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ABSTRACT

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

We document the skill content of college majors as perceived by employers and expressed in the near universe of U.S. online job ads. Social and organizational skills are general in that they are sought by employers of almost all college majors, whereas other skills are more specialized. In turn, general majors—Business and General Engineering—have skill profiles similar to all majors; Nursing and Education are specialized. These cross-major differences in skill profiles explain considerable wage variation, with little role for within-major differences in skills across areas. College majors can thus be reasonably conceptualized as portable bundles of skills.

JEL Classification: I26, J23, J24

Keywords: college major, skill demand

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I. 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, & 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 et al., 2013; Kirkeboen, Leuven, & 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 plays 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), comprising the near universe of all 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

[1] In contrast, recent research has documented the importance of skill heterogeneity between and within *occupations* in explaining spatial wage variation (Deming & Kahn, 2018). But because occupation reflects post-labor-market selection, the role of *pre-market* skill acquisition as captured by college major remains underexplored.
[2] In 2021, after we acquired the data, Burning Glass Technologies merged with EMSI, a similar firm, and the company is now known as EMSI Burning Glass.

to characterize demand along these dimensions. In contrast to previous studies that document skill-major linkages mediated through occupation (Altonji, Kahn, & Speer 2014; Long, Goldhaber, & Huntington-Klein, 2015), the job postings data allow us to measure skill-major linkages at the individual job level and to account for substantial within-occupation variation in skill demand (which may be correlated with college major). 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). With these 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 under-representation of certain skills within a major provides evidence on the specificity of that field of study. We then construct major-specific skill vectors for each metropolitan statistical area (MSA). This permits us to examine the extent to which variation across MSAs in major-specific earnings can be explained by functions of their granular skill differences.

Our analysis reveals marked differences in the skills associated with different majors. 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. In turn, we find 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 Foreign Language, on the other hand, are more specific, with jobs ads requesting skills demanded relatively infrequently in other majors. Together these results suggest that employers view majors as meaningfully encompassing different skill bundles.

Further evidence that employers view majors as a bundle of skills, which are fairly portable across areas, comes from our geographic and earnings analysis. The vast majority of variation in skill demand across major-MSA cells is accounted for by major, whereas a much smaller share is accounted for by MSA. Nonetheless, there are substantial remaining cross-area skill differences even within majors. However, cross-area skill differences within majors have only a weak relationship with major earnings premia across areas. Fixed effects for majors explain a considerable share of the variation in cross-cell wages and greatly diminish the predictive power of the individual skill composites. For instance, cognitive, financial, and project management skills are strongly positively associated with cell-level wages, but these patterns are fully accounted for by college majors. This strengthens our conclusion that majors can be thought of 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 & Kahn, 2018; Hershbein & Kahn, 2018). Most work on the supply of college majors focuses on skill-major linkages through occupation (Altonji, Kahn, & Speer 2014; Long, Goldhaber, & Huntington-Klein, 2015). However, occupations are heterogeneous bundles of skills and tasks, and skill demand can vary dramatically across jobs within occupations (Busso, Muñoz, & Montaño, 2020). Our analysis highlights the importance of college major as a measurable dimension along which skill demand varies separate from that mediated by occupation.

A second strand of literature looks at whether majors are general versus specialized, which has implications for their returns over the lifecycle. Prior work has examined the benefits of a general versus specialized curriculum in the labor market (Hanushek et al, 2017; Deming & Noray, 2018; Martin, 2021). Several papers do this by quantifying the link between majors and occupations (e.g., Altonji, Blom, & Meghir, 2012; Li, Sebastian, & Shimao 2021; Ransom & Phipps, 2017) or via variation in major premia across occupations (Kinsler & Pavan, 2015; Leighton & 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, & Mogstad, 2016; Andrews, Imberman, & Lovenheim, 2017; Martin, 2021) as well as differences in cost 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, 2020) and spatial differences in the returns to education (Black, Kolesnikova, & Taylor, 2009). In contrast to Deming and Kahn (2018), who find that employer skill demands predict 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.

The rest of this article proceeds as follows. Section II describes the data and sample. Section III details the relationship between majors and skills. In Section IV we document the geographic variation in the skill-major linkage and then relate skill variation to earnings variation. Section V concludes.

II. Data and Samples

A. Job Ad Data

We use the near universe of all online job ads posted in the United States from 2010 to 2018, obtained from Burning Glass Technologies (BGT or Burning Glass). BGT scours about 40,000 online job boards and company 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 JOLTS, the Current Population Survey, and the Occupational Employment Statistics. Their analysis suggests 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.[3] Moreover, since we focus on job ads requiring a bachelor's degree, the skill skew is of even less concern.

B. 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. Importantly, 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.[4] These education and skill requirements leave 12.8% of the original 153 million job postings. Most of our analyses also restrict the sample to ads that list at least one college major posted in metropolitan statistical areas (MSAs). This additional requirement reduces the analytic sample to about 18.5 million unique job postings.[5] We exclude ads specifically targeting workers with graduate education as we are interested in measuring the association between undergraduate majors and skills. In addition, 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

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

[4] Approximately 17% of all postings ask for 12 years of education, 5% ask for 14 years of education, 3% are for 18 years and 1% ask for 21 years of education. The remaining postings are missing information on education (roughly 50% 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%) but majors are less frequently listed in postings that specify 12, 14, or 21 years of education (6.5%, 37%, and 46%, respectively).

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

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 & Acemoglu, 2011). The higher concentration of job postings in Management (22% vs. 12%) and Business (15% vs. 7%) 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 (3.4% vs. 0.23%), Building Cleaning and Maintenance (1.11% vs. 0.04%), Sales occupations (11.76% vs. 4.38%), and Office & Administrative Support (9.96% vs. 3.02%).

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% vs. 1.3%), Protective Service occupations (0.3% vs. 0.2%), Sales occupations (8.2% vs. 4.4%), and Office/Admin Support (4.3% vs. 3.0%), with lower proportions in Computer/Math (22.1% vs. 25.8%) and Architecture/Engineering (6.7% vs. 9.3%). 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% 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 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% 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 to just 29%.[6] These results suggest that differences in extremely detailed

[6] **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.

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. It is thus 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.[7]

C. College Majors

Among job postings that require exactly a bachelor's degree, 54% 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 (though some ads are initially coded with less granularity), which we first aggregate 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% of postings listing a single major, 30% listing two, and 15% listing three or more. For the purposes of analyzing skill demand by major, we further aggregate college majors into 70 categories.[8] We aim to produce categories that have meaningful quantities of both job ads (BGT) and degrees granted according to IPEDS. 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).[9] **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% of postings in the analytic sample, including both Business and Computer and Information

[7] In related work, we are applying machine learning methods to estimate the full latent distribution of majors demanded in job postings.

[8] 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 post-baccalaureate or graduate programs (e.g., Residency Programs), or trade specific (e.g., Mechanic and Repair Technologies/Technicians).

[9] Our process for aggregating college majors is described in **Appendix A**. The full list of all major groups is reported in **Appendix Table A4**.

Sciences, which are listed on 29% and 26% 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% of job ads. The least frequently demanded majors in our sample include Theology (0.07%), Atmospheric Sciences and Meteorology (0.03%), Other Physical Sciences (0.03%), and Philosophy and Religion (0.02%).

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.[10] 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.

D. Categorizing Skills

Burning Glass parses over 15,000 individual skills from the job postings. 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 (see **Table 2**) and then had pairs of our research team manually assign a subset of the skills to one of the composites, using a pre-set process to resolve discrepancies. (We describe the procedure in detail in **Appendix B**.)

[10] 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.

This approach provides a few benefits over the application of the keyword approach from Deming and Kahn (2018) or Hershbein and Kahn (2018).[11] 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% of postings), organizational skills (16%), detail-oriented (12%), scheduling (12%), building effective relationships (11%), creativity (10%), troubleshooting (6%) and multi-tasking (8%). 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.[12] 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 (or major-by-job posting) can reflect multiple 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

[11] In **Appendix C**, we conduct a thorough analysis of 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 of constructing skill composites.

[12] 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.

most frequently occurring skills. Their estimate of the shares of ads seeking cognitive and social skills were 37% and 36%, respectively.[13]

E. 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. 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 these majors tend to enter (**Table A5**). 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 list 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.

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. This pattern is consistent with employers facing a fixed cost of

[13] 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.

posting a vacancy, but relatively low marginal cost of including additional information like major.[14] 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 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 & 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 expect applicants from each major to possess. How intensity of skill level within type of skill can be inferred from job ads is an important direction for further research.

F. 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

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

(FTFY), 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 (PCE) deflator from the Bureau of Economic Analysis (BEA). 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.[15] **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.

III. 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.[16] There is a substantial range across fields for many of these skill aggregates. For instance, the share of ads desiring specific software skills ranges from less than 4% 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.

[15] In both cases we employ sample weights when aggregating to major-MSA cells.
[16] Full results for all 70 majors are in **Appendix Table A6**.

A. 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:

$$LQ_{sm} = \frac{(N_{sm}/N_m)}{(N_s/N)} = \frac{(N_{sm}/N_s)}{(N_m/N)},$$

where N_m is the number of ads that list major *m*, N_{sm} 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 skill composite (*s*) and major (*m*) 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 one. 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*) to be 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 $(\widehat{N}_{s})$ so that $\widehat{N}_{s} = \sum_{m} N_{sm}$. With these changes, the adjusted LQ for a dyad of major m and skill s is:

$$\widehat{LQ_{sm}} = \frac{(N_{sm}/N_{m})}{(\widehat{N}_{s}/\widehat{N})} = \frac{(N_{sm}/\widehat{N}_{s})}{(N_{m}/\widehat{N})}$$

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: $\sum_{s=1}^{11} abs(\widehat{LQ_{sm}} - 1)$. 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.[17] 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 one.

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

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 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.

B. 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. 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 one, and then sum the absolute deviations across all skills for a major.[18] 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 one for all skill aggregates. These majors can be thought of as *general* 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 towards the bottom are *specialized* 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 but very low with software, computers, financial, and writing. Among postings that demand a Nursing major, 23% demand computer skills, which is roughly half the market-wide demand of 42%, 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% of postings that list a Nursing major but only 46% 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, 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.

These results are robust to including postings that demand 16 years of education but do not list a major when calculating the LQ denominator. 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 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

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

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

C. 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 use the metric itself, rather than the rank, as the outcome (**Appendix Table A7**). 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.[19]

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 >.8), including Business, Library Science, English, Liberal Arts, Humanities, and Communication & Media Studies.

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

[19] 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.

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.

D. Comparison to Prior Work on College Major Specificity

Our measure of college major specificity complements those constructed by other scholars, which primarily rely 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 strong correlation between major rankings when cells are weighted by the number of ads (.47), but minimal correlation when they are unweighted (.004), suggesting that inferences about specialization are more robust for more common majors.[20]

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 measured based on realized occupational sorting. Our measure of specificity, which is

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

based on skill demand, additionally permits investigation of specific mechanisms that likely contribute to major wage premia—particularly related to the role of geography.

IV. 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 & Kahn, 2018). In this section, we quantify the extent of variability in skills associated with each major across areas and use this variability to examine how skills and majors relate to earnings. Substantial variation across space in skill demand for the same major may indicate that local postsecondary providers will need to tailor program curricula to suit local labor market needs.

A. Geographic Variation in Skill Demand

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 darker shading have larger shares of Business major ads that demand cognitive skills. Contrast Jasper, Indiana and London, Kentucky. Both locations have similar quantities of job postings for Business majors (~500–700 job postings). However, in Jasper, roughly 82% of job postings for Business majors demand cognitive skills compared to only 46% in London, KY. Even though these two localities are only a 3–4 hour drive apart, employers in these areas demand very different skills from Business majors. Next, beam down to Roswell, NM and nearby Andrews, TX. 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. We construct major-MSA cells containing the share of ads seeking each skill. Majors account for the vast majority of the variation across these cells—major accounts for almost 90% of the cross-cell variation in demand for software skills and three-quarters of the variation for customer service skills. Place accounts for only 3–11% of the cross-cell variation in skill demand. The remaining, unexplained variation in major-specific skill demand across areas is substantial—up to 50% for organizational and communication skills.

B. Skill Demand and Earnings

Is this variation consequential in terms of wages? **Figure 4** showed substantial wage variation across majors and areas. We now examine whether such differentials are associated with differences in skill demand. Returning to the previous examples, in Jasper, IN, the average adjusted hourly earnings among Business majors is $44.30, which is about 5% higher than the adjusted hourly earnings of $41.90 in London, KY, a place where employers demand relatively less cognitive skill of Business majors. The average adjusted hourly earnings in Andrews, TX ($43.70) are 7.5% higher than in Roswell, NM, also consistent with the relatively higher 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:

$$Y_{jk} = \sum_{s=1}^{S} \beta_s PctSkill_{sjk} + \gamma_k + \gamma_j + \varepsilon_{jk}$$

where Y_{jk} is the log of mean hourly earnings (2019 dollars) among college graduates in major k in MSA j from the ACS, and $PctSkill_{sjk}$ is a vector of skill demand in the major-MSA cell measured by the share of ads that list each skill. The coefficient β_s indicates the approximate hourly earnings change associated with a 100-percentage-point increase in the share of job ads requiring the skill. The inclusion of major (γ_k) or MSA (γ_j) fixed effects isolates the association between skills and earnings that occurs within majors and MSAs, respectively. We weight each observation by the number of employed people in each cell using person weights from the ACS.[21]

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

[21] Although we mostly 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.

demand and log mean hourly earnings in a major-MSA cell. Skill demand is highly correlated with earnings. Major-MSA 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 is associated with a 4% increase in average wages. Greater demand for people management, social, and basic computer skills (conditional on other skills) are negatively correlated with earnings. These traits may be markers for lower-paid occupations. Collectively the 11 skill composites explain 34% of the wage variation across MSA-major cells and are jointly statistically significant at a 1% 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, 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 & 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 of the individual skill composites. This suggests that majors can be thought of as portable bundles of skill composites. Once we account for major and MSA, the remaining variation in skill demand measured by the skill composites explains relatively little additional wage variation (F-statistic = 2.8, p = 0.004). As **Table 4** showed, this is not because there is no remaining variation in skill demand within majors across areas; one-third of the variation in demand for cognitive skills remains in this final regression, 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% decrease in average wage.

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) before aggregating up to the major-MSA 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 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.[22] 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 documented in **Figures 10**, does not correlate with earnings. A caveat, however, is that this analysis is silent about whether variation in *individual* skills within majors across places—as opposed to skill composites—relates to earnings.

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.[23] 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

[22] 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% require 5 years or fewer (including 25% that do not require any experience), and only 2% of ads seek more than 10 years of experience.

[23] We attempt to replicate Deming and Kahn (2018) in **Appendix D**. 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.

interpreting occupations as uniform bundles of tasks: 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. For instance, technology jobs may be disproportionately filled by Computer Science majors in Silicon Valley but by Business majors in Scranton.

V. 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 inspired by the logic of location quotients (LQs) from the literature on industry concentration, 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., Leighton & Speer, 2020; Li, Linde, & 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 over-concentrated among job ads listing those majors. Other majors, such as Nursing, are more specific in being closely associated with skills that are not widely sought in the labor market for college graduates.

Mapping similarities among majors based on our skill demand measures 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 are likely to have similar labor market payoffs. Hence, one implication is that policymakers and higher education leaders may want to adopt a broader and more multi-dimensional 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 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.

References

Acemoglu, D., & D. Autor, 2011. “Skills, Tasks and Technologies: Implications for Employment and Earnings.” In *Handbook of Labor Economics: Volume 4B*, edited by D. Card and O. Ashenfelter. Amsterdam: Elsevier. pp. 1043–1171.

Arcidiacono, Peter. 2004. “Ability sorting and the returns to college major. *Journal of Econometrics,* 121(1–2):343–75.

Altonji, J. G., E. Blom, & C. Meghir, 2012. “Heterogeneity in Human Capital Investments: High School Curriculum, College Major, and Careers." *Annual Review of Economics,* 4(1): 185–223.

Altonji, J. G., P. Arcidiacono, & A. Maurel, 2016. “Chapter 7 - The Analysis of Field Choice in College and Graduate School: Determinants and Wage Effects.” In *Handbook of the Economics of Education, Vol. 5*, edited by E. Hanushek, S. Machin, and L.Woessmann. Amsterdam: Elsevier. pp. 305–396.

Altonji, J., L. Kahn, & J. Speer, 2014. “Trends in Earnings Differentials across College Majors and the Changing Task Composition of Jobs.” *American Economic Review,* 104(5): 387–393.

American Association of Colleges and Universities, 2018. *Fulfilling the American Dream: Liberal Education and the Future of Work: Selected Findings from Online Surveys of Business Executives and Hiring Managers.* Retrieved from https://www.aacu.org/sites/default/files/files/LEAP/2018EmployerResearchReport.pdf

Andrews, Rodney, S. Imberman, & M. Lovenheim, 2017. "Risky Business? The Effect of Majoring in Business on Earnings and Educational Attainment." NBER WP 23575.

Atalay, Enghin, Phai Phongthiengtham, Sebastian Sotelo, and Daniel Tannenbaum. 2020. "The Evolution of Work in the United States." *American Economic Journal: Applied Economics,* 12 (2): 1-34.

Busso, M., J. S. Muñoz, & S. Montaño. 2020. “Unbundling Returns to Degrees and Skills: Evidence from Postsecondary Education in Colombia.” Inter-American Development Bank Working Paper IDB-WP-1089.

Black, D., N. Kolesnikova, & L. Taylor, 2009. “Earnings Functions When Wages and Prices Vary by Location.” *Journal of Labor Economics,* 27(1): 21-47.

Delbanco, A., 2012. *College: What it Was, Is, and Should be*. Princeton: Princeton University Press.

Deming, D., 2017. “The Growing Importance of Social Skills in the Labor Market.” *Quarterly Journal of Economics,* 132(4): 1593–1640.

Deming, D., & L. Kahn, 2018. “Skill Requirements Across Firms and Labor Markets: Evidence from Job Postings for Professionals.” *Journal of Labor Economics,* 36(S1): S337–S369.

Deming, D., & K. Noray, 2018. “STEM Careers and the Changing Skill Requirements of Work.” NBER Working Paper 25065. September.

Hanushek, E., G. Schwerdt, L. Woessmann, & L. Zhang, 2017. “General Education, Vocational Education, and Labor-Market Outcomes over the Lifecycle.” *Journal of Human Resources,* 52(1): 48–87.

Hastings, Justine S., Christopher A. Neilson, and Seth D. Zimmerman, 2013. “Are Some Degrees Worth More Than Others? Evidence from College Admission Cutoffs in Chile.” NBER WP 19241.

Hemelt, S., K. Stange, F. Furquim, A. Simon, & J. Sawyer, 2021. “Why is Math Cheaper than English? Understanding Cost Differences in Higher Education.” *Journal of Labor Economics,* 39(2): 397–435.

Hershbein, B., & L. Kahn, 2018. “Do Recessions Accelerate Routine-biased Technological Change? Evidence from Vacancy Postings.” *American Economic Review,* 108(7): 1737–1772.

Kinsler, J. and R. Pavan. 2015. “The Specificity of General Human Capital: Evidence from College Major Choice.” *Journal of Labor Economics,* 33(4): 933-972.

Kirkebøen, L., E. Leuven & M. Mogstad. 2016. “Field of Study, Earnings, and Self-Selection.” *Quarterly Journal of Economics,* 131(3): 1057-1111.

Leighton, M., & J. Speer, 2020. “Labor Market Returns to College Major Specificity.” *European Economic Review,* 128: 103489.

Li, X., S. Linde, & H. Shimao, 2021. “Major Complexity Index and College Skill Production.” Villanova University Working Paper.

Long, M., D. Goldhaber, & N. Huntington-Klein, 2015. “Do Completed College Majors Respond to Changes in Wages?” *Economics of Education Review,* 49: 7911–14.

Martin, Shawn, 2021. “Job Search and Earnings Growth: General and Specific Majors”. *Unpublished Manuscript.*

Paglin, M. and A. Rufolo, 1990. “Heterogeneous Human Capital, Occupational Choice, and Male-Female Earnings Differences.” *Journal of Labor Economics*, 8 (1 Part 1) Jan., 1990.

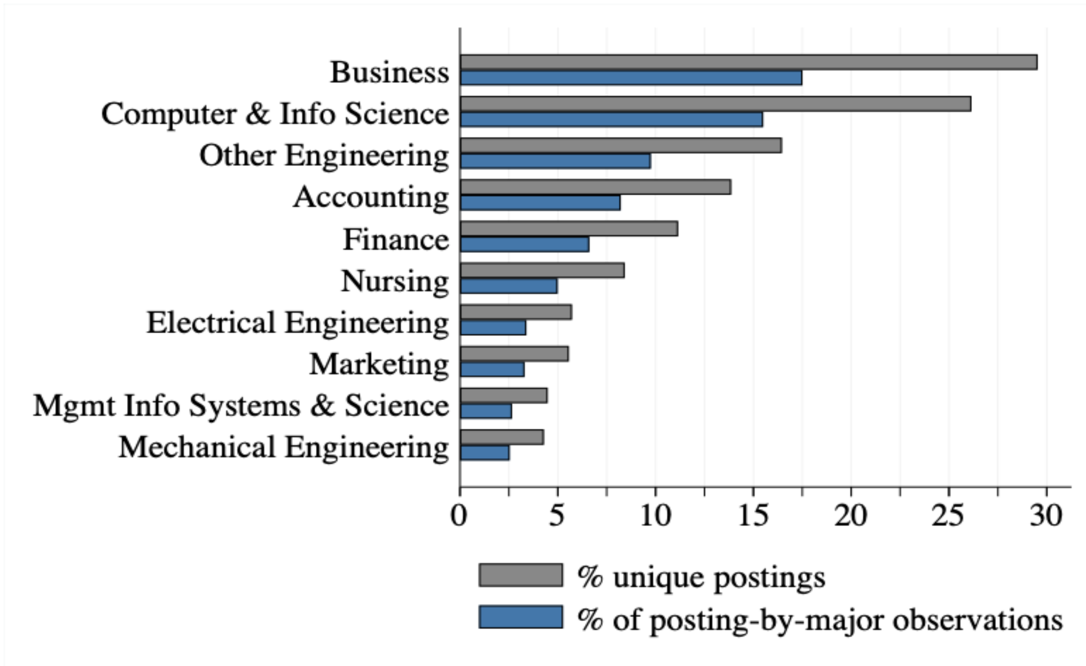
Ransom, T., 2020. “Selective Migration, Occupational Choice, and the Wage Returns to College Majors.” IZA Working paper No 13370.

Ransom, M. R., and A. Phipps (2017): “The Changing Occupational Distribution by College Major,” *Research in Labor Economics*, 45(1).

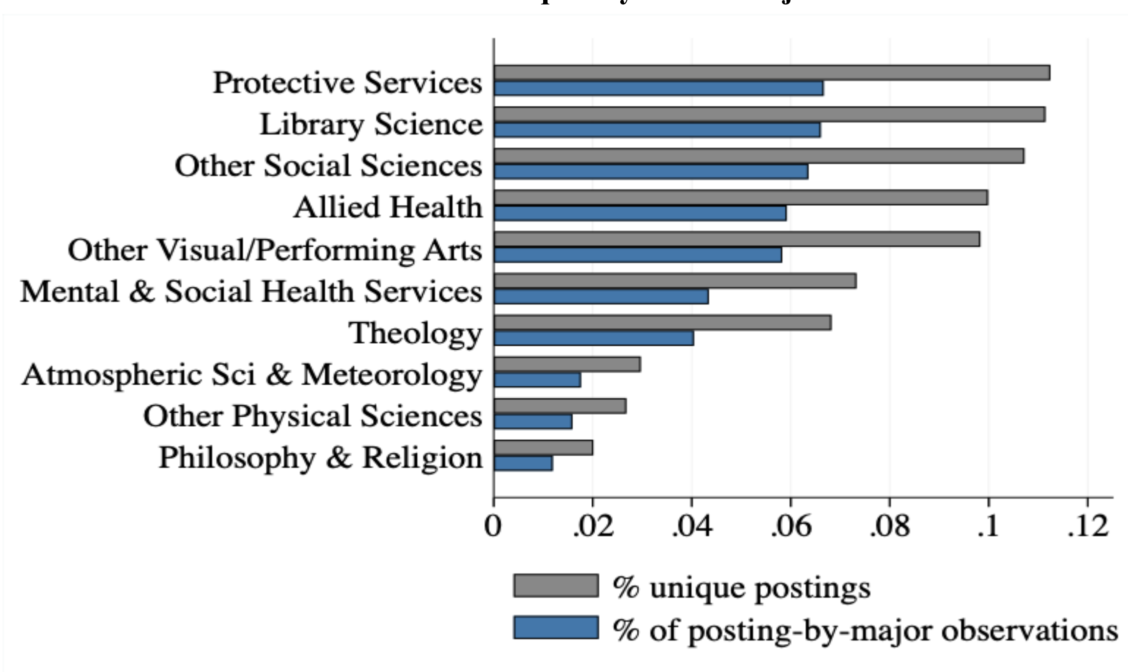
Webber, D., 2014. “The Lifetime Earnings Premia of Different Majors: Correcting for Selection Based on Cognitive, Noncognitive, and Unobserved Factors.” *Labour Economics,* 28: 14–23..

Figure 1. Most and Least Frequently Demanded Majors

A. Most Frequently Listed Majors

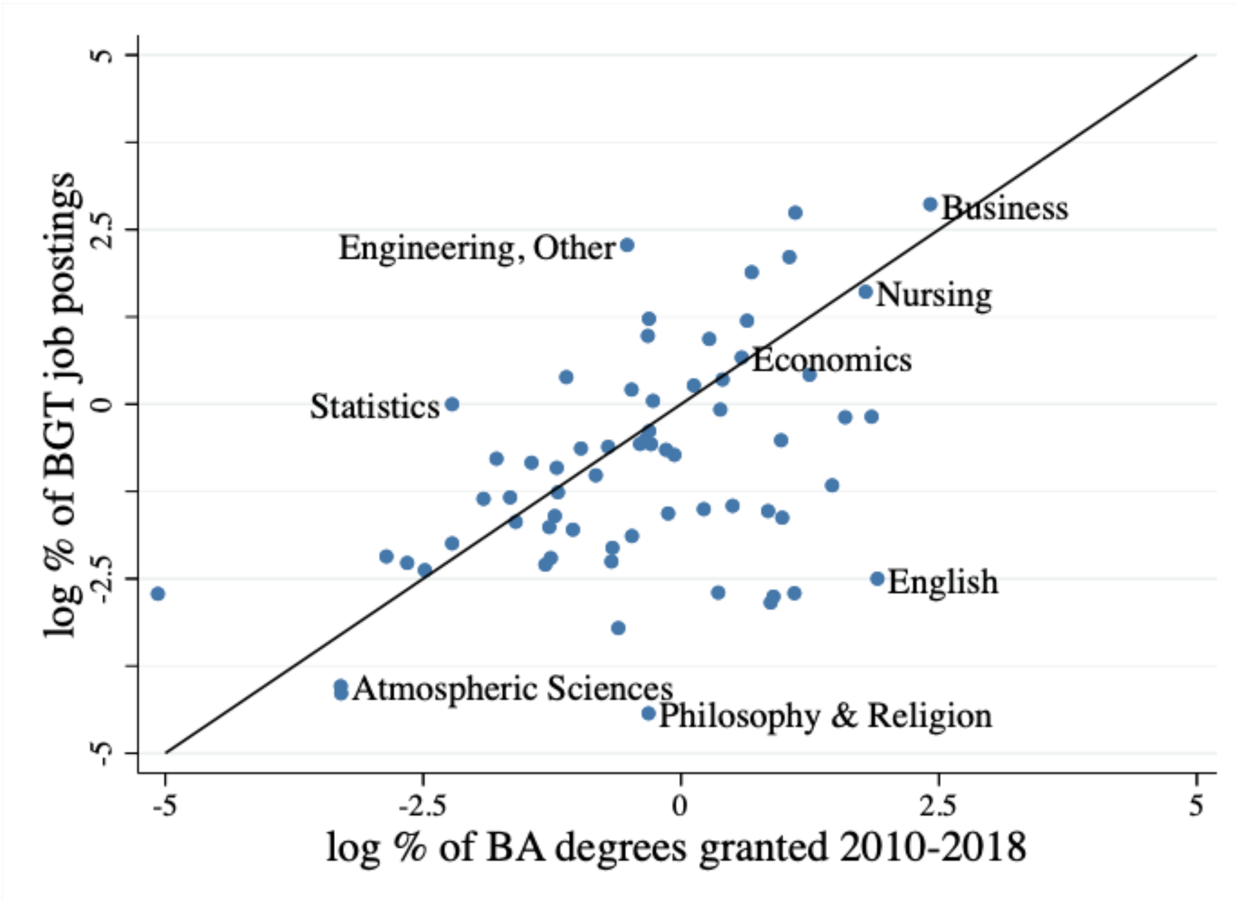


B. Least Frequently Listed Majors



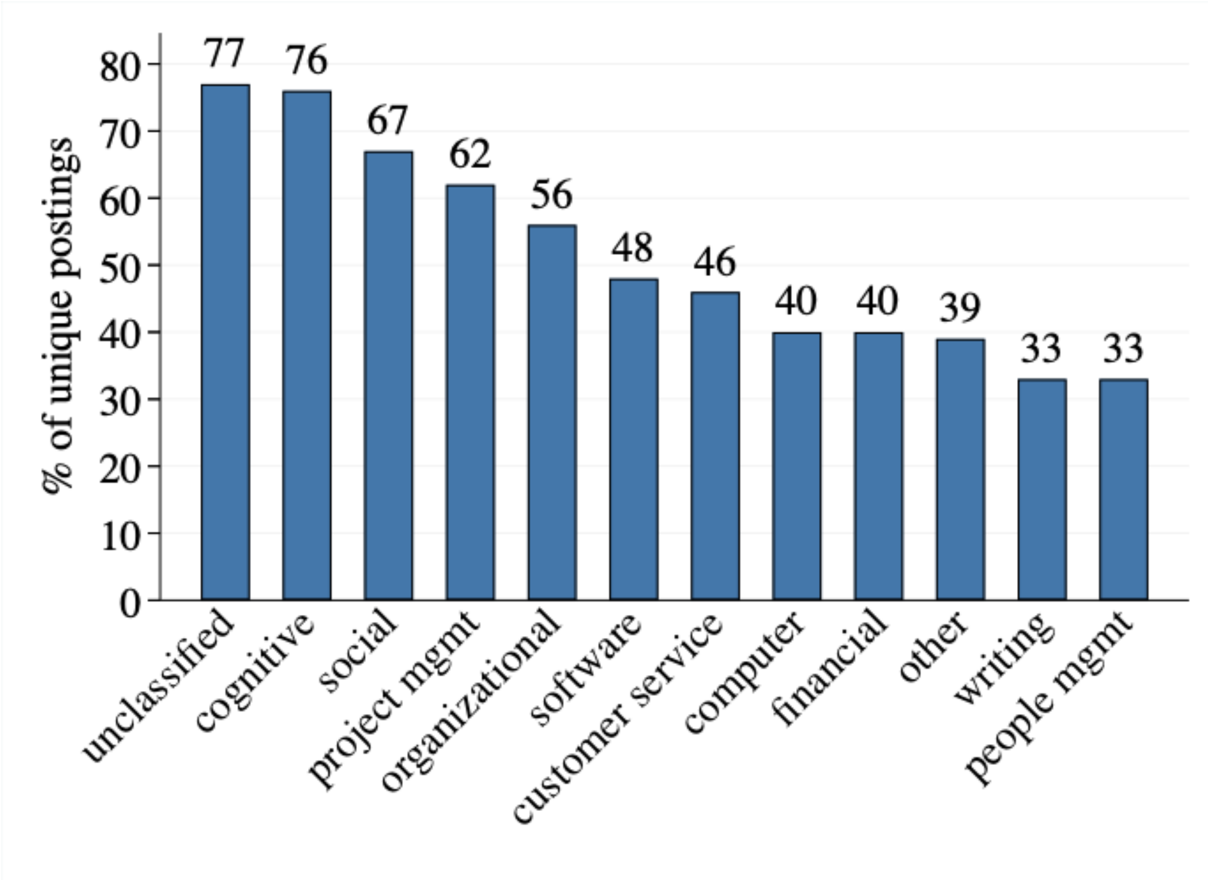
Notes: Sample includes all job ads posted between January 2010 and May 2018 in metropolitan statistical areas that list 16 years of required education, at least one skill, and at least one major.

Figure 2. Comparison between Major Share in Ads vs. BA Completions



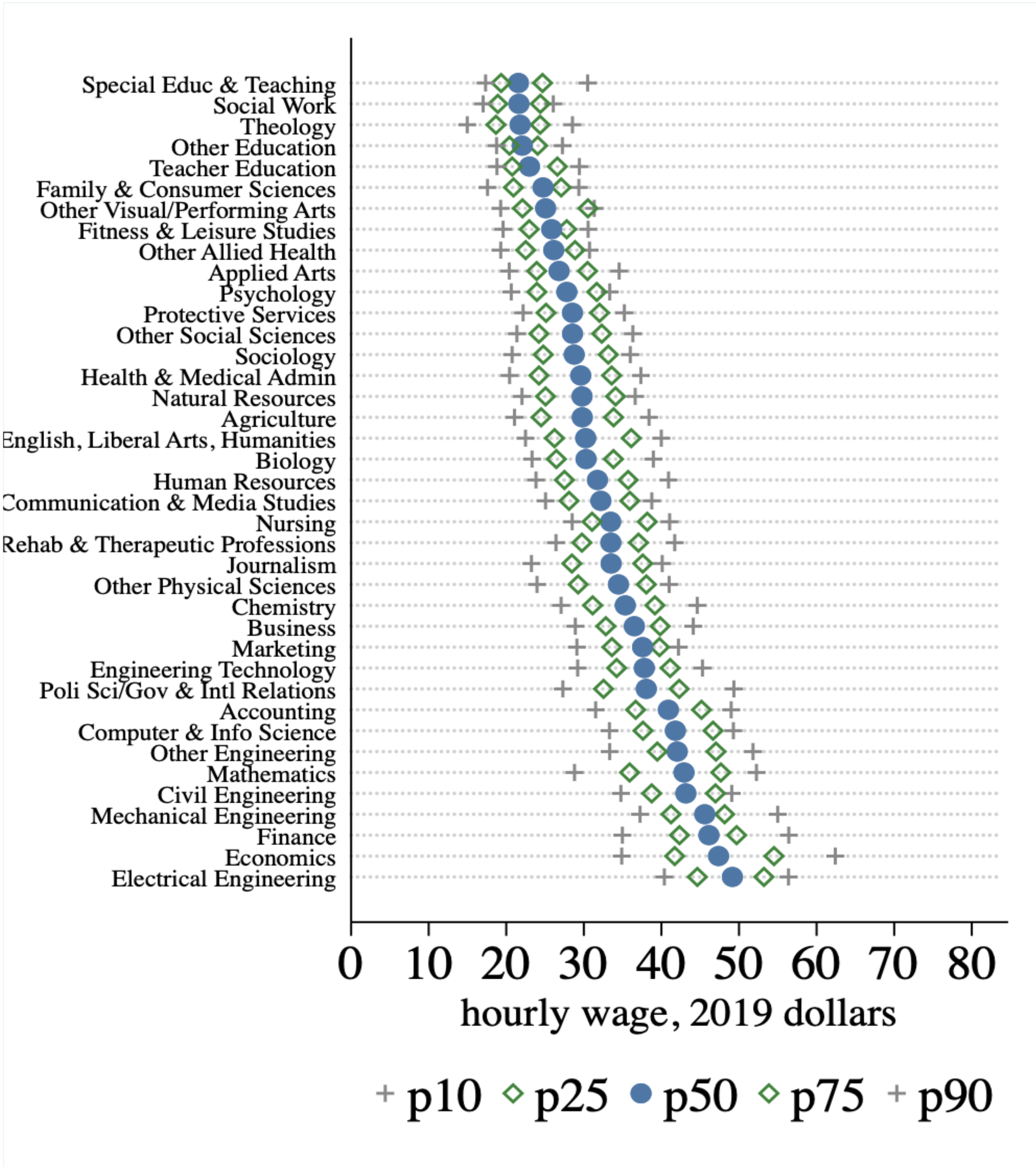
Notes: Figure plots the log percentage of BGT job postings listing each major against the log percentage of degrees granted (from IPEDs data) in years 2010-2018.

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



Notes: Figure plots the percentage of BGT job postings listing a skill in each of 11 skill composites constructed from the 1000 most frequent skills. A twelfth composite, "unclassified," is the share of ads containing a skill outside the 1000 most frequent. Only 0.2% of postings list none of our 11 composites (excluding "unclassified"). Across job postings, the mean and median number of composite skills listed is five (excluding "unclassified").

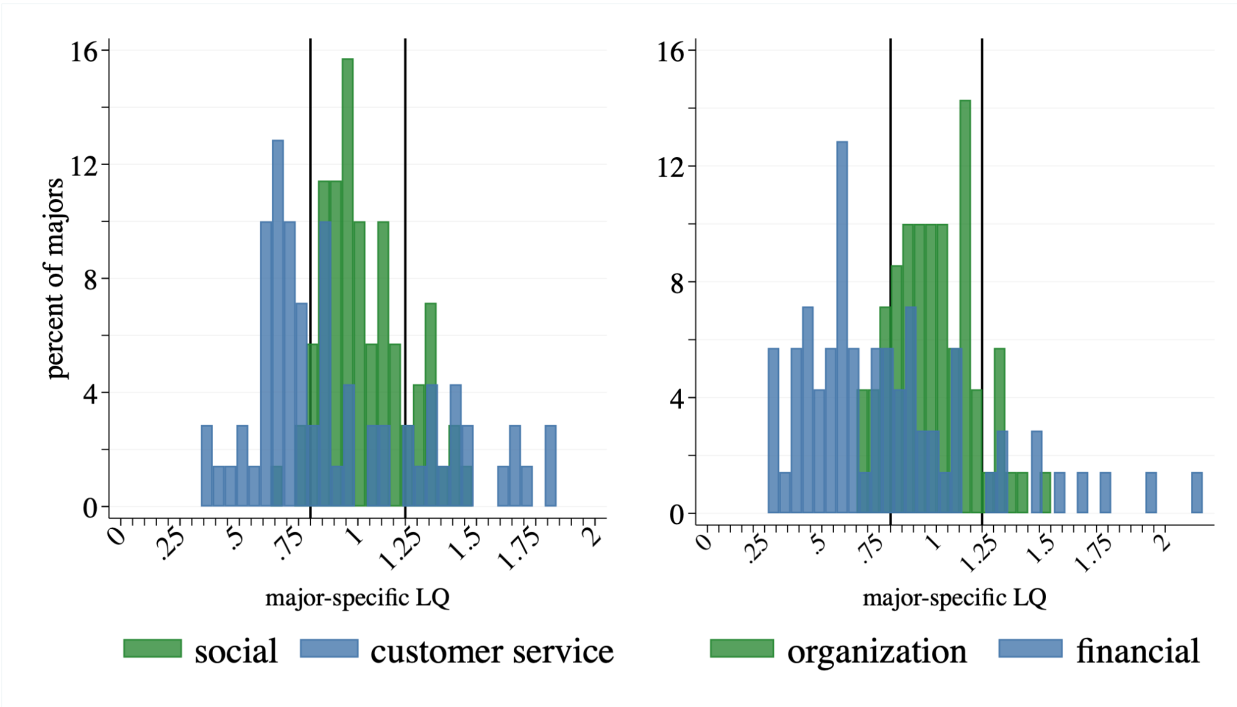
Figure 4. Distribution of Average Wage Across Majors and Areas



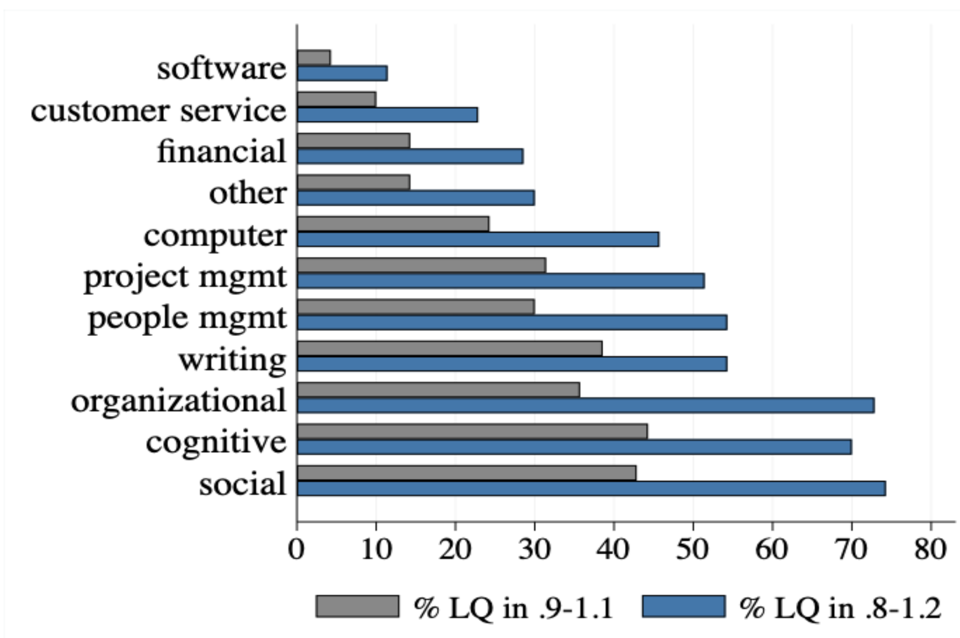
Notes: Mean hourly wages for each major-MSA cell in the U.S. are computed from the American Community Survey 2009–2018. Sample includes only full-time, full-year, prime-age workers with exactly a bachelor's degree. Figure includes the 39 majors (out of 70 we classify) with estimates in at least 600 CBSAs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

Figure 5. Distribution of of Skill Concentration Across Majors

A. Full Distribution for Four Skill Composites

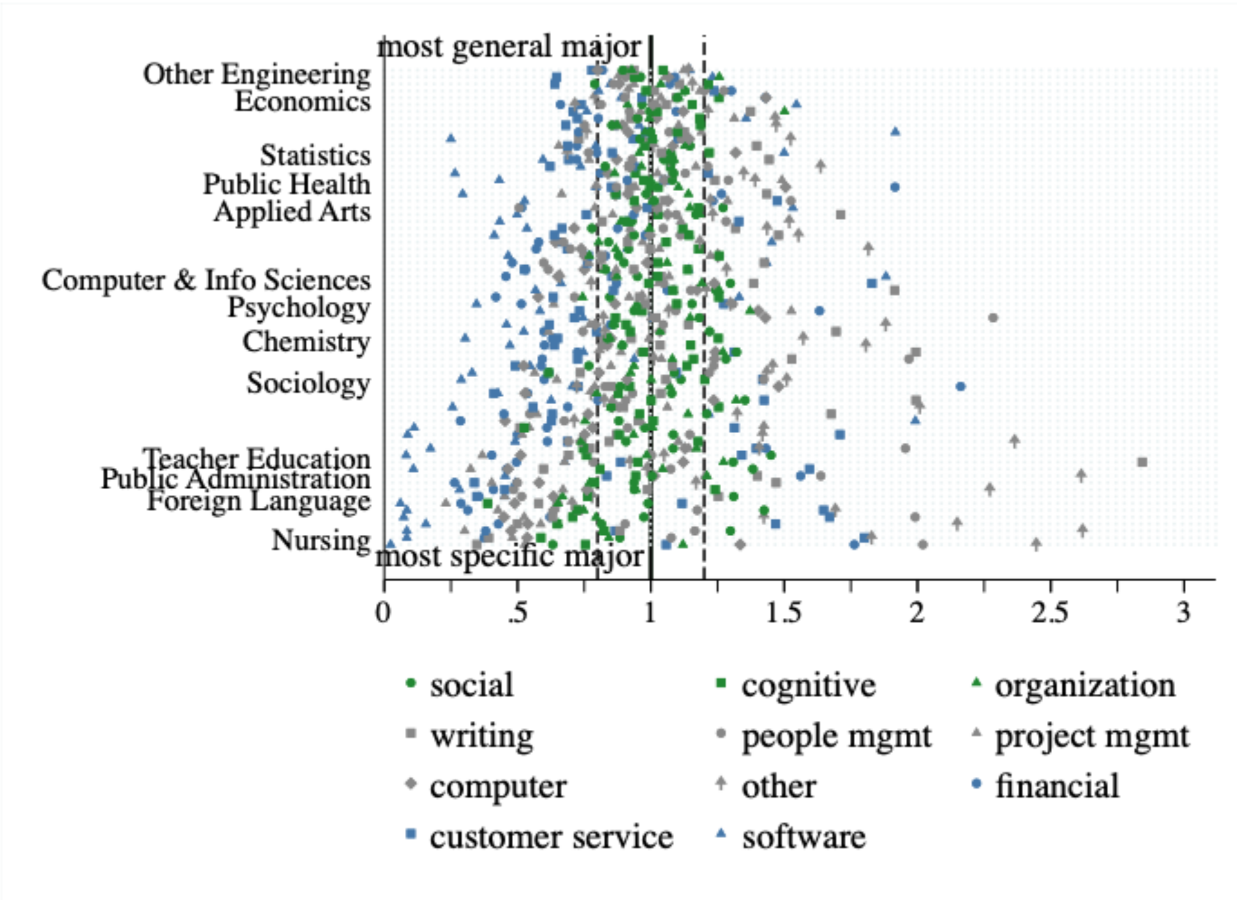


B. Skills Ranked by Specificity to Major



Notes: 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 LQs that are within a narrow range of 1. Lower values indicate skills that are more major-specific.

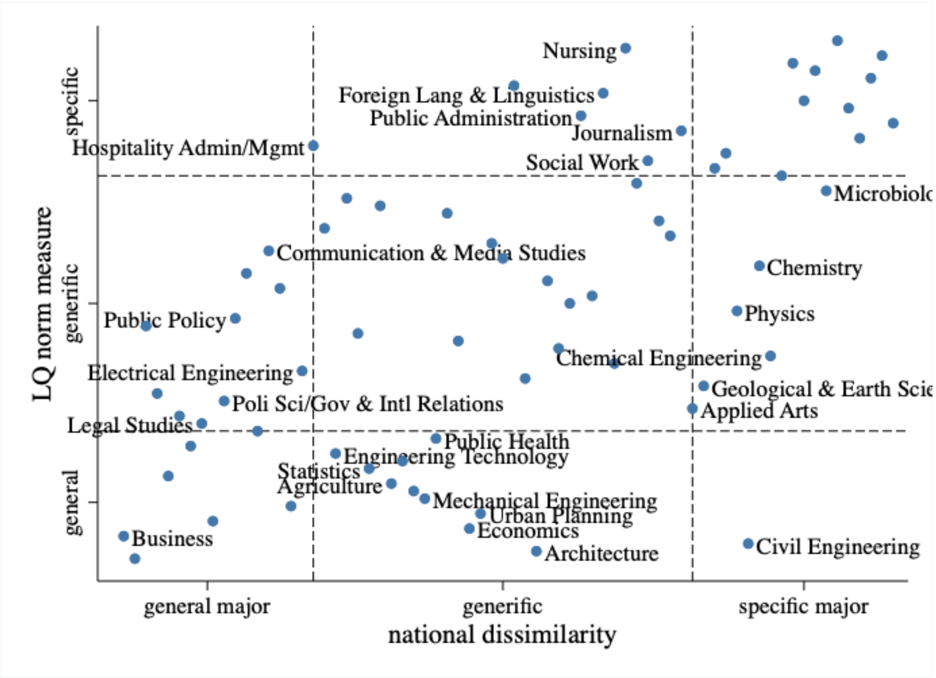
Figure 6. Skill Concentration for All Majors



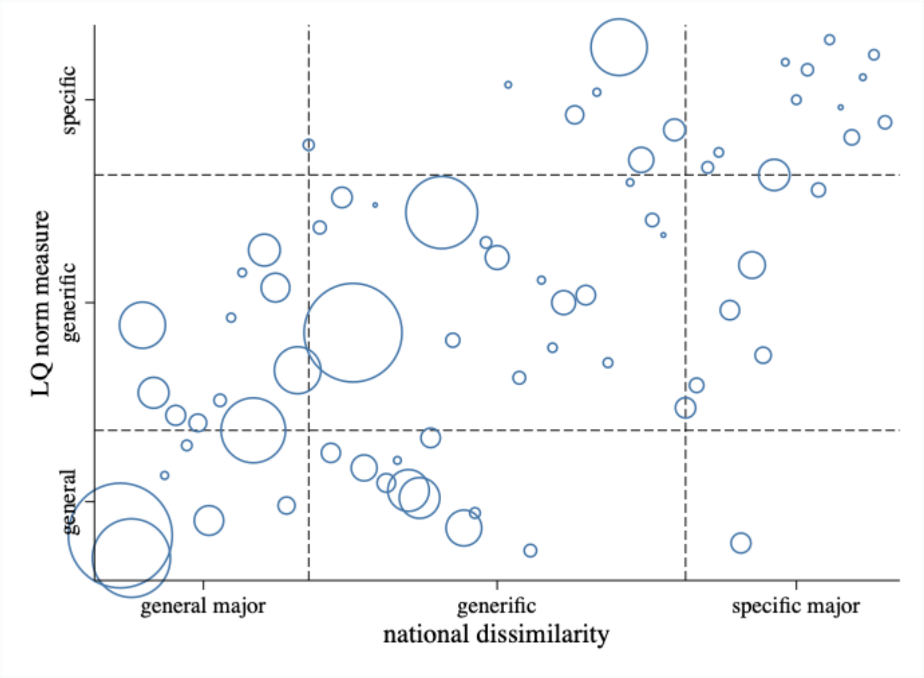
Notes: Figure plots the location quotients (LQ) for 11 skill clusters for 70 majors. An LQ greater than 1 indicates that ads with a given major are more likely to seek the skill than ads overall. An LQ less than 1 indicates that ads with the major are less likely to seek the skill than ads overall.

Figure 7. Skill Composite vs. Similarity Index Measure of Concentration

A. Unweighted

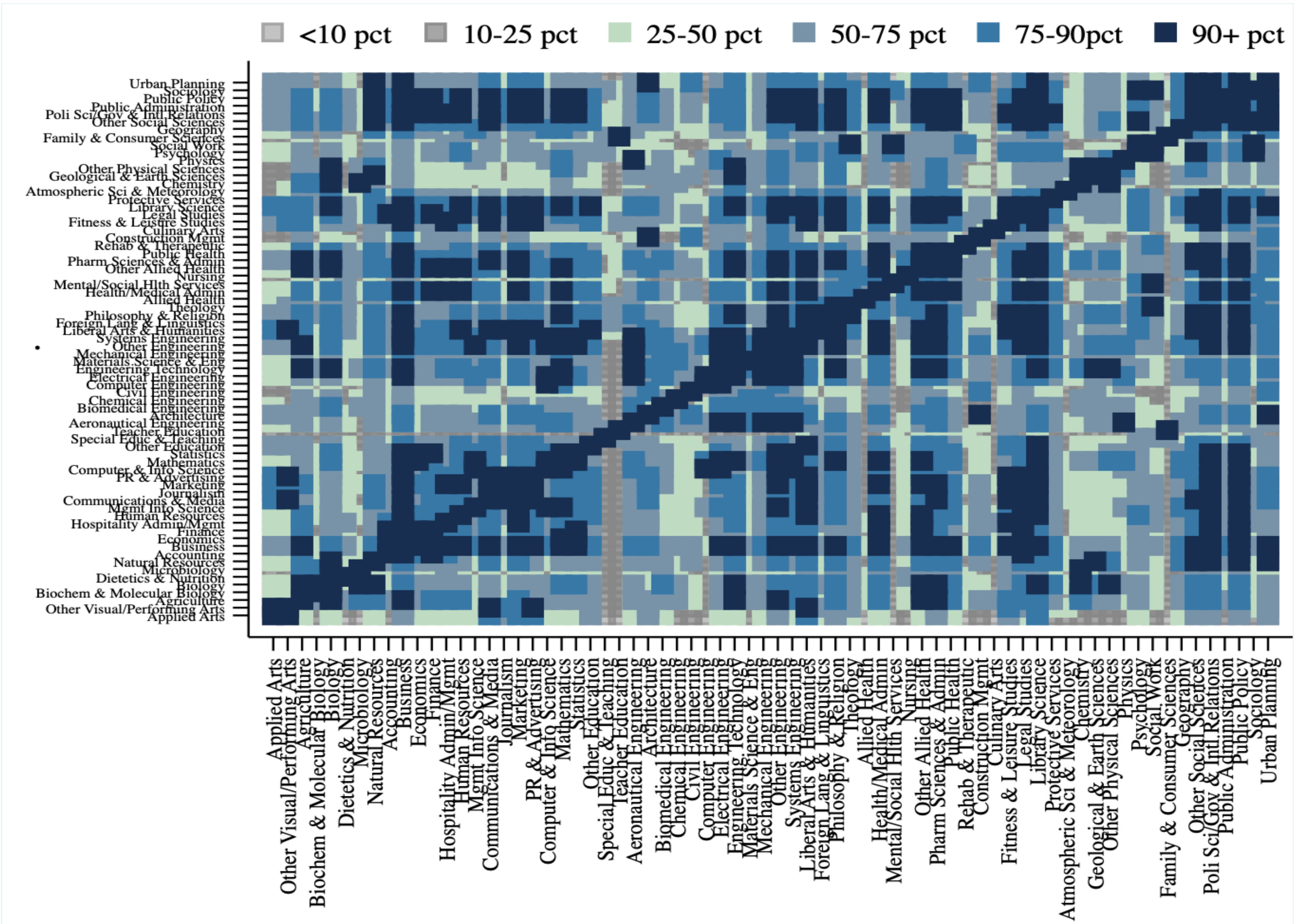


B. Weighted by Number of Job Ads



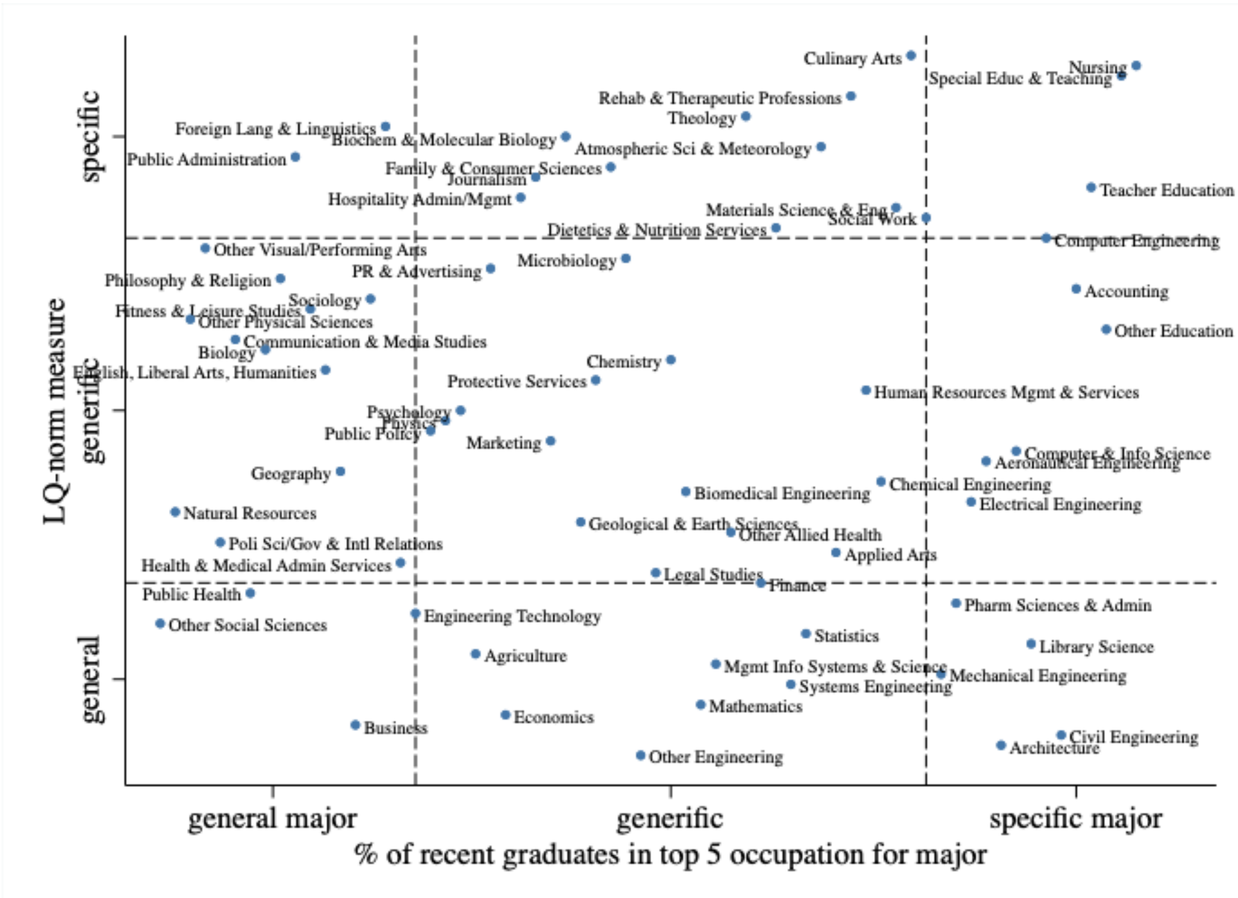
Notes: Figure plots the rank of 70 majors using two different measures of skill similarity. The y-axis plots the rank of majors from general (rank=1) to specific (rank=70). Majors are ranked according to the sum of the absolute deviation of the major's 11 LQs, from 1: sum(abs(LQ-1)). The X-axis plots the rank of each major using the cosine similarity measure constructed using the 9000 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



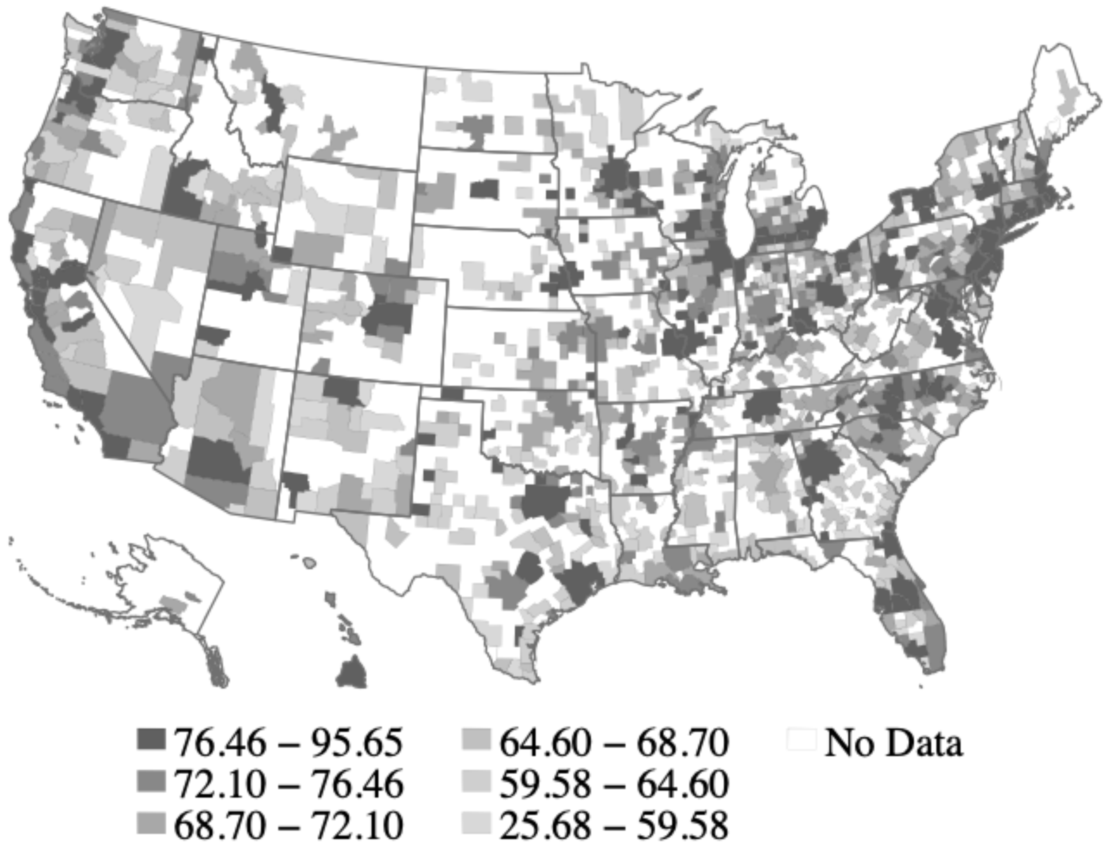
Note: Figures plots the similarity measure between each pair of majors. Similarity between majors is calculated using the cosine similarity measure and each major's vector of the 9000 most frequent skills. Cells are colored according to the unweighted percentiles of the distribution of the similarity 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



Notes: 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). Majors are ranked according to the sum of the absolute deviations of the major's 11 LQs from 1: sum(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



Notes: 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			3.391	3.649	3.682
Occupation					
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%

Source: 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 & 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
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	

Table 3. Share of Ads for Select Majors Indicating Demand for Each Skill Composite

Major	Major code (CIP)	Cognitive	Social	Project Mngt	Organizational	Software	Customer Service	Computer	Financial	Writing	People Mngt	Communications (included in Social)	Other Skills (> top 1000)	Other Skills (< top 1000)
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 & Info 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%
Mechanical Engineering	1419	94%	58%	72%	51%	48%	31%	38%	37%	30%	25%	43%	56%	84%
Foreign Lang & Linguistics	1600	61%	90%	30%	39%	23%	16%	27%	15%	44%	17%	28%	30%	84%
English, Liberal Arts, 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: Mean and standard deviation are calculated equally weighting 70 majors; minimum and maximum are across all 70 majors.

Source: Authors' analysis of BGT job postings data.

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

	Variation in skill-share explained by...			
	Major	CBSA	Major & CBSA	Unexplained
Cognitive	0.69	0.07	0.74	0.26
Computer	0.58	0.07	0.64	0.36
Customer service	0.75	0.04	0.78	0.22
Financial	0.84	0.03	0.86	0.14
Organizational	0.42	0.07	0.48	0.53
People mgmt	0.64	0.05	0.68	0.32
Project mgmt	0.71	0.05	0.75	0.25
Social	0.64	0.07	0.71	0.29
Communication skills (included in Social above)	0.41	0.11	0.52	0.48
Software	0.87	0.07	0.90	0.10
Writing	0.69	0.06	0.73	0.27
Other (top 1000)	0.69	0.06	0.74	0.26
Unclassified (outside top 1000)	0.61	0.07	0.66	0.34

Notes: Table reports R-squareds from regressions of the share of ads in a MSA-major cell that mention the skill composite in each row on major FEs, CBSA FEs, and both sets of fixed effects. Each row represents a separate regression. Residual variation reflects variation in skill demand within majors across areas after netting out overall differences across areas. Sample is weighted by the number people appearing in each MSA-Major cell from the ACS.

Source: Authors' analysis of BGT job postings and American Community Survey data.

Table 5. Relationship between Skills and MSA-Major Average Earnings

	Panel A. Base Model			Panel B. Robustness							
	log(raw hourly income)			Adjusted income		Unweighted		Wages age <35		Ads experience 0 to 2	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Share of ads requiring											
Cognitive skills	0.399***	0.223*	-0.00001	0.259**	-0.00793	0.271***	0.0002	0.0554	-0.007	0.224**	0.0176
	(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**	-0.0658	-0.0540***	-0.0202	-0.0687***	-0.0408	-0.0143	-0.130**	-0.0693***	-0.00843	-0.0384**
	(0.106)	(0.070)	(0.016)	(0.060)	(0.017)	(0.046)	(0.015)	(0.060)	(0.019)	(0.063)	(0.015)
Customer skills	0.0809	0.0432	0.0291	0.125	0.0257	-0.03	0.0152	0.144*	0.0201	0.0275	0.0195
	(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***	-0.00855	0.158**	-0.0102	0.0506	-0.010	0.188***	0.00877	0.212***	-0.0125
	(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**	-0.00845	-0.258***	-0.0139	-0.176***	-0.0115	-0.282***	-0.00354	-0.243***	-0.0058
	(0.113)	(0.108)	(0.016)	(0.094)	(0.016)	(0.038)	(0.013)	(0.106)	(0.022)	(0.087)	(0.012)
People management skills	-0.609***	-0.489***	-0.0184	-0.345***	-0.0147	-0.178***	0.00603	-0.278***	0.00614	-0.437***	-0.0401
	(0.146)	(0.130)	(0.032)	(0.095)	(0.033)	(0.055)	(0.015)	(0.093)	(0.025)	(0.115)	(0.026)
Project management skills	0.401***	0.375***	0.0206	0.207**	0.00502	0.280***	0.0187	0.324***	0.00384	0.312***	0.00827
	(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***	0.00794	-0.365***	0.0156	-0.193***	0.00396	-0.442***	-0.00115	-0.431***	-0.00665
	(0.146)	(0.119)	(0.019)	(0.104)	(0.019)	(0.051)	(0.016)	(0.113)	(0.019)	(0.098)	(0.014)
Software skills	0.02	-0.0372	0.018	-0.0955	0.0245	0.0405	0.00346	0.115	-0.0054	-0.0211	0.0311
	(0.115)	(0.101)	(0.023)	(0.085)	(0.024)	(0.060)	(0.018)	(0.096)	(0.022)	(0.095)	(0.021)
Writing skills	0.000129	-0.0546	-0.00841	-0.0417	0.000973	-0.114***	0.0119	-0.102	-0.0249*	-0.0813	-0.000185
	(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 1000)	-0.102	-0.0478	-0.0486*	0.0114	-0.0503*	-0.0333	-0.0312**	-0.0556	-0.0482*	-0.0573	-0.0342*
	(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-squared	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	major-MSA perwt	major-MSA perwt	major-MSA perwt	major-MSA perwt	major-MSA perwt	none	none	major-MSA perwt	major-MSA perwt	major-MSA perwt	major-MSA 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	13.239	2.863	8.894	2.583	15.829	2.41	15.266	2.389	12.532	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: Each observation is a major-MSA cell with underlying sample restricted to full-time, year-round workers who are not enrolled in education at the time of the survey. Standard errors are two-way clustered by MSA and major.

Source: Authors' analysis of BGT job postings and American Community Survey data.

*** p<0.01, ** p<0.05, * p<0.1

Appendix A. Defining Major Categories

To aggregate the almost 400 four-digit majors of the CIP taxonomy into a smaller set of 70 aggregated categories (hereafter referred to as *final major*), 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 & Secondary Diplomas and Certificates (53)); that are predominantly post-baccalaureate or graduate programs (Residency Programs (60)); that are predominantly trade-specific and usually sub-BA (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% of all degrees granted by four-year postsecondary institutions over the 2010–2017 period and appear on less than 0.1% 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. Two-digit major categories that have few postings (less than 0.1%, or about 22,000 unique postings in our sample) are aggregated together 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 (1) Architecture and (2) Urban and Regional Planning and 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: (1) Special Education and Teaching, (2) Teacher Education, and (3) Other Education.

In some cases, pulling an individual four-digit major out of 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% of postings for the two-digit category, and the entire two-digit family becomes *final major* Family and 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 and Social Health Services, and Nursing.

We next deal with 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 8 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 category 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 and Science (5298), Museology/Museum Studies (3014) into Library Science (2500), and Behavioral Sciences (3017) into Psychology (4200).

Appendix B. 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% of postings), organizational skills (16%), detail-oriented (12%), scheduling (12%), building effective relationships (11%), creativity (10%), troubleshooting (6%) and multi-tasking (8%).

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% 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% 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.

<u>Skill Composite Definitions:</u>

- **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 C. 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. 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 1000 most frequent skills, while our preferred approach classifies all 1000. 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 the table below.

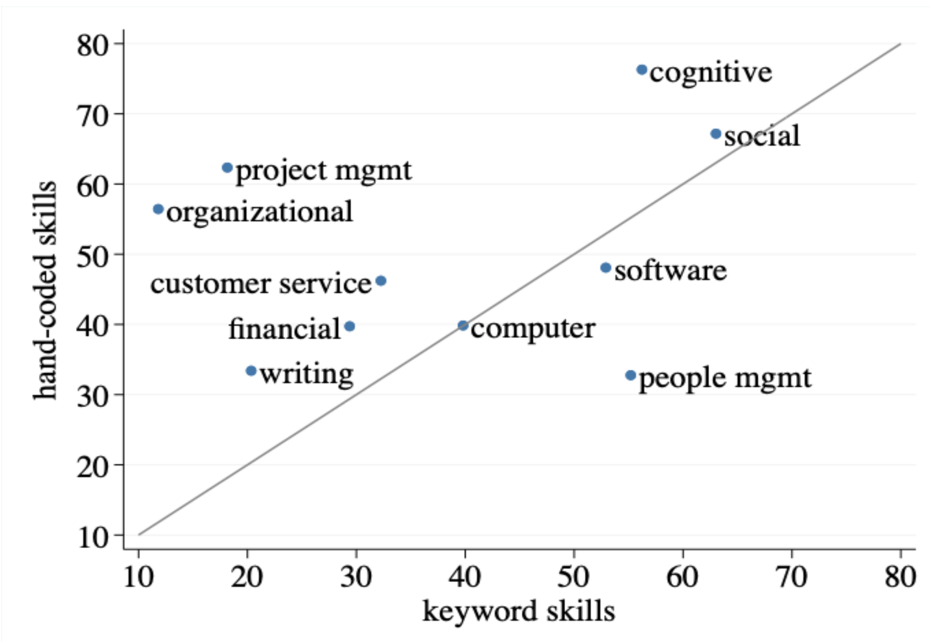
		Hand-coded		Keyword	
Skill composite number	Skill composite	Count of skills in 1000 most frequent	Count of skills across all skills	Count of skills in 1000 most frequent	Count of skills across all skills
1	social	56	56	15	78
2	people mgmt	43	43	85	476
3	cognitive	168	168	46	431
4	writing	20	20	8	50
5	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 mgmt	111	111	1	476
11	other	116	116		
	unclassified	0	14,260	602	12,081

B. Share of Ads in Each Composite

Figure A1 below compares the share of unique ads that contain each skill composite across the two different classification approaches.

Figure A1. Keyword (Old) vs Hand-coded (New) Skill Composites - % of Unique Ads



Note: Figure plots the percent of unique job postings that demand each skill composite. "Keyword" skills refer to the Deming & Kahn (2018) versions of the skill composites and "hand-coded" refers to the versions from Hemelt et al. (2021).

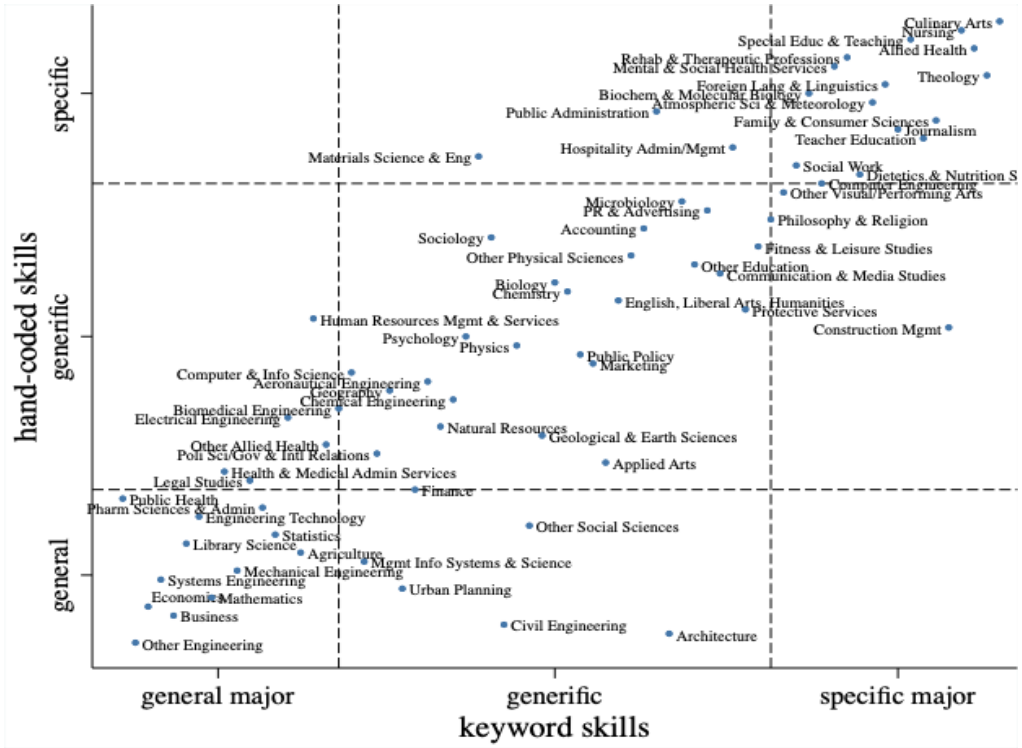
C. Characterization of Major Skill Concentration

Figure A2 compares our classification of major skill concentration between the two methods for classifying skills into composites. 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.[1] 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 & 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." Panel B shows the specificity of selected majors under the two categorization systems in bar chart form.

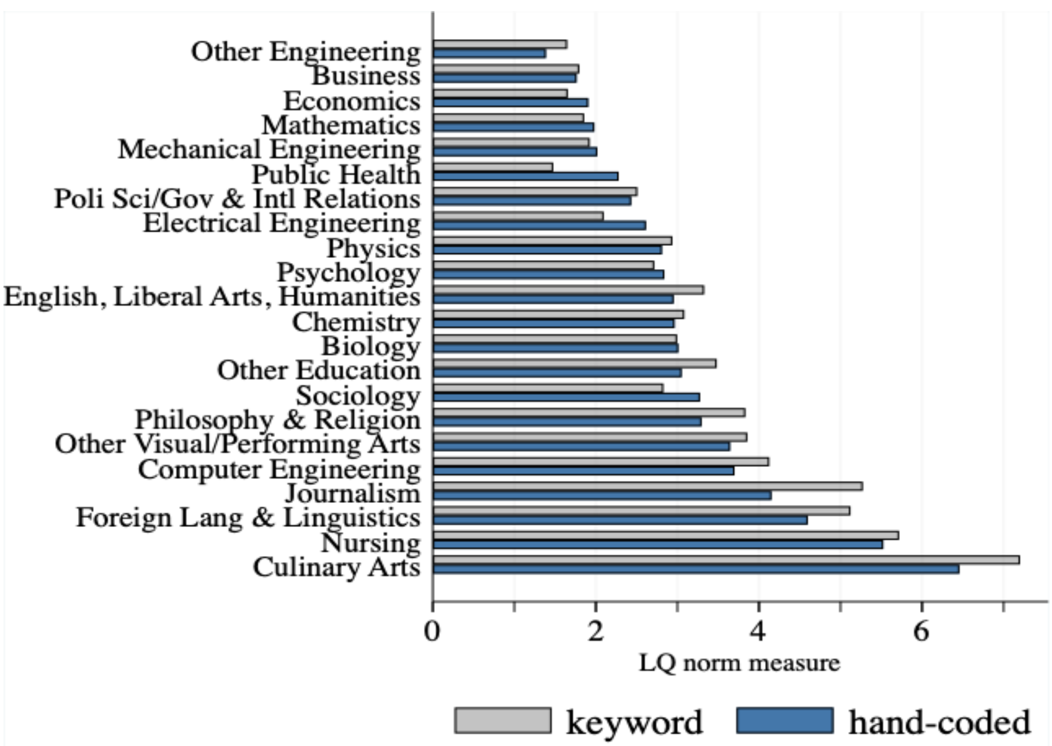
[1] The "general" category includes majors ranked 1 through 18 based on location quotient (LQ) similarity, "generific" includes those ranked 19 through 51, and "specific" includes those ranked 52 through 70. These roughly correspond to the top quartile, middle half, and bottom quartile of majors.

Figure A2. Skill Specificity of Majors Using Different Methods to Classify Skills

A. Rank Correlation



B. Measure of Skill Specificity



Appendix D. Replication of Deming and Kahn (2018)

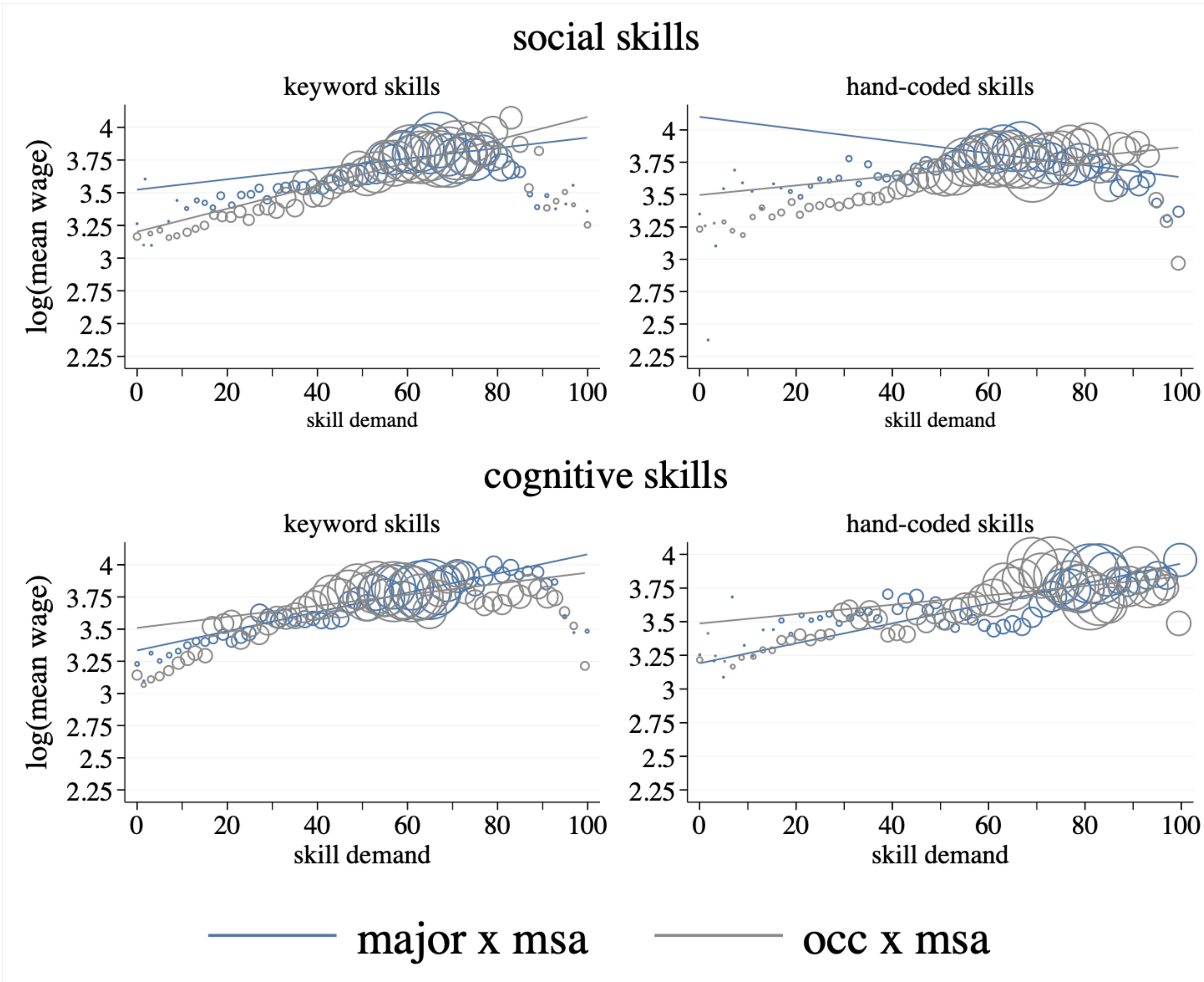
In order to better understand how our findings compare to those of Deming and Kahn (2018, DK), we attempt to replicate and extend their main cell-level analysis. DK regress log mean wages in a MSA-occupation cell on shares of job ads seeking cognitive skills, social skills, and their interaction. They 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% (0.5%) higher 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 A3**, 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 A3. 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. Circles are sized based on the total number of job postings in the bin. "Keyword" skills refer to the skill composites from Deming & Kahn (2018) and "hand-coded" refers to the procedure described in the text.

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

	(1)	(2)	(3)	(4)	(5)	(6)
Model SS	10928.4	12747.2	13138.9	21199.4	22288.4	25544.6
Residual SS	75920.3	74101.5	73709.7	65649.2	64560.2	61304.1
Total SS	86848.7	86848.7	86848.7	86848.7	86848.7	86848.7
R-squared	0.1258	0.1468	0.1513	0.2441	0.2566	0.2941
Adjusted R-squared	0.1218	0.1428	0.1473	0.2395	0.251	0.2722
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		
1000 most frequent skills					x	
9000 most frequent skills						x
Number of variables	1611	1614	1625	2125	2624	10574
Number of skill dummies	0	0	0	500	999	8949
Observations	350,233	350,233	350,233	350,233	350,233	350,233

Note: The dependent variable is an indicator for whether or not a job posting lists at least one college major. For computational expedience, we use a 1% 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(skills) is a cubic in the number of skills per job posting.

Table A2: Has-Major F-Test

	Number of variables	Partial SS	F-test
Occupation (soc6)	482	7769.44	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 or not 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% 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.

Source: Authors' analysis of BGT job postings data.

Table A3. 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

Source: Authors' analysis of BGT job postings data.

Table A4. Complete List of Major Aggregates

Code	Name	Code	Name	Code	Name
0100	Agriculture	1600	Foreign Language and Linguistics	5098	Design, Photography, Video, and Applied Arts
0300	Natural Resources	1900	Family and Consumer Sciences	5099	Other Visual/Performing Arts
0402	Architecture	2200	Legal Studies	5107	Health and Medical Administrative Services
0499	Urban and Regional Planni	2499	English, Liberal Arts, Humanities	5109	Allied Health Diagnostic, Intervention, and Treatment Professions
0904	Journalism	2500	Library Science	5115	Mental and Social Health Services and Allied Professions
0909	Public Relations, Advertisi	2602	Biochemistry, Biophysics and Mo	5120	Pharmacy, Pharmaceutical Sciences, and Administration
0999	Communication and Media	2605	Microbiology	5122	Public Health
1100	Computer and Information	2699	Biology	5123	Rehabilitation and Therapeutic Professions
1205	Culinary Arts	2705	Statistics	5131	Dietetics and Clinical Nutrition Services
1310	Special Education and Teac	2799	Mathematics	5138	Registered Nursing, Nursing Administration, Nursing Research and Clinical Nursing
1398	Teacher Education	3100	Fitness, Recreation and Leisure St	5199	Allied Health
1399	Other Education	3800	Philosophy and Religion	5203	Accounting and Related Services
1402	Aeronautical Engineering	3900	Theology	5208	Finance and Financial Management Services
1405	Biomedical Engineering	4004	Atmospheric Sciences and Meteor	5209	Hospitality Administration/Management
1407	Chemical Engineering	4005	Chemistry	5210	Human Resources Management and Services
1408	Civil Engineering	4006	Geological and Earth Sciences/Ge	5214	Marketing
1409	Computer Engineering	4008	Physics	5220	Construction Management
1410	Electrical, Electronics and	4019	Materials Science and Engineerin	5298	Management Information Systems and Science
1419	Mechanical Engineering	4099	Other Physical Sciences	5299	Business, general
1497	Systems, Industrial, Manuf	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	Political Science, Government, and International Relations		
		4511	Sociology		
		4599	Other Social Sciences		

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	0.989	Early Childhood Education	0.682	Journalism	1.000
Communication Skills	0.523	Teaching	0.622	Writing	0.672
Microsoft Excel	0.464	Child Development	0.456	Editing	0.623
Research	0.328	Child Care	0.432	Communication Skills	0.511
Planning	0.254	Organizational Skills	0.308	Creativity	0.412
Problem Solving	0.25	Communication Skills	0.284	Social Media	0.394
Accounting	0.241	Lesson Planning	0.256	Research	0.323
Teamwork / Collaboration	0.237	Health Education	0.187	Teamwork / Collaboration	0.299
Microsoft Powerpoint	0.21	Planning	0.181	Organizational Skills	0.264
Budgeting	0.206	Teamwork / Collaboration	0.166	Detail-Oriented	0.254
N(ads)	607,518	N(ads)	97,314	N(ads)	211,471

Source: 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 Management	Organizational	Software	Customer Service	Computer	Financial	Writing	People Management	Communications Skills	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 Stu	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, Human	2499	73%	84%	40%	60%	26%	36%	44%	26%	60%	25%	44%	32%	75%
Library Science	2500	78%	79%	43%	65%	40%	31%	46%	31%	49%	38%	48%	39%	80%
Biochem & Molecular Biolog	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%

Table A6. Share of Ads for Each Major Indicating Demand for Each Skill Composite

Major	Code	Cognitive	Social	Project Management	Organizational	Software	Customer Service	Computer	Financial	Writing	People Management	Communications Skills	Other Skills (top 1000)	Other Skills (< top 1000)
All postings	0	80%	68%	65%	58%	50%	46%	42%	43%	35%	33%	46%	38%	78%
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 & Meteorolo	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 Ser	5107	75%	69%	84%	58%	26%	67%	45%	53%	37%	51%	44%	47%	75%
Allied Health	5109	52%	56%	38%	38%	8%	67%	23%	18%	18%	30%	27%	82%	96%
Mental & Social Health Servi	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 Profess	5123	56%	67%	34%	46%	4%	76%	19%	27%	22%	67%	29%	54%	87%
Dietetics & Nutrition Service:	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%

Table A6. Share of Ads for Each Major Indicating Demand for Each Skill Composite

Major	Code	Cognitive	Social	Project Managem ent	Organizati onal	Software	Customer Service	Computer	Financial	Writing	People Manageme nt	Communica tions Skills	Other Skills (top 1000)	Other Skills (< top 1000)
All postings	0	80%	68%	65%	58%	50%	46%	42%	43%	35%	33%	46%	38%	78%
Hospitality Admin/Mgmt	5209	59%	74%	75%	68%	9%	64%	47%	61%	27%	65%	41%	54%	62%
Human Resources Mgmt & S	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 & Scienc	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: Mean and standard deviation are calculated equally weighting 70 majors.

Source: Authors' analysis of BGT job postings data.

Table A7. Correlation between Different Measures of Major Skill Specificity

	A. Outcome = Similarity based on 9000 skills				B. Outcome = LQ measure			
	Rank		Measure		Rank		Measure	
Outcome	No weight	weighted	No weight	weighted	No weight	weighted	No weight	weighted
LQ measure (only top 1000 skills)	0.372	0.533	0.410	0.573				
Similarity (Full)					0.372	0.533	0.410	0.573
Similarity (top 1000)	0.895	0.964	0.896	0.989	0.358	0.579	0.388	0.579
Similarity (1001+)	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 9000 skills. Top 1000 is the cosine similarity using only the 1000 most frequent skills. 1001+ is cosine similarity using skills ranked 1001-9000 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-squared 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 (top 10)	Culinary Arts	Family & Consumer Sciences	Primary/General Education
	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
	Theology	Microbiology	Finance
	Foreign Language & Linguistics	Rehab & Therapeutic Professions	Precision Production/Industrial Arts
	Biochem & Molecular Biology	Biochem & Molecular Biology	Commercial Art and Design
	Atmospheric Science & Meteorology	Allied Health	Marketing
Most general (top 10)	Other Engineering	Business	Music/Speech/Drama
	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	Pharmacy Sciences & Administration	Area Studies
	Systems Engineering	Legal Studies	Social Work/Human Resources
	Mechanical Engineering	Mathematics	Mathematics
	Management Information Systems & Science	Political Science, Government, International Relations	Engineering Tech

Notes: 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 x 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	0.34	0.201	0.697	1.409	0.29
Urban Planning	499	0.235	0.14	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 Stu	999	2.569	1.523	0.82	3.041	1.512
Computer & Info Science	1100	26.149	15.504	0.792	2.701	1.375
Culinary Arts	1205	0.19	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	0.28	0.166	0.719	3.052	1.631
Aeronautical Engineering	1402	0.444	0.263	0.73	2.686	0.858
Biomedical Engineering	1405	0.186	0.11	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	0.57	1.633	0.324
Computer Engineering	1409	2.483	1.472	0.545	3.701	2.2
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	0.52	0.798	2.16	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	0.95
English, Liberal Arts, Human	2499	0.138	0.082	0.839	2.955	1.211
Library Science	2500	0.111	0.066	0.872	2.072	0.56
Biochem & Molecular Biolog	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	0.02	0.012	0.777	3.297	1.448
Theology	3900	0.068	0.04	0.717	5.089	3.141
Atmospheric Sci & Meteorolo	4004	0.03	0.018	0.453	4.57	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	0.53	0.571	2.81	1.006
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	0.62	3.814	2.119
Economics	4506	3.289	1.95	0.728	1.907	0.535
Geography	4507	0.169	0.1	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	0.62	3.647	1.56

Table A9. Major Specific Skill Similarity Measures

Major	Code	% of unique postings	% of posting x major	cosine similarity	LQ norm measure 1	LQ norm measure 2
Health & Medical Admin Ser	5107	0.951	0.564	0.861	2.411	0.922
Allied Health	5109	0.1	0.059	0.514	5.389	3.501
Mental & Social Health Servi	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	2.28	0.88
Rehab & Therapeutic Profess	5123	0.312	0.185	0.506	5.312	3.409
Dietetics & Nutrition Service	5131	0.29	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	1.94
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 & S	5210	2.076	1.231	0.817	2.921	2.085
Marketing	5214	5.567	3.301	0.88	2.716	1.202
Construction Mgmt	5220	0.906	0.537	0.629	2.908	1.242
Mgmt Info Systems & Scienc	5298	4.485	2.659	0.749	2.041	1.047
Business	5299	29.535	17.512	0.958	1.764	0.375

Note: For each major, cosine similarity is constructed using the major's vector of share of all ads listing each of the 9,000 most common skills and the national vector using the same skills.

For each major, 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.

For each major, LQ norm measure 1 is calculated as the sum across all 11 skill composites of the squared deviations of the LQs from 1.

Source: Authors' analysis of BGT job postings data.

Table A10. Replication and Extension of Deming & 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	6-digit occ FE, MSA FE, % of postings in 2 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 BG					Job postings from BG		Person wt from ACS	

Notes: DK estimates are from Table 3 column 5 of Deming & Kahn (2018). 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 social and cognitive skill content and wages, Robustness

	MSA x major (1)	MSA x occ (2)	MSA x major (3)	MSA x occ (4)	MSA x major (5)	MSA x occ (6)
Share cognitive						
Keyword	0.855***	0.569***	0.399***	0.290***	0.746***	0.430***
	(0.0101)	(0.0089)	(0.0106)	(0.0067)	(0.0114)	(0.0090)
Handcode	0.498***	0.359***	0.417***	0.187***	0.745***	0.347***
	(0.0122)	(0.0092)	(0.0112)	(0.0068)	(0.0122)	(0.0094)
Share social						
Keyword	0.205***	0.688***	0.141***	0.257***	0.394***	0.875***
	(0.0130)	(0.0104)	(0.0120)	(0.0072)	(0.0146)	(0.0113)
Handcode	-0.601***	0.0222**	-0.282***	-0.0459***	-0.464***	0.369***
	(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

Notes: 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.