit concentration within the major.

1. Introduction

Research on the wage payoffs associated with college majors has constituted an important strand of the "returns to schooling" literature from its genesis in the 1980s (Angle & Wissmann, 1981; Berger, 1988; Daymont & Andrisani, 1984) through recent, innovative efforts to identify causality (Arcidiacono, 2004; Hastings, Neilson, & Zimmerman, 2014; Kirkeboen, Lueven, & Mostad, 2016). Across four decades, the rationale for a focus on college major has invariably been that we observe substantial variation in wages—even after eliminating heterogeneity in school quantity (by focusing on college graduates) and, in some cases, school quality (by using data for a single institution)—because a college education imparts different skills depending on the field of study. Among workers with a bachelor's degree, college major has long been regarded as a suitable proxy for skill.[1]

In this study, we contribute to ongoing efforts to account for skill heterogeneity among college graduates by supplementing college major dummies in log-wage models with detailed measures of college coursework—*viz.*, the percentage of total college credits completed in each subject area.[2] Even among college graduates with the same major, college credit distributions and, in turn, skills can differ dramatically as a result of heterogeneity in abilities and preferences, the desire to diversify portfolios against future labor market risks, the timing of major selection, institutional requirements, and major-specific requirements. Not all data sources that support the identification of wage payoffs to college majors provide transcript records or similarly detailed information on college credits by field. When the requisite data *are* available, however, we demonstrate that a great deal can be learned by including coursework measures in the analysis. Course credit distributions not only measure skills in more detail than do binary indicators of college major, but they enable us to separate credentialing effects of majors from the skill effects captured by each worker's distribution of completed courses.[3]

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[1] A particularly clear example of this belief is provide by Grogger and Eide (1995), who write (p. 281): "The skills one acquires while in college are likely to depend on one's major field of study…"

[2] We use "coursework" to refer to courses completed for credit toward a bachelor's degree. Because course counts do not have a uniform meaning across institutions, we measure coursework with a 13-variable array summarizing each student's credit distribution across fields. We experimented with grade-weighted credit distributions to account not only for the percentage of credits acquired in a given field but also the performance in each course, but this proved not to affect our findings; details are provided in section 3.

[3] In their overview of existing evidence on the returns to college major, Altonji *et al.* (2012) allude to the value of including coursework information (p. 211): "Whether one includes college variables, such as 'semesters of math,' depends on whether one wishes to measure the total effect of a particular college major (including human capital accumulation in the form of coursework and grades) or the effect of the title of the degree, net of substantive skill differences…(Explaining differences in the returns to majors with differences in course content and grades, as opposed to the credential effect of the field of degree, is an interesting challenge for research.)"

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To pursue this extension, we use a sample of bachelor's degree recipients who participated in the 1997 National Longitudinal Survey of Youth (NLSY97) and for whom college transcripts were collected and coded. We use transcript data to identify each sample member's college major (using a 13-field taxonomy) and percentage of total college credits earned in each of 13 fields. We first summarize the extent to which major-specific credit concentrations as well as overall credit distributions differ within and across major. We then estimate log-wage models in which the key regressors are, alternatively, college major dummies, "percentage of total college credit" variables, and *both* sets of major and credit variables. By identifying college major coefficients with and without controls for credit distributions, we are able to separate "gross" college major effects from their credentialing effects net of skills. By assigning workers alternative credit distributions corresponding to low, medium, or high levels of concentration in their majors, we can compare conventionally-estimated, "average" payoffs to each major with a *range* of estimates that account for skill differences within and across major.

Our key findings are three-fold: First, college students with the same major often have markedly different credit distributions, although some majors contain more heterogeneity than others. For example, the interquartile range in the percentage of credits completed in the major is as low as 13.2 percentage points for agriculture majors and as high as 34.7 percentage points among students majoring in health professions. Second, the addition of college credit variables to a log-wage model leads to a 42–68% decrease in estimated major coefficients for the most remunerative fields (engineering, health professions, and mathematics/computer science), but an *increased* point estimate for the least remunerative major (arts). This implies that the highest-paying majors impart substantial rewards to skill *and* credentialing, while skill effects are negative among arts majors. Third, the estimated log-wage gap between majors is often (but not always) orders-of-magnitude different depending on the assumed credit distributions. For example, we estimate a log-wage gap of 0.073 between social sciences and humanities majors when controlling for major only (along with baseline controls). When we also control for credit distributions, the estimated gap falls to an imprecisely estimated 0.033 if we compare a low-concentration social sciences major to a low-concentration humanities major, and it almost doubles to 0.130 when we instead compare high-concentration majors. At the same time, the estimated log-wage gap between health and business majors remains between 0.15 and 0.18 regardless of how or whether we account for credit distributions. Based on these (and other) findings, we argue that the incorporation of credit measures leads to a more nuanced understanding of wage payoffs to a college education than can be obtained from college major controls alone.

2. Background

In this section we provide a brief overview of research on the returns to college major, and then summarize a number of ways in which measures of college credits have been analyzed in the literature. Throughout, we focus on studies that are most relevant to our analysis.

Most analyses of the links between college major and post-college wages fall into one of three categories: (1) efforts to control as completely as possible for skill differences between men and women in an effort to explain the gender wage gap (Black, Haviland, Sanders, & Taylor, 2008; Brown & Corcoran, 1997; Daymont & Andrisani, 1984; Joy, 2003); (2) assessments of the wage payoff to the quality of the match between field of study and occupation (Kinsler & Pavan, 2015; Lemieux, 2014; Robst, 2007a, 2007b); and (3) efforts to identify returns to different types of skill investments as proxied by college majors (Altonji, Blom, & Meghir, 2012; Altonji, Kahn, & Speer (2014); Arcidiacono, 2004; Chevalier, 2011; Hamermesh & Donald, 2008; Grogger & Eide, 1995; Hastings et al., 2014; Kirkeboen et al., 2016; Rumberger & Thomas, 1993; Webber, 2014, 2016). Our goal is to extend the third strand of the literature to include detailed college credit distributions; we defer extensions to the analysis of gender differences and major-occupation matching to future work.

Studies that identify wage payoffs to alternative college majors invariably predict large gaps between workers with the highest and lowest paying majors. A widely-cited finding reported in Altonji et al. (2012) is that, among men, the predicted log-wage gap between electrical engineering and general education majors (0.561) is remarkably similar to the predicted log-wage gap between high school and college graduates (0.577). While Altonji et al. (2012) use data from the American Community Survey, Hamermesh and Donald (2008) predict a similar log-wage gap of roughly 0.5 between "hard" business majors and education majors using a mixed-sex sample of University of Texas undergraduates. Webber (2016) combines data from multiple surveys to compute the present discounted value of degrees in various fields; for a student with the median ability level, he finds that a degree in a STEM field is worth $191,469 more than a degree in the arts or humanities. Using data for college graduates in the U.K., Chevalier (2011) reports evidence that is particularly germane to our analysis: the estimated wage gap *within* majors (obtained by comparing the 10th and 90th percentiles) is as large as 0.8–0.9 log-points, which is considerably higher than the estimated wage gap *between* most majors (obtained by comparing means). This suggests considerable skill heterogeneity within majors.

In identifying wage payoffs to college majors the challenge, of course, is to separate the causal skill effect associated with a degree from the confounding effects of innate (or pre-college) ability and other factors. The most rigorous solutions to this endogeneity problem use structural estimation (Arcidiacono, 2004; Beffy, Fougère, & Maurel, 2012) or exploit discontinuities around admissions cutoffs that arise when admission into degree programs is granted via a formal, centralized process (Hastings et al., 2014; Kirkeboen et al., 2016). The majority of studies use a "selection on observables" approach where pre-college test scores and other background measures are used to control for ability, preferences, and other factors that affect the choice of major (Altonji et al., 2012; Grogger & Eide, 1995; Rumberger & Thomas, 1993; Webber, 2014). In our application, where college majors and the distribution of credits across fields are jointly self-selected (an issue that we return to in Section 4), selection on observables appears to be the only feasible identification strategy.

Only a handful of studies have specified wage models in which measures of individual workers' college coursework are included along with college majors.[4] In the study by Hamermesh and Donald (2008) mentioned above, the log-wage models used to identify major-specific intercepts also control for SAT scores and high school rank, the (combined) number of credits in upper-level mathematics and science courses, and the grade point average in those courses. OLS estimates indicate that 15 upper-level math/science credits are associated with a wage increase of 3.2%, while a B-average (GPA = 3.0) in all upper-level math/science courses is associated with a 7.1% increase. In her analysis of the gender wage gap among college graduates, Joy uses data from the 1993–94 Baccalaureate and Beyond to estimate a log-wage model that conditions on college GPA, college major, credits in each field and college characteristics, as well as such job characteristics as industry, occupation, and sector. She finds that course credits account for 6% (7%) of the gap while major accounts for 1% (9%) when male (female) weights are used, suggesting that heterogeneity in coursework plays a substantial role in explaining wages conditional on major—although the combined effects of industry and hours worked are the dominant factors in explaining the wage gap. James, Alsalam, Conaty, and To (1989) use data from the National Longitudinal Study of the High School Class of 1972 to estimate log-wage models with controls for a range of college quality variables in addition to college major dummies,

[4] Brown and Corcoran (1997), Dolton and Vignoles (2002), Hall (2016), and Tchuente (2016) use measures of coursework completed in high school.

the number of college credits completed in mathematics courses, college GPA, and numerous other factors. Their goal is to determine whether college quality leads to increased wages—and while they find that it does, they estimate higher payoffs to an engineering degree (0.349 log-points relative to majoring in "other"), math courses (0.0215 log-points per 10 credits) and a high GPA (0.0826 log-points per 1-point increase) than to college quality.

Another, related group of studies exploits college coursework data to construct major-specific, rather than individual-specific, regressors. Speer (2017) uses Baccalaureate and Beyond data to compute major-specific averages of the number of courses taken in each of seven fields, which he uses along with other major-specific characteristics to characterize each of 51 majors as a "bundle of characteristics" for an analysis (based on data from the NLSY97 and the 1979 National Longitudinal Survey of Youth) of gender gaps in college majors. Astorne-Figari and Speer (2019) use the same major-specific credit distributions and other traits as determinants of the decision to switch majors. In a similar vein, Leighton and Speer (2018) use average shares of credits earned in each field among students in each major to construct a Hirschman-Herfindahl Index of the extent to which each major's typical credit distribution is concentrated within a single field; this index serves as a proxy for the skill-specificity of each major in an analysis of the wage returns to specific skills.

Another approach involves using college coursework information to measure the specialization of individual workers' skill portfolios. Artz, Kimle, and Orazem (2014) use administrative records for agriculture majors at Iowa State University to measure specialization (following Lazear, 2005) as the number of credits in agriculture minus the number of credits in the most "concentrated" non-major field. They find that this specialization measure is weakly, negatively correlated with post-college wages. Silos and Smith (2015) use college credit distributions available in the 1980 High School & Beyond survey to construct a measure of college graduates' level of concentration ("specialization") in their major field. They find that graduates with a relatively specialized skill portfolio tend to earn higher wages when they remain in a single occupation than if they switch occupations, while those with relatively diversified portfolio are predicted to earn more if they switch than if they stay; these findings are consistent with the notion that workers face a tradeoff between specializing in skills with the highest expected payoff and diversifying their portfolio to mitigate occupational risk.

In summary, an extensive body of research has identified wage differences among college majors, and a much smaller set of studies has exploited information on college coursework. The discrepancy is unsurprising, given that relatively few data sources link individual college graduates' post-school wages with college transcript data or even with summary information on college coursework. When such data are available, however, the question remains: Why focus exclusively on college major dummies to characterize skills acquired in college when the addition of detailed credit distributions are likely to paint a much more accurate picture?

3. Data

We use data from the 1997 National Longitudinal Survey of Youth (NLSY97), which is an ongoing, nationwide survey of individuals born in 1980–84 and residing in the U.S. at the time of their first interview in 1997. Respondents were interviewed annually from 1997 to 2011 and biennially from 2013 onward. We use data from 1997 through 2015, which was the last interview round for which data were available when we conducted the analysis. The original sample consisted of 8,984 individuals, although attrition and missed interviews reduced the sample size to 7,103 respondents (79.1% of the original sample) in 2015. The original sample was 51% male and, due to over-samples of Hispanics and blacks, 21% Hispanic and 26% (non-Hispanic) black.

We opted to use NLSY97 data for our analysis for the following reasons: First, transcripts were collected from most postsecondary institutions attended by NLSY97 respondents, so we are able to identify college majors and course credit distributions for a large sample of bachelor's degree recipients. Second, the Armed Services Vocational Aptitude Battery (ASVAB) was administered to respondents in 1997–98 at ages 12–18. These pre-college, cognitive test scores enable us to "net out" the effect of ability on college major and coursework decisions. Third, the survey collects detailed employment information from age 14 onward and is therefore an ideal data source for estimating early-career wage models.

3.A. Sample selection

We apply the following selection criteria to construct our sample. First, we eliminate 6,587 (73.3%) of the original 8,984 respondents because they did not earn a bachelor's degree before their last interview according to self-reported schooling information and/or the transcript records. We then eliminate 332 (13.9%) of the remaining 2,397 respondents for whom ASVAB scores are unavailable. Among the 2,065 respondents remaining in the sample, we drop another 556 (26.9%) for whom no college transcripts were collected, typically because they declined to sign a waiver or because their institution(s) did not comply with the transcript request. Among the remaining 1,509 bachelor's degree recipients, we drop 30 (2.0%) because the degree date is indeterminate and another 171 (11.6% of 1,479) because their transcript records include fewer than 20 courses; in most cases, incomplete transcripts arise when respondents attended multiple institutions and transcripts were not collected for each institution.[5] We lose another 56 respondents (4.3% of 1,308) because their college major cannot be determined by the process described in Section 3.B. Finally, we drop 72 (5.8% of 1,252) respondents because they fail to report at least one valid wage after their college graduation date and before the end of the observation period, which we define as the earlier of their last interview date or the first interview where the highest degree earned is no longer a bachelor's degree. We consider a wage to be valid if (*i*) the corresponding job's start date is identified; (*ii*) at least half the job's observed duration occurs after college graduation (to avoid using wages for "college jobs" that last a month or so beyond graduation); (*iii*) the respondent is not enrolled in school when the wage is earned; and (*iv*) the computed, average, hourly wage is between \$1 and \$300.

These selection rules produce a sample of 10,595 wage observations for 1,180 individuals. Women account for 677 (57.4%) of the 1,180 respondents and 6,287 (59.3%) of the 10,595 wage observations, despite comprising only 49% of the original NLSY97 sample. This is consistent with the fact that women received 57% of the bachelor's degrees conferred in the U.S. in 2005–06, which was the modal graduation year for NLSY97 respondents.[6]

As noted, we are forced to drop 727 of 2,397 college graduates from our sample due to missing or highly incomplete transcript information. Although these sample deletions are unavoidable, they would be

[5] For each two- and four-year institution attended between high school and college graduation, we divide the total number of credits by the modal, per-course credits for the institution, excluding courses taken prior to high school graduation or after college graduation, or that did not fall into one of the 13 aggregate fields described in section 3.B. The sum of these "credit-adjusted" course totals across institutions must be 20 or greater. Although 20 courses is unlikely to represent a complete transcript, we use this cut-off to maintain sample size and because we believe a reasonably accurate distribution of course credits can be obtained from partial records. In our final sample, the median respondent's transcript record contains 41 credit-adjusted courses, and 95% (75%) of respondents complete at least 27 (37) courses.

[6] The gender decomposition of bachelor's degree recipients is taken from Table 322.20 of the 2017 *Digest of Education Statistics* (U.S. Department of Education, National Center for Education Statistics), available at https://nces.ed.gov/programs/digest/d17/tables/dt17_322.20.asp.

problematic if college graduates with missing transcripts had dramatically different characteristics than those who remain in our sample. To establish that this is not a concern, we compare the "full" sample of 2,065 college graduates for whom ASVAB scores are available with the 1,308 college graduates who meet our transcript-related selection criteria. Specifically, we compare sample means for scores on composite ASVAB math and verbal scores (described in Section 3.C), indicators of black, Hispanic, male, and mother's highest grade completed. Differences in mean values across samples are statistically indistinguishable from zero for each factor except the two test scores, where the means are slightly higher in the final sample of 1,308 college graduates (difference = 0.045, p-value = 0.008 for math; difference = 0.048, p-value = 0.002 for verbal). This suggests that our final sample is "slightly selected" on higher-ability respondents, who perhaps were more willing to sign waivers, or on higher-quality institutions that were more likely to provide transcripts.

3.B. Key regressors

Our analysis focuses on estimated wage benefits associated with college major dummies (M_{if}) and the percentage of total college credits completed in each field (PC_{if}), where subscripts i and f refer to individual and field, respectively. We describe the estimation strategy used to model relationships between M_{if}, PC_{if}, and log-wages in Section 4 and additional variables included in the log-wage models in Section 3.C. Here, we discuss our construction of M_{if} and PC_{if}.

During the 14th and 15th interview rounds (2010–2011), NLSY97 respondents who had ever attended a postsecondary institution were asked to sign a waiver authorizing the release of their transcript(s). Transcripts were successfully collected and coded for almost 87% of respondents who signed waivers. We rely on variables created from coded transcript information—referred to in NLSY97 documentation as Post-Secondary Transcript Study (PTRAN) variables—to construct measures of college major and college credit distributions.

To identify each sample member's college major, we rely on several PTRAN variables that identify (*i*) field of study, using two-digit College Course Map (CCM) codes; (*ii*) the nature of the field of study (first or second major, first or second minor, first or second plan, *etc.*); and (*iii*) degree type (associate's degree, bachelor's degree, *etc.*).[7] Ideally, we would simply select the field of study associated with "first major" and "bachelor's degree" for each sample member. However, that strategy produces an implausibly high frequency of college majors identified as "liberal arts and sciences, general studies and humanities" (CCM code = 24), apparently because broader program areas, divisions, or colleges were often coded as the first major due to differences in transcript terminology across institutions.[8] Whenever this problem arises, we cycle through remaining fields (first plan, second major, *etc.*) until we obtain a CCM code other than 24; if the relevant PTRAN variables do not provide an alternative CCM code, we use the college major reported by the respondent as long as it is reported within 12 months of the date of bachelor's degree recipiency.

Having identified the two-digit CCM code corresponding to each respondent's college major, our next step is to aggregate these fields from 48 (the number of two-digit CCM codes) to a more manageable number. Our goal is to satisfy the dual objectives of (*i*) having enough observations for each aggregate field to identify field-specific parameters; and (*ii*) forming aggregate fields that are as homogenous as possible. Table A1 lists the 13 aggregate fields that we selected, along with the two-digit CCM codes contained within each aggregate field and the codes used for self-reported major in rounds 1–13; the latter are used for a small number of respondents to whom we assign a self-reported major instead of the "liberal arts and sciences" coded from the transcript.

As revealed by Table A1, some of our aggregate fields are dictated by the CCM taxonomy: all fields within the visual and performing arts are assigned a single two-digit CCM code, as are all fields in the social sciences and all fields related to business, management and marketing. None of these fields (arts, social sciences, and business) can be defined more finely given the PTRAN coding, and all contain sufficient observations not to require further aggregation. Other aggregate fields (biological/physical sciences, communications, mathematics/computer science, health professions, humanities) are, we believe, logical combinations of closely-related fields. In forming the remaining aggregates—and combining, e.g., architecture with engineering, family and consumer science with psychology, and legal professions and military science/technologies with public administration—we experimented with alternative combinations before selecting those that minimize within-group variation in PC_{if} and wages. We also established that our findings are robust to reclassifications of the relatively disparate fields (e.g., construction trades, military science, family and consumer science), given that none contain more than a handful of observations.

The college major indicators (M_{if}) are dummy variables indicating that individual i majored in field f, where f indexes the 13 aggregate fields discussed above and summarized in Table A1. We define the percentage of total college credits completed in each field (PC_{if}) by summing the number of credits completed in field f across all two- and four-year institutions attended between high school and college graduation and expressing each sum as a percentage of all credits completed across all 13 fields.[9] Means and standard deviations for our key regressors (M_{if} and PC_{if}) appear in the left-most columns of Table A2a.

Our rationale for introducing college credit distributions (PC_{if}) is that we believe they do a better job of measuring skills than do binary college major variables (M_{if}); in particular, controls for PC_{if} *conditional* on M_{if} enable us to account for within-major heterogeneity in the percentage of credits completed in the major, as well as in all other fields. To incorporate an additional, performance-related component of skill acquisition, we experimented with the use of course-specific grades. Specifically, we defined the percentage of *grade-weighted* credits completed in each field (PGC_{if}) by multiplying the credits completed in each course by the final course grade ($A = 4$, $B = 3$, *etc.*), summing those grade-weighted credits for each field f, and expressing each field-specific sum as a percentage of the sum across all 13 fields. Somewhat surprisingly, the addition of grade weights had virtually no effect on our findings; i.e., substituting PGC_{if} for PC_{if} in the log-wage models described in Section 4 produced small and statistically insignificant changes in the relevant coefficient estimates. This robustness reflects the fact that students tend to earn the highest grades in fields in which they complete the most credits, so the introduction of grade weights has little effect on the variation used for identification. In light of this finding, we do not pursue the use of grade information.

[7] The 2010 College Course Map (CCM) is a taxonomy for coding post-secondary fields and courses titles devised by the National Center of Education Statistics of the U.S. Department of Education. The complete taxonomy is available at https://nces.ed.gov/pubs2012/2012162rev.pdf.

[8] To provide a concrete example, "real world" transcripts for mathematics majors at one large, public university identify the students' *program* as Arts & Sciences and their *plan* as mathematics. If one of these students were an NLSY97 respondent, in all likelihood the PTRAN variables would identify *major 1* as "liberal arts and sciences, general studies and humanities" (CCM code 24) and *plan 1* as mathematics and statistics (CCM code 27).

[9] Because credits are not assigned uniformly across all institutions, we begin by dividing credits for each course by the modal number of per-course credits observed for that institution (see footnote 5). This step is necessary only for respondents whose transcript information is obtained from multiple institutions. Courses that do not fit into one of the 13 aggregate categories (*e.g.*, remedial courses) are excluded from both the numerator and denominator of our PC_{if} calculations.

3.C. Additional variables

The dependent variable used in our regression models is the natural logarithm of the average hourly wage, deflated by the CPI-U with 2000 as the base year. As noted in Section 3.B, we only retain observations if the average hourly wage is between $1 and $300 and if it is earned after the receipt of a bachelor's degree while the individual is not enrolled in school.

We include a large set of baseline regressors in each specification of our log-wage model; means and standard deviations are reported in Table A2b. Chief among these regressors is a set of pre-college ability measures intended to proxy for ability and preferences that affect the choice of college major and the distribution of college credits: the average score for the mathematical knowledge and arithmetic reasoning components of the ASVAB (ASVAB math score), the average score for the paragraph comprehension and word knowledge components (ASVAB verbal score), indicators of whether advanced placement exams were taken in high school in biology, chemistry, computer science, mathematics, or physical science (AP math) and, alternatively, in art, English, French, German, history, Latin, or Spanish (AP humanities), and the highest grade completed by the respondent's mother. Pre-college factors also include indicators of whether the respondent is male, black, and Hispanic.

To control for heterogeneity in college-related experiences, we include a measure of employment experience accrued between the 16th birthday and the date of college graduation, and indicators of whether the individual (*i*) earned three or more credit hours at a two-year college enroute to a bachelor's degree; (*ii*) earned an associate's degree; and (*iii*) switched college majors. We also control for the age at which each individual earned his or her bachelor's degree. We include these controls because students with longer and more circuitous college paths often gain considerable work experience and establish themselves in the labor market prior to leaving college; omitting measures of pre-college work experience could cause the gains to college majors and coursework to be overstated in the same way estimated "returns" to years of school are overstated (Light, 2001). Moreover, we suspect that decisions related to college major and coursework distributions might be constrained when students transfer between institutions and/or switch their majors. Although modeling such decision-making is beyond the scope of this analysis, our goal is to abstract from these complications to the extent possible.

Note that several dimensions of the college experience are *not* among our controls. We do not attempt to control for whether students had a double-major or minor field of study for two reasons: First, as alluded to in Section 3.B, college transcripts differ in the terms used to indicate majors and minors, which resulted in primary majors being coded alternatively as a major, plan, concentration, or degree title by the relevant NLSY97 PTRAN variable. As a result of this ambiguity, we are not confident that we can accurately identify second majors and minors. Second, a student might complete relatively few credits in her major because she pursues a second major or a minor, or for any number of other reasons. Distinguishing between different "types" of students with identical majors and credit distributions is a task we cannot tackle satisfactorily without a substantially larger sample. In the same vein, we do not control for college characteristics because we lack the sample sized needed to identify wage benefits associated with majors and credit distributions separately for, e.g., high-quality versus low-quality institutions, nor do we have the detailed information needed to determine whether/when institutional requirements affected students' credit distributions across fields. Although the NLSY97 PTRAN variables include grades received in each course, as noted in Section 3.B we chose not to use this information after determining that our findings are largely invariant to whether we control for credit distributions or grade-weighted credit distributions.

Our final group of baseline regressors are time-varying, post-college factors that are typically included in log-wage models. We control for years of total work experience and its square, years of job tenure and its square, marital status indicators (cohabiting, married, or separated/divorced/widowed, with "single" the omitted group), and indicators of whether a minor child resides in the household, whether the respondent resides in an urban area, region of residence, and calendar year.[10]

4. Analytic strategy

We begin our regression analysis by obtaining benchmark estimates of log-wage gaps between workers with different college majors, based on a conventional log-wage model in which each college major has its own intercept. We then determine how those estimated wage gaps change when we account for each worker's distribution of college credits across fields. To do so, we introduce one specification that *replaces* college major dummies with controls for the percentage of college credits in each field, and another specification that *augments* college major dummies with the credit variables.

Before discussing each specification in more detail, we highlight three premises that are particularly important to our analytic strategy. First, we drop the assumption that is often (implicitly) made in the "returns to college major" literature that major is a proxy for skills acquired in college. As we demonstrate in Section 5, there is considerable within-major heterogeneity in the percentage of credits completed in the major and in the overall credit distribution. Second, we assume college students jointly determine their major and coursework. Altonji et al. (2012) present a life-cycle model in which college students choose their general (non-specialized) coursework in the first enrollment period and choose their major (which implies a specialized set of courses) in the second period. Empirical research (Astorne-Figari & Speer, 2019; Griffith, 2010; Rask & Tiefenthaler, 2008) reveals a considerable amount of major switching that, in many cases, is influenced by performance in "early" courses. While the consensus appears to be that coursework affects the choice of major and the choice of major affects coursework, we abstract from the dynamics of the decision-making and simply assume the two are jointly determined. Third, we assume that employers observe workers' majors but *not* their credit distributions. We are unable to document this rigorously, but an informal survey of U.S. job search websites suggests that college-educated job applicants often reveal their majors via resumes or job applications, while it is relatively uncommon for employers to check college transcripts—and transcript checks are more likely to occur for degree verification than to learn what courses were taken. The assumption that college major is "known" underlies the argument that estimated major effects encompass both a skill and a credentialing component (Altonji et al., 2012).

Turning to our three log-wage model specifications, we begin with the conventional approach:

$$Y_{it} = \alpha_1 + \sum_{f=1}^{12} \beta_{1f} M_{if} + \delta_1 X_{it} + \varepsilon_{1it} \tag{1}$$

where Y_{it} is the log-wage for individual *i* at (post-graduation) time *t*, M_{if} represents time-constant dummy variables indicating that individual *i* majored in field *f*, and X_{it} is the vector of controls (both time-constant and time-varying) for pre-college, in-college, and post-college factors described in Section 3.[11] Each estimated $\hat{\beta}_{1f}$ identifies a conditional, average log-wage for individuals in the major, and reflects (*i*) the labor market value of skills gained via "average" coursework for the major and (*ii*) credentialing (or signaling) effects of the major; it does *not* account for coursework variation among individuals in the major. In

[10] The measures of total labor market experience and job tenure are counts of "weeks worked" over the relevant interval, divided by 52. Although both are potentially endogenous to the choice of college major and coursework, our findings are substantially unchanged if we instead drop tenure and its square and substitute a measure of elapsed time since college graduation for experience.

[11] The 13 fields (majors) are listed in Tables 1 and A1. Education is the omitted major in all specifications.

presenting findings in Section 5, we focus on differences between select pairs of $\hat{\beta}_{1f}$, which serve as benchmark estimates of the log-wage gap between those two majors.

As an alternative to specification 1, we replace the 12 major dummies (M_{if}) with 12 time-constant variables indicating the percentage of credits taken in each field (PC_{if}):

$$Y_{it} = \alpha_2 + \sum_{f=1}^{12} \gamma_{2f} PC_{if} + \delta_2 X_{it} + \varepsilon_{2it}. \tag{2}$$

As detailed in Section 3, the 12 included PC_{if} variables plus the omitted variable (for education) sum to 100 for each individual. In contrast to specification 1, which identifies an average "starting wage" for individuals in each major without accounting for heterogeneity in coursework, this alternative specification controls for each individual's entire credit distribution without accounting for college major. Specification 2 offers two, related advantages that specification 1 lacks: PC_{if} is a more detailed measure of skills gained in college than is M_{if} and the entire vector $\hat{\gamma}_{2f}$ can be used to predict log-wages for *any* assumed credit distribution; in other words, we can move beyond a focus on predicted log-wages for individuals with "average" credit distributions. Specification 2 also suffers from two disadvantages: identification of $\hat{\gamma}_{2f}$ uses both within- and between-major variation in credits, and credentialing effects of college major are not brought to bear. As our presentation of findings in Section 5 will make clear, a comparison of specifications 1, 2 and 3 is useful, but the hybrid specification 3 is our preferred model.

Before turning to the hybrid model, we elaborate on our method for using the vector $\hat{\gamma}_{2f}$ to predict log-wages for individuals with alternative credit distributions. To reduce the number of alternatives to a manageable number, we consider the subset of individuals in each major whose major-specific level of concentration is low, medium, or high (corresponding to percentages in percentile ranges 15–35, 40–60 and 65–85, respectively) and use the average credit distribution for each type. As shown in Table A3, the typical arts major with a high credit concentration in arts completes almost 62% of her college credits in arts, another 16% in the humanities, and 5% in both biological/physical sciences and social sciences, with less than 4% in each of the remaining nine fields. We can predict the log-wage for this individual and compare it to a similar prediction for, say, a business major with a high credit concentration in business; as seen in Table A3, that individual completes 48% of her credits in business, 15% in humanities, 11% in social sciences, almost 7% in mathematics, and 0.3–5% in each remaining field. By conducting numerous comparisons in this vein, we account for the considerable heterogeneity in actual coursework seen both within and across majors.

Our final specification is a hybrid of specifications 1 and 2:

$$Y_{it} = \alpha_3 + \sum_{f=1}^{12} \beta_{3f} M_{if} + \sum_{f=1}^{12} \gamma_{3f} PC_{if} + \delta_3 X_{it} + \varepsilon_{3it}. \tag{3}$$

Specification 3 identifies each major coefficient ()$\hat{\beta}_{3f}$ *conditional* on the distribution of college credits across fields, which can be interpreted as a credentialing effect—*i.e.*, the effect on log-wage of being awarded a degree in a given field, holding constant skills acquired via college coursework. Similarly, (3) identifies marginal skill effects ($\hat{\gamma}_{3f}$) *conditional* on college major, or using only within-major variation for identification. In contrast, $\hat{\beta}_{1f}$ from specification 1 represents the sum of credentialing effects and skill effects associated with the average credit distribution for each field, and $\hat{\gamma}_{2f}$ from specification 2 identifies marginal skill effects using both within- and between-major variation. With these differences in interpretation in mind, our comparisons across three specifications allow us to determine how heterogeneity in coursework affects inferences about which fields have the largest labor market payoffs.

We use ordinary least squares (OLS) to estimate specifications 1–3 for pooled samples of men and women and correct the standard errors for nonindependence of wage observations over time for a given individual. Although most studies that identify wage effects of college majors use separate sample of men and women (Black et al., 2008; Chevalier, 2011; Daymont & Andrisani, 1984; Grogger and Eide 1995; Rumberger & Thomas, 1993) or focus solely on men (Berger, 1988; Kinsler & Pavan, 2015; Webber, 2014), the use of pooled samples is not without precedent (Altonji et al., 2014; Hamermesh & Donald, 2008; Hastings et al., 2014, Kirkeboen et al., 2016; Lemieux, 2014). We opted to use a pooled sample after failing to reject at a 0.05 significance level the null hypothesis that the key parameters (β_f, γ_f) are jointly equal for men and women (for all f) for specifications 1–3. Given the small sample sizes within many gender-field cells, this finding might reflect our inability to identify gender-specific parameters with precision. We reject the null hypothesis of "gender equality" for several components of X_{it}; interactions between those variables and a male dummy are among the controls (see Table A2b).

We can interpret $\hat{\beta}_{1f}$, $\hat{\gamma}_{2f}$, $\hat{\beta}_{3f}$, and $\hat{\gamma}_{3f}$ as causal effects if log-wages are independent of PC_{if} and M_{if} conditional on X_{it} or, stated differently, if individuals (jointly) choose their college majors and credit distributions solely on the basis of X_{it}. This "selection on observables" assumption is often made by analysts attempting to identify wage benefits associated with college major (Altonji et al., 2012; Daymont & Andrisani, 1984; Rumberger & Thomas, 1993; Grogger & Eide, 1995; Joy, 2003; Webber, 2014). Because we account for students' choices of major *and* their credit distributions across 13 fields, alternative identification strategies (*e.g.*, Arcidiacono, 2004; Hastings et al., 2014; Kirkeboen et al., 2016) would be exceedingly difficult to adapt to our application. Fortunately, as described in Section 3, the NLSY97 provides sufficiently detailed pre-college and college-related information to produce credible "selection on observables" estimates.

5. Findings

5.A. Variation in course credits by college major

Before turning to findings based on our log-wage models, we consider the extent to which course credit distributions vary within and across majors. The analysis summarized in Table 1 uses a sample containing one observation per person (n = 1,180), disaggregated into 13 major-specific subsamples. To clarify the presentation, the first row reveals that among 33 agriculture majors, the median (p50) student acquired 22.9% of his credits in agriculture courses, 18.0% in biological science, physical science, and mathematics (including computer science) courses, and 25.0% in humanities, social science and psychology courses. In this example each value is the 17th highest "percentage of total credits" for the 33-person subsample, so the median student is not necessarily the same in all three p50 columns.

Focusing first on the own-major columns, Table 1 indicates that the median level of concentration within one's own major ranges from a high of 52.0% for biological/physical science majors (followed by 44.5% for arts majors) to a low of 22.9% for agriculture majors (followed by 24.8% for health majors).[12] Science also has the highest credit concentration (40.7%) at the 25th percentile, but arts (30.3%) falls to the fourth place behind business (31.0%), and humanities (30.6%); at the 75th percentile, arts (61.2%) is slightly more concentrated than science (58.6%). At the other extreme, health professions (7.6%) and public administration (11.5%) have the lowest concentrations at the 25th percentile, while agriculture (22.9% and 32.5%) is the lowest ranked field at the 50th and 75th percentiles.

[12] Throughout our presentation of findings, we use shortened descriptors for each aggregate major (*e.g.,* agriculture for "agriculture and natural resources," arts for "fine and applied arts," and math for "mathematics and computer science"). See Table A1 for a detailed description of the fields within each aggregate major.

Table 1
Distribution of course credits, by major.

Major	Own Major p25	p50	p75	Science & Math p25	p50	p75	Humanities & Soc. Sci. p25	p50	p75	N
Agriculture	19.3	22.9	32.5	13.2	18.0	34.1	18.9	25.0	31.1	33
Arts	30.3	44.5	61.2	4.1	7.5	12.2	19.6	27.3	35.7	65
Bio/physical sciences	40.7	52.0	58.6	52.2	59.2	66.8	21.4	25.8	32.8	67
Business	31.0	40.7	47.4	7.6	12.3	16.9	26.0	31.9	37.7	235
Communications	20.9	28.5	34.6	6.3	9.3	13.0	32.5	41.4	52.0	65
Mathematics	27.1	39.3	52.3	37.6	52.5	59.8	19.3	25.4	30.5	52
Education	18.5	30.2	43.7	9.4	12.9	19.0	27.5	33.1	44.7	87
Engineering	28.4	40.3	48.3	23.9	30.5	37.5	14.5	17.7	20.0	70
Health	7.6	24.8	42.3	13.2	20.9	32.6	21.1	29.4	37.6	60
Humanities	30.6	40.7	57.0	6.5	9.9	16.6	46.4	66.3	78.1	202
Psychology	18.1	27.3	36.6	8.2	11.9	17.0	54.4	67.6	76.7	92
Public administration	11.5	26.1	36.4	6.5	8.5	12.8	43.3	50.0	60.8	47
Social sciences	20.8	28.0	39.1	7.0	10.6	15.6	55.6	68.5	76.9	105
All	23.3	36.4	48.0	7.8	12.9	22.6	26.4	37.5	59.9	1,180

Note: Each row shows the 25th, 50th, and 75th percentile values of the percent of total college credits accounted for by courses in (*i*) one's major (left-most columns); (*ii*) biological sciences, physical sciences, mathematics and computer science (middle columns); and (*iii*) humanities, social sciences, and psychology (right-most columns), among individuals earning a bachelor's degree in the given major. See Table A1 for a list of fields included in each major.

Overall, Table 1 reveals *substantial* variation in the percentage of credits that students devote to their majors. Across majors, a student in the most-concentrated major completes 33.1 percentage points more credits in his/her major than does a student in the least-concentrated major at the 25th percentile, 29.1 percentage points more credits at the median, and 28.7 percentage points more credits at the 75th percentile. Within majors, the interquartile range varies from a low of 13.2 percentage points for agriculture majors to a high of 34.7 percentage points for students majoring in the health professions.[13] Whether an individual's college major is a suitable proxy for her skill level in that field appears to depend intrinsically on both the major and the extent to which she chose to concentrate course credits within her major.

We do not attempt to account for major-specific and institutional factors that affect students' credit distributions across fields, but we note that *all* students invariably accumulate credits in core fields (biological/physical sciences, math, humanities, social sciences), while nonmajors rarely sample courses in the more specialized fields (agriculture, health professions, public administration). This contributes to most core fields (biological/physical sciences, math, humanities) having relatively high major-specific concentrations and many specialized fields (agriculture, health, public administration) having low concentrations—although Table 1 reveals that social sciences (core) and arts (specialized) are two fields that do not conform to this pattern.

To pursue this issue, in the center and right-most columns in Table 1 we report credit concentrations by major in two aggregations of the core fields. Unsurprisingly, individuals majoring in biological/physical sciences, math, engineering, and health professions tend to complete a higher percent of credits in science/math than do their counterparts in other majors. Less expected is the finding that health majors are more concentrated in science/math than in health at the 25th percentile (13.2% vs. 7.6%) and agriculture majors are slightly more concentrated in science/math than in their major field at the 75th percentile (34.1% vs. 32.5%). Turning to the aggregate humanities/social sciences/psychology field, we see that a number of majors are more concentrated in the aggregate field than in their own major, including communications, education, psychology, and public administration at all three points in the distribution. It is also noteworthy that the percentage-point gaps between the most- and least-concentrated majors are 48 (p25), 52 (p50) and 55 (p75) for science/math and 41 (p25), 51 (p50) and 58 (p75) for humanities/social sciences, versus only 33 (p25) and 29 (p50, p75) in the major-specific columns. To the extent that college graduates are valued for a range of skills—including skills largely unrelated to their major—Table 1 demonstrates, again, that "major" is a poor proxy for each individual's overall skill set.[14]

5.B. Estimated wage effects of college major and course credits

The patterns seen in Table 1 suggest that controls for credit distributions in log-wage models will be useful for capturing skill heterogeneity among college graduates, even after controlling for major. To investigate this further, we turn to estimates based on specifications 1–3 of our log-wage model.

Estimated college major coefficients for specification 1—which is a conventional specification that *excludes* controls for course credits—appear in appendix Table A2a; additional estimates are shown in Table A2b. Table A2a reveals that estimated log-wage gaps between each major and education (the omitted group) range from a high of 0.402 for engineering to a low of −0.168 for arts. The ranking and magnitudes of estimated log-wage gaps in Table A2a are unsurprising, with one exception: the estimated difference of 0.057 between biological/physical sciences and education makes science a slightly less lucrative major than social science (0.064); in other studies (*e.g.*, Altonji et al., 2012), the ranking of biological/physical sciences and social sciences tends to be reversed.[15] We attribute this minor anomaly to the fact that we have only 67 science majors (510 wage observations) in our sample, which allows a

[13] The ranking of interquartile ranges differs slightly from the ranking of (within-major) standard deviations, which range from lows of 10.8 for communications, 12.0 for psychology and 12.7 for agriculture to highs of 18.8 for humanities, 18.9 for arts and 20.7 for health.

[14] For a subset of seven majors (discussed further in section 5.B), we present complete credit distributions corresponding to low, medium, and high major-specific concentrations in Table A3. In most cases, no more than 8% of total credits are completed in fields outside the major and core fields, although there are exceptions. For example, low-concentration math majors complete almost 17% of their credits in business, and low-concentration health majors complete almost 12% of their credits in psychology and another 11% in agriculture.

[15] We use estimated major coefficients in table 3 in Altonji *et al.* (2012) for comparison. Because Altonji *et al.* (2012) control for 24 majors, we average their estimates over multiple majors to replicate our 13-major taxonomy (*e.g.*, English language and literature, liberal arts, and history form "humanities"). Three of our majors (agriculture, psychology, and public administration) are excluded from their analysis, so we are left with nine common majors. Altonji *et al.* (2012) rank biological/physical sciences above social sciences for men and women; for men, they rank math above health professions (nursing), and for women they rank communications above social sciences. Aside from those differences, their rankings are identical to ours.

small number of low-wage individuals to affect the estimate.

Rather than focus solely on the log-wage gap between each major and education, in Table 2 we report 21 pairwise comparisons for a subset of seven majors. This subset includes one core and one noncore major that are among the highest paying (mathematics and engineering), one core and one noncore major that are among the lowest paying (humanities and arts), and one core and one noncore major that are intermediate (social science and business). We include business because it is the most popular major in our sample and health because, as seen in Table 1, it has the highest variation in own-major credit concentration. More generally, we chose this subset of seven majors after confirming that the 21 pairwise comparisons reveal every pattern of interest across all three model specifications. We focus the remainder of our presentation of findings on comparisons among these seven majors; additional differences between pairs can be calculated from the estimates reported in Table A2a.

Continuing our discussion of specification 1, the top panel of Table 2 shows that the typical engineering major is predicted to earn 0.117 log-points (0.402–0.285) more than her counterpart in health, and 0.570 log-points more than her counterpart in arts, which is the lowest-paying major. The predicted log-wage gap between social sciences and arts (0.231) is quite large, while the gap between humanities (a low-paying field in its own right) and arts is a substantial, precisely estimated 0.159. If we were to base our inferences solely on these estimates—and, in particular, if we interpret these as *causal* effects of both the (average) skill and credential associated with each major—we would conclude, as others have, that high-tech and high-demand fields such as engineering, math, computer science, and nursing are better choices than low-paying fields in the humanities and arts. Throughout the rest of our discussion, we use these estimates as a benchmark for comparison with estimates based on specifications 2–3.

Our next step is to ask how estimated college major coefficients change when we condition on course credit distributions. In Table A2a we report estimated major coefficients for specification 3 and, in the right-most column, differences between the specification 1 and specification 3 estimates. Two noteworthy patterns emerge: First, the estimated major coefficients *decrease* in magnitude for all majors except arts when credit distributions are added to the model (although the decrease of 0.012 for humanities is statistically indistinguishable from zero at conventional significance levels). We interpret the specification 1 estimates as “gross” log-wage effects of skills and credentials associated with each major, and the specification 3 estimates as credentialing effects net of skills. Therefore, it is surprising to infer a *negative* skill effect for arts. Second, for all majors except arts the estimated coefficient decreases by 0.012 to 0.202 log-points, or 42% to 359% relative to the specification 1 values (excluding a 1200% change for agriculture, which is an outlier because the specification 1 value is close to zero). Once we net out skill effects, most majors prove to be considerably less remunerative—and more alike—than specification 1 suggests. This comparison alone suggests that there is value to including coursework measures in the log-wage model.

We extend this assessment by comparing the top and bottom panels of Table 2. The inclusion of credit distributions in specification 3 causes estimated log-wage gaps between health-business and health-social sciences to increase slightly (albeit insignificantly) because the estimated coefficient for health decreases less in magnitude than do the estimated coefficients for business and social sciences. For the remaining 19 pairs, the estimated gaps decrease by anywhere from 0.003 to 0.290 log-points. Most pairs exhibit a 36–77% decrease relative to the specification 1 values, although some (business-humanities, social sciences-humanities, social sciences-arts) approach or exceed a 100% decrease. Clearly, inferences about the labor market value of one major relative to another are highly sensitive to whether we identify “gross” effects or credentialing effects.

Having compared estimated major coefficients with and without controls for course credits (specifications 1 vs. 3), we now compare estimated credit coefficients with and without controls for major (specifications 2 vs. 3). Table A2a reports these estimated coefficients. For both specifications, each estimate is scaled to represent the marginal effect of a 20 percentage-point increase in credits. In the right-most column of Table A2a we report differences between the scaled estimates (specification 2 minus specification 3).

Table A2a reveals that the ranking of fields based on estimated major coefficients (specification 1) is largely maintained when we switch to estimated credit coefficients (specification 2), with two

Table 2
Difference in predicted log-wage for select pairs of majors (accounting for major but not course credits).

Specification 1 (course credits excluded)						
	Major 2					
Major 1	Health	Math	Bus	SS	Hum	Arts
Engineering	.117**	.119**	.284**	.339**	.411**	.570**
Health		.002	.167**	.222**	.294**	.453**
Mathematics (Math)			.165**	.220**	.293**	.451**
Business (Bus)				.054**	.127**	.286**
Social sciences (SS)					.073**	.231**
Humanities (Hum)						.159**
Specification 3 (course credits included)						
	Major 2					
Major 1	Health	Math	Bus	SS	Hum	Arts
Engineering	.034	.110*	.214**	.265**	.222**	.280**
Health		−.076	.180**	.231**	.188**	.246**
Mathematics (Math)			.104**	.155**	.112**	.170**
Business (Bus)				.051	.008	.066
Social sciences (SS)					−.043*	.015
Humanities (Hum)						.059

Note: Each number is the estimated coefficient for major 1 minus the estimated coefficient for major 2; ** and * indicate that the difference is statistically distinguishable from zero at a significance level of 0.05 and 0.10, respectively. Specification 1 excludes controls for course credits (PC_f); specification 3 includes PC_f but their estimated coefficients are not used for the computations. See Table A2a for estimated coefficients.

Table 3
Difference in estimated marginal effect of major-specific course credits for select pairs of majors.

Specification 2 (major dummies excluded)						
	Major 2					
Major 1	Health	Math	Bus	SS	Hum	Arts
Engineering	.020	.012	.095**	.077**	.164**	.204**
Health		−.009	.074**	.057**	.144**	.184**
Mathematics (Math)			.083**	.066**	.153**	.193**
Business (Bus)				−.017	.070**	.110**
Social sciences (SS)					.087**	.127**
Humanities (Hum)						.040**
Specification 3 (major dummies included)						
	Major 2					
Major 1	Health	Math	Bus	SS	Hum	Arts
Engineering	.017	−.032	.019	−.016	.086**	.108**
Health		−.049*	.002	−.033	.069**	.091**
Mathematics (Math)			.051*	.016	.118**	.140**
Business (Bus)				−.035*	.067**	.089**
Social sciences (SS)					.102**	.124**
Humanities (Hum)						.022

Note: Each number is the estimated marginal effect of a 20 percentage- point increase in course credits associated with major 1 minus the analogous estimate for major 2; ** and * indicate that the difference is statistically distinguishable from zero at a significance level of 0.05 and 0.10, respectively. Specification 2 excludes controls for major (M_f); specification 3 includes M_f but their estimated coefficients are not used for the computations. See Table A2a for estimated coefficients.

Table 4
Difference in predicted log-wage for select pairs of majors (accounting for major and course credits).

Specification 3: low credit concentration in major

	Major 2					
Major 1	Health	Math	Bus	SS	Hum	Arts
Engineering	.157**	.127**	.281**	.344**	.377**	.492**
Health		.030	.154**	.217**	.250**	.365**
Mathematics (Math)			.124**	.187**	.220**	.335**
Business (Bus)				.063**	.096**	.211**
Social sciences (SS)					.033	.148**
Humanities (Hum)						.115**

Specification 3: medium credit concentration in major

	Major 2					
Major 1	Health	Math	Bus	SS	Hum	Arts
Engineering	.104**	.130**	.285**	.365**	.402**	.575**
Health		−.026	.155**	.235**	.272**	.445**
Mathematics (Math)			.181**	.262**	.298**	.471**
Business (Bus)				.080**	.117**	.290**
Social sciences (SS)					.037*	.210**
Humanities (Hum)						.173**

Specification 3: high credit concentration in major

	Major 2					
Major 1	Health	Math	Bus	SS	Hum	Arts
Engineering	.090**	.129**	.308**	.359**	.489**	.639**
Health		−.039	.178**	.230**	.359**	.510**
Mathematics (Math)			.217**	.269**	.399**	.549**
Business (Bus)				.051**	.181**	.331**
Social sciences (SS)					.130**	.280**
Humanities (Hum)						.150**

Specification 3: high (low) credit concentration in major 1 (2)

	Major 2					
Major 1	Health	Math	Bus	SS	Hum	Arts
Engineering	.188**	.158**	.312**	.375**	.408**	.523**
Health		−.068*	.183**	.246**	.279**	.394**
Mathematics (Math)			.222**	.285**	.318**	.433**
Business (Bus)				.068**	.100**	.215**
Social sciences (SS)					.049**	.164**
Humanities (Hum)						.034

Specification 3: low (high) credit concentration in major 1 (2)

	Major 2					
Major 1	Health	Math	Bus	SS	Hum	Arts
Engineering	.059	.098**	.276**	.328**	.458**	.602**
Health		.059	.149**	.201**	.331**	.481**
Mathematics (Math)			.119**	.171**	.301**	.451**
Business (Bus)				.047**	.177**	.327**
Social sciences (SS)					.114**	.264**
Humanities (Hum)						.231**

Note: Each number in the top 3 panels is the predicted log-wage for a student with major 1 and a credit distribution (across 13 fields) corresponding to a low, medium, or high concentration in the major, minus the analogous estimate for major 2; each number in the 4th panel is the predicted log-wage for a student with major 1 and a credit distribution (across 13 fields) corresponding to a high concentration in the major, minus the predicted log-wage for a student in major 2 with a low concentration; each number in the bottom panel assigns a low (high) concentration to major 1 (2); ** and * indicate that the difference is statistically distinguishable from zero at a significance level of 0.05 and 0.10, respectively. See Table A2a for estimated coefficients and Table A3 for distributions corresponding to low and high credit concentrations.

Table 5
Difference in predicted log-wage for select pairs of majors (accounting for course credits but not major).

Specification 2: low credit concentration in major

	Major 2					
Major 1	Health	Math	Bus	SS	Hum	Arts
Engineering	.138**	.224**	.192**	.230**	.300**	.354**
Health		−.086**	−.032**	.006	.076**	.130**
Mathematics (Math)			.054**	.092**	.162**	.216**
Business (Bus)				.038**	.108**	.161**
Social sciences (SS)					.070**	.124**
Humanities (Hum)						.054**

Specification 2: medium credit concentration in major

	Major 2					
Major 1	Health	Math	Bus	SS	Hum	Arts
Engineering	.098**	.185**	.233**	.283**	.363**	.501**
Health		−.087**	.048**	.098**	.178**	.316**
Mathematics (Math)			.135**	.185**	.265**	.403**
Business (Bus)				.050**	.130**	.268**
Social sciences (SS)					.080**	.218**
Humanities (Hum)						.138**

Specification 2: high credit concentration in major

	Major 2					
Major 1	Health	Math	Bus	SS	Hum	Arts
Engineering	.092**	.158**	.300**	.332**	.490**	.616**
Health		−.066*	.142**	.174**	.332**	.456**
Mathematics (Math)			.208**	.240**	.398**	.522**
Business (Bus)				.032	.190**	.315**
Social sciences (SS)					.158**	.282**
Humanities (Hum)						.124**

Note: Each number is the predicted log-wage for a student with major 1 and a credit distribution (across 13 fields) corresponding to a low, medium, or high concentration in the major, minus the analogous estimate for major 2; ** and * indicate that the difference is statistically distinguishable from zero at a significance level of 0.05 and 0.10, respectively. See Table A2a for estimated coefficients and Table A3 for distributions corresponding to low, medium and high credit concentrations.

exceptions: The estimated coefficient for a business major (0.118) is significantly larger than the estimated coefficients for social sciences and communications in specification 1; in specification 2, the estimated coefficient for business credits (0.057) is somewhat smaller than those for social sciences and communications. Similarly, the estimated coefficient for biological/physical science is twice as large as for communications (0.057 vs. 0.029) in specification 1 (although neither is statistically distinguishable from zero), while the ranking is reversed in specification 2.

Turning to a comparison of specifications 2 and 3, Table A2a reveals that the estimated marginal effects of course credits decrease for the three highest-paying majors (engineering, health, and math) when we add college major controls to the model and increase for the remaining nine fields, although the change is statistically distinguishable from zero for only four majors. Specification 3 relies solely on within-major variation to identify marginal effects of course credits, so we interpret an increase (decrease) relative to specification 2 to mean the log-wage payoff to additional credits is relatively larger (smaller) for individuals within the major. That said, when we compute differences between estimated marginal effects for all 21 pairs of majors in our seven-major subset (Table 3), we find that they decrease when we switch from specification 2 to specification 3 (albeit not always significantly) for *all* pairs except social sciences-humanities, which increases from 0.087 to 0.102.[16] As a result, the estimated gap between social sciences and humanities is among the largest when we use specification 3 to isolate marginal credit effects, which is in marked contrast to the predicted gaps based on college major (Table 2).

The field-specific credit coefficients that we just described are "ceteris paribus" estimates of increased credit concentrations in a given field. A key advantage of specifications 2–3, of course, is that they bring

[16] As seen in Table A2a, the estimated payoff to a 20 percentage-point increase in social science credits increases by 0.021 when we switch from specification 2 to specification 3, while the estimated payoff to humanities credits increases by only 0.007.

Table A1
List of major codes included in each aggregate major category.

Major	CCM two-digit codes[a]	NLSY97 codes[b]
Agriculture and natural resources ("*agriculture*")	01 Agriculture	1 Agriculture & natural resources
	03 Natural resources & conservation	42 Other (electrical maintenance & repair technology)
	12 Personal & culinary services	
	31 Parks, recreation & leisure studies	39 Other (automobile mechanics technology)
	32 Basic skills & developmental education	
	33 Citizenship activities	
	35 Interpersonal & social skills	
	36 Leisure & recreational activities	
	37 Personal awareness & self improvement	
	46 Construction trades	
	47 Mechanic & repair technologies	
	48 Precision production	
Arts	50 Visual & performing arts	16 Fine & applied arts
Biological and physical sciences	26 Biological & biomedical sciences	6 Biological sciences
	40 Physical sciences	25 Physical sciences
Business	52 Business, management, marketing	7 Business management 37 Hotel management
Communications	09 Communications & journalism	8 Communications
	10 Communications technologies	
Mathematics and computer science ("*mathematics*")	11 Computer & information science	9 Computer & information science
	27 Mathematics & statistics	21 Mathematics 48 Other (applied sciences)
Education and library science	13 Education 25 Library science	12 Education
Engineering and architecture ("*engineering*")	14 Engineering	13 Engineering
	15 Engineering technologies	4 Architecture/Environmental design
	4 Architecture	
Health professions ("*health*")	51 Health professions	22 Nursing 23 Other health professions
	34 Health-related knowledge	27, 29, 30 Pre-dental/med/vet
	60 Residency program	36 Nutrition & dietetics
Humanities	05 Area/ethnic/cultural/gender/group studies	5, 15 Area/Ethnic studies
	16 Foreign languages/lit & linguistics	17 Foreign languages
	23 English language & literature	14 English
	24 Liberal arts & sciences, humanities	38 Other (liberal arts & sciences)
	30 Interdisciplinary studies	20 Interdisciplinary studies
	38 Philosophy & religious studies	24 Philosophy
	39 Theology & religious vocations	33 Theology/Religious studies
	54 History	18 History
Psychology	42 Psychology	31 Psychology
	19 Family & consumer science	19 Home economics
Public administration and law ("*public administration*")	22 Legal professions & studies	28 Pre-law
	28 Military science, leadership	47 Other (legal support services)
	29 Military technologies	46 Other (security & protective service)
	43 Law enforcement & protective services	40 Other (human services)
	44 Public administration & social services	41 Other (social work)
	49 Transportation & materials moving	45 Other (transportation & materials moving)
Social sciences	45 Social sciences	2 Anthropology 3 Archaeology
		10 Criminology 11 Economics
		26 Political science & government
		32 Sociology
		44 Other (international relations & affairs)
		43 Other (geography)

Note: Seemingly disparate fields were included in certain majors (*e.g.*, construction trades in agriculture; architecture in engineering) after determining that (a) within-major variation in coursework and wages does not increase; and (b) findings are unaffected by these groupings.
[a] Two-digit, 2010 College Course Map (CCM) codes were used for all transcript-reported majors and for self-reported majors from round 14 onward.
[b] NLSY97 codes were used for self-reported majors from rounds 1 through 13.

to bear each individual's *entire* distribution of course credits across 13 fields. To exploit this advantage fully, we predict log-wages for individuals in each major after assigning them "representative" credit distributions for their major. Beginning with specification 3, in Table 4 we report differences in predicted log-wages between pairs of majors using (*i*) the low-concentration distribution for both; (*ii*) the medium-concentration distribution for both; (*iii*) the high-concentration distribution for both; (*iv*) the high-concentration distribution for major 1 and the low-concentration distribution for major 2; and (*v*) the low-concentration distribution for major 1 and the high-concentration distribution for major 2.[17]

Table 4 contains a large number of pairwise comparisons, but we can summarize the key findings with three observations. First, there are no systematic patterns as we switch from assigning both members of each pair the credit distribution corresponding to a low, medium, or high credit concentration for the given major. To take three examples, as we move from low to medium to high the predicted difference in log-wages between engineering and arts increases substantially from 0.492 to 0.575 to 0.639, the predicted difference between engineering and health decreases from 0.157 to 0.104 to 0.090, and the predicted difference between engineering and social sciences changes non-monotonically (and insignificantly) from 0.344 to 0.365 to 0.359. Similarly, when we switch from high-low to low-high Table 4, some estimates increase (e.g., 0.034 to 0.231 for humanities-arts) and some decrease (e.g., 0.222 to 0.119 for math-business).

Second, the estimates in the second panel of Table 4—representing

[17] The low, medium, and high distribution for each major is given in Table A3. See section 4 for details on how we construct each distribution.

Table A2a
Summary statistics and estimated coefficients for college major and course credit variables.

Variable	Mean	SD	Specification 1 Coeff.	S.E.	Specification 2 Coeff.	S.E.	Specification 3 Coeff.	S.E.	Δ[b]	S.E.
1 if major = =										
Engineering	.05		.402**	.032			.200**	.059	.202**	.055
Health	.05		.285**	.032			.167**	.047	.119**	.035
Mathematics	.04		.284**	.034			.091*	.049	.193**	.035
Public admin.	.03		.151**	.035			−.020	.050	.171**	.034
Business	.19		.118**	.024			−.013	.041	.132**	.034
Social sciences	.09		.064**	.027			−.065*	.039	.128**	.028
Bio/Phys. science	.05		.057*	.032			−.077*	.047	.134**	.035
Communications	.06		.029	.030			−.075	.047	.104**	.033
Agriculture	.03		.007	.038			−.077*	.045	.084**	.029
Humanities	.18		−.009	.024			−.021	.034	.012	.024
Psychology	.08		−.021	.028			−.071*	.039	.051*	.030
Arts	.07		−.168**	.029			−.080*	.046	−.088**	.039
% of total credits:[a]										
Engineering	3.04	9.71			.152**	.016	.080**	.028	.072**	.025
Health	2.84	7.66			.131**	.018	.063**	.025	.069**	.018
Mathematics	7.17	9.41			.140**	.016	.112**	.023	.028*	.016
Public admin.	2.15	6.60			.114**	.019	.122**	.027	−.008	.017
Business	9.94	16.66			.057**	.012	.061**	.020	−.004	.016
Social sciences	11.04	10.30			.074**	.015	.096**	.020	−.021	.014
Bio/Phys. science	10.72	12.99			.055**	.013	.068**	.020	−.013	.016
Communications	4.60	7.99			.071**	.017	.095**	.025	−.024	.019
Agriculture	3.87	7.24			.004	.019	.028	.024	−.024*	.015
Humanities	24.95	16.03			−.013	.013	−.006	.018	−.007	.013
Psychology	7.19	9.74			.003	.016	.025	.022	−.023	.016
Arts	8.36	13.98			−.053**	.013	−.028	.021	−.025	.017

Note: Education is the omitted field for both college major and "percent credits." Estimated coefficients for additional variables are in Table A2b.
[a] Estimated coefficients are multiplied 20 to represent the marginal effect of a 20 percentage-point increase in credits.
[b] The first 12 rows report the difference between the estimated "major" coefficient for specification 1 minus Specification 3. The next 12 rows report the difference between the estimated "percent of total credits" coefficient (multiplied by 20) for Specification 2 minus Specification 3.

differences in predicted log-wages for individuals with (approximately) median-level credit concentrations in their majors—are similar to the benchmark (specification 1) estimates in the top panel of Table 2. If we consider the difference between each Table 2 estimate and the corresponding Table 4 estimate, some are positive and some are negative, but all but two are less than 2.8 percentage-points in absolute value. It appears that the medium-concentration credit distributions are similar to the unobserved averages that implicitly drive the identification of major effects in specification 1.

In drawing our third inference we exploit the fact that, for each pair of majors, the five estimated log-wage gaps reported in Table 4 place a band around the benchmark (specification 1) estimate reported in Table 2. In some cases, the band is quite narrow. For example, we estimate a log-wage gap of 0.167 between health and business majors using specification 1, and a range from 0.149 to 0.183 using specification 3. Regardless of the assumed own-major credit concentration—each of which implies a unique credit distribution across 13 fields—the estimates are close to the benchmark for this pair of majors. The estimated wage gap between health and social sciences majors (0.222 with specification 1 versus 0.201–0.246 with specification 3) is another example of relatively low sensitivity to the specification. For other pairs of majors, estimates of relative wage payoffs differ dramatically depending on whether we use specification 1 or specification 3. With specification 1, for example, we estimate a log-wage gap between math and arts majors of 0.451; with specification 3, the estimated gap falls to 0.335 if both majors have a low own-major concentration, and increases by 0.214 log-points to 0.549 if both majors have a high own-major concentration. Similarly, the range of estimates revealed by Table 4 is 0.034–0.231 for humanities-arts (versus 0.159 with specification 1) and 0.220–0.399 for math-humanities (versus 0.293 with specification 1). The comparison of social sciences and humanities provides another striking example: the estimated log-wage gap is 0.073 using specification 1, but it falls to an imprecisely estimated 0.033 if both majors are assigned a low-intensity credit concentration and almost doubles to 0.130 if both majors are assigned a high-intensity concentration. Specification 1 provides a single estimate of the log-wage gap between each pair of majors without accounting for the tremendous heterogeneity in credit distributions within and across majors. Once that heterogeneity is accounted for, our inferences about the relative value of each major often differ by orders of magnitude.

For completeness, in Table 5 we replicate the top three panels of Table 4 for specification 2, in which credit distributions are among the controls but college majors are not. As with specification 3, for some pairs of majors the range of estimates reported in Table 5 represents a fairly narrow band around the benchmark estimate in Table 2. For example, the estimated difference in log-wage between engineering and health majors ranges from 0.092 to 0.138 in Table 5, depending on whether we assign low, medium, or high own-major credit concentrations; the benchmark estimate in Table 2 is 0.117. For other pairs, however, the range shown in Table 5 *fails to include* the benchmark estimate; *e.g.*, the specification 2 range is −0.032 to 0.142 for health-business, while the specification 1 benchmark is 0.167. These comparisons indicate that credit distributions alone are not suitable substitutes for college major dummies in the log-wage model. In contrast, we have seen that a model that includes major dummies *and* credit distributions among the controls sheds new light on the relative wage payoff associated with each major.

6. Concluding comments

In this analysis, we address a straightforward question: If the goal is to attribute wage differences among college graduates to heterogeneity

Table A2b
Summary statistics and estimated coefficients for baseline variables.

Variable	Mean	SD	Specification 1 Coeff.	S.E.	Specification 2 Coeff.	S.E.	Specification 3 Coeff.	S.E.
Dependent variable:								
ln(average hourly wage)	2.60	.62						
Pre-college factors (time-invariant):								
1 if male	.41		−.022	.018	−.032	.018	−.035	.018
1 if black	.14		.036	.018	.034	.018	.026	.018
1 if Hispanic	.10		−.002	.029	−.002	.029	−.012	.029
1 if Hispanic · 1 if male			−.035	.038	−.025	.038	−.025	.038
Mother's highest grade completed	14.32	3.07	.004	.002	.006	.002	.006	.002
ASVAB math score	.49	.72	.084	.012	.079	.012	.076	.012
ASVAB verbal score	.24	.66	−.057	.012	−.040	.013	−.039	.013
1 if any AP math/science courses	.23		.061	.014	.048	.015	.049	.015
1 if any AP humanities courses	.34		.058	.013	.064	.013	.065	.013
In-college controls (time invariant):								
Pre-graduation work experience (years)	4.46	2.12	−.033	.005	−.034	.005	−.033	.005
1 if attended 2-year college	.17		.041	.025	.063	.025	.053	.025
1 if attended 2-year college · 1 if male			−.025	.030	−.040	.030	−.031	.030
1 if received Associate's degree	.09		−.089	.021	−.099	.021	−.098	.022
1 if attended multiple 4-year colleges	.15		−.053	.025	−.073	.025	−.060	.025
1 if multiple 4-year colleges · 1 if male			.051	.032	.071	.032	.051	.032
Age at receipt of Bachelor's degree	23.22	1.53	−.018	.006	−.017	.006	−.017	.006
1 if switched major	.54		.070	.018	.054	.017	.064	.018
1 if switched major · 1 if male			−.073	.023	−.058	.022	−.068	.023
Post-college controls (time-varying):								
Total work experience (years)	9.27	3.69	.046	.008	.052	.008	.049	.008
Total work experience squared			−.085	.036	−.109	.036	−.098	.036
Job tenure (years)	2.40	2.53	.052	.006	.048	.006	.049	.006
Tenure squared			−.035	.006	−.032	.006	−.032	.006
1 if marital status is cohabiting	.14		.023	.016	.012	.016	.015	.016
married	.35		.109	.015	.111	.015	.109	.015
separated/div.	.03		.050	.034	.049	.034	.050	.034
1 if any children in household	.24		−.005	.016	−.009	.016	−.006	.016
1 if reside in urban area	.85		.080	.016	.078	.016	.078	.016
Root MSE	—		.554		.553		.551	
No. of observations	10,595		10,595		10,595		10,595	

Note: Each specification also includes the variables shown in Table A2a, dummies for region of residence and calendar year, and an indicator that mother's highest grade completed is missing (and set equal to the sample mean).

in acquired skills, why use "college major" as the sole proxy for skills when we can also control for each student's distribution of course credits across fields? Using a sample of college graduates from the NLSY97 for whom transcripts are available, we compare estimated log-wage gaps between various pairs of majors using specifications that include, in addition to baseline controls, (*i*) college major dummies; (*ii*) measures of the percentage of total credits completed in each field; and (*iii*) both college major dummies and credit variables. This approach allows us to compare the "gross" effect of each major (i.e., the sum of skill and credentialing effects) to the credentialing effect net of skills. It also allows us to predict wage payoffs to each major that account for whether the credit distribution corresponds to a low, medium, or high level of concentration within the major.

To illustrate the nature of our findings, we focus on the highest- and lowest-paying majors in our sample: engineering and arts. We estimate a log-wage gap of 0.570 between these majors using a conventional model that controls for majors but does not account for within-major heterogeneity in credit distributions. That heterogeneity proves to be substantial: an engineering major with a low concentration in her major completes only 28% of total credits in engineering, versus 48% for her high-concentration counterpart; arts majors have an even broader spread, from 30% to 61%. When we control for credit distributions along with major in a log-wage model, the estimated "major effect" falls by 50% for engineering, and *increases* by 50% for arts. This indicates that half the conventional engineering effect is due to skills and the other half is due to credentialing, while the conventional arts effect masks a negative return to skills. Moreover, the estimated log-wage gap between engineering and arts majors falls to 0.492 if we compare two low-concentration majors, and increases to 0.639 if we compare two high-concentration majors—a band of 0.147 around the conventional estimate of 0.570.

Unsurprisingly, our analysis does not lead us to reverse well-established findings that, *e.g.*, engineering majors earn more than arts majors. What it *does* demonstrate is that students in every major are heterogeneous with respect to the percentage of credits completed in their major and, more generally, with respect to their overall credit distributions. Estimated wage payoffs associated with many majors prove to be highly sensitive to how college coursework is distributed across fields of study. This finding is relevant to higher education policies that focus on encouraging students to pursue high-wage majors in science, engineering, and other STEM fields (Bettinger, 2010; Khan & Ginther, 2017). Our analysis suggests that students should be concerned with their entire credit distribution and not just their choice of major.

In light of our evidence that course credit distributions have an important effect on skill acquisition, we believe our approach is worth extending in a number of dimensions. With larger data sets (perhaps from state-specific administrative records), it would be worth exploring gender differences in payoffs to college credits and also conducting analyses that exploit within-institution variation to identify parameters of interest. In addition, an exploration of wage payoffs associated with the quality of the match between college credit distributions and occupations (as opposed to college majors and occupations) would be of interest, as would a formal analysis of curriculum choice (as opposed to major choice).

Table A3
Credit distributions corresponding to low, medium and high credit concentrations in select majors.

Field	Arts Low	Arts Med	Arts High	Business Low	Business Med	Business High	Mathematics Low	Mathematics Med	Mathematics High	Engineering Low	Engineering Med	Engineering High
Agriculture	4.33	3.02	1.05	3.11	2.35	2.64	1.41	2.49	1.50	3.50	5.05	.54
Arts	**31.12**	**45.32**	**61.58**	5.11	3.29	5.25	7.51	2.88	4.04	2.84	2.19	.94
Bio/Physical Sciences	8.69	6.42	4.57	7.56	5.04	4.62	7.18	12.44	8.03	17.27	15.11	14.59
Business	2.26	2.07	.37	**30.11**	**40.80**	**47.66**	17.15	7.44	3.94	3.91	1.10	.83
Communications	7.69	4.08	2.83	3.48	3.35	2.92	4.60	2.07	2.58	2.34	2.43	1.39
Mathematics	2.91	4.05	2.85	8.09	9.10	6.84	**26.89**	**38.81**	**51.47**	18.27	15.58	15.04
Education	1.49	2.05	.22	.30	.32	.27	4.30	1.19	.00	.52	.00	.38
Engineering	8.49	1.41	3.53	2.53	.82	.31	2.95	3.31	4.73	**28.99**	**40.04**	**48.53**
Health	.73	1.21	.16	1.42	.84	1.11	.17	.41	.77	1.20	.63	1.15
Humanities	19.41	21.80	15.50	19.21	18.43	15.01	18.38	16.95	16.43	13.84	11.33	10.54
Psychology	7.79	2.17	1.70	4.52	3.01	2.15	2.84	2.74	1.28	1.93	1.09	1.21
Public Administration	.70	.75	.81	1.52	.65	.69	.36	.94	1.10	1.06	.54	.00
Social Sciences	4.47	5.66	4.87	13.04	11.96	10.53	6.18	8.34	4.20	4.33	4.79	4.82
Field	Health			Humanities			Social Sciences					
Agriculture	10.93	2.36	.93	3.18	1.44	1.80	1.26	2.97	2.53			
Arts	3.56	2.46	2.28	10.13	7.34	8.35	4.30	4.16	4.65			
Bio/Physical Sciences	29.32	19.61	20.25	11.61	6.93	5.61	6.14	8.74	4.51			
Business	1.43	2.99	.97	4.55	3.47	2.26	3.44	8.15	2.63			
Communications	4.93	4.77	2.48	3.11	4.25	1.45	6.32	1.54	1.39			
Mathematics	6.59	3.44	2.59	5.17	5.28	3.18	3.57	6.52	5.07			
Education	1.82	1.95	.54	5.55	4.27	2.19	2.30	1.67	.21			
Engineering	.34	1.18	.16	.90	.73	.37	.28	1.25	.00			
Health	**7.51**	**25.64**	**43.35**	2.32	.72	.91	2.91	.54	1.42			
Humanities	16.37	17.48	13.28	**29.52**	**41.45**	**57.14**	27.93	31.60	29.17			
Psychology	11.82	10.68	8.05	9.00	7.18	4.68	11.66	3.03	5.97			
Public Administration	.44	.56	.78	1.50	3.20	.70	10.00	1.72	3.44			
Social Sciences	5.02	6.84	4.39	13.42	13.75	11.36	**19.93**	**28.17**	**39.06**			

Note: The "low" distribution for a given major is the average percentage of credits in each field among individuals with that major whose percentage is between the 15th and 35th percentile in the major-specific distribution. The "medium" and "high" distributions use 40th-60th and 65th-85th percentile ranges, respectively. Major-specific concentrations are in bold-face.

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