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College Majors and Skills: Evidence from the Universe of Online Job Ads

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ABSTRACT

We use the near universe of U.S. online job ads to document four new facts about the skills employers demand from college majors. First, some skills—social and organizational—are demanded from all majors whereas others—financial and customer service—are demanded from only particular majors. Second, some majors have skill demand profiles that mirror overall demand for college graduates, such as Business and General Engineering, while other majors, such as Nursing and Education, have relatively rare skill profiles. Third, cross-major differences in skill profiles explain considerable wage variation. Fourth, although major-specific skill demand varies across place, this variation plays little role in explaining wage variation. College majors can thus be reasonably conceptualized as portable bundles of skills.

Key Words: college major, skill demand, job ads

JEL Classification Codes: I26, J23, J24

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INTRODUCTION

The choice of college major is one of the most direct ways for college graduates to acquire skills and signal competencies to employers. Indeed, earnings differences among college graduates with different majors can be larger than earnings differences between college and high school graduates (Altonji, Blom, and Meghir 2012; Webber 2014). Some of the earnings heterogeneity among majors is undoubtedly due to selection, but recent evidence also points to the importance of human capital development from the major itself (Hastings, Neilson, and Zimmerman 2013; Kirkeboen, Leuven, and Mogstad 2016). College major provides much of the structure for the courses students take and thus the competencies and skills they develop during college. Because demand for certain skills has grown in recent years (Deming 2017; Atalay et al. 2020), it is possible that employers' perceptions of the skills associated with graduates from different majors play a large role in explaining earnings heterogeneity among college graduates. Somewhat surprisingly, however, there is little work that systematically characterizes the skills employers associate with college majors and their relation to differences in earnings.[1]

To start to fill this void, this paper answers two main questions: First, how does employer skill demand differ across majors? For example, is the desire for social skills concentrated among job postings in only a few majors or is it widely demanded across majors? Second, how does skill variation relate to earnings variation across majors? In answering these questions, we develop a new measure of the specificity of college majors based on their patterns of skill concentration. We also explore the role of place as it relates to within-major, cross-area differences in skill demand and earnings.

We measure the skills employers associate with particular majors using job vacancy data obtained from Burning Glass Technologies (BGT, or Burning Glass), comprising the near universe of online job ads from 2010–2018.[2] A unique feature of this data source—beyond its scale and universality—is the inclusion of information on majors, detailed skills, locations, and occupations, which permits us to characterize demand along these dimensions. In contrast to previous studies

[1] In contrast, recent research has documented the importance of skill heterogeneity between and within *occupations* in explaining spatial wage variation (Deming and Kahn 2018). But because occupation reflects post–labor market selection, the role of *premarket* skill acquisition as captured by college major remains underexplored.

[2] In 2021, after we acquired the data, BGT merged with EMSI, a similar firm, and the company is now known as Lightcast.

that document skill-major linkages mediated through occupation (Altonji, Kahn, and Speer 2014; Long, Goldhaber, and Huntington-Klein 2015), the job postings data allow us to measure skill-major linkages at the individual job level. Moreover, this information precedes the employment choices of individuals and is thus a more proximate and direct signal of skill demand independent of occupational sorting.

To answer our descriptive questions we take advantage of the more than 15,000 unique and detailed skills listed in job ads to create a tractable number of skill composites, adapting the approach of Deming and Kahn (2018).[3] Using the skill composites, we construct skill location quotient indices by major, similar to the approach typically used to measure industrial or occupational concentration. More specifically, we compare the vector of skills listed among job ads for each major to the vector of skills among jobs ads for all college-educated workers. The relative over- or underrepresentation of certain skills within a major provides evidence on the specificity of that field of study.

Our approach assumes that employers list all appropriate skills alongside majors jointly, instead of listing majors in place of skills. We propose that employers face a fixed cost of posting an online vacancy, but that the marginal cost of including additional information is low enough that they include such information even when it is closely related to other material already included (e.g., listing "teaching skills" and Teacher Education major together). We present descriptive evidence supportive of this assumption. Note that we measure the skills employers *expect* (or *perceive*) graduates to possess; although these may not accord exactly with the skills graduates (or even hires) actually possess, they are likely highly correlated in equilibrium.

Our analysis reveals marked differences in the skills associated with different majors. First, some skills—even composites—are concentrated within a small subset of majors whereas others are near universal. Employers demand social and organizational skills at similar rates across all majors, but customer service and financial skills appear specialized to relatively few majors. Second, we find that some *majors* are more typical of overall skill demand than others. For example, average skill demand for Business, Economics, and General Engineering majors accords reasonably closely with the average skill demand across all majors. Nursing, Education, and

[3] Although the economics literature often draws a theoretical distinction between skills and tasks (e.g., Acemoglu and Autor 2011), it is not clear employers do so when posting job ads, which contain only "skills" in our data. In our analysis, we thus follow Deming and Kahn (2018) and Hershbein and Kahn (2018), among others, and treat all listed proficiencies as skills, even when some may sound more like tasks (e.g., "manages people").

Foreign Language, on the other hand, are more specific, with job ads requesting skills demanded relatively infrequently in other majors. Common classification systems based on college curricula (such as the Classification of Instructional Programs, or CIP) thus may fail to reflect salient dimensions of difference (or commonality) across fields of study. Together these results imply that employers view majors as meaningfully encompassing different skill bundles.

We further corroborate this premise through an analysis of earnings variation across majors and places. We use BGT data to measure skill demand for each combination of major and metropolitan statistical area (MSA), and we use American Community Survey (ACS) data to measure mean wages. We find that major—rather than MSA—accounts for the bulk of the variation in skill demand across MSA-major cells. Nevertheless, remaining within-major, cross-area variation in skill demand could play a role in explaining the appreciable differences in earnings for the same major across areas. However, we find that this is not the case. We show that cross-major differences in skill profiles explain the vast majority of wage variation across major-MSA cells. Major fixed effects greatly diminish the capacity of the skill composites to predict earnings, and cross-area skill differences within majors have only a weak relationship with major earnings premia across areas. This finding strengthens our conclusion that majors can be conceptualized as a portable bundle of skills.

Our work contributes to the intersection of several strands of literature. First, we contribute to the broad literature that explores variation in skill demand across firms, markets, and time (e.g., Deming and Kahn 2018; Hershbein, and Kahn 2018). Most work on the supply of college majors focuses on skill-major linkages through occupation (Altonji, Kahn, and Speer 2014; Long, Goldhaber, and Huntington-Klein 2015). However, occupations are heterogeneous bundles of skills and tasks, and skill demand can vary dramatically across jobs within occupations (Busso, Muñoz, and Montaño 2020). Our analysis highlights the importance of college major as a measurable dimension along which skill demand varies separate from occupation, and before market sorting occurs.

A second strand of literature looks at whether majors are general versus specialized, which has implications for their returns over the life cycle. Prior work has examined the benefits of a general versus specialized curriculum in the labor market (Hanushek et al. 2017; Deming and Noray 2020; Martin 2022). Several papers do this by quantifying the link between majors and occupations (e.g., Altonji, Blom, and Meghir 2012; Ransom and Phipps 2017; Li, Sebastian, and

Shimao 2021) or via variation in major premia across occupations (Kinsler and Pavan 2015; Leighton and Speer 2020). Our approach abstracts from concerns about selection of college graduates into occupations by using information from job ads prior to employment and realized earnings. Thus, we look at the specific skills associated with each major as perceived by employers and view our approach as complementary to these occupation-based approaches. Our description of the skills employers associate with college majors illustrates one source of the large returns to college major (e.g., Arcidiacono 2004; Kirkebøen, Leuven, and Mogstad 2016; Andrews, Imberman, and Lovenheim 2017; Martin 2022) as well as differences in the costs of producing them (Hemelt et al. 2021).

Finally, we contribute to the understanding of spatial differences in wages, particularly cross-area major wage premia (Ransom 2021) and spatial differences in the returns to education (Black, Kolesnikova, and Taylor 2009). In contrast to Deming and Kahn (2018), who find that employer skill demand predicts occupational wage premia across areas, we find minimal association between skill demand and cross-area major wage premia. Cognitive and social skills in particular have minimal association with major premia across areas, in contrast to findings for occupational wage premia. This suggests that spatial variation in wages is driven by factors other than within-major skill specialization, at least at the level of aggregate skill composites.[4]

The rest of this article proceeds as follows. The following section describes the data and sample. The third section details the relationship between majors and skills. In the fourth section we document the geographic variation in the skill-major linkage and then relate skill variation to earnings variation. The fifth section concludes.

DATA AND SAMPLES

Job Ad Data

We use the near universe of all online job ads posted in the United States from 2010 to 2018, obtained from BGT.[5] Burning Glass scours about 40,000 online job boards and company

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[4] Indeed, geographic heterogeneity in the sorting of majors into occupations, and the mechanisms behind it, are promising areas for further research.

[5] Several recent papers have used BGT data to study cross-sectional skill demand (Deming and Kahn 2018; Brüning and Mangeol 2020; Alekseeva et al. 2021), cyclical and structural changes in skill or labor demand (Hershbein

websites to aggregate job postings, parse and deduplicate them into a systematic, machine-readable form, and create labor market analytic products. The data contain detailed information on over 70 standardized fields including occupation, geography, skill requirements, education and experience demands, and firm identifiers. There are over 15,000 individual skills standardized from the open text in each job posting. Our data cover the United States and contain approximately 153 million individual job postings.

Since the database covers only vacancies posted on the internet, the jobs are representative of a subset of the employment demand in the entire economy. Hershbein and Kahn (2018) conduct a detailed analysis of the industry-occupation mix of vacancies in the BGT data for years 2010–2015 and compare the distribution to other data sources, including the Job Openings and Labor Turnover Survey, the Current Population Survey, and the Occupational Employment Statistics. They conclude that although BGT postings are disproportionately concentrated in occupations and industries that typically require greater skill, the distributions are relatively stable across time, and the aggregate and industry trends in the number of vacancies track other sources reasonably closely.[6] Moreover, since we focus on job ads requiring a bachelor's degree, the skill skew is of even less concern.

Sample

We restrict to job postings that list at least one skill, require exactly 16 years of education (i.e., a bachelor's degree), and list at least one college major. Just over half of the job postings that demand 16 years of education and at least one skill also explicitly list at least one college major.[7] These education and skill requirements leave 12.8 percent of the original 153 million job postings. Most of our analyses also restrict the sample to ads posted in MSAs, reducing the analytic sample to about 18.5 million unique job postings.[8] We exclude ads specifically targeting workers with

and Kahn 2018; Modestino, Shoag, and Ballance 2016; Modestino, Shoag, and Ballance 2020; Forsythe et al. 2020), and labor market concentration (Azar et al. 2020).

[6] See online Appendix A of Hershbein and Kahn (2018).

[7] Approximately 17 percent of all postings ask for 12 years of education, 5 percent ask for 14 years of education, 3 percent are for 18 years and 1 percent ask for 21 years of education. The remaining postings are missing information on education (roughly 50 percent of all postings). For postings that demand 18 years of education, a major is listed as frequently as in postings that demand 16 years of education (54 percent) but majors are less frequently listed in postings that specify 12, 14, or 21 years of education (6.5 percent, 37 percent, and 46 percent, respectively).

[8] The vast majority of postings are from metropolitan statistical areas, so this restriction drops only about 5 percent of the "education 16" sample with at least one major (around 1,000,000 postings).

graduate education as we are interested in measuring the association between undergraduate majors and skills. Most job postings require 0–5 years of experience, which is more relevant for individuals prior to graduate education.

Given the large reduction in the sample size after imposing these restrictions, one might worry that the types of job postings in our restricted sample differ from the set of all job postings. Table 1 compares the occupational composition of job postings in our analytic sample to two larger samples. Differences are mostly due to the bachelor's education requirement. It is well documented that typical job tasks performed in occupations that employ workers with less formal education differ from those that employ workers with more formal education (e.g., Autor and Acemoglu 2011). The higher concentration of job postings in Management (22 percent vs. 12 percent) and Business (15 percent vs. 7 percent) occupations in our analytic sample relative to all job postings concurs with this stylized fact. Analogously, the full sample of ads has a higher proportion of job postings in Food Prep (3.38 percent vs. 0.23 percent), Building Cleaning and Maintenance (1.11 percent vs. 0.04 percent), Sales occupations (11.76 percent vs. 4.38 percent), and Office and Administrative Support (9.96 percent vs. 3.02 percent).

While the occupational distribution of job postings in the analytic sample (column 5 of Table 1) is similar to that of the broader sample requiring 16 years of education and at least one skill (column 3), there are still a few differences of note. The latter sample has a higher proportion of ads listing Education/Training/Library Occupations (2.5 percent vs. 1.3 percent), Sales occupations (8.2 percent vs. 4.4 percent), and Office/Admin Support (4.3 percent vs. 3.0 percent), with lower proportions in Computer/Math (22.1 percent vs. 25.8 percent) and Architecture/Engineering (6.7 percent vs. 9.3 percent). This pattern suggests that ads that list a college major on average call for occupations associated with higher pay than those that do not.

We more formally investigate these differences using a 1 percent random sample of job postings that demand a college degree. We regress a binary indicator for whether a job posting lists at least one college major on over 900 metro- and micro-statistical area fixed effects, 99 year-by-month fixed effects, more than 500 six-digit occupation codes, and more than 90 two-digit industry codes. The baseline model, which includes roughly 1,600 covariates, explains only 13 percent of the variation in whether a job posting lists a major. The explained variation doubles when we include a cubic for the number of skills per posting, indicators for eleven skill composites (described below), and indicators for whether a posting has each of the 1,000 most frequently listed skills. Individually controlling for the 9,000 most frequent skills increases the explained variation by just another 4 percentage points, to 29 percent.[9] These results suggest that differences in extremely detailed observables explain only a modest share of the variation in whether a job ad lists a college major. While our findings rely on the sample of job ads that explicitly list a college major, the degree of unexplained variation in listing a major hints at idiosyncratic reasons for including a major on a job ad. Thus, it is plausible that our findings would apply to the broader sample of job ads that require 16 years of education. In addition, we assess the robustness of our measures of specificity of skills and majors to the inclusion of ads that do not explicitly list a desired college major.

College Majors

Among job postings that require exactly a bachelor's degree, 54 percent also list at least one college major. While the exact method used to extract majors from job ads is proprietary to Burning Glass, our discussions with them suggest they do minimal cleaning or imputation beyond standardizing majors into consistent categories. Majors are coded into the Classification of Instructional Programs (CIP) taxonomy at up to six digits, and we first aggregate these into four-digit CIP codes. Importantly, a job ad can list multiple college majors. On average, the number of majors listed per ad (conditional on having at least one) remains fairly stable across the analysis period at around 1.7, with about 55 percent of postings listing a single major, 30 percent listing two, and 15 percent listing three or more. For the purposes of analyzing skill demand by major, we further aggregate college majors into 70 categories.[10] We aim to produce categories that have meaningful quantities of both job ads (BGT) and degrees granted according to the Integrated Postsecondary Education Data System (IPEDS). Because we want our categorization of majors to reflect the fields that students at four-year institutions encounter when making choices about paths

[9] Appendix Table A1 shows these results. Appendix Table A2 reports F-tests on the blocks of covariates in the baseline model and reveals that job postings that list a major differ in terms of occupational distribution, industry, and location.

[10] There is a 71st category which contains majors that we omit from our analysis. This category contains college majors that are traditionally sub-baccalaureate or remedial programs (e.g., Basic Skills and Developmental/Remedial Education), that are predominantly postbaccalaureate or graduate programs (e.g., Residency Programs), or trade specific (e.g., Mechanic and Repair Technologies/Technicians).

of study, we use the CIP coding hierarchy wherever possible and combine majors that tend to appear in ads together or that require similar sets of skills (as indicated in the job ads).[11]

Figure 1 plots the share of job postings that list the 10 least and most common majors under this broader method of aggregation. Five majors appear in at least 10 percent of postings in the analytic sample, including both Business and Computer & Information Sciences, which are listed on 29 percent and 26 percent of unique job postings, respectively. The frequency of the remaining 65 majors is quite heterogeneous, with half of all majors showing up on less than 0.5 percent of job ads. The least frequently demanded majors in our sample include Theology (0.07 percent), Atmospheric Sciences and Meteorology (0.03 percent), Other Physical Sciences (0.03 percent), and Philosophy and Religion (0.02 percent).

Since the college majors listed on these job postings have received little scrutiny, an important but open question is how major-specific demand measured in these job postings relates to the composition of bachelor's degrees granted or supplied over time. Figure 2 compares the distribution of majors listed on job postings in the BGT data to the distribution of degrees granted for the same majors in the U.S. from years 2010–2018 using IPEDs data. Majors for which the share of job postings is proportional to the share of degrees granted should fall on the 45-degree line, majors overrepresented (underrepresented) in the BGT data will fall above (below) the 45-degree line. Some majors, including Nursing and Economics, have demand that is proportional to the number of degrees awarded for the major. Engineering and Statistics, however, are overrepresented in the BGT data relative to degrees granted, whereas Philosophy and Religion, Atmospheric Sciences, and English are underrepresented.[12] This discrepancy likely reflects a disconnect between the supply and demand for specific college majors, an important topic beyond the scope of this current paper, rather than an issue with the representativeness of the job postings data itself.

Categorizing Skills

Burning Glass parses over 15,000 individual skills from the job postings. As is common practice in previous studies using BGT data to categorize skill demand in the labor market (Deming

[11] Appendix B describes our process for aggregating college majors. Appendix Table A3 reports the complete list of major groups.

[12] A similar pattern of over- and under-representation is apparent if, instead of IPEDS, we measure supply using the distribution of prime-age workers in the U.S with degrees as measured on the 2009–2018 waves of the ACS.

and Kahn 2018; Hershbein and Kahn 2018), we do not empirically distinguish between skills—a worker's endowment of capabilities—and tasks—a unit of work activity that produces goods and services. Although the literature separates these theoretically (Acemoglu and Autor 2011), in practice employers do not always clearly differentiate between them in job postings, and thus we consider all these proficiencies to be "skills."

We categorize by hand the 1,000 most frequent skills into 11 mutually exclusive skill composite categories. To do so, we crafted detailed definitions of the skill composites and then had pairs of our research team manually assign a subset of the skills to one of the composites, using a preset process to resolve discrepancies. (We describe the procedure in detail in Appendix C and provide examples for the top 40 skills in Appendix Table A4.)

This approach provides a few benefits over the application of the keyword approach from Deming and Kahn (2018) or Hershbein and Kahn (2018).[13] First, some of the most frequently listed individual skills are not captured by any skill composite using the keyword approach. Examples include planning (appears on 20 percent of postings), organizational skills (16 percent), detail-oriented (12 percent), scheduling (12 percent), building effective relationships (11 percent), creativity (10 percent), troubleshooting (6 percent) and multitasking (8 percent). Second, the keyword approach can result in the misclassification of some broad groups of skills. For example, the composite "people management" includes the keyword "management" and thus captures a wide variety of general management activities that do not specifically pertain to managing people, including account management, pain management, and operations management. Similarly, underwriting is also included in the writing composite using the keyword approach, even though that skill is quite distinct.

Table 2 provides a description of each of the 11 categories along with the most frequent skills in each category.[14] The final column lists the words used to define these categories based on the keyword approach. Our resulting skill composites are mutually exclusive at the skill level—that is, a detailed skill maps to at most one composite—but a given job posting can have multiple

[13] In **Appendix D**, we assess the differences between the keyword approach used in Deming and Kahn (2018) and Hershbein and Kahn (2018) and our hand-coding approach. While the keyword approach categorizes more total skills into composites, it misses many relevant and frequent skills, and also results in some inconsistent categorizations. Nonetheless, our results largely hold under either method.

[14] Our main analysis focuses on 11 skill composites. In some tables or figures we also provide results for a twelfth skill, communication skills (which is a proper subset of the "social" composite), and a thirteenth composite, unclassified—which consists of all skills outside the 1,000 most frequent.

skill composites. Figure 3 shows the share of all ads containing a skill falling in each of the 11 categories. "Cognitive" skills are listed in more than three-quarters of all job ads and constitute the most frequently occurring composite (aside from the "unclassified" group, which picks up any skill outside the 1,000 most frequently occurring). In contrast, "people management" and "writing" are the least likely to appear, each mentioned in about one-third of all ads. We note that a much higher share of ads fall into our skill composites than those used by Deming and Kahn (2018), since we have explicitly categorized the 1,000 most frequently occurring skills. Their estimate of the shares of ads seeking cognitive and social skills were 37 percent and 36 percent, respectively.[15]

Inferring Desired Skills from Co-Listing with Majors

Our approach assumes that employers list all appropriate skills alongside majors, instead of listing majors in place of desired (or assumed) skills.[16] If employers choose to list a desired major instead of listing the constituent skills, then our metrics will understate the importance of these core skills to a given major. This does not seem to be the case; the most frequent skills appearing alongside majors tend to be core skills required by the jobs that graduates with these majors tend to enter (Appendix Table A5).[17] For instance, the top skills for Economics majors include "Microsoft Excel" and "research," those associated with Teacher Education majors include "early childhood" and "child development," and Journalism majors are expected to have "writing" and "editing" skills. Further, when we look at ads for individual occupations, the listed skills tend to be similar regardless of whether a major is listed or not. For example, the top 10 most frequently listed skills on job postings that denote the occupation "Managers, All Others" are nearly identical between postings that list a major and those that do not, as are the shares of postings listing each of these skills. This conclusion generally holds for other occupations we examined, including Healthcare and Social Workers, Computer Programmers, Accountants and Auditors, Mechanical Engineers, and Registered Nurses.

[15] We note that their sample was restricted to professional and managerial occupations but not restricted by education. Our sample is restricted to ads requiring exactly 16 years of education but is not restricted by occupation.

[16] Other papers that use BGT data to measure skill demand make an analogous assumption: employers list all appropriate skills alongside occupation (or industry), instead of treating these as substitutes. See, for example, Modestino, Shoag, and Ballance (2016), Deming and Kahn (2018), Hershbein and Kahn (2018), Modestino, Shoag, and Ballance (2020), and Alekseeva et al. (2021).

[17] This finding also permits us to reject the notion that listed skills are perfect complements to listed major(s); indeed, such an assumption would require that employers idiosyncratically list only skills that are not implied by the major(s).

Finally, it does not appear that employers are more prone to list a desired major instead of skills in cases where the major has very specific training for particular occupations. While it is true that postings for these majors tend to list fewer skills, there is an extensive amount of variation across majors and even among the more specific majors. For example, postings for Theology majors on average list 6 skills, those for Nursing and Social Work list an average of 10 skills, and those for Electrical Engineering, Business, and Biochemistry & Molecular Biology average 15–17 skills.

Hence, we conclude that employers do not simply list majors as a substitute for listing the skills they seek in job applicants.[18] This pattern is consistent with employers facing a fixed cost of posting a vacancy, but relatively low marginal cost of including additional information like major.[19] The benefits of listing additional information on a posting, even when this additional information is closely related to other material already on the postings (e.g., Teacher Education major and Teaching skill), appear to exceed the costs.

While job postings illustrate differences in the *types* of skills associated with each major, we are unable to infer differences in the *level* of skill demanded within each type; wage information attached to the ads is uncommon in our sample and likely not representative. Two positions both seeking applicants with "writing" skills may require quite different levels of this skill (e.g., jobs for Journalism majors require more advanced writing skills relative to jobs for other majors). Furthermore, the composite skills we construct also likely mask differences in skill intensity that may be reflected in the detailed set of skills. In either case, to the extent we understate differences in the intensity of skill demand across majors, the large cross-major differences documented below are likely conservative.

A final consideration is that students of varying levels of general ability sort into different majors (Paglin and Rufolo 1990; Arcidiacono 2004). Skills stated in job ads may thus reflect employers' perceptions of student sorting, perceptions of human capital accumulation, or both. We do not take a stand on this distinction; either interpretation reflects employers' views of the skills they *perceive* applicants from each major to possess. Moreover, employer skill demand may not

[18] That is, we assume that skills are co-listed with a major with an imperfect elasticity of substitution. This situation could arise in the plausible case that heterogeneous employers differ in their skill demand for a given major or occupation (Deming and Kahn 2018). We associate skills that appear more frequently with a major as more tightly with the major, but our framework allows this association to exist on a continuum.

[19] Online postings are likely to be quite different from print job ads in this regard.

exactly match (but likely correlates with) the skills graduates actually possess. Understanding this correlation, as well as measuring intensity of skill level from job ads, are important directions for further research.

Earnings by Major

To measure average earnings by major across space, we combine the 2009–2018 waves of the American Community Survey (ACS) to create earnings measures at the major-by-MSA level. The baseline sample includes individuals aged 25–54 with at least a bachelor's degree. We drop observations with imputed or negative earnings or imputed majors. We keep all individuals with positive years of potential experience and positive weeks worked. Finally, we impose the additional restrictions that workers are not enrolled in school and are full-time, full-year workers, where full-year is defined as at least 40 weeks a year and full-time is defined as 30 hours a week.

We construct hourly earnings by dividing annual earnings by the product of weeks worked during the past 12 months and usual hours worked per week. We adjust earnings for inflation to 2019 dollars using the Personal Consumption Expenditures deflator from the Bureau of Economic Analysis. In our analyses, we use two versions of real hourly earnings. The first is the log of raw mean hourly earnings in the major-MSA cell. For the second, we regression-adjust for compositional differences across majors. Specifically, we regress the log of hourly earnings at the individual level on indicators for female, Black, and Hispanic, as well as a quartic in potential experience, and we then take the mean of the residuals within each major-MSA cell.[20] Figure 4 shows substantial geographic variation both across and within majors in the mean hourly wage of full-time, full-year, prime-aged workers in the United States. We later assess the extent to which this variation can be explained by differences in the skill content across and within majors.

SKILLS ASSOCIATED WITH COLLEGE MAJORS

Table 3 reports the share of ads listing each of the skill clusters separately for a handful of majors, along with the minimum and maximum share across 70 different majors.[21] There is a substantial range across fields for many of these skill aggregates. For instance, the share of ads

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[20] In both cases we employ sample weights when aggregating to major-MSA cells.

[21] Full results for all 70 majors are in Appendix Table A6.

desiring specific software skills ranges from less than 4 percent for Nursing to (unsurprisingly) nearly all job ads in Computer Science. Project management skills are sought in nearly all job ads for Public Health majors but rarely for jobs seeking Education or Foreign Language majors. People management is rarely desired on job ads associated with Accounting majors, but appears on more than half of ads targeting Public Administration majors. Because "communication skills" constitute such a large share of the "social skills" composite, we separately report statistics for this skill.

Measuring Skill Content

We formalize this variation in skill demand across majors in two ways. First, we construct a location quotient (LQ) for each major-skill-composite combination. This measure is commonly used to characterize the concentration of industry- or occupation-specific employment in a region relative to the nation. The LQ is the ratio of the demand for a skill among job postings listing a particular major relative to the demand for that skill among all job postings. For the dyad of major *m* and skill component s, the LQ is computed as:

$$LQ_{ms} = \frac{(N_{ms}/N_m)}{(N_s/N)} = \frac{(N_{ms}/N_s)}{(N_m/N)}, \tag{1}$$

where N_m is the number of ads that list major *m*, N_{ms} is the number of ads that list major *m* and skill *s*, N_s is the number of ads that list skill *s*, and *N* is the total number of ads. In our main specification, we measure national skill demand (also referred to as the market demand) using all postings that require 16 years of education and list at least one college major. We construct one LQ for each major (m) and skill composite (s) combination. An LQ around 1 indicates that the demand for a skill among job postings with major *m* is the same as the market demand for that same skill. An LQ > 1 indicates that the skill is concentrated among ads that list major *m* because the fraction of ads demanding the skill in the entire market is lower than the fraction of major *m* ads listing that skill.

One complication in practice is that a job posting can list multiple majors and multiple skills; this is not an issue in more commonly used settings in which the allocations of workers to occupations and regions are mutually exclusive. In the common setting, regional employment sums to national employment, and the occupation-specific employment in a region sums to total regional employment. As a result, the average of occupation-by-region LQs for a given region weighted by the occupation's share of national employment for each region equals 1. In our case, because we treat a single job posting that lists *X* different majors as *X* different observations, the above properties no longer hold, muddying interpretation of the LQ.

To recover the desirable properties of LQs, we make a few adjustments. First, we redefine the total count of job postings (*N*) as the total number of job-posting-by-major observations ($\widehat{N}$) so that $\sum_m N_m = \widehat{N}$. Second, we analogously redefine the total count of unique job postings with skill *s*, N_s, to be the total of job-posting-by-major observations that list skill *s* (that is, $\widehat{N}_s$), so that $\widehat{N}_s = \sum_m N_{ms}$. With these changes, the adjusted LQ for a dyad of major *m* and skill *s* is:

$$\widehat{LQ_{ms}} = \frac{(N_{ms}/N_m)}{(\widehat{N_s}/\widehat{N})} = \frac{(N_{ms}/\widehat{N_s})}{(N_m/\widehat{N})}. \tag{2}$$

The distribution of the adjusted LQs across majors for a given skill now has a weighted average of 1, where the weights are equal to the shares of all job-posting-by-major combinations that list major m. As a result, we can compare the adjusted LQs to 1 to determine relative concentration.

To characterize the degree of specialization of a major as reflected by the skill composites, we examine whether a major has LQs close to 1 for each of its skill composites. Specifically, for each major, we compute the absolute value of the deviation of each skill composite LQ from 1. We then sum the absolute value of the deviations within major and across all 11 skill composites: $\sum_{s=1}^{11} abs(\widehat{LQ_{ms}} - 1)$. Majors with a higher sum are more specialized.

Our second approach compares the skills demanded from each major to national skill demand using a cosine similarity measure and the 9,000 most frequently listed skills.[22] Specifically, for all job ads in the national analytic sample and for ads listing each of 70 different majors, we construct a vector containing the share of all ads listing each of the 9,000 skills. We then construct the cosine similarity between the national skill distribution and major-specific distributions. We measure the distance between a major's 9,000-dimensional skill demand vector and the 9,000-dimensional national skill demand vector using the angle between the two vectors. Majors with a value closer to zero have skill demand that is very different from national demand and are thus more specialized, whereas more general majors with a skill demand vector that is similar to the national vector will have a cosine similarity near 1.

The cosine similarity and LQ measures of skill concentration provide complementary information. The former measures how similar a given major is to the broad set of jobs based on

[22] We narrow our focus from the complete set of 15,000 skills to the roughly 9,000 skills found on at least 0.001 percent of all job postings.

nearly the entire skill vector, which includes many infrequent and specific skills. In contrast, the latter focuses on similarity based on the large clusters of the most common skills. The LQ-based measure also permits us to characterize skill differences across majors along a tractable number of dimensions. We assess the empirical correspondence between these two measures in a subsequent section.

Skill Specificity of College Majors Based on Location Quotient

Across the 70 majors and 11 skill composites, we construct nearly 800 different LQs, one for each skill-by-major combination. The first row of Table 3 reports the denominator of the LQ for each skill composite, which is roughly equivalent to the percentage of job postings that list each skill. In Table 3, for a selected set of majors, we list the share of each major's postings that list each skill composite. This term is the numerator of the LQ and is particular to a given major-by-skill combination. The LQ is simply the ratio between each subsequent row and the top row.

We summarize our findings from the LQ calculations graphically. Panel A of Figure 5 plots the distribution of LQs across majors for four skill composites. Social and organizational skills have a large number of major-specific LQs that are clustered around 1, indicating that most majors require similar levels of these skills. Customer service and financial skills are more varied; some majors are associated with very high levels of those skills (such as Social Work and Construction Management, respectively) and others very low (Atmospheric Science and Theology). Panel B combines the LQs into a single index—the share of the LQs that are within narrow bounds around 1—which measures the specificity of skills to majors. For a given skill, if most majors have an LQ around 1, then the demand for that skill is not particularly concentrated among any subset of majors. Most majors have an LQ for social skills near 1 because most majors have the same fraction of ads demanding social skills as does the entire market. Social skills are thus general—a skill that is demanded across ads for most majors. In contrast, Financial and Customer Service skills are specific.

Figure 6 plots the LQs for all majors and the 11 skill composites. Majors are ordered according to the degree of overlap between a major's skill demand and national demand. For each skill composite, we measure the absolute deviation of the major's LQ from 1, and then sum the absolute deviations across all skills for a major.[23] For some majors, including Business, Economics, and General Engineering, the measure is very small, suggesting that they have a skill profile similar to that of the broader job market: LQs fall close to 1 for all skill aggregates. These majors can be thought of as "general" majors in the sense that they are associated with skills that are demanded by a large number and wide variety of jobs in the college-educated labor market.

Majors toward the bottom are *specialized* (i.e., "specific" majors) in the sense that they reflect a skill profile that is quite distinct from the labor market overall. These include Nursing, with a high co-occurrence with customer service skills but very low with software, computers, financial, and writing skills. Among postings that demand a Nursing major, 23 percent demand computer skills, which is roughly half the marketwide demand of 42 percent, yielding an LQ of 0.5. The demand for writing and software skills for Nursing is even lower. A desire for customer service skills, however, is overrepresented: they appear on 82 percent of postings that list a Nursing major but only 46 percent of job postings in the wider sample. Foreign Language has a high concentration of social skills and writing but low need for software or financial skills.

Majors in the middle ("generific" majors), such as Computer Science and Psychology, have a skill profile broadly reflective of the national one, but with a few skill categories that are particularly over- or underrepresented.[24]

These results are robust, when calculating the LQ denominator, to including postings that demand 16 years of education but do not list a major. Our main measure compares the share of each major's postings that list each skill to the percentage of all job postings with a college major that list each skill. However, it is possible that the postings that do not explicitly list a college major are searching for workers with any form of disciplinary training. If so, then the skill demand on these postings represents the skills employers expect the average college graduate to possess. To assess this, we reconstruct the LQ measures with all postings that demand exactly 16 years of

[23] Specifically, for each major, the measure is [Σ(abs(LQ−1))] where the sum is taken across skill composites within a major. We also order majors using the sum of squared deviations [Σ((LQ−1)^2)]. The ranking of majors based on the two measures is highly correlated (0.96).

[24] One potential concern with our approach is that the largest majors, by virtue of being large, might mechanically be classified as general. We first note that the five largest majors are not all categorized as general under our approach. However, to further examine this concern, for each of the five largest majors we recompute our LQ-based metric of major specificity removing the focal major from our characterization of national demand. Only two of the five majors change categories, both shifting toward more specific categorizations. That is, Computer & Information Sciences and Accounting move from the middle category (generific) to the specific category—and both were initially on the boundary between those two categories.

education (irrespective of whether a major is listed) in the denominator.[25] The ranking of college majors is almost identical to our preferred specification ($R^2 > 0.95$).

Measuring Specificity with All Skills

We also compare our LQ-based measure to the cosine similarity measure. The cosine similarity metric captures the similarities between each major and all job ads nationally along the vector of 9,000 skills, which incorporates more information about less frequent, possibly more specialized, skills. Figure 7 shows that the two metrics produce broadly similar rankings of specificity across majors. The R^2 from the bivariate regression between major rankings of the two indices is 0.37 when majors are equally weighted and 0.53 when majors are weighted by the number of ads; the association is similar if we compare the metric itself, rather than the rank (Appendix Table A.7). This strong correspondence reflects the fact that most of the variation in the cosine similarity measure comes from variation in the 1,000 most frequent skills ($R^2 = 0.90$), which are the ones that enter our LQ-based index.[26]

Figure 8 plots the similarity of skill demand between each pair of majors along the vector of 9,000 skills. Majors that have similar skill demand have a value closer to 1 and are substitutes in terms of skill demand; these are represented by a darker shade. Unsurprisingly, some of the closest major pairs occur within the same broad CIP category, including the pairs of Finance and Accounting; Communication & Media Studies and PR & Advertising; and Statistics and Mathematics. However, close majors are also found across different broad categories of study, including the pairs Other Engineering and Business; and Political Sci/Gov & Intl Relations and English, Liberal Arts, & Humanities. Finally, some majors have many substitutes, which we proxy by the share of other majors to which the given major is very similar (similarity measure > 0.8), including Business, Library Science, English, Liberal Arts, Humanities, and Communication & Media Studies.

[25] In fact, if we treat the subset of ads that require 16 years of education but do not list any major as a "major" (i.e., the unspecified major group) and then characterize that group using the approaches we develop in this paper, we find that this unspecified major would be classified as the most general major. This provides additional reassurance about our sample restrictions and empirical conceptualizations of the specificity of majors. In related work, we apply machine learning methods to estimate the full latent distribution of majors demanded in job postings.

[26] In addition, the R^2 from the bivariate regression between major rankings using the LQ-based measure and the cosine similarity measure based on only the 1,000 most frequent skills is almost identical to that yielded when the cosine similarity measure is instead based on the top 9,000 skills.

The graph also clearly highlights specific majors: Teacher Education and Nursing are both represented by light boxes across the graph, as their skill vector is quite different from almost all other majors and they have few substitutes. Both our LQ-based and cosine-similarity-based metrics distinguish general from specific majors, though they use employers' stated skills in different ways. Furthermore, the extent of skill substitutability clearly differs across majors, often in ways not captured by the CIP code classification hierarchy.

Comparison to Prior Work on College Major Specificity

Our measure of college major specificity complements those constructed by other scholars, which rely primarily on major-occupational linkages and earnings premia across majors. Figure 9 compares our measure to one based on the occupational concentration of college majors, specifically the share of recent college graduates with a given major represented in the top five most frequent occupations in the ACS. There is a moderate correlation between major rankings when cells are weighted by the number of ads (0.47), but minimal correlation when they are unweighted (0.004), suggesting that inferences about specialization are more robust for more common majors.[27]

Leighton and Speer (2020) construct a Gini coefficient of wage premia across occupations. The notion is that majors with highly occupation-dependent wage premia are likely providing more specialized skills. Kinsler and Pavan (2015) develop a similar idea by focusing on wage differences between workers in jobs that are or are not related to their major. Relatedly, Li, Linde, and Shimao (2021) build a complexity measure of majors based on the breadth of occupations to which a major maps and the narrowness of majors that in turn feed into those occupations. Ransom and Phipps (2017) use major-to-occupational flows to construct measures of major occupational "distinctiveness" and "variety." Appendix Table A8 compares the most/least specific majors using our two skill-based metrics to those published by Leighton and Speer (2020). A few majors appear on multiple lists, most notably Nursing and Education (most specific) and Mathematics (most general).

Thus, there is a correspondence between which majors are considered general or specific when skills are measured based on employers' perceptions as expressed on job postings and when they are implicitly measured based on realized occupational sorting. Our measure of specificity,

[27] Appendix Table A7 presents correlations between all of the specificity measures we construct.

which is based on the arguably more primal skill demand, additionally permits investigation of specific mechanisms that likely contribute to major wage premia—particularly related to the role of heterogeneous demand on the basis of geography.

SKILL VARIATION ACROSS AREAS AND EARNINGS VARIABILITY

The prior analysis demonstrated the substantial variation in skills associated with college majors, aggregated across all years and labor markets. However, the universality and granularity of the BGT data also enable us to analyze major-specific variation across space; geographic skill variation has been shown to be important for occupations (Deming and Kahn 2018). In this section, we quantify how skill demand associated with each major varies across areas, and we then use this variation to examine how skills and majors relate to earnings. Substantial variation across space in skill demand for the same major may indicate an opportunity for local postsecondary providers to tailor program curricula to suit local labor market needs.

Geographic Variation in Skill Demand

As an example of what the granularity of our data allows, Figure 10 depicts variation across the more than 900 U.S. micropolitan and metropolitan statistical areas in the share of job postings for Business majors that seek cognitive skills. Areas with grayer shading have larger shares of Business major ads that demand cognitive skills. Compare, for instance, Jasper, Indiana, and London, Kentucky. Both locations have similar quantities of job postings for Business majors (~500–700 job postings throughout our sample period). However, in Jasper, roughly 82 percent of job postings for Business majors demand cognitive skills compared to only 46 percent in London. Even though these two localities are only a 3-to-4-hour drive apart, employers in these areas demand very different skills from Business majors. Next, beam down to Roswell, New Mexico, and nearby Andrews, Texas. These locales differ in both the quantity of job postings that list Business majors and the percentage of those job postings that demand cognitive skills.

Table 4 quantifies the amount of variation in skill demand captured by majors and places. Specifically, we construct over 15,000 major-MSA cells containing the share of ads seeking each skill composite; we then regress these shares for each composite on a set of fixed effects for majors, MSAs, or both.[28] We find that majors alone account for the vast majority of the variation across cells—indeed, major accounts for over 90 percent of the variation in the demand for software and financial skills, and three-quarters for people management skills.[29] Geography by itself accounts for only 5–20 percent of the cross-cell variation in skill demand. When both sets of fixed effects are included, R^2s are slightly less than the sum of when each set of fixed effects is included separately, indicating only modest correlation between majors and MSAs. However, there remains some unexplained variation, especially for organizational (24 percent) and communication (29 percent) skills. This remaining variation could reflect differences in the occupation or industry mix across place, as well as differences in employer characteristics.

Skill Demand and Earnings

Is this variation consequential in terms of wages? Figure 4 showed substantial wage variation across majors and areas, and we now examine whether such differentials are (descriptively) associated with differences in skill demand. Returning to the previous examples, in Jasper, Indiana, the average adjusted hourly earnings among Business majors is \$44.30, which is about 5 percent higher than the adjusted hourly earnings of \$41.90 in London, Kentucky, a place where employers demand relatively less cognitive skill of Business majors. The average adjusted hourly earnings in Andrews, Texas (\$43.70), are 7.5 percent higher than in Roswell, New Mexico, also consistent with a greater demand for cognitive skills.

To systematically examine whether skill requirements on job postings are related to earnings, we estimate variations of the following regression model:

$$Y_{jk} = \sum_{s=1}^{S} \beta_s PctSkill_{sjk} + \gamma_j + \delta_k + \varepsilon_{jk} \quad (3)$$

where Y_{jk} is the log of mean hourly earnings (2019 dollars) among college graduates in MSA j with major k from the ACS, and $PctSkill_{sjk}$ is a vector of skill demand in the MSA-major cell measured by the share of ads that list each skill. The coefficient β_s indicates the approximate $\left[(e^{\ s} - 1) \times 100\right]$ percent change in hourly earnings associated with a 100 percentage point increase in the share of job ads requiring the skill. The inclusion of MSA (γ_j) or major (δ_k) fixed

[28] Including all metropolitan areas and 70 majors would yield just over 25,000 cells, but we restrict the analysis in Table 4 to cells with at least 30 postings to reduce measurement error.

[29] If we weight cells using ACS person weights instead of the number of jobs ads, we find that major still explains the vast majority of the variation, although unexplained variation is about 50 percent larger.

effects isolates the association between skills and earnings that occurs within MSAs and majors, respectively. We weight each observation by the number of employed people in each cell using person weights from the ACS.[30]

We report results from our preferred specification in Panel A of Table 5. The first model, in column 1, includes only the 11 skill composites and reports the raw correlation between skill demand and log mean hourly earnings in an MSA-major cell. Skill demand is highly correlated with earnings. MSA-major cells with high demand for cognitive, financial, and project management skills have much higher hourly earnings than those with low demand for such skills. A 10 percentage point increase in the share of ads demanding cognitive skills (conditional on other skills) is associated with a 4 percent increase in average wages. Greater demand for people management, social, and basic computer skills, in contrast, are negatively correlated with earnings. These traits may be markers for lower-paid occupations. Collectively the 11 skill composites explain 34 percent of the wage variation across MSA-major cells and are jointly statistically significant at a 1 percent level (F-statistic = 17.9, p = 0.000).

Specification (2) includes MSA fixed effects, accounting for any systematic pay or cost-of-living differences that correlate with the skill content of jobs across areas. If in certain MSAs employees are more likely to work in teams, for example, employers will demand more social skills from all majors in the MSA. Alternatively, firms may list more skill requirements in cities that have more skilled workers (Deming and Kahn 2018). The inclusion of MSA fixed effects accounts for these MSA-level aspects of skill demand as well as pay differences that are due to MSA-wide factors including cost of living. The inclusion of MSA fixed effects does not alter the overall patterns seen in the raw differences. Cognitive, financial, and project management skills are still associated with higher wages. While geographic variation in wages is important—underscored by the near doubling of the explained variation—it is mostly uncorrelated with skill demand among our sample of workers with bachelor's degrees.

Finally, specification (3) adds major fixed effects, absorbing any systematic pay differences across majors that occur in all labor markets. Fixed effects for majors explain a considerable share of the variation in cross-cell wages and greatly diminish the predictive power

[30] Although we focus on weighted regressions, we also estimate models in which each major-MSA combination is equally weighted. Unweighted estimates are generally consistent with weighted estimates, with a few exceptions that we discuss below.

of the individual skill composites. Once we account for MSA and major, the remaining variation in skill demand measured by the skill composites explains relatively little additional wage variation (with the partial $R^2 = 0.001$). As Table 4 showed, this is not because there is no remaining variation in skill demand within majors across areas, but its level does not systematically correlate with earnings. The only remaining statistically significant skill-wage correlation is that demand for basic computer skills is associated with lower wages. This association is small in magnitude: a 10 percentage point increase in the share of ads desiring basic computer skills is associated with a 0.5 percent decrease in average wage. Taken in aggregate, these patterns suggest that majors can be thought of as portable bundles of skill composites.

Panel B of Table 5 demonstrates the robustness of these results. We report only specifications that include MSA fixed effects, analogous to specifications (2) and (3) in Panel A. Specifications (4) and (5) adjust wages for individual-level demographics (age, sex, race, and a quartic in potential experience) before aggregating up to the MSA-major cell level. Specifications (6) and (7) weight each cell equally. Specifications (8) and (9) compute cell-level wages for workers under the age of 35 to better reflect the wages of recent college graduates. The final two specifications, (10) and (11), restrict analysis to skills derived from job ads that have no more than minimal work experience required in order to reflect entry-level skill demand among college graduates. Across all specifications, results are similar and the qualitative picture does not change. This suggests that the skill-wage relationship we document is not driven by demographics, density of majors, age profiles, or demand for experience by major.[31] The broad patterns hold: skill demand can explain an appreciable share of the cross-cell wage variation, but most of this can be accounted for by major-specific effects. Cross-area variation in composite skill demand within majors, as illustrated in Figures 10, does not correlate with earnings. A caveat, however, is that this analysis is silent about whether variation in *detailed* skills within majors across places—as opposed to skill composites—relates to earnings.

Thus, our broad conclusion is that within-major, cross-MSA wage variation is explained by something other than differences in skill demand (at the composite level), including possibly differential sorting on unobserved characteristics on the demand side (e.g., granular skills) or

[31] Using a wider experience window (0 to 4 years, 0 to 6, etc.) produces very similar results. The vast majority of job ads list minimal experience. Nearly 80 percent require 5 years or fewer (including 25 percent that do not require any experience), and only 2 percent of ads seek more than 10 years of experience. We also find similar patterns of results when we instead use median (rather than mean) earnings as the outcome.

supply side (e.g., latent worker preferences) that are independent of the demanded skill composites. This finding stands in contrast to Deming and Kahn (2018), who find that local employer (composite) skill demand predicts wages across areas, even after controlling for occupation and other confounders.[32] In particular, we find that both social and cognitive skills have minimal association with major earnings premia, while Deming and Kahn (2018) find that these skills are associated with area-specific occupational wage premia. Their result suggests caution in interpreting occupations as uniform bundles of tasks, as there remains ample variation in skill demand across place and within occupation that is relevant to wages. In contrast, a worker's college major can more reasonably be considered a portable bundle of skills. Differences in skill demand within majors may happen at a much more granular level than the level of aggregation captured by our skill composites. Further, these patterns could also indicate differential sorting of majors into occupations across places.[33] For instance, technology jobs may be disproportionately filled by Computer Science majors in Silicon Valley but by Business majors in Scranton.

CONCLUSION

In this paper, we provide a comprehensive account of the skills associated with college majors as perceived by employers and expressed in job ads. The choice of field of study during college is one of the most direct ways college-educated individuals acquire skills and signal capabilities to employers. Thus, a more thorough understanding of the relationship that conjoins majors, skills, and jobs stands to inform policy leaders in higher education and industry.

We use data from the near universe of online job postings over the period 2010–2018 to develop measures of skill and major specificity based on location quotients (LQs) as well as measures based on cosine similarity to capture high-dimensional vectors of skills. These measures of skill and major specificity complement and extend recent developments in this space (e.g.,

[32] We attempt to replicate Deming and Kahn (2018) in Appendix E. Differences can be explained by some combination of skill classification method (keyword vs. hand-coding the top 1,000 skills), weighting, and manner of aggregation (occupation-MSA vs. major-MSA), with little role for sample differences. Further, we conclude that associations between wages and social skills are especially sensitive to these decisions.

[33] As we frame at the outset, this exercise is descriptive in nature. We are interested in the degree to which observed wage variation at the major-MSA level can be explained by differences in the skills requested by employers in job ads. Observational data in the ACS reflect sorting into major, job, and location—and thus, even conditional on observables, our estimated coefficients on the skill composites should not be interpreted causally (as the marginal value of those skills).

Leighton and Speer 2020; Li, Linde, and Shimao 2021) by focusing on specific skill demand manifested in job ads, thereby allowing us to compute such measures based on information that precedes the employment choices of individuals, a more proximate and direct signal of skill demand independent of occupational sorting.

We find that some majors such as Business and Engineering are general due to the fact that demand for most of their component skills is neither under- nor overconcentrated among job ads listing those majors. Other majors, such as Nursing, are more specific because they are closely associated with skills that are not widely sought in the labor market for college graduates.

Mapping similarities among majors based on our measures of skill demand highlights the fact that common classification systems based on curricula (such as CIP) may not reflect salient dimensions of different fields of study. That is, a student can develop project management skills through interactions with a variety of substantive material—and majors that develop such skills well may have similar labor market payoffs.[34] Hence, one implication is that policymakers and higher education leaders may want to adopt a broader and more multidimensional view of how college majors relate to competencies demanded by the labor markets most relevant for their institutions' graduates.

We use information on earnings by major from the ACS to characterize associations between majors, skill demand, and earnings across locations. We document substantial variation across space in both skill demand and average earnings by major. Despite the fact that variation in skill demand remains after accounting for major and geographic location, we find little evidence that such remaining variation meaningfully correlates with variation in earnings. This suggests that majors can generally be conceptualized as bundles of aggregate skills that are fairly portable across areas in ways that occupations are not. However, our analysis leaves open the possibility that a more fine-grained categorization of skills—such as the thousands that are available in job postings—could still matter for explaining wage variation within major and across place. Further analysis of the detailed dimensions of skill demand by college major would add to our understanding of worker-employer matching in the growing labor market for college graduates, and it could also provide better pathways for institutions of higher education to differentiate the skill sets with which they equip particular majors. For example, efforts to adjust the supply of

[34] Understanding major-specific wage premia in relation to detailed skills is a fruitful area for future research.

workers with particular skills to meet local employment needs should consider that the hiring decisions of firms depend on their perception of the skills possessed by particular types of workers.

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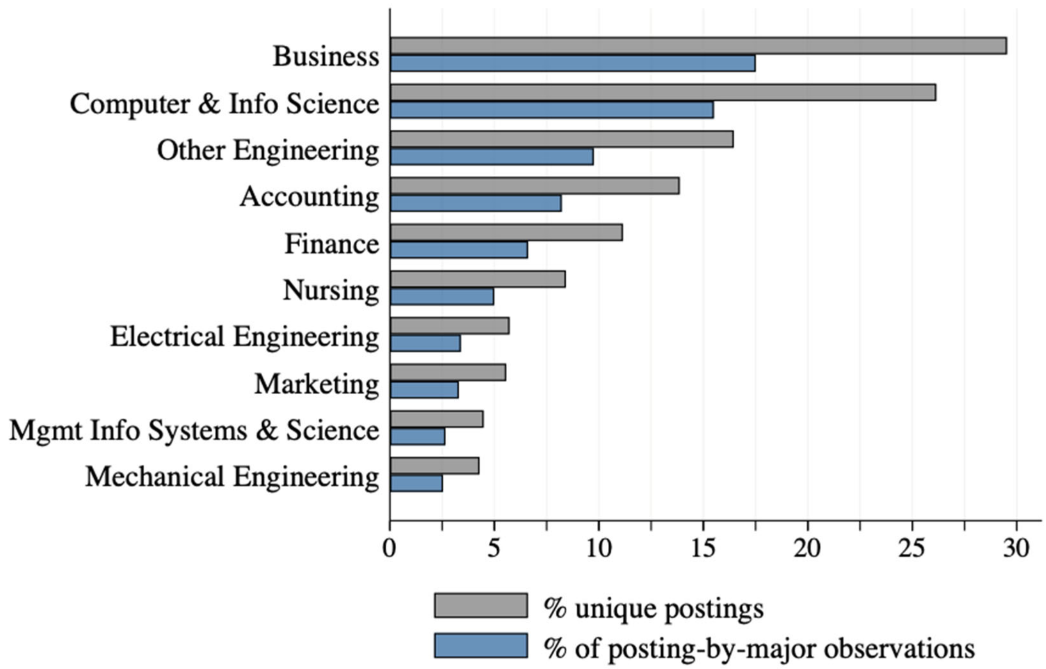
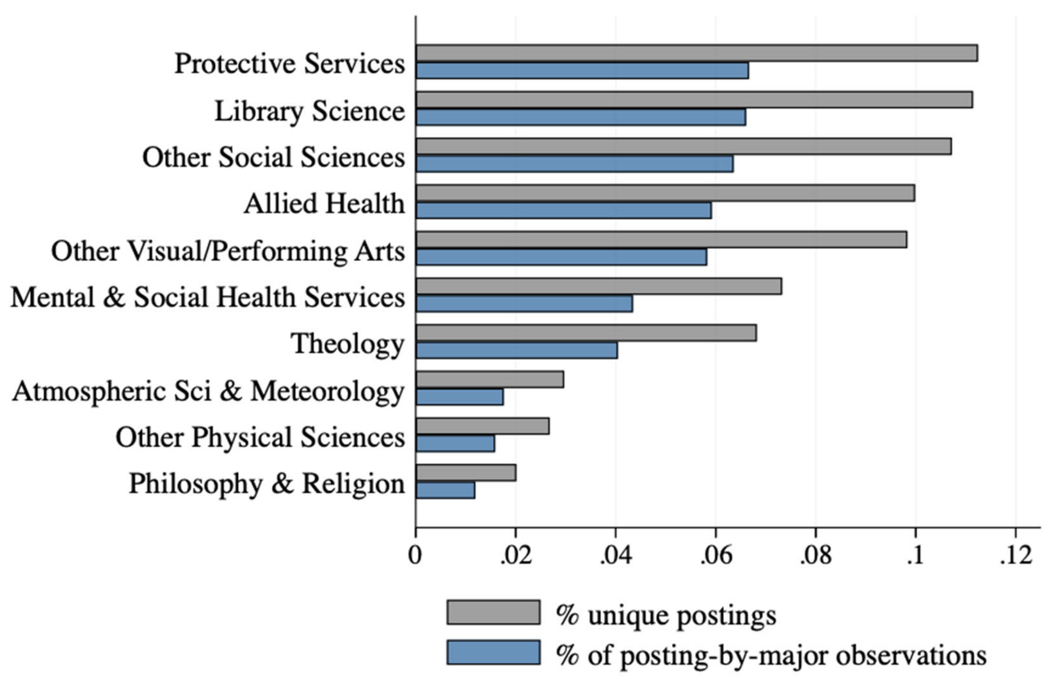
Figure 1 Most and Least Frequently Demanded Majors
A. Most Frequently Listed Majors

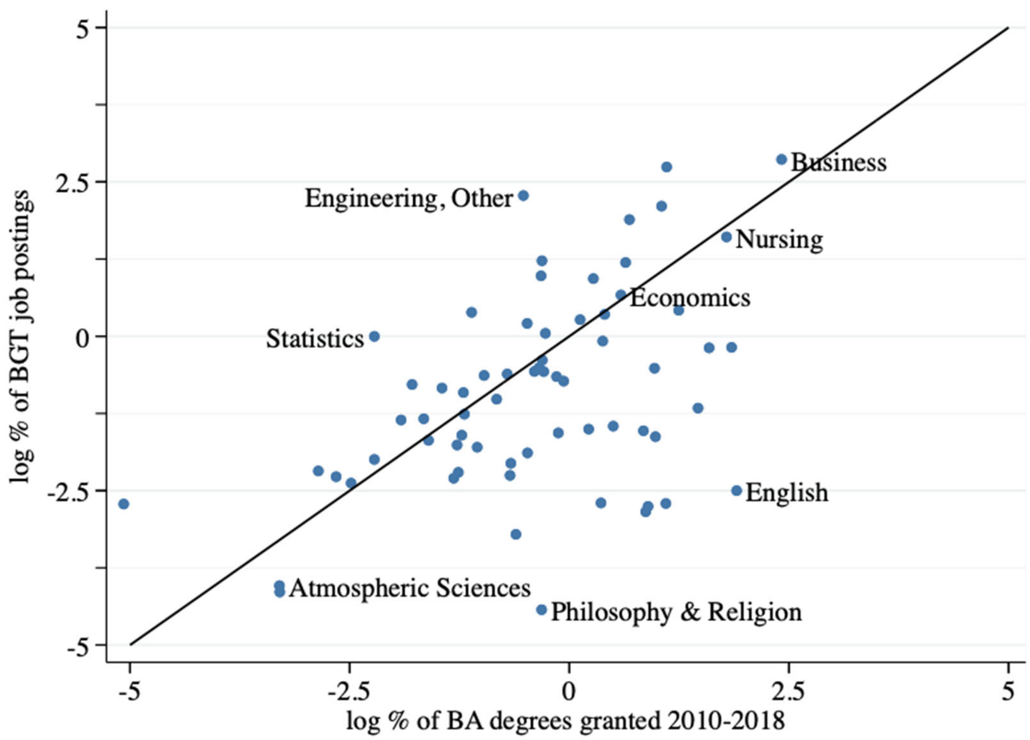


B. Least Frequently Listed Majors



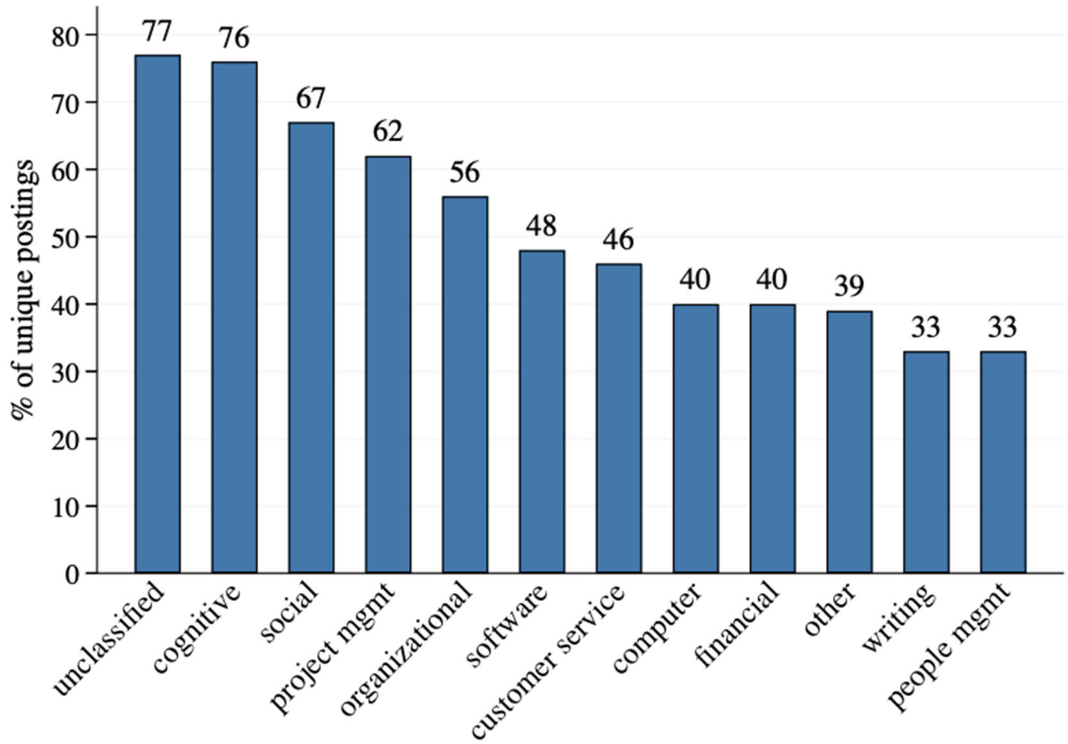
NOTE: Figure plots the percentage of Burning Glass job postings listing each major. Sample includes all job ads posted between January 2010 and May 2018 in metropolitan statistical areas that list 16 years of required education, at least one skill, and at least one major.

Figure 2 Major Share in Ads vs. Bachelor's Degree Completions



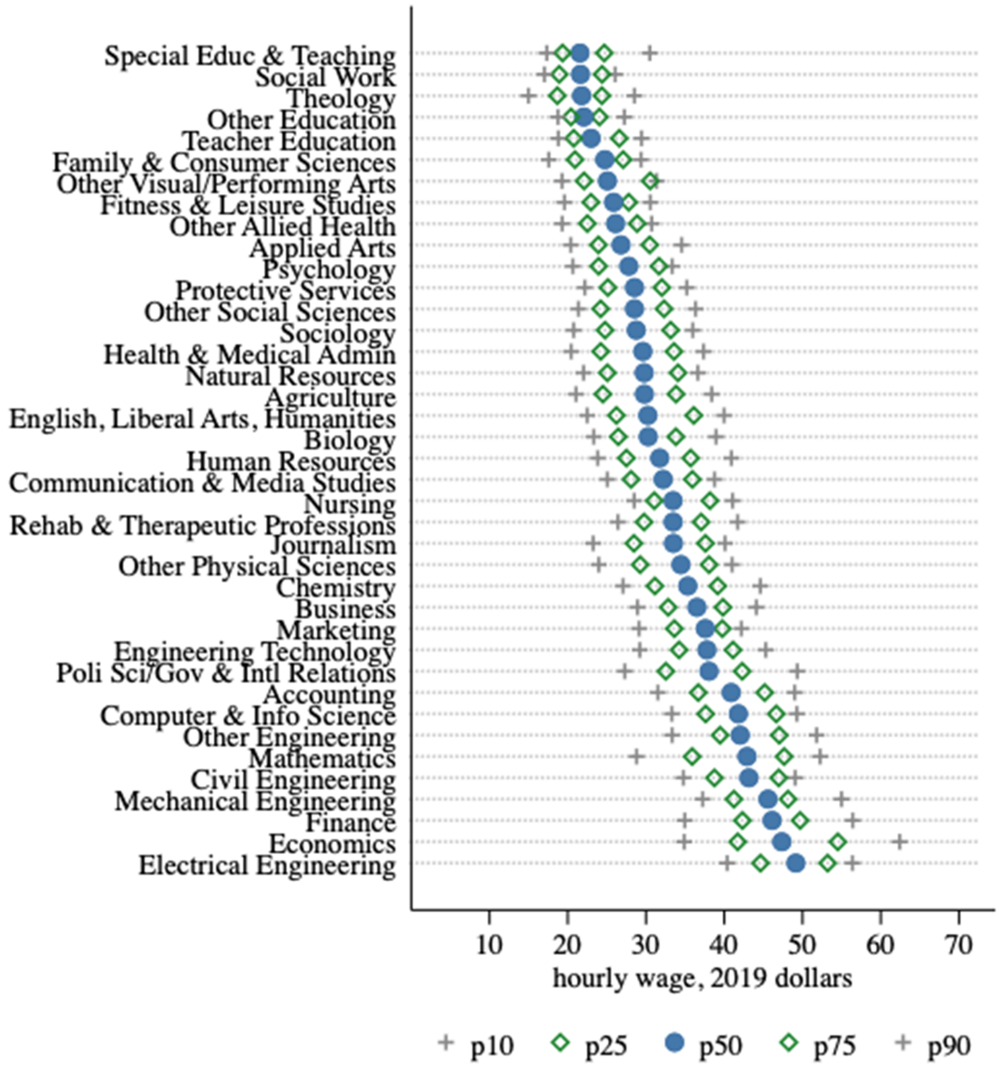
NOTE: Figure plots the log percentage of BGT job postings listing each major against the log percentage of degrees granted (from IPEDs data) in years 2010–2018.

Figure 3 Skill Composites: Percentage of Unique Job Postings Containing Skill Composite



NOTE: Figure plots the percentage of BGT job postings listing a skill in each of 11 skill composites constructed from the 1,000 most frequent skills. A twelfth composite, "unclassified," is the share of ads containing a skill outside the 1,000 most frequent. Only 0.2 percent of postings list none of our 11 composites (excluding "unclassified"). Across job postings, the mean and median number of composite skills listed is 5 (excluding "unclassified").

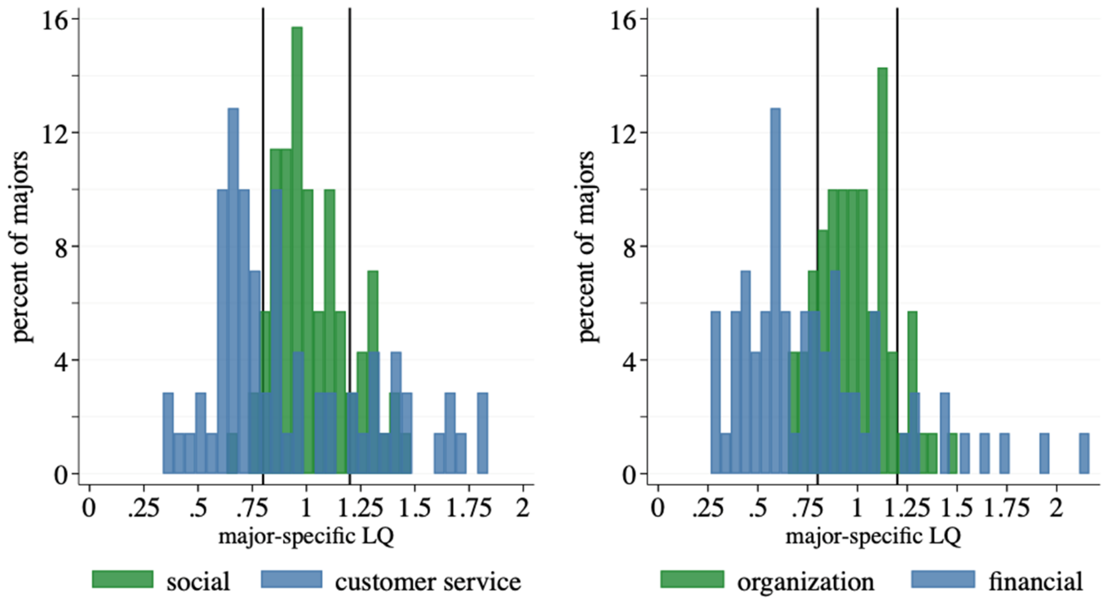
Figure 4 Distribution of Average Wage Across Majors and Areas



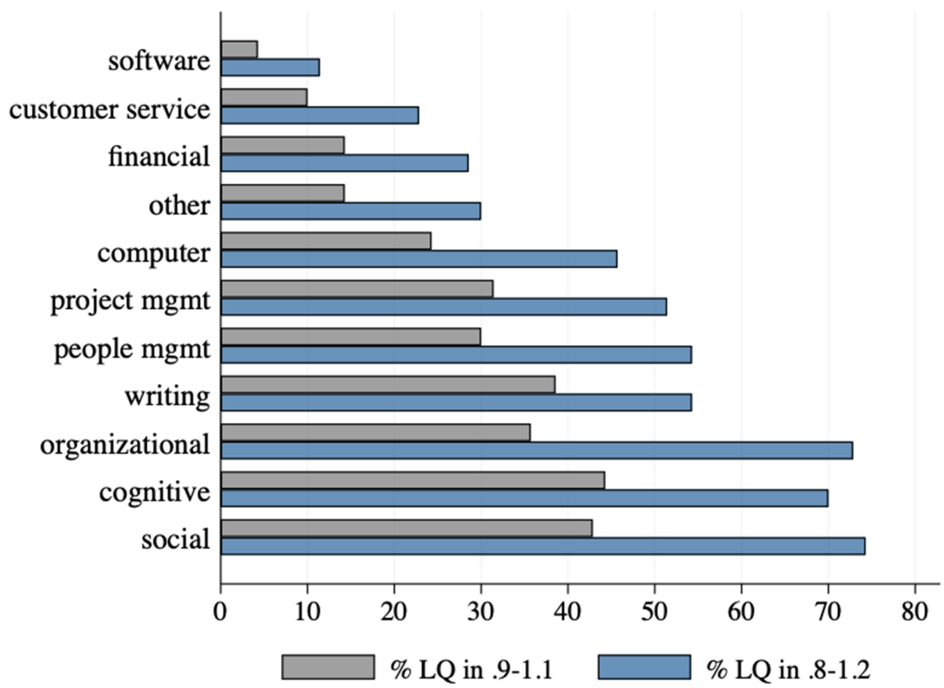
NOTE: Mean hourly wages for each major-MSA cell in the United States are computed from the American Community Survey 2009–2018. Sample includes only full-time, full-year, prime-age workers with exactly a bachelor's degree. Figure includes the 39 majors (out of 70 we classify) with estimates in at least 600 CBSAs (metropolitan and micropolitan areas).

Figure 5 Distribution of Skill Concentration across Majors

A. Full Distribution for Four Skill Composites

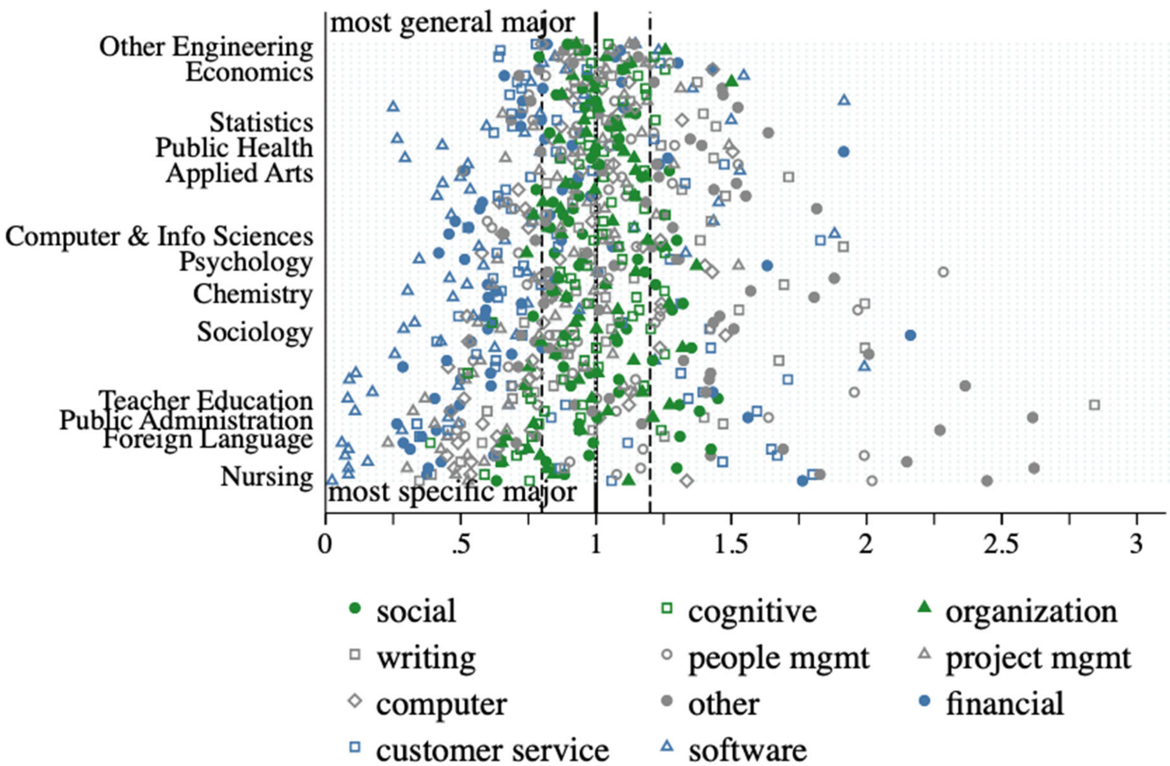


B. Skills Ranked by Specificity to Major



NOTE: Panel A plots the distribution of location quotients (LQ) across all 70 unique majors for each of four skill composites. A LQ greater than 1 indicates that ads with a given major are more likely to seek the skill than ads overall. Sample includes 37.1 million major-ad combinations. Panel B plots the (unweighted) share of majors for which LQs are within a narrow range of 1. Lower values indicate skills that are more major-specific.

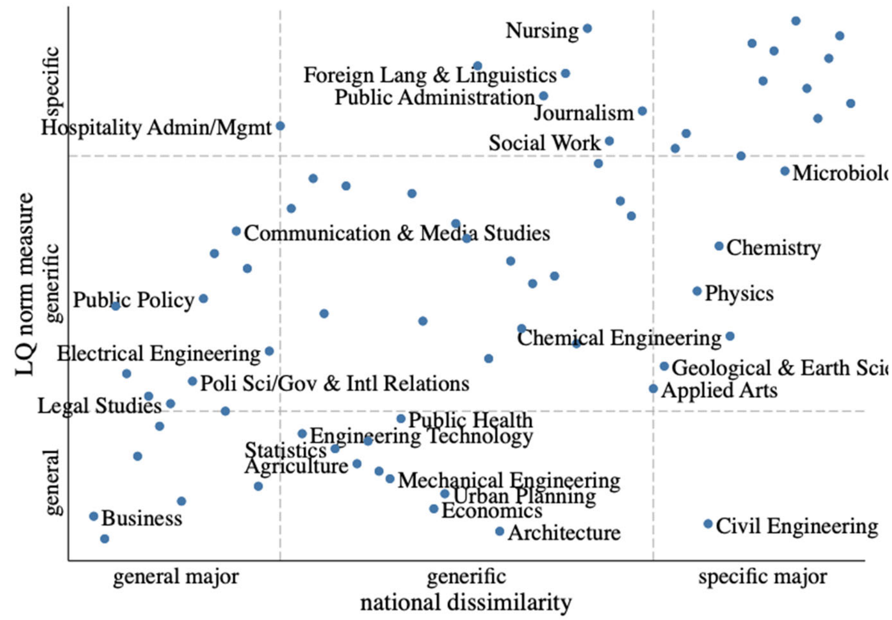
Figure 6 Skill Concentration for All Majors



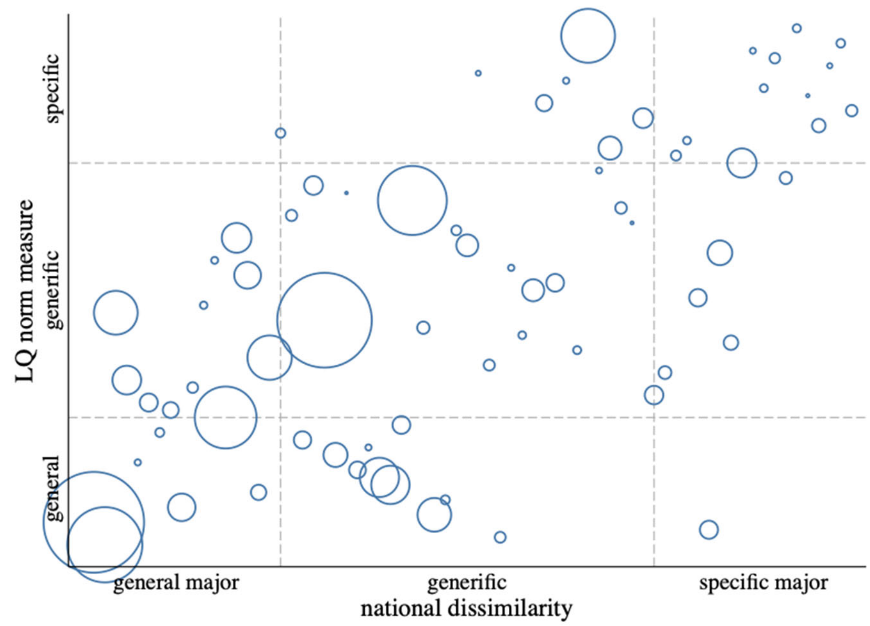
NOTE: Figure plots the location quotients (LQ) for 11 skill clusters for 70 majors. An LQ greater than 1 indicates that ads with a given major are more likely to seek the skill than ads overall. An LQ less than 1 indicates that ads with the major are less likely to seek the skill than ads overall. Skill composites indicated by green markers are considered more general skills, skill composites indicated by blue markers are specific and skills indicated by gray markers are generific.

Figure 7 Skill Composite vs. Similarity Index Measure of Concentration

A. Unweighted

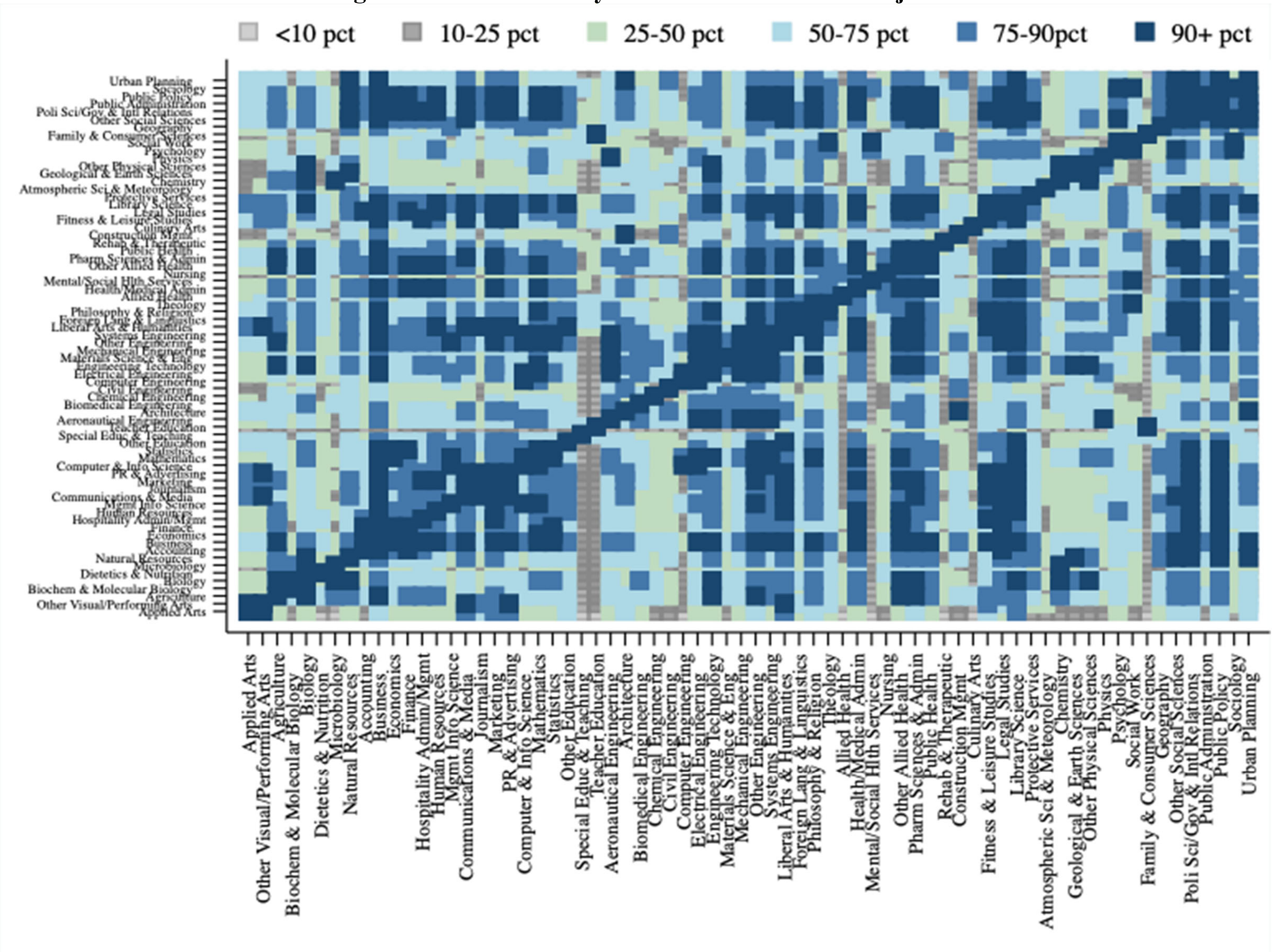


B. Weighted by Number of Job Ads



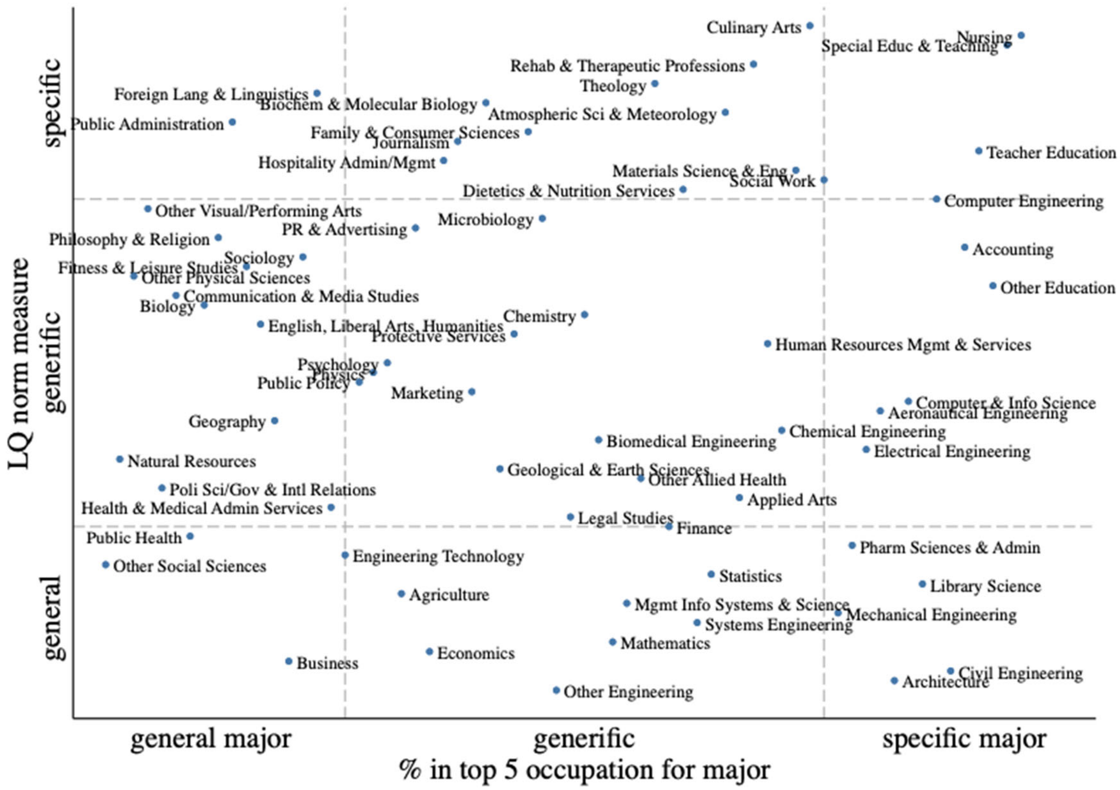
NOTE: Figure plots the rank of 70 majors using two different measures of skill similarity. The y-axis plots the rank of majors from general (rank=1) to specific (rank=70), according to the sum of the absolute deviation of the major's 11 LQs from 1: that is, Σ(abs(LQ−1)). The x-axis plots the rank of each major using the cosine similarity measure constructed using the 9,000 most frequent skills. In panel A, majors are unweighted; in Panel B, the circle size represents the number of job postings for the major.

Figure 8 Skill Similarity between Each Pair of Majors



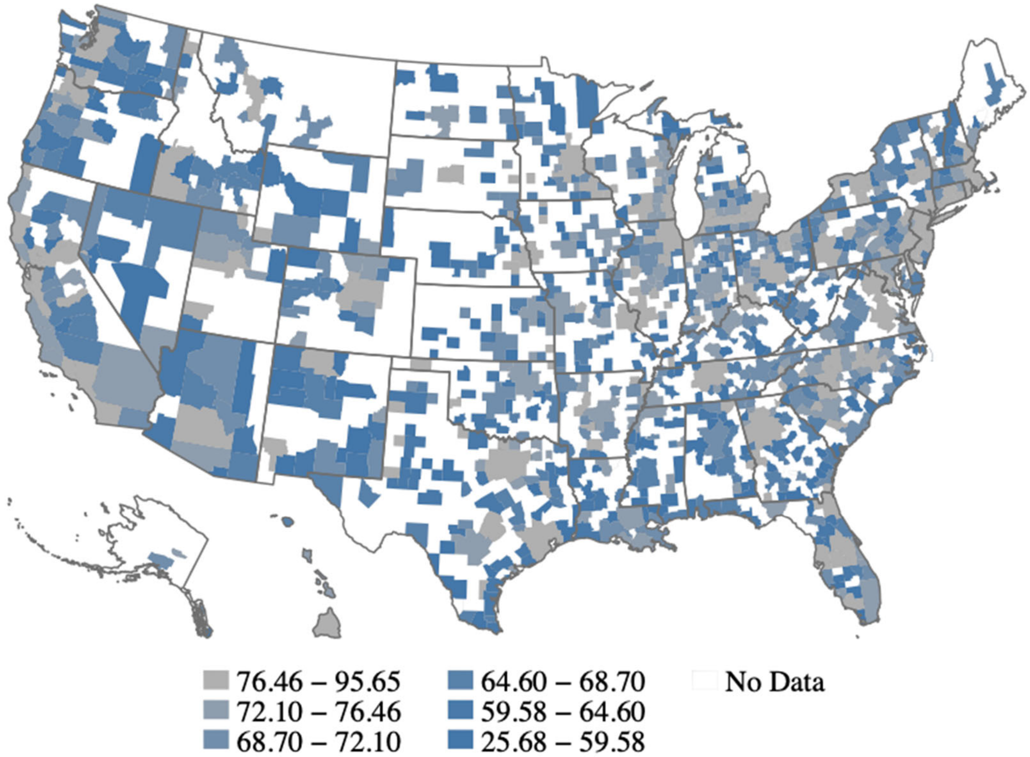
NOTE: Figure plots the cosine similarity between each pair of majors based on each major's vector of the 9,000 most frequent skills. Cells are colored according to the unweighted percentiles of the distribution of the similarity measures across all majors. Darker cells represent majors that are more similar in terms of skill demand. Similarity measures at different percentiles of the distribution are: 0–10th percentile (similarity = 0–0.21), 10th–25th percentile (0.21–0.40), 25th–50th percentile (0.40–0.51), 50th–75th percentile (0.51–0.63), 75th–90th percentile (0.63–0.72), and above the 90th percentile (0.72–1.00).

Figure 9 Skill Similarity Index vs. Occupational Measure of Concentration



NOTE: Figure plots the rank of 70 majors using two different measures of skill similarity. The y-axis plots the rank of majors from general (rank=1) to specific (rank=70), according to the sum of the absolute deviation of the major's 11 LQs from 1: that is, Σ(abs(LQ−1)). The x-axis plots the rank of each major using the percentage of recent college graduates found in the five most frequent occupations for the major as measured in the American Community Survey (ACS). Majors with a lower percentage of recent graduates in the top five occupations are considered more general. Correlation = 0.469 (weighted by number of job postings) and 0.004 (unweighted).

Figure 10 Variation in Cognitive Skill Demand Across MSAs, Business Majors



NOTE: Figure plots the percentage of a metro- or micro-statistical area's Business major job postings that require cognitive skills.

Table 1 Occupational Distribution by Sample (%)

	Sample				
	All Postings	At least 1 skill	Educ = 16 At least 1 skill	Educ = 16 At least 1 skill At least 1 major	Analysis Educ = 16 At least 1 skill At least 1 major In Metro CBSAs
	(1)	(2)	(3)	(4)	(5)
Count of unique ads	153,031,199	148,000,000	35,938,213	19,519,480	18,471,199
Count of unique ad-major (4-digit CIP)				32,847,216	31,153,536
% of original sample remaining		96.71	23.48	12.76	12.07
Experience level (years)			3.391	3.649	3.682
Occupation (SOC Code)					
Management (11)	11.70	11.92	22.22	21.93	21.84
Business/Financial (13)	6.64	6.80	14.30	14.82	15.02
Computer/Math (15)	11.54	11.85	22.13	25.23	25.83
Architecture/Engineering (17)	3.15	3.22	6.70	9.50	9.26
Life/Physical/Social Science (19)	1.00	1.03	1.69	2.04	1.97
Community/Social Service (21)	1.09	1.09	1.38	1.40	1.28
Legal (23)	0.85	0.87	0.41	0.25	0.26
Education/Training/Library (25)	2.49	2.52	2.48	1.31	1.25
Arts/Design/Entertainment (27)	2.37	2.42	2.53	2.29	2.32
Healthcare Practitioners (29)	12.27	12.24	7.58	8.21	8.01
Healthcare Support (31)	2.03	2.06	0.01	0.01	0.01
Protective Service (33)	1.00	0.99	0.33	0.22	0.21
Food Prep/Serving (35)	3.38	3.24	0.24	0.23	0.23
Building/Cleaning/Maintenance (37)	1.11	1.11	0.06	0.04	0.04
Personal Care (39)	1.75	1.75	0.27	0.21	0.20
Sales (41)	11.76	12.03	8.20	4.37	4.38
Office/Admin Support (43)	9.96	10.17	4.28	3.02	3.02
Farming/Fishing/Forestry (45)	0.06	0.06	0.02	0.02	0.02
Construction/Extraction (47)	0.97	0.98	0.09	0.11	0.11
Installation/Maintenance/Repair (49)	2.94	3.00	0.31	0.27	0.25
Production (51)	2.45	2.45	0.64	0.56	0.52
Transportation/Material Moving (53)	5.81	4.51	0.14	0.09	0.09
Military (55)	0.07	0.07	0.03	0.02	0.02
Missing (0)	3.61	3.61	3.93	3.84	3.85

NOTE: Authors' analysis of Burning Glass Technologies (BGT) job postings data. Occupations are two-digit Standard Occupation Classification (SOC) codes.

Table 2 Skill Composite Definition and Examples

Skill	Definition	# skills in top 1000	Top 3 skills	Keywords (similar to Deming and Kahn)
Social	Communicating, persuading, or negotiating with others, which involves adept presentation or exchange of information and perspectives as well as the capacity to accurately infer the motivations of others.	56	Communication Skills Teamwork / Collaboration Building Effective Relationships	communication, teamwork, collaboration, negotiation, presentation
People Management	Supervising, motivating, or directing people internal to the business toward defined goals.	43	Staff Management Leadership Mentoring	supervisory, leadership, management, mentoring, staff
Cognitive	Applying analytic, logical, quantitative or qualitative reasoning, evaluation, or critical thinking to understand patterns and solve problems.	168	Problem Solving Research Creativity	solving, research, analy-, thinking, math, statistics, decision
Writing	Composing, drafting, and editing of books, papers, reports, releases, scripts and other text-based documents; excludes underwriting (which is cognitive).	20	Writing Written Communication Editing	writing
Customer Service / Client Management	Attracting, soliciting, maintaining, and retaining clients and customers; most forms of sales fall here if there is a personal contact (sales engineering or analysis is cognitive).	110	Customer Service Sales Customer Contact	customer, sales, client, patient
Organization	Organizing, planning, managing, and expediting meetings, conferences, events, and other time-sensitive activities; but not logistics or supply chains (which are project management); ability to balance and prioritize among competing demands, apportion work, and meet deadlines.	37	Planning Organizational Skills Detail-Oriented	organized, detail-oriented, multitasking, time management, meeting deadlines, energetic
Computer	General computer tasks and knowledge, including MS Office and related frontline computer support; excludes computer engineering, hardware, design, and other specialized tasks.	22	Microsoft Excel Microsoft Office Computer Literacy	computer, spreadsheets, microsoft excel, powerpoint, microsoft office, microsoft word
Software	Use or design of any specialized software, as well as any computer hardware design and engineering, and computer security or network management.	233	SQL Software Development Oracle	skill is categorized as software by BGT
Financial	Preparing or auditing payroll, budgets, accounting or tax documents, and financial reports and statements; excludes financial trading (social), financial engineering, or quantitative financial analysis (both cognitive) -- the distinction is that the financial composite captures highly prescribed and rules-based activities that are often ancillary to main activities (unless the main activity is auditing/accounting).	84	Budgeting Accounting Procurement	budgeting, accounting, finance, cost

Skill	Definition	# skills in top 1000	Top 3 skills	Keywords (similar to Deming and Kahn)
Project Management	Orchestrating, overseeing, or directing programs, projects, processes, and operations -- the distinction with people and client management is that the emphasis here is not on people, but rather on the substance of the plans and activities executed by people.	111	Project Management Quality Assurance and Control Business Process	project management
Other	Highly discipline-specific skills (often in health) or physical skills that do not readily generalize to other tasks	116	Physical Abilities Retail Industry Knowledge Repair	

NOTE: Table lists the author-created 11 mutually exclusive skill composite categories based on the 1,000 most frequent skills in the Burning Glass data. Columns list the definitions of the skill composites and the three most frequently listed skills in each category. Final columns lists the phrases and words used to define these categories in Deming and Kahn (2018). See text for details.

Table 3 Share of Ads for Select Majors Indicating Demand for Each Skill Composite (%)

Major	Major Code	Cognitive	Social	Project Mngt	Organiz-ational	Software	Customer Service	Computer	Financial	Writing	People Mngt	Communications (subset of Social)	Other Skills (> top 1,000)	Other Skills (< top 1,000)
All postings		80	68	65	58	50	46	42	43	35	33	46	38	78
Journalism	904	76	90	44	74	34	40	47	21	100	26	51	35	85
Computer Science	1100	82	65	70	50	94	39	27	19	36	29	47	25	84
Teacher Education	1398	60	99	24	57	4	61	22	17	24	34	28	40	51
Mech. Engineering	1419	94	58	72	51	48	31	38	37	30	25	43	56	84
Foreign Language	1600	61	90	30	39	23	16	27	15	44	17	28	30	84
Humanities	2499	73	84	40	60	26	36	44	26	60	25	44	32	75
Biology	2699	91	61	54	51	24	29	35	26	36	27	41	69	93
Public Administration	4404	75	69	79	70	23	38	43	67	49	55	36	100	76
Economics	4506	100	75	68	64	45	44	60	61	39	30	52	30	79
Sociology	4511	96	76	42	58	14	65	38	26	37	48	34	58	74
Public Health	5122	77	74	98	58	22	48	44	39	44	43	46	53	84
Nursing	5138	47	60	31	49	4	82	23	16	14	36	30	70	62
Accounting	5203	73	61	52	62	35	33	62	92	30	28	46	28	68
Business	5299	78	77	77	65	40	56	51	56	36	43	53	35	75
Minimum		31	43	15	38	1	15	19	11	12	16	20	25	40
Maximum		100	99	100	87	100	84	63	92	100	76	63	100	100
Mean		79	70	56	57	33	42	38	34	38	34	42	49	81
Standard Deviation		15	12	19	10	24	17	12	17	14	12	9	18	12

NOTE: Entries are the percent of job postings for the major that list each skill as measured in the Burning Glass data. Mean and standard deviation are calculated equally weighting 70 majors; minimum and maximum are across all 70 majors. Communication skills are also included in Social skills. Major codes are a hybrid between CIP and our classification system (see Appendix B). Computer Science also includes Information Science; Foreign Language also includes linguistics; and Humanities also includes Liberal Arts and English.

Table 4 Fraction of Variation in Skill Content Explained by Major and Place

	Variation in skill share explained by...			
		MSA	Major and MSA	Unexplained
Cognitive	0.83	0.07	0.87	0.13
Computer	0.84	0.09	0.89	0.11
Customer service	0.91	0.05	0.93	0.07
Financial	0.96	0.05	0.97	0.03
Organizational	0.70	0.09	0.76	0.24
People mgmt	0.77	0.09	0.83	0.17
Project mgmt	0.87	0.05	0.90	0.10
Social	0.72	0.14	0.84	0.16
Communication (subset of Social)	0.56	0.20	0.71	0.29
Software	0.95	0.09	0.97	0.03
Writing	0.82	0.08	0.87	0.13
Other (top 1,000)	0.84	0.11	0.89	0.11
Unclassified (outside top 1,000)	0.78	0.12	0.85	0.15

NOTE: Table reports R^2 values from regressions of the share of ads in a MSA-major cell that mention the skill composite in each row on fixed effects for majors, MSAs, or both. Each row represents a separate regression. Sample is weighted by the number of job postings in each MSA-Major cell. We keep only cells with at least 30 postings. N=15,358 observations.

Major

Table 5 Relationship between Skills and MSA-Major Average Earnings

	Panel A: Base Model			Panel B: Robustness							
	Outcome = log(raw hourly income)			Adjusted income		Unweighted		Wages age <35		Ads exp: 0–2 years	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Share of ads requiring:											
Cognitive skills	0.399***	0.223*	−0.000	0.259**	−0.008	0.271***	0.000	0.055	−0.007	0.224**	0.018
	(0.142)	(0.117)	(0.026)	(0.117)	(0.029)	(0.078)	(0.013)	(0.105)	(0.025)	(0.098)	(0.022)
Computer skills	−0.253**	−0.066	−0.054***	−0.020	−0.069***	−0.041	−0.014	−0.130**	−0.069***	−0.008	−0.038**
	(0.106)	(0.070)	(0.016)	(0.060)	(0.017)	(0.046)	(0.015)	(0.060)	(0.019)	(0.063)	(0.015)
Customer skills	0.081	0.043	0.029	0.125	0.026	−0.030	0.015	0.144*	0.020	0.028	0.020
	(0.110)	(0.089)	(0.023)	(0.078)	(0.022)	(0.066)	(0.013)	(0.081)	(0.024)	(0.078)	(0.020)
Financial skills	0.303***	0.235***	−0.009	0.158**	−0.010	0.051	−0.010	0.188***	0.009	0.212***	−0.013
	(0.079)	(0.069)	(0.024)	(0.066)	(0.023)	(0.062)	(0.016)	(0.067)	(0.022)	(0.063)	(0.016)
Organizational skills	−0.187	−0.269**	−0.008	−0.258***	−0.014	−0.176***	−0.012	−0.282***	−0.004	−0.243***	−0.006
	(0.113)	(0.108)	(0.016)	(0.094)	(0.016)	(0.038)	(0.013)	(0.106)	(0.022)	(0.087)	(0.012)
People mgt skills	−0.609***	−0.489***	−0.018	−0.345***	−0.015	−0.178***	0.006	−0.278***	0.006	−0.437***	−0.040
	(0.146)	(0.130)	(0.032)	(0.095)	(0.033)	(0.055)	(0.015)	(0.093)	(0.025)	(0.115)	(0.026)
Project mgt skills	0.401***	0.375***	0.021	0.207**	0.005	0.280***	0.019	0.324***	0.004	0.312***	0.008
	(0.112)	(0.093)	(0.024)	(0.080)	(0.025)	(0.073)	(0.016)	(0.091)	(0.024)	(0.085)	(0.018)
Social skills	−0.317**	−0.477***	0.008	−0.365***	0.016	−0.193***	0.004	−0.442***	−0.001	−0.431***	−0.007
	(0.146)	(0.119)	(0.019)	(0.104)	(0.019)	(0.051)	(0.016)	(0.113)	(0.019)	(0.098)	(0.014)
Software skills	0.020	−0.037	0.018	−0.096	0.025	0.041	0.0035	0.115	−0.005	−0.021	0.031
	(0.115)	(0.101)	(0.023)	(0.085)	(0.024)	(0.060)	(0.018)	(0.096)	(0.022)	(0.095)	(0.021)
Writing skills	0.000	−0.055	−0.008	−0.042	0.001	−0.114***	0.012	−0.102	−0.025*	−0.081	−0.000
	(0.112)	(0.102)	(0.022)	(0.088)	(0.021)	(0.037)	(0.015)	(0.095)	(0.015)	(0.083)	(0.013)
Other skills (top 1k)	−0.102	−0.048	−0.049*	0.011	−0.050*	−0.033	−0.031**	−0.056	−0.048*	−0.057	−0.034*
	(0.115)	(0.100)	(0.025)	(0.099)	(0.030)	(0.056)	(0.015)	(0.088)	(0.029)	(0.082)	(0.020)
Constant	3.648***	3.908***	3.665***	3.789***	3.668***	3.458***	3.474***	3.632***	3.377***	3.878***	3.660***
	(0.169)	(0.146)	(0.040)	(0.150)	(0.047)	(0.088)	(0.018)	(0.142)	(0.041)	(0.121)	(0.028)
Observations	22,151	22,151	22,151	22,151	22,151	22,151	22,151	19,480	19,480	21,614	21,614
R^2	0.342	0.621	0.870	0.588	0.830	0.228	0.466	0.587	0.806	0.616	0.871
Age restriction	25–54	25–54	25–54	25–54	25–54	25–54	25–54	23–34	23–34	25–54	25–54
Weights	MSA-major perwt	MSA-major perwt	MSA-major perwt	MSA-major perwt	MSA-major perwt	none	none	MSA-major perwt	MSA-major perwt	MSA-major perwt	MSA-major perwt
Major FE	NO	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
MSA FE	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
F-test (all 11 skills)	17.94	13.24	2.86	8.89	2.58	15.83	2.41	15.27	2.39	12.53	2.91
F-test p-value	0.000	0.000	0.004	0.000	0.009	0.000	0.014	0.000	0.015	0.000	0.004

NOTE: Variables are the share of job postings in the MSA-major cell that list each skill as measured in the Burning Glass data. Outcome is the log of mean hourly earnings (2019 dollars) among college graduates in each MSA-major cell as measured in the 2009-2018 American Community Survey (ACS). Adjusted income is regression-adjusted for compositional differences across majors in terms of age, race/ethnicity, sex and a quartic in potential experience. Earnings sample is restricted to full-time, year-round workers who are not enrolled in education at the time of the survey. Observations include all workers aged 25-54 except in columns 8 and 9, which are restricted to ages 23-34. The F-test is a test of joint significance for all skill variables. Standard errors are two-way clustered by MSA and major. Weights are the sum of person weights (perwt) within the MSA-major cell from the ACS. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix A: Additional Tables

Table A1 Explained Variation in Whether a Job Posting Lists at least One College Major

	(1)	(2)	(3)	(4)	(5)	(6)
Model SS	10,928.4	12,747.2	13,138.9	21,199.4	22,288.4	25,544.6
Residual SS	75,920.3	74,101.5	73,709.7	65,649.2	64,560.2	61,304.1
Total SS	86,848.7	86,848.7	86,848.7	86,848.7	86,848.7	86,848.7
R^2	0.1258	0.1468	0.1513	0.2441	0.2566	0.2941
Adjusted R^2	0.1218	0.1428	0.1473	0.2395	0.2510	0.2722
AIC	−532,254	−540,741	−542,576	−582,136	−586,996	−589,221
BIC	−514,910	−523,364	−525,080	−559,257	−558,745	−475,378
Baseline variables	X	X	X	X	X	X
f(n skills)		X	X	X	X	X
Skill composites			X	X	X	X
500 most frequent skills				X		
1,000 most frequent skills					X	
9,000 most frequent skills						X
Number of variables	1,611	1,614	1,625	2,125	2,624	10,574
Number of skill dummies	0	0	0	500	999	8,949
Observations	350,233	350,233	350,233	350,233	350,233	350,233

NOTE: Table presents regression estimates from six separate regressions. The dependent variable is an indicator for whether a job posting lists at least one college major. For computational expedience, we use a 1% random sample of all postings that require a bachelor's degree. The baseline variables include 941 metro- and micro-statistical region fixed effects, 99 year-by-month fixed effects, 504 six-digit occupation codes and 96 two-digit industry codes. F(n skills) is a cubic in the number of skills per job posting.

Table A2 Presence of Major on Job Ad

	Number of variables	Partial SS	F-test
Occupation (soc6)	482	7,769.44	134.88***
Industry (naics2)	96	971.11	47.46***
Internship	1	84.13	386.52**
Year-by-month FEs	99	44.45	2.05***
Metro- / micro-statistical area	932	494.87	7.51***

NOTE: The table presents F-tests on blocks of covariates from a model in which an indicator for whether a job posting lists at least one college major is regressed on 941 metro- and micro-statistical region fixed effects, 99 year-by-month fixed effects, 504 six-digit occupation codes and 96 two-digit industry codes. Some fixed effects are omitted due to singleton observations. The sample is a 1% random sample of all postings that require a bachelor's degree. Partial SS is the partial sum of squares from an ANOVA analysis of the baseline model and indicates the magnitude by which total sum of squares would decrease in a model that excludes the block of covariates. Authors' analysis of BGT job postings data. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3 Complete List of Major Aggregates

Code	Name	Code	Name	Code	Name
0100	Agriculture	1600	Foreign Language & Linguistics	5098	Design, Photography, Video, & Applied Arts
0300	Natural Resources	1900	Family & Consumer Sciences	5099	Other Visual/Performing Arts
0402	Architecture	2200	Legal Studies	5107	Health & Medical Administrative Services
0499	Urban & Regional Planning & Design	2499	English, Liberal Arts, & Humanities	5109	Allied Health Diagnostic, Intervention, & Treatment Professions
0904	Journalism	2500	Library Science	5115	Mental & Social Health Services & Allied Professions
0909	Public Relations, Advertising, & Applied Communication	2602	Biochemistry, Biophysics & Molecular Biology	5120	Pharmacy, Pharmaceutical Sciences, & Administration
0999	Communication & Media Studies	2605	Microbiology	5122	Public Health
1100	Computer & Information Science	2699	Biology	5123	Rehabilitation & Therapeutic Professions
1205	Culinary Arts	2705	Statistics	5131	Dietetics & Clinical Nutrition Services
1310	Special Education & Teaching	2799	Mathematics	5138	Registered Nursing, Nursing Administration, Nursing Research, & Clinical Nursing
1398	Teacher Education	3100	Fitness, Recreation, & Leisure Studies	5199	Allied Health
1399	Other Education	3800	Philosophy & Religion	5203	Accounting & Related Services
1402	Aeronautical Engineering	3900	Theology	5208	Finance & Financial Management Services
1405	Biomedical Engineering	4004	Atmospheric Sciences & Meteorology	5209	Hospitality Administration/Management
1407	Chemical Engineering	4005	Chemistry	5210	Human Resources Management & Services
1408	Civil Engineering	4006	Geological & Earth Sciences/Geosciences	5214	Marketing
1409	Computer Engineering	4008	Physics	5220	Construction Management
1410	Electrical, Electronics, & Comms Engineering	4019	Materials Science & Engineering	5298	Management Info Systems & Science
1419	Mechanical Engineering	4099	Other Physical Sciences	5299	Business, general
1497	Systems, Industrial, & Ops Engineering	4200	Psychology		
1499	Other Engineering	4300	Protective Services		
1500	Engineering Technology	4404	Public Administration		
		4405	Public Policy		
		4407	Social Work		
		4506	Economics		
		4507	Geography		
		4510	Poli Science, Gov, & Int'l Relations		
		4511	Sociology		
		4599	Other Social Sciences		

NOTE: This table lists the full set of “final majors” that results from the steps detailed in Appendix B.

Table A4 Categorization of 40 Most Frequently Listed Skills

Individual Skill	Composite	Individual Skill	Composite
1 Communication Skills	social	21 Microsoft Word	computer
2 Planning	organization	22 Troubleshooting	cognitive
3 Microsoft Excel	computer	23 Accounting	financial
4 Teamwork / Collaboration	social	24 Multi-Tasking	organization
5 Problem Solving	cognitive	25 SQL	software
6 Organizational Skills	organization	26 Staff Management	people mgmt
7 Microsoft Office	computer	27 Customer Contact	customer service
8 Budgeting	financial	28 Presentation Skills	social
9 Research	cognitive	29 Quality Assurance and Control	project mgmt
10 Writing	writing	30 Time Management	organization
11 Project Management	project mgmt	31 Verbal / Oral Communication	social
12 Customer Service	customer service	32 Leadership	people mgmt
13 Sales	customer service	33 Software Development	software
14 Detail-Oriented	organization	34 Analytical Skills	cognitive
15 Written Communication	writing	35 Business Development	customer service
16 Scheduling	organization	36 Physical Abilities	other
17 Computer Literacy	computer	37 English	social
18 Building Effective Relationships	social	38 Patient Care	customer service
19 Creativity	cognitive	39 Oracle	software
20 Microsoft Powerpoint	computer	40 Teaching	social

NOTE: Table lists the 40 most commonly listed skills in the Burning Glass data and authors' skill composite.

Table A5 Top Skills Associated with Three Majors

Economics Majors		Teacher Education Majors		Journalism Majors	
Skill	% of postings	Skill	% of postings	Skill	% of postings
Economics	98.9	Early Childhood Education	68.2	Journalism	100.0
Communication Skills	52.3	Teaching	62.2	Writing	67.2
Microsoft Excel	46.4	Child Development	45.6	Editing	62.3
Research	32.8	Child Care	43.2	Communication Skills	51.1
Planning	25.4	Organizational Skills	30.8	Creativity	41.2
Problem Solving	25.0	Communication Skills	28.4	Social Media	39.4
Accounting	24.1	Lesson Planning	25.6	Research	32.3
Teamwork / Collaboration	23.7	Health Education	18.7	Teamwork / Collaboration	29.9
Microsoft Powerpoint	21.0	Planning	18.1	Organizational Skills	26.4
Budgeting	20.6	Teamwork / Collaboration	16.6	Detail-Oriented	25.4
N(ads)	607,518	N(ads)	97,314	N(ads)	211,471

NOTE: Table presents 10 of the most commonly listed skills on the postings for three different majors in the Burning Glass data. Authors' analysis of BGT job postings.

Table A6 Share of Ads for Each Major Indicating Demand for Each Skill Composite (%)

Major	Code	Cognitive	Social	Project Mgt	Organizational	Software	Cust. Service	Comput.	Financial	Writing	People Mgt	Comms.	Other Skills (top 1000)	Other Skills (< top 1000)
All postings	0	80	68	65	58	50	46	42	43	35	33	46	38	78
Agriculture	100	80	66	64	58	13	43	48	47	26	37	44	58	79
Natural Resources	300	91	64	60	66	21	29	42	42	52	37	45	59	93
Architecture	402	75	66	69	73	62	30	45	46	34	30	42	34	88
Urban Planning	499	81	68	63	87	38	32	47	47	48	31	43	46	100
Journalism	904	76	90	44	74	34	40	47	21	100	26	51	35	85
PR & Advertising	909	80	93	56	76	31	65	52	34	70	30	56	32	85
Communication & Media Studies	999	77	90	58	73	37	60	52	31	70	32	56	31	82
Computer & Info Science	1100	82	65	70	50	94	39	27	19	36	29	47	25	84
Culinary Arts	1205	60	43	34	65	1	48	56	75	12	68	20	93	40
Special Educ & Teaching	1310	66	89	20	47	4	40	20	16	31	39	29	100	72
Teacher Education	1398	60	99	24	57	4	61	22	17	24	34	28	40	51
Other Education	1399	92	88	68	62	47	33	52	25	54	66	63	39	88
Aeronautical Engineering	1402	91	57	57	48	57	24	32	23	33	21	44	49	87
Biomedical Engineering	1405	94	63	68	50	46	31	31	24	35	23	44	69	99
Chemical Engineering	1407	100	60	80	44	23	35	32	35	29	27	44	48	86
Civil Engineering	1408	97	54	61	60	43	29	37	46	39	29	39	44	88
Computer Engineering	1409	80	60	63	44	100	29	19	12	33	23	44	27	86
Electrical Engineering	1410	84	58	63	46	73	30	27	25	32	22	43	45	88
Mechanical Engineering	1419	94	58	72	51	48	31	38	37	30	25	43	56	84
Systems Engineering	1497	94	65	86	57	68	33	43	34	32	32	50	56	83
Other Engineering	1499	83	61	74	54	57	36	34	35	33	31	44	44	83
Engineering Technology	1500	85	57	77	56	37	28	39	40	32	41	40	62	89
Foreign Lang & Linguistics	1600	61	90	30	39	23	16	27	15	44	17	28	30	84
Family & Consumer Sciences	1900	64	95	21	60	5	73	20	20	21	36	25	38	50
Legal Studies	2200	69	67	44	66	15	40	38	54	50	33	42	33	74
English, Liberal Arts, Humanities	2499	73	84	40	60	26	36	44	26	60	25	44	32	75

Major	Code	Cognitive	Social	Project Mgt	Organizational	Software	Cust. Service	Comput.	Financial	Writing	People Mgt	Comms.	Other Skills (top 1000)	Other Skills (< top 1000)
Library Science	2500	78	79	43	65	40	31	46	31	49	38	48	39	80
Biochem & Molecular Biology	2602	99	64	44	55	14	21	32	17	35	16	49	87	97
Microbiology	2605	100	58	69	49	13	25	36	29	32	29	39	77	90
Biology	2699	91	61	54	51	24	29	35	26	36	27	41	69	93
Statistics	2705	97	74	69	55	75	39	55	34	37	26	51	26	84
Mathematics	2799	92	66	67	53	78	34	42	28	37	27	47	27	82
Fitness & Leisure Studies	3100	49	74	37	53	17	50	34	26	26	41	41	55	77
Philosophy & Religion	3800	70	74	35	46	21	19	22	23	36	31	34	30	70
Theology	3900	31	68	15	38	3	51	21	12	20	22	36	27	47
Atmospheric Sci & Meteorology	4004	63	64	26	44	25	15	24	11	52	17	33	45	100
Chemistry	4005	100	57	65	49	15	30	36	27	33	27	42	60	87
Geological & Earth Sciences	4006	89	53	60	58	27	30	30	37	46	35	35	55	94
Physics	4008	100	58	60	43	67	29	24	18	34	24	41	37	83
Materials Science & Eng	4019	94	62	72	43	25	31	31	26	30	23	47	90	87
Other Physical Sciences	4099	90	53	56	54	27	22	22	25	38	41	35	56	89
Psychology	4200	87	79	42	55	17	58	36	22	34	44	39	50	74
Protective Services	4300	72	59	50	50	23	28	33	36	40	35	33	72	84
Public Administration	4404	75	69	79	70	23	38	43	67	49	55	36	100	76
Public Policy	4405	86	85	71	73	28	39	49	45	67	38	59	46	83
Social Work	4407	70	74	34	54	4	78	32	21	31	38	32	54	64
Economics	4506	100	75	68	64	45	44	60	61	39	30	52	30	79
Geography	4507	82	62	50	61	72	35	41	20	50	20	42	31	97
Poli Sci/Gov & Intl Relations	4510	82	80	56	68	25	35	45	40	60	37	49	47	78
Sociology	4511	96	76	42	58	14	65	38	26	37	48	34	58	74
Other Social Sciences	4599	86	72	50	63	30	32	37	31	51	31	38	41	91
Applied Arts	5098	94	87	52	66	77	45	40	22	36	17	46	39	92
Other Visual/Performing Arts	5099	76	83	37	66	61	29	32	19	59	18	42	51	95
Health & Medical Admin Services	5107	75	69	84	58	26	67	45	53	37	51	44	47	75

Major	Code	Cognitive	Social	Project Mgt	Organizational	Software	Cust. Service	Comput.	Financial	Writing	People Mgt	Comms.	Other Skills (top 1000)	Other Skills (< top 1000)
Allied Health	5109	52	56	38	38	8	67	23	18	18	30	27	82	96
Mental & Social Health Services	5115	57	98	28	43	4	75	27	13	26	39	25	65	68
Pharm Sciences & Admin	5120	75	74	67	50	13	55	35	35	38	38	52	51	85
Public Health	5122	77	74	98	58	22	48	44	39	44	43	46	53	84
Rehab & Therapeutic Professions	5123	56	67	34	46	4	76	19	27	22	67	29	54	87
Dietetics and Nutrition Services	5131	42	67	36	58	6	60	33	26	18	31	28	54	91
Nursing	5138	47	60	31	49	4	82	23	16	14	36	30	70	62
Other Allied Health	5199	72	64	73	51	22	61	39	39	29	43	41	58	75
Accounting	5203	73	61	52	62	35	33	62	92	30	28	46	28	68
Finance	5208	82	68	62	64	40	39	63	82	32	29	50	30	71
Hospitality Admin/Mgmt	5209	59	74	75	68	9	64	47	61	27	65	41	54	62
Human Resources Mgmt and Services	5210	69	81	66	66	37	33	60	43	36	76	55	31	73
Marketing	5214	79	89	67	69	33	84	52	37	49	35	56	30	79
Construction Mgmt	5220	77	64	100	79	29	33	59	70	34	37	43	41	76
Mgmt Info Systems and Science	5298	88	68	78	57	96	45	38	31	40	36	50	29	81
Business	5299	78	77	77	65	40	56	51	56	36	43	53	35	75
Minimum		31	43	15	38	1	15	19	11	12	16	20	25	40
Maximum		100	99	100	87	100	84	63	92	100	76	63	100	100
Mean		79	70	56	57	33	42	38	34	38	34	42	49	81
Standard Deviation		15	12	19	10	24	17	12	17	14	12	9	18	12

NOTE: Table presents the percentage of each major's postings that list each skill composite. Communications is a proper subset of Social. Mean and standard deviation are calculated equally weighting 70 majors. Authors' analysis of Burning Glass job postings data.

Table A7 Correlation between Different Measures of Major Skill Specificity

	A. Outcome = Similarity based on 9,000 skills				B. Outcome = LQ measure			
	Rank		Measure		Rank		Measure	
Outcome	unweighted	weighted	unweighted	weighted	unweighted	weighted	unweighted	weighted
LQ measure (only top 1,000 skills)	0.372	0.533	0.410	0.573				
Similarity (Full)					0.372	0.533	0.410	0.573
Similarity (top 1,000)	0.895	0.964	0.896	0.989	0.358	0.579	0.388	0.579
Similarity (1,001+)	0.320	0.474	0.300	0.563	0.166	0.374	0.195	0.374
% of recent grads in top 5 occupations	0.050	0.317	0.075	0.342	0.004	0.469	0.019	0.469

NOTE: "Full similarity" is the cosine similarity (or rank) of a major using all 9,000 skills. Top 1,000 is the cosine similarity using only the 1,000 most frequent skills. 1,001+ is cosine similarity using skills ranked 1,001-9,000 in terms of overall frequency. LQ is location quotient across 11 skill composites (calculated as sum(abs(LQ-1) across the composites) and expressed in either rank or actual measure. Percent of recent graduates in top 5 occupations measures the fraction of a major's graduates aged 23–27 that are found in the 5 most frequent occupations for the major in the ACS. Panel A regresses a major's rank (measure) for the full similarity on the rank (measure) of the variable in the first column. Panel B does the same but with outcomes based on sum(abs(LQ-1)). Each regression has 70 observations (1 for each major) except for % in top 5 occupations which has 66 observations because 4 majors are missing from the ACS. Each cell is the adjusted R^2 from the regression. In weighted regressions, majors are weighted by the number of job postings. Source: Authors' analysis of BGT job postings and ACS data.

Table A8 Comparison of Major Rankings by Measure of Specificity

	LQ-based rank	Cosine-based rank	Gini-based rank
Most specific	Culinary Arts	Family & Consumer Sciences	Primary/General Education
(top 10)	Nursing	Special Education & Teaching	Secondary Education
	Special Education & Teaching	Mental & Social Health Services	Nursing
	Allied Health	Teacher Education	Medical Tech
	Rehab & Therapeutic Professions	Atmospheric Science & Meteorology	Computer Programming
	Mental & Social Health Services	Culinary Arts	Other Med/Health Services
		Microbiology	Finance
	Foreign Language & Linguistics	Rehab & Therapeutic Professions	Precision Production/Industrial Arts
	Biochem & Molecular Biology	Biochem & Molecular Biology	Commercial Art and Design
Theology	Atmospheric Science & Meteorology	Allied Health	Marketing
Most general	Other Engineering		Music/Speech/Drama
(top 10)	Architecture	Other Engineering	Other Social Sciences
	Civil Engineering	Marketing	Philosophy/Religion
	Business	Other Allied Health	Environmental Studies
	Economics	Library Science	Psychology
	Mathematics	Health & Medical Admin Services	Accounting
	Urban Planning Business	Pharmacy Sciences & Administration	Area Studies
	Systems Engineering	Legal Studies	Social Work/Human Resources
	Mechanical Engineering	Mathematics	Mathematics
	Management Info Systems & Science	Poli Science, Gov, Int'l Relations	Engineering Tech

NOTE: This table mirrors the layout of Table 3 in Leighton and Speer (2020), comparing the top and bottom 10 majors in terms of specificity based on different measures: thus, majors in the "Most specific" panel are listed from most specific to least specific; majors in the "Most general" panel are listed from least specific (i.e., most general) to more specific. Our two ranking measures appear in italics. Rankings in the Gini-based column come from Table 3 in Leighton and Speer (2020).

Table A9 Major Specific Skill Similarity Measures

Major	Code	% of unique postings	% of posting × major	Cosine similarity	LQ norm measure 1	LQ norm measure 2
Agriculture	100	0.815	0.483	0.777	2.048	0.961
Natural Resources	300	0.353	0.209	0.712	2.547	1.076
Architecture	402	0.340	0.201	0.697	1.409	0.290
Urban Planning	499	0.235	0.140	0.721	1.984	0.612
Journalism	904	1.145	0.679	0.597	4.154	4.112
PR & Advertising	909	1.014	0.601	0.797	3.314	1.691
Communication & Media Studies	999	2.569	1.523	0.820	3.041	1.512
Computer & Info Science	1100	26.149	15.504	0.792	2.701	1.375
Culinary Arts	1205	0.190	0.113	0.457	6.458	5.643
Special Educ & Teaching	1310	0.216	0.128	0.405	5.447	4.819
Teacher Education	1398	0.527	0.312	0.439	4.045	2.313
Other Education	1399	0.280	0.166	0.719	3.052	1.631
Aeronautical Engineering	1402	0.444	0.263	0.730	2.686	0.858
Biomedical Engineering	1405	0.186	0.110	0.624	2.642	1.174
Chemical Engineering	1407	0.609	0.361	0.561	2.643	0.748
Civil Engineering	1408	0.953	0.565	0.570	1.633	0.324
Computer Engineering	1409	2.483	1.472	0.545	3.701	2.200
Electrical Engineering	1410	5.726	3.395	0.815	2.615	0.844
Mechanical Engineering	1419	4.288	2.543	0.739	2.018	0.516
Systems Engineering	1497	0.678	0.402	0.817	1.993	0.602
Other Engineering	1499	16.459	9.759	0.922	1.388	0.209
Engineering Technology	1500	0.877	0.520	0.798	2.160	0.744
Foreign Lang & Linguistics	1600	0.113	0.067	0.627	4.599	2.189
Family & Consumer Sciences	1900	0.375	0.222	0.394	4.348	2.537
Legal Studies	2200	0.729	0.432	0.849	2.394	0.950
English, Liberal Arts, Humanities	2499	0.138	0.082	0.839	2.955	1.211
Library Science	2500	0.111	0.066	0.872	2.072	0.560
Biochem & Molecular Biology	2602	0.177	0.105	0.511	4.583	3.276
Microbiology	2605	0.435	0.258	0.498	3.491	2.023
Biology	2699	1.397	0.829	0.718	3.011	1.356
Statistics	2705	1.683	0.998	0.781	2.143	0.626
Mathematics	2799	2.204	1.307	0.847	1.982	0.634
Fitness & Leisure Studies	3100	0.365	0.216	0.809	3.246	1.301
Philosophy & Religion	3800	0.020	0.012	0.777	3.297	1.448
Theology	3900	0.068	0.040	0.717	5.089	3.141
Atmospheric Sci & Meteorology	4004	0.030	0.018	0.453	4.570	2.374
Chemistry	4005	1.768	1.048	0.568	2.965	1.245
Geological & Earth Sciences	4006	0.477	0.283	0.591	2.435	0.788
Physics	4008	0.894	0.530	0.571	2.810	1.006

Major	Code	% of unique postings	% of posting × major	Cosine similarity	LQ norm measure 1	LQ norm measure 2
Materials Science & Eng	4019	0.173	0.103	0.582	3.938	2.678
Other Physical Sciences	4099	0.027	0.016	0.606	3.206	1.231
Psychology	4200	1.408	0.835	0.663	2.841	1.109
Protective Services	4300	0.112	0.067	0.697	2.949	1.402
Public Administration	4404	0.772	0.458	0.631	4.411	3.902
Public Policy	4405	0.156	0.093	0.842	2.747	1.282
Social Work	4407	1.559	0.925	0.620	3.814	2.119
Economics	4506	3.289	1.950	0.728	1.907	0.535
Geography	4507	0.169	0.100	0.681	2.643	0.962
Poli Sci/Gov & Intl Relations	4510	0.332	0.197	0.847	2.433	0.972
Sociology	4511	0.393	0.233	0.609	3.277	1.469
Other Social Sciences	4599	0.107	0.064	0.758	2.147	0.629
Applied Arts	5098	1.005	0.596	0.594	2.429	0.937
Other Visual/Performing Arts	5099	0.098	0.058	0.620	3.647	1.560
Health & Medical Admin Services	5107	0.951	0.564	0.861	2.411	0.922
Allied Health	5109	0.100	0.059	0.514	5.389	3.501
Mental & Social Health Services	5115	0.073	0.043	0.408	5.282	3.096
Pharm Sciences & Admin	5120	0.229	0.136	0.856	2.162	0.822
Public Health	5122	0.915	0.542	0.737	2.280	0.880
Rehab & Therapeutic Professions	5123	0.312	0.185	0.506	5.312	3.409
Dietetics & Nutrition Services	5131	0.290	0.172	0.587	3.772	1.948
Nursing	5138	8.424	4.995	0.621	5.525	3.626
Other Allied Health	5199	2.402	1.424	0.876	2.434	0.865
Accounting	5203	13.867	8.222	0.731	3.285	1.940
Finance	5208	11.152	6.612	0.825	2.381	1.238
Hospitality Admin/Mgmt	5209	0.255	0.151	0.809	4.023	2.292
Human Resources Mgmt & Services	5210	2.076	1.231	0.817	2.921	2.085
Marketing	5214	5.567	3.301	0.880	2.716	1.202
Construction Mgmt	5220	0.906	0.537	0.629	2.908	1.242
Mgmt Info Systems & Science	5298	4.485	2.659	0.749	2.041	1.047
Business	5299	29.535	17.512	0.958	1.764	0.375

NOTE: Table displays three different measures of a major's skill specificity using the skills listed on job postings in the Burning Glass data. For each major, cosine similarity is constructed using a vector of the share of ads listing each of the 9,000 most common skills for each major and for all job postings in the analysis sample. The LQ norm measure 1 is calculated as the sum across all 11 skill composites of the absolute value of the deviations of the LQs from 1, and LQ norm measure 2 is calculated as the sum of the squared deviations. Authors' analysis of BGT job postings data.

Table A10 Replication and Extension of Deming and Kahn (2018)

		Replication: Occupation-MSA Cell				Our sample: Major-MSA cells			
		All education levels		Education = 16		Education = 16		Education = 16	
	DK estimates	Keyword	Hand code	Keyword	Hand code	Keyword	Hand code	Keyword	Hand code
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share cognitive	0.0792***	0.0484	0.0601*	0.0359	0.0593*	−0.0021	0.125*	0.0076	−0.0049
		(0.0357)	(0.0341)	(0.0303)	(0.0345)	(0.0519)	(0.0685)	(0.0193)	(0.0246)
Share social	0.0517***	0.0508*	−0.0129	0.0566*	0.0174	0.0642	0.0509	−0.0123	0.0090
		(0.0264)	(0.0385)	(0.0328)	(0.0149)	(0.0422)	(0.0438)	(0.0169)	(0.0199)
Observations		54,216	54,216	43,848	43,848	22,151	22,151	22,151	22,151
Controls	six-digit occ FE, MSA FE, % of postings in two-digit industry, education, experience					Major FE, MSA FE			
Outcome	log(mean hourly wage) from OES					log(mean hourly wage) from ACS			
Weights	Job postings from BGT					Job postings from BGT		Perwt from ACS	

NOTE: Outcome is the average of log of mean hourly earnings (2019 dollars) among college graduates as measured in the American Community Survey (ACS) or from the Occupation Employment and Wage Statistics (OES). Each observation is a major-MSA or occupation-MSA cell. DK estimates are from Table 3 column 5 of Deming and Kahn (2018). Additional controls includes six-digit occ FE, % of postings in two-digit industry, education and experience. All models also include the share of ads in each cell that require customer service, financial, organizational, people management, project management, writing, basic computer, and software skills.

Table A11 Raw cell-level correlations between cognitive and social skill content and wages: Robustness

	MSA × major	MSA × occ	MSA × major	MSA × occ	MSA × major	MSA × occ
	(1)	(2)	(3)	(4)	(5)	(6)
Share cognitive						
	0.855***	0.569***	0.399***	0.290***	0.746***	0.430***
Keyword	(0.0101)	(0.0089)	(0.0106)	(0.0067)	(0.0114)	(0.0090)
	0.498***	0.359***	0.417***	0.187***	0.745***	0.347***
Handcode	(0.0122)	(0.0092)	(0.0112)	(0.0068)	(0.0122)	(0.0094)
Share social						
	0.205***	0.688***	0.141***	0.257***	0.394***	0.875***
Keyword	(0.0130)	(0.0104)	(0.0120)	(0.0072)	(0.0146)	(0.0113)
	−0.601***	0.0222**	−0.282***	−0.0459***	−0.464***	0.369***
Handcode	(0.0126)	(0.0112)	(0.0121)	(0.0073)	(0.0137)	(0.0115)
Weights	ACS perwt	soc emp	none	none	postings	postings
Observations	22,151	43,852	22,151	43,852	22,151	43,852

NOTE: Each cell is a separate regression of cell-level log mean wages (major-MSA or occupation-MSA) on the share of ads requiring each skill. Outcome is the average of log of mean hourly earnings (2019 dollars) among college graduates as measured in the American Community Survey (ACS) or from the Occupation Employment and Wage Statistics (OES). Share cognitive (social) is the percent of job postings in major-MSA or occupation-MSA cell that demand the skill demand as measured in the Burning Glass data. Weights in Column (2) (soc emp) is total employment count from the OES.

Appendix B: Defining Major Categories

We want our categorization of majors to reflect the fields that students at four-year institutions encounter when making choices about paths of study. Thus, we use the CIP taxonomy as our starting frame for aggregation. We aggregate the over 400 codes at the four-digit CIP level to a group of 70 major categories (hereafter called *final major*). This appendix details the steps we take to arrive at that final group of majors.

We start with the CIP's aggregation of four-digit majors (cip4) into 49 two-digit major codes (cip2). We omit from our categorization 14 two-digit categories that are traditionally sub-baccalaureate or remedial programs: Interpersonal and Social Skills (cip2=35), Basic Skills and Developmental/Remedial Education (32), Citizenship Activities (33), Health-Related Knowledge and Skills (34), Personal Awareness and Self-Improvement (37), High School and Secondary Diplomas and Certificates (53); that are predominantly postbaccalaureate or graduate programs: Residency Programs (60); that are predominantly trade-specific and usually sub-baccalaureate: Science Technologies/Technician (41), Construction Trades (46), Mechanic and Repair Technologies/Technicians (47), Precision Production (48), and Transportation and Materials Moving (49); or that operate in separate or specific labor markets: Military Science, Leadership, and Operational Art (28) and Military Technologies and Applied Sciences (29). Together these categories comprise less than 1 percent of all degrees granted by four-year postsecondary institutions over the 2010–2017 period and appear on less than 0.1 percent of job postings in our analytic sample. For similar reasons we also omit particular four-digit majors (not already in omitted two-digit categories) that are primarily sub-baccalaureate or graduate programs, including Funeral Service and Mortuary Science (1203), Cosmetology and Related Personal Grooming Services (1204), Medical Clinical Sciences/Graduate Medical Studies (5114), Chiropractic (5101), and Dentistry (5104).

For the remaining two-digit categories, we calculate the total number of job postings shared among the four-digit majors contained in the two-digit category. We combine two-digit major categories that have few postings (less than 0.1 percent, or about 22,000 unique postings in our sample) as described below. For the large two-digit major categories we make a few general adjustments. First, we pull out some four-digit majors that are particularly large in terms of job postings. For example, in the two-digit category Architecture and Related Services (cip2=04), the four-digit major Architecture (cip4=0402) accounts for more than half of postings and degrees granted for the two-digit category. We thus split the two-digit category into the two *final major* groupings of (a) Architecture and (b) Urban and Regional Planning & Design. For the two-digit group Social Sciences (cip2=45), we disaggregate the four-digit majors of Sociology (cip4=4511), Economics (cip4=4506), and Geography (cip4=4507), all of which have large numbers of job postings and four-year degrees granted during 2010–2017, into three separate *final majors*, combine International Relations and National Security Studies (cip4=4509) and Political Science and Government (cip4=4510) into another *final major*, and aggregate most of the remaining four-digit majors into a *final major* called Other Social Sciences. As a final example, the 15 four-digit majors in the broad category of Education are grouped into three *final major* categories: (a) Special Education & Teaching, (b) Teacher Education, and (c) Other Education.

In some cases, extracting an individual four-digit major from a two-digit category would result in an aggregation of the other remaining four-digit majors with a relatively small number of job postings. In these cases, we do not disaggregate the two-digit category; instead the two-digit category remains a *final major* category. For example, in the broad category of Family and Consumer Sciences & Human Sciences (19), the four-digit major Human Development, Family Studies, and Related Services (1907) constitutes over 86 percent of postings for the two-digit category, and the entire two-digit family becomes *final major* Family & Consumer Science. In other cases, although individual four-digit majors have both a large number of postings and degrees granted, the four-digit majors are commonly co-listed together on job postings. We aggregate these four-digit majors together into a *final major*. For example, within the two- digit category of Computer and Information Sciences and Support Services (11) the three most frequently occurring four-digit majors of Computer and Information Science, General (1101), Computer Science (1107), and Information Sciences/Studies (1104) are often listed on job postings together.

Finally, there are a few particular two-digit major categories that we split into more narrow *final major* categories, based on similarity of content or labor market outcomes. For example, in the broad category of Engineering there are over 39 four-digit majors which we aggregate into 10 *final major* categories including Mechanical Engineering, Computer Engineering, Electrical Engineering, and Civil Engineering. The 35 four-digit majors within the two-digit category Health Professions and Related Programs are aggregated into *final major* categories including Allied Health, Mental & Social Health Services, and Nursing.

We next tackle two-digit major categories that have few job postings, including Area, Ethnic, Cultural and Gender Studies (cip2=05), Communications Technologies/Technicians and Support Services (cip2=10), English Language and Literature/Letters (cip2=23), Liberal Arts and Sciences, General Studies Humanities (cip2=24), History (cip2=54), and Multi/Interdisciplinary Studies (cip2=30). To find the best fitting final major categories for each of these, we calculate the skill distance between the group and other four-digit majors. Generally, we use this method to find for each four-digit major the closest other four-digit majors, and assign it to the same *final major* category. Specifically, for each major we calculate the proportion of category postings for each of eight skill composites ([# of ads with skill=s & majorcat=c]/[# of ads with majorcat=c]) on a sub-sample of our data. We then use the proportions to calculate a measure of cosine similarity: $\frac{\sum_{S}^{s=8}(a_i \times b_i)}{\sqrt{\sum_{S}^{s=8} a_i^2} \times \sqrt{\sum_{S}^{s=8} b_i^2}}$ where a and b are two different majors and a_i and b_i are the share of major a's and major b's postings that demand skill composite i, respectively. Finally, for a given major we sort other majors based on how similar skill demand is according to the cosine similarity measure. Using this method, we decided to combine the three two-digit majors of English, Liberal Arts and Humanities, and History into one *final major*, and the two-digit major Area Studies into the *final major* Other Social Sciences. We also used this method to find the most similar four-digit major for each of the majors in the fairly heterogeneous two-digit group of Multi/Interdisciplinary Studies. As a result, we aggregated Systems Science and Theory (3006) into Management Information Systems & Science (5298), Museology/Museum Studies (3014) into Library Science (2500), and Behavioral Sciences (3017) into Psychology (4200).

Appendix C: Constructing Skill Composites

We initially followed the keyword approach of Deming and Kahn (2018) to allocate individual skills to skill composites. Our decision to reallocate individual skills to composites stemmed from three observations about the skill-to-composite mappings resulting from the keyword approach.

First, some of the most frequently listed skills did not fall into any skill composite. Examples include planning (20 percent of postings), organizational skills (16 percent), detail-oriented (12 percent), scheduling (12percent), building effective relationships (11 percent), creativity (10 percent), troubleshooting (6 percent) and multitasking (8 percent).

Second, our use of the keyword approach meant that some skills were misclassified. The most prominent example is the case of using the keyword "management" to allocate skills to the skill composite "people management." The term "management" captures a wide variety of general management activities that do not specifically pertain to HR or personnel, including account management, pain management, operations management, case management, and management consulting. Another example was character (organizational) skills, which was initially defined as keywords "organized, detail-oriented, multitasking, time management, meeting deadlines, energetic" and as a result missed the very common variant skills of "multi-tasking" and "organizational skills."

Third, the ill-fitting mapping of skills to composites occurred for some of the most frequent skills. In the case of relatively rare skills, misclassification of individual skills can be viewed as a form of measurement error that should not have a large impact on empirical results. However, since some individual skills are sufficiently common and get assigned to composites that seem incorrect *a priori*, we believe misclassification may bias the interpretation of a given skill composite. Thus, we focus on reallocating the individual skills that appear with the highest frequency.

We use the following procedure to map the 1,000 most frequent individual skills listed on job postings that demand a bachelor's degree to 11 skill composite categories. (The 1,000th most frequent skill appears on 0.2 percent of job postings that demand 16 years of education.) First, for each individual skill, two different individuals on the research team independently assigned the skill to one of the 11 categories according to the definition of the skill categories shown below. In roughly 40 percent of cases, two individuals assigned an individual skill to different skill composites. For the 10 most frequent skills in which individual coding to composites differed, we discussed as a group which skill composite would be most fitting. We then refined our skill composition definitions, and pairs of individuals revisited and resolved cases in which a single skill was assigned to multiple skill composites. After this step there remained roughly 50 individual skills that pairs of reviewers still believed could fit into multiple categories. We allocated these skills to a single skill composite by consulting the occupation distribution of ads listing the skill. Table 2 displays the final number of individual skills, and the three most frequent skills, allocated to each skill composite. Appendix Table A3 shows the assigned skill composite for the 40 most frequently listed skills.

Skill Composite Definitions

- **Social:** Communicating, persuading, or negotiating with others, which involves adept presentation or exchange of information and perspectives as well as the capacity to accurately infer the motivations of others.
- **People Management:** Supervising, motivating, or directing people internal to the business toward defined goals.
- **Cognitive:** Applying analytic, logical, quantitative or qualitative reasoning, evaluation, or critical thinking to understand patterns and solve problems.
- **Writing:** Composing, drafting, and editing of books, papers, reports, releases, scripts and other text-based documents; excludes underwriting (which is cognitive).
- **Customer Service/Client Management:** Attracting, soliciting, maintaining, and retaining clients and customers; most forms of sales fall here if there is a personal contact (sales engineering or analysis is cognitive).
- **Organization:** Organizing, planning, managing, and expediting meetings, conferences, events, and other time-sensitive activities; but not logistics or supply chains (which are project management); ability to balance and prioritize among competing demands, apportion work, and meet deadlines.
- **Computer:** General computer tasks and knowledge, including MS Office and related frontline computer support; excludes computer engineering, hardware, design, and other specialized tasks.

- **Software:** Use or design of any specialized software, as well as any computer hardware design and engineering, and computer security or network management.
- **Financial:** Preparing or auditing payroll, budgets, accounting or tax documents, and financial reports and statements; excludes financial trading (social), financial engineering, or quantitative financial analysis (both cognitive)—the distinction is that the financial composite captures highly prescribed and rules-based activities that are often ancillary to main activities (unless the main activity is auditing/accounting).
- **Project Management:** Orchestrating, overseeing, or directing programs, projects, processes, and operations—the distinction with people and client management is that the emphasis here is not on people, but rather on the substance of the plans and activities executed by people.
- **Other:** Highly discipline-specific skills (often in health) or physical skills that do not readily generalize to other tasks.

Appendix D: Hand-Coded vs. Keyword Skill Composites

Our preferred approach to classifying skills was to assign by hand the 1,000 most frequent skills, as described above in Appendix C. This appendix describes the sensitivity of our approach to the alternative of using the keywords displayed in Table 2 to identify skill composites.

A. Coverage

For all composites except software and people management, the share of ads assigned to the composite increases with our approach. About 1 in 500 postings do not list any of our 11 composites; this figure was closer to 1 in 25 based on the keyword approach, which covered only 8 composites. Notably, the keyword approach captured only 400 of the 1,000 most frequent skills, while our preferred approach classifies all 1,000. Preferred composites are now mutually exclusive: under the keyword approach, about 200 individual skills fell into more than one composite (70% of these involve software, and 30% involve customer service, people management, and cognitive).

The composites under our preferred approach capture a different number of individual, detailed skills than does the keyword approach. Under the latter system, for example, character (organization) contained only three detailed skills: “time management,” “meeting deadlines,” and “energetic.” Our preferred method also captures “multi-tasking,” “prioritizing tasks,” and “organizational skills.” This change means that some of the most common skills are now classified as “organizational skills,” as shown in Table D1 below.

Table D1 Hand-Coded vs. Keyword Skill Composites: Counts of Included Detailed Skills

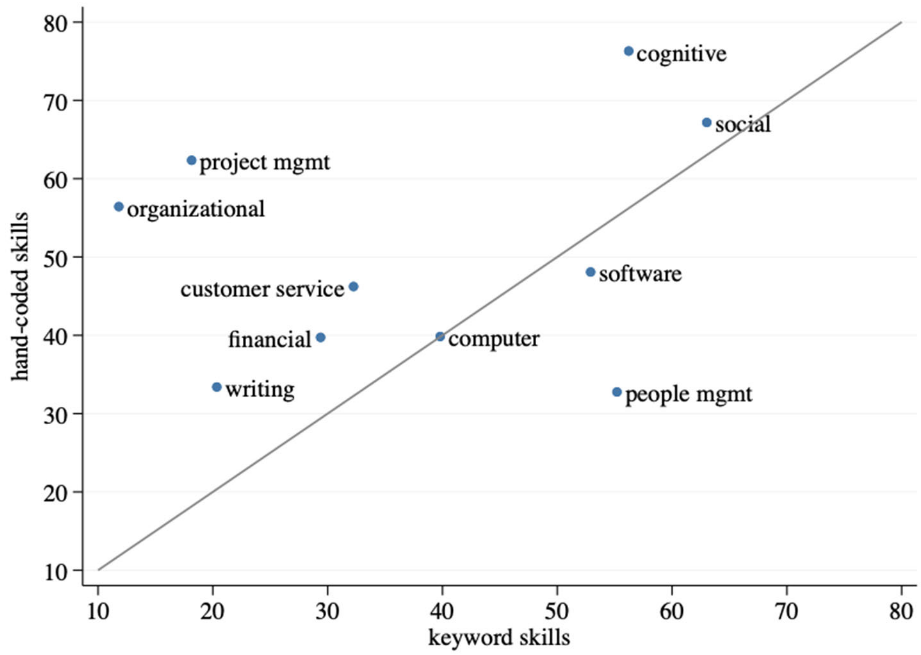
		Hand-coded		Keyword	
Skill composite number	Skill composite	Count of skills in 1,000 most frequent	Count of skills across all skills	Count of skills in 1,000 most frequent	Count of skills across all skills
1	social	56	56	15	78
2	people management	43	43	85	476
3	cognitive	168	168	46	431
4	writing	20	20	8	50
5	customer service	110	110	56	372
6	organizational	37	37	3	3
7	computer	22	22	12	64
8	software	233	233	175	1703
9	financial	84	84	19	113
10	project management	111	111	1	476
11	other	116	116	–	–
	unclassified	*0*	*14,260*	*602*	*12,081*

NOTE: The counts indicate the number of detailed skills, among the specified set, that are coded to the skill composite shown in each row.

B. Share of Ads in Each Composite

Figure D1 below compares the share of unique ads that contain each skill composite across the two different classification approaches.

Figure D1. Keyword (Old) vs. Hand-Coded (New) Skill Composites, Percentage of Unique Ads



NOTE: Figure plots the percent of unique job postings that demand each skill composite. "Keyword" skills refer to the Deming and Kahn (2018) versions of the skill composites and "hand-coded" refers to the versions from this paper.

C. Characterization of Major Skill Concentration

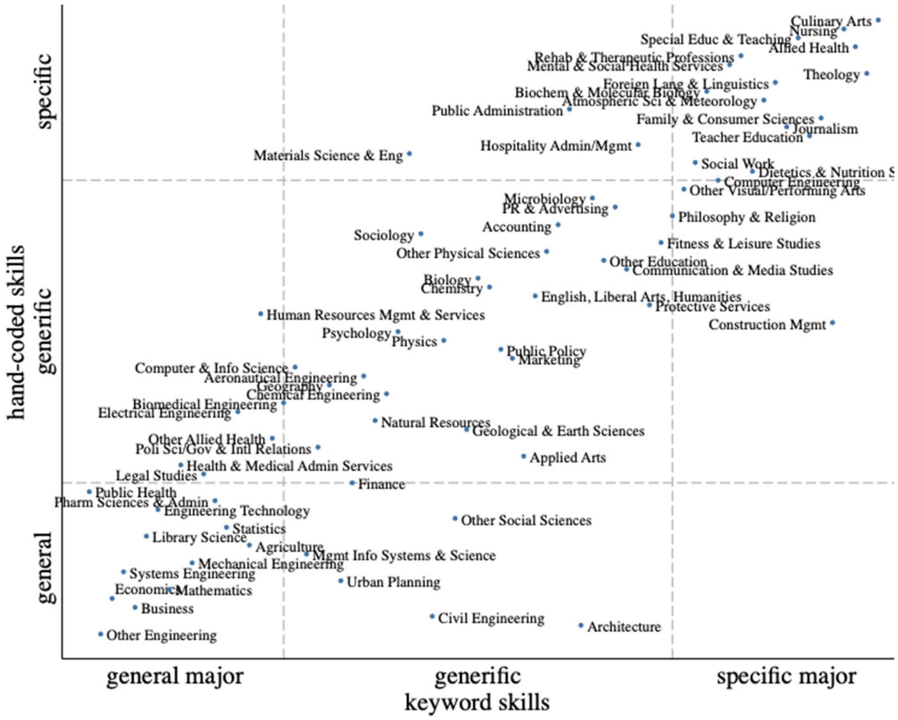
Figure D2 compares our classification of major skill concentration between the two methods for classifying skills into composites. Figure D2 Panel A compares rank correlation between the two measures; 52 of 70 final majors stay in the same broad category (general, generific, specific) when shifting from the keyword approach to our preferred hand-coding approach.[35] Specifically, 12 majors are general (bottom left grouping) under both schemes, 24 stay generific (central grouping), and 16 stay specific (top right grouping). Nine majors become more specific when switching from the keyword to hand-coding method: for example, Biomedical Engineering and Legal, which move from general to generific, and Material Sciences &

[35] The general category includes majors ranked 1 through 18 based on location quotient (LQ) similarity, generific includes those ranked 19 through 51, and specific includes those ranked 52 through 70. These roughly correspond to the top quartile, middle half, and bottom quartile of majors.

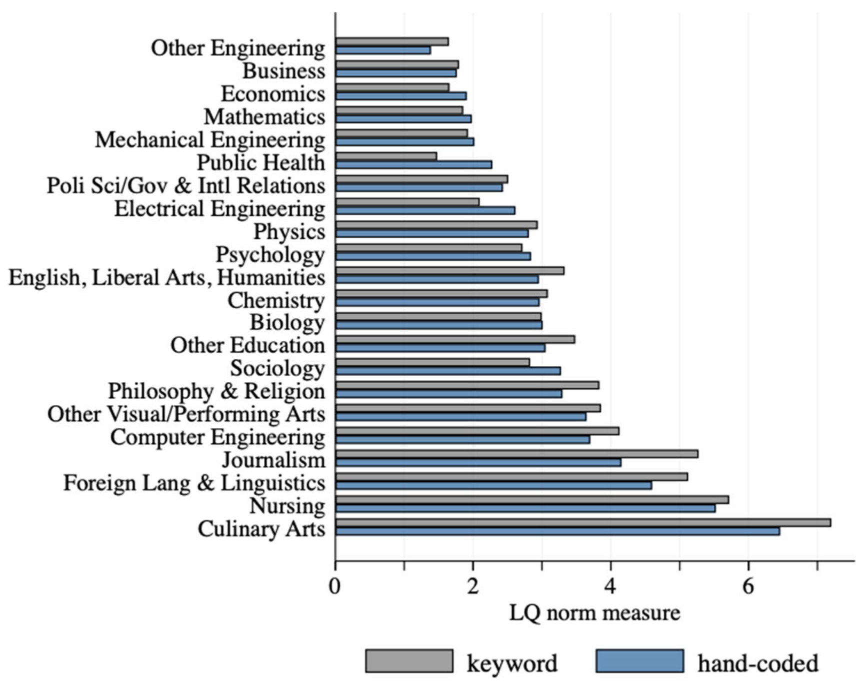
Engineering and Public Administration, which move from generific to specific. The last set of nine majors becomes more general, including Philosophy and Other Visual & Performing Arts, which move from specific to generific, and Architecture and Other Social Sciences, which move from generific to general. Figure D2 Panel B shows the specificity of selected majors under the two categorization systems in bar chart form.

Figure D2 Skill Specificity of Majors Using Different Methods to Classify Skills

A. Rank Correlation



B. Measure of Skill Specificity



NOTE: Panel A plots the ranking of each major using skill composites. "Keyword" skills refer to the Deming and Kahn (2018) versions of the skill composites and "hand-coded" refers to the versions from this paper. Panel B plots the LQ norm measure for select majors.

Appendix E: Replication of Deming and Kahn (2018)

In order to better understand how our findings compare to those of Deming and Kahn (2018, DK), we attempt to replicate and extend their main cell-level analysis. DK regress log mean wages in a MSA-occupation cell on shares of job ads seeking cognitive skills, social skills, and their interaction. They control for average years of education and experience, the share of ads with each of eight other job skills, and an increasingly rich set of job characteristics, such as MSA and six-digit occupation fixed effects. Their main finding is that cognitive and social skill requirements are positively correlated with wages, both with and without rich controls. Their specification with the most complete set of controls finds that a 10 percentage point increase in the share of ads requiring cognitive (social) skills is associated with 0.8 percent (0.5 percent) higher average wages. They conclude that skill requirements in local labor markets influence local wages even within narrowly defined occupations.

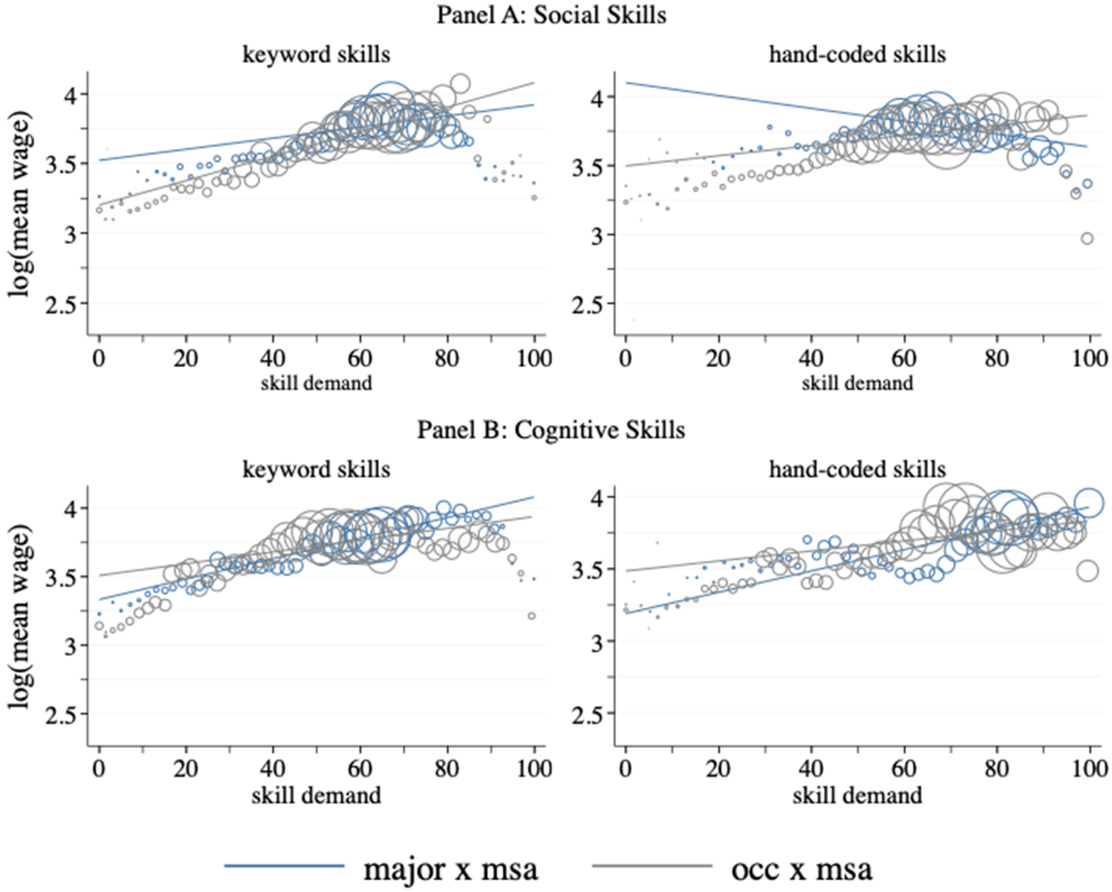
This conclusion contrasts with our finding of minimal association between skill requirements and major premia after netting out MSA and major fixed effects. These differences could stem from several factors, including the range of education levels considered in job postings, the years of job ad data included, the way in which skill composites are constructed, the vintage of the BGT data, the weighting scheme, and the type of aggregation (occupation vs. major). To assess the importance of these factors we replicate some of the main results found in DK's Table 3. Specifically, we follow DK and construct the log of average hourly earnings in MSA-by-six-digit-occupation cells using Occupation Employment Statistics (OES) data from 2012–2015. We then reconstruct the sample of job postings to match DK's by including job postings irrespective of the required education level. We collapse the data to MSA-by-occupation cells rather than MSA-by-major cells. Finally, we measure skill demand using both versions of the composites: the keyword approach used by DK and our hand-coded composites. Table A10 presents our replication results.

We are able to replicate the main, fully controlled estimates reasonably well (column 1). Differences in the sample (column 3 vs. 1) have little influence on the estimates; however, the method for classifying skills does. Social skill requirements classified using the keyword approach have a positive association with earnings, but the association is zero or even negative when skills are hand-classified (columns 2 and 4). The final four columns report results for our sample, which aggregates ads into MSA-by-major cells and includes a full set of MSA and major fixed effects.

We assess the importance of weighting and the classification method. The final column is quite similar to our preferred estimates in Table 5. The classification method and weighting scheme both matter. Estimates are closer to zero when we weight by incumbent workers (as measured in the ACS) rather than by job ads.

We were less successful in replicating the estimates from more parsimonious specifications in column 1 of DK's Table 3. However, in Table A11 we present raw cell-level correlations between social and cognitive skill requirements and wages, where cells are constructed either by MSA-occupation or MSA-major. Cognitive skill requirements are consistently positively associated with cell-level wages regardless of aggregation process, weighting, or classification method. However, the patterns for social skills are not robust—the keyword approach generates positive associations with wages, but the hand-coding approach generates weaker or even negative associations. These patterns also appear in Figure E1, which presents scatter plots of cell-level skill demand and wages. This analysis reinforces our conclusion that the skill classification process, weighting scheme, and the manner in which ads are aggregated all contribute to differences between our results and those of DK. Further, the association between social skills and wages is much more sensitive to these choices than is the relationship between cognitive skills and wages.

Figure E1 Correlation between Cell-Level Skill Demand and Wages



NOTE: Figure plots the binned averages of log(mean wage) across MSA-major (blue) and MSA-occupation (gray) cells. The cells for each category are divided into 50 bins, shown along the x-axis, based on the share of job postings in the cell that specify the indicated skill; each bin is thus two percentiles wide. The y-axis plots the average of log(mean wage) for all cells in the bin. A cell's log(mean wage) is the log of the average wage across individuals employed in the MSA-major or MSA-occupation, as captured in the ACS. Circle sizes reflect the total number of job postings in the bin. "Keyword" skills refer to the skill composites from Deming and Kahn (2018) and "hand-coded" refers to the procedure described in the text.