The skill content of college majors: Evidence from the universe of online job ads*

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May 15, 2021

Abstract

The choice of college major is one of the most direct ways through which college-educated workers develop skills. In this paper we document the skill content of college majors as perceived by employers and expressed in the near universe of online job ads. Some general skills -- such as social and organizational skills -- are sought by employers of almost all college majors. More specific skills such as customer service and understanding basic budgeting are associated with fewer majors. Majors that provide these specialized skills -- such as nursing and education -- are thus more specialized than those that mostly provide general skills. The skills-major linkage varies across the country, with high-wage MSAs demanding more of most types of skills in generalist majors such as Business. However, within-major cross-area variation in skill content has only a weak association with major-specific earnings across geographic areas.

* We thank Bledi Taska and Hal Bonella from Burning Glass Technologies for several helpful discussions about the data and seminar participants at the AEFP Annual 2021 conference, Upjohn, University of Michigan, Hebrew University, and University of Bristol for feedback. We are grateful to the Russell Sage Foundation (grant #1811-09737) and the National Science Foundation (grant #1919360) for financial support. Shawn Martin is grateful for support from the PR/Award R305B150012 and the Institute of Education Sciences, U.S. Department of Education. Hayden Le and Jonathan Hartman provided terrific research assistance and Andrew Simon and Johnathan Conzelmann provided helpful comments.

I. Introduction

Employers regularly cite a gap between the skills they need and those new college graduates possess. A recent survey of hiring managers identified "the ability to effectively communicate orally" as very important but extremely challenging to find (American Association of Colleges and Universities, 2018). One explanation for this disconnect is that technological change, industrial restructuring, and international trade continually evolve the demand for skills in the labor market (Autor, Levy, & Murnane, 2003; Deming, 2017), but that investment is slow to respond. Skill demand varies both across and within occupations, varies across labor markets for the same occupation (Deming & Kahn, 2018), and accelerates during recessions (Hershbein & Kahn, 2018). To highlight one specific skill, the demand for social skills – an adeptness at productively working with others in flexible, team-based settings – has increased (Deming, 2017). Moreover, jobs that require high levels of both cognitive and social skills have seen the largest employment and wage growth while those that require high cognitive skill and low social skill, including some STEM-based jobs, have fared relatively poorly (Deming, 2017).

Despite growing work on the evolution of skill demand, little research has focused on how workers might acquire these skills. Arguably, the most direct way for individuals to acquire skills, at least for the nearly two-thirds who attend college, is through their choice of college major. College major provides much of the structure for the courses students take and thus the competencies students develop during college. While large earnings differences between majors have been documented (Webber, 2014), the relationship between college majors, skills, and jobs remains underexplored, as does the variability of such relationships across geographies.

This project fills this void by providing systematic descriptive evidence on the relationship between college majors and skills and how skill content relates to earnings. We use employer demand to understand the skill sets employers associate with particular majors, drawing on job vacancy data obtained from Burning Glass Technologies (BGT) comprising the near universe of all job ads from 2010-2018. A unique feature of this data source – beyond its scale and universality – is the inclusion of information on majors, detailed skills, and occupations, which permits us to characterize demand along these three dimensions.

We use these data and aggregates of more than 15,000 unique skills to answer three questions: First, which college majors are relatively more specific versus general in their skill content? We construct skill concentration indices by major that are typically used to measure industrial concentration. Second, how do skills associated with majors differ across geographic areas? We measure this by comparing major-specific skill demand across all metropolitan statistical areas (MSAs) and by contrasting demand in high-wage and low-wage MSAs. Finally, is variation in skill demand across majors and across areas (within majors) associated with earnings differences?

We find that social and organizational skills are general in that they are not particularly concentrated among job postings for a subset of majors. In contrast, customer service and financial skills are concentrated in jobs seeking specific majors, such as nursing and accounting, respectively. Some majors including business, economics, and general engineering are general because the demand for most skills is neither under- nor over-concentrated among job postings listing these majors. Other majors, including nursing and foreign language, are more specific.

We also find that the major-skill demand relationship varies across space, with high-wage MSAs demanding higher levels of skills for certain majors. Again contrasting business and nursing, the former has a stronger connection between average wages and skill content than the latter. This may be because business is a general major with significant scope for skill heterogeneity across the country, whereas nursing programs prepare students for a narrow set of occupations for which task content is nationally standardized. Average major-specific earnings also vary considerably across space. Nonetheless, we find that cross-area *skill* differences within majors have only a weak relationship with major-specific earnings premia across areas. For the most part, majors can thus be thought of as a bundle of skills that are fairly transportable across areas.

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 over time (e.g., Deming & Kahn, 2018; Hershbein & Kahn, 2018). On the supply side, most work on 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).

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 general versus specialized curriculum in the labor market (Hanushek et al, 2017). Several papers do this by quantifying the link between majors and occupations (e.g., Altonji, Blom, Meghir, 2012) or via variation in major premiums across occupations using a Gini coefficient (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 explicitly at the skills associated with each major as perceived by employers and view our approach as complementary to these occupation-based approaches.

Finally, we contribute to the understanding of spatial differences in wages, particularly cross-area major wage premia (Ransom, 2020). 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, in contrast with that found for occupational wage premia.

These basic descriptive patterns are novel and relate to perceived skill shortages among employers. They also have the capacity to inform postsecondary policymakers attempting to strengthen curricular alignment with the evolving needs of local and regional labor markets.

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 examines 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 every MSA in the United States and contain roughly 148 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 quantity of vacancies track other sources reasonably closely. We do not repeat or reproduce their analysis here but direct the curious reader to the online Appendix A of Hershbein and Kahn (2018). Moreover, since we focus on jobs ads requiring a bachelor's degree, the skill skew is of even less concern.

B. Sample

We restrict attention to job postings that list at least one skill and require exactly 16 years of education (e.g., a bachelor's degree). Most analysis also restricts the sample to ads that list at least one college major. The education requirement leaves 28% of the original sample. Importantly, a large subset of the job postings that demand 16 years of education also list college majors. The college major requirement further reduces the sample to 13% of the original 148 million job postings, yielding a sample of about 20 million unique job postings.

Given the large reduction in the sample size after imposing these restrictions, one might worry that the types of job postings in our restricted sample differ from the set of all job postings. **Table 1** compares the occupational composition of job postings in our analytic sample to two larger samples. Differences are mostly due to the bachelor's education requirement. It is well documented that typical job tasks performed in occupations that employ workers with less formal education differ from those that employ workers with more formal education (e.g., Autor & Acemoglu, 2011). The higher concentration of job postings in Management (21% vs. 12%) and Business (14% vs. 7%) occupations in our analytic sample relative to all job postings is consistent with this stylized fact. Similarly, the full sample of ads has a higher proportion of job postings in Food Prep (3.24% vs. 0.27%), Building Cleaning and Maintenance (1.11% vs. 0.04%), Sales occupations (12.03% vs. 4.71%), and Office & Administrative Support (10.17% vs. 3.4%).

While the nature of job postings in the analytic sample is more similar to the "education 16" sample, there are a few differences worth noting. The "education 16" sample has a higher proportion of ads listing Education/Training/Library Occupations (2.39% vs. 1.36%), Protective Service Occupations (0.41% vs. 0.26%), Sales occupations (9.25% vs. 4.71%), and Office/Admin Support (5.31% vs. 3.40%). Taken together, this suggests that ads that list a college major on average call for skills associated with higher pay than those that do not.

We more formally investigate these differences by regressing 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. We implement this regression on a 1% random sample of job postings that demand a college degree. **Table A1** in the Appendix presents an ANOVA analysis. This baseline model, which includes roughly 1,600 covariates, explains 13% of the variation in whether a job posting lists a major. However, even when we add a cubic for the number of skills per posting, indicators for eight skill composites, and indicators for whether a posting has each of the 1,000 most frequently listed skills, we explain only 26% of the variation in whether a job posting lists a major. The explained variation rises to 28% when we instead control for the 9,000 most frequent skills. Results from F-tests on the blocks of covariates in the baseline model reported in **Table A2** reveal that job postings listing a major differ in terms of the occupation distribution ($F=191.52$ $p<0.005$), industry listed ($F=55.54$, $p<0.005$), and location

(F=4.39, p<0.005). Altogether these results suggest that the distribution of observables between job postings with a major differ from those without a major, but even with a very detailed set of observable controls, there still remains unexplained a substantial portion of variation in whether a posting lists a major.[1]

C. College Majors

Among job postings that require exactly a bachelor's degree, 54% also list a college major. In the job ad data college majors are coded in the 6-digit Classification of Instructional Programs (CIP) taxonomy which we first aggregate into 4-digit CIP codes. On average, the number of majors listed per ad remains fairly stable across the analysis period at around 1.6 majors. **Figure 1 Panel A** plots proportions of unique job postings listing exactly 1, 2, and 3+ majors for each year and month, using 4-digit CIP codes. We see that there are not substantial compositional changes over time in the number of majors per job posting: about 55% of job postings list 1 major, 30% list 2 majors and 15% list 3 or more. **Figure 1 Panel B** plots the count of unique job postings and the count of job-posting-by-major observations for each month of the 2010-2018 analytic period, again treating each 4-digit CIP code as a unique major. Reflecting seasonality, within-year variation can be quite substantial, with differences of 100,000 job postings across ads. From 2010 to 2018 there has been a notable uptick in the number of job ads per month – an increase from roughly 200,000 per month in 2010 to 500,000 per month in 2018. This mostly reflects the strengthening labor market, as well as an increasing share of job ads posted online.

For the purposes of analyzing skill demand by major we further aggregate college majors into 71 categories.[2] We aim to produce categories that will have both job ads (BGT) and degrees granted in them according to IPEDS. We use the CIP coding hierarchy wherever possible and try to combine majors that tend to appear in ads together or that require similar sets of skills (as indicated in the job ads).[3] **Figure 2** plots the share of job postings that list the 10 least and most common majors. Only five majors appear on over 10% of postings in the analytic sample, with the most common majors including business and computer and information sciences, which are listed on 29% and 26% of unique job postings, respectively. On average, the other 66 majors each appear on about 1% of job postings; however, half of

[1] In current work, we are using machine learning methods to label the unlabeled set of ads to estimate the full distribution of majors demanded on job postings.
[2] One of the 71 categories contains majors that we omit from descriptive analysis. This category contains college majors found in two-digit CIP categories that are traditionally sub-baccalaureate or remedial programs (e.g. Basic Skills and Developmental/Remedial Education) or that are predominantly post-baccalaureate or graduate programs (e.g. Residency Programs) or trade specific (e.g. Mechanic and Repair Technologies/Technicians).
[3] Our process for aggregating college majors is described in Appendix A. The full list of all major groups is reported in Appendix Table A4.

all majors show up on less than 0.5% of job ads. The least frequently demanded majors in our sample include theology (0.05%), 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 yet to be used for analytical purposes, we know little about how major-specific demand measured in these job postings relates to the composition of bachelor's degrees granted over time. **Figure 3** compares the distribution of majors listed on job postings in the BGT data to the total number 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 over-represented (under-represented) in the BGT data will fall above (below) the 45 degree line. Some majors, including nursing and economics, have demand via job ads that is proportional to the number of degrees awarded for the major. Engineering and statistics are over-represented in the BGT data relative to degrees granted, while philosophy and religion, atmospheric sciences and English are underrepresented.[4]

D. Categorizing Skills

Burning Glass parses over 15,000 individual skills from the job postings. We categorize the 1,000 most frequent of these by hand into 11 mutually exclusive categories. To do so we crafted detailed definitions of the skill composites and then had pairs of researchers manually assign a subset of the skills to one of the 11 skill composites. We then collectively resolved the roughly 40% of cases in which researchers initially disagreed on the appropriate skill composite. Finally, in some cases we also allocated skills by consulting the occupation distribution of ads listing the skill. Full details are in the appendix.

This approach provides a few benefits over the application of the keyword approach from Deming & Kahn (2018) or Hershbein & Kahn (2018).[5] 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%).

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

[5] We also followed Hershbein and Kahn (2018) and Deming and Kahn (2018) and aggregated individual skills into composites which are groups of keywords or phrases, indicated in Table 2. A job posting is characterized as listing the skill composite if it lists at least one of the keywords in the collection. While the keyword approach categorizes more skills into composites, including less frequent ones, inspection revealed some inconsistent categorizations as described in the text. Nonetheless, the results are quite similar using our hand categorization and the keyword approaches to generate skill composites.

Second, our initial use of the keyword approach resulted in the misclassification of some broad groups of skills. For example, the composite People Management includes the keyword "management" and captures a wide variety of general management activities that do not specifically pertain to HR or personnel, including Account Management, Pain Management, and Operations Management. Underwriting was also included in the Writing composite using the key word approach.

Table 2 provides a description of each of the 11 categories along with the most frequent skills in each category.[6] The final column reports the words used to define these categories using an alternative key-word approach. The resulting skill composites are mutually exclusive at the skill level, but a given job posting (or major-by-job posting) can reflect multiple skill composites.[7] **Figure 4** 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, which is similar to the share of ads that list a skill falling outside the top 1,000 most frequent (and thus "unclassified" by our approach). Among the skill composites, people management and writing are the least likely to appear, mentioned in about one-third of all ads. We note that a much higher percentage of ads fall into our skill composites than those used by Deming and Kahn (2018), since we have explicitly categorized the 1000 more frequently occurring skills. Their estimate of the share of ads seeking Cognitive and Social skills were 37% and 36%, respectively.

E. 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-metropolitan statistical-area (MSA) level. The baseline sample includes individuals aged 23-34, with a bachelor's degree or higher. 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 (FTFY), where full year is defined as 40 plus weeks a year and full-time is defined as 30 hours a week.

Hourly earnings are calculated as annual earnings divided by the product of weeks worked during the past 12 months and usual hours worked per week. Earnings are adjusted to 2019 values using the Personal Consumption Expenditures (PCE) inflator from the Bureau of Economic Analysis (BEA). In our

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[6] Our main analysis focuses on 11 skill composites. In some tables or figures we also provide results for a twelfth composite - communication skills - and a thirteenth composite - unclassified - which consists of all skills besides the top 1000.

[7] Appendix B provides more detail on our motivation and approach to aggregating individual skills into composites. Appendix C demonstrates the robustness of our results to using a key-word approach to classify skills into composites.

analyses, we use two versions of the outcome variable. The first is the log of raw mean hourly earnings in the major-MSA cell. The second is regression adjusted for compositional differences across majors. Specifically, we regress log hourly earnings on indicators for female, Black, and Hispanic, as well as a quartic in potential experience and take the mean of the residual in the major-MSA cell. **Figure 5** shows substantial variation both across majors and within majors across areas in the mean hourly wage of full-time, full-year prime-aged workers in the United States. We assess the extent to which this variation can be explained by differences in the skill content across and within majors.

IV. The Skill Content of College Majors

Table 3 reports the share of ads listing each of these skill clusters separately for a handful of majors, along with the minimum and maximum share across 70 different majors.[8] "Communication Skills," the most frequent individual skill listed in job ads, is included in the "Social Skills" aggregate, but is also shown separately. 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 nearly all job ads in computer science (unsurprisingly). 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 is on more than half of ads targeting Public Administration majors.

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.[9] One LQ is constructed for each skill

[8] Results for all 70 majors are included in **Appendix Table A6**.

[9] The two expressions above are mathematically equivalent but differ slightly in their interpretation. The first measures how concentrated the demand for a skill is among ads with a particular major relative to the demand for

composite (s) and each major (m) combination. An LQ around one 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, the 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 and muddy interpretation of the LQ.

To recover the properties of LQs, we make few adjustments. First, because the sum of major-specific observations could exceed the total number of unique postings, 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, the total number of unique job postings that list skill s could be less than the total number of job-posting-by-major observations that list skill s. We 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 component s is:

$$\widehat{LQ_{sm}} = \frac{(N_{sm}/N_m)}{(\widehat{N}_s/\widehat{N})} = \frac{(N_{sm}/\widehat{N}_s)}{(N_m/\widehat{N})}$$

Thus, the distribution of LQs across majors for a given skill has a weighted average of 1, where the weights are equal to the share of all job-posting-by-major combinations that list major m. Therefore, we can compare the adjusted LQs to 1 to determine relative concentration. To characterize how specialized or general a major is on all the measured skill composites we examine whether a major has LQs close to one for many of the skill composites. Specifically, for each major we sum across all 11 skill composites the

that skill across job postings listing any major. The second captures the concentration of a major among job postings listing a particular skill relative to the frequency of that major among all job postings.

absolute value of the deviations of the LQs from 1 : $\sum_{s=1}^{11} abs(\widehat{LQ_{sm}} - 1)$. Majors with a higher sum are considered more specialized.

Our second approach measures the similarity of the entire vector of 9,000 skills for each major to the national one using a cosine similarity measure.[10] For all job ads nationally and for ads listing each of 70 different majors, we construct the vector containing the share of all ads listing each of the 9,000 most common skills. We then construct the cosine similarity between the national skill distribution and that for each major. Specifically, this approach computes the distance between a major's 9,000 dimensional skill demand vector and the 9,000 dimensional national skill demand vector by measuring the angle between the two vectors. Majors with a value of the cosine similarity closer to zero are considered more specialized, whereas majors with a skill demand vector that is similar to the national vector will have a cosine similarity near one.

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. The latter, in contrast, focuses on similarity based on the large clusters of the most common skills. We present results on the empirical correspondence between these two measures in a subsequent section.

B. Do Employers List Majors Instead of Desired Skills?

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. It does not appear that this is 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 specific 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

[10] We narrow our focus from 15,000 skills to the roughly 9,000 skills that fall on .001% of all job postings.

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

C. Skill Specificity of College Majors Based on Location Quotient

For 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 for each skill composite, which is roughly equivalent to the percent of job postings that list each skill. The numerator of the LQ is specific to each major-by-skill combination. In **Table 3,** we list the share of each major's postings that list each skill for a selected set of majors. The LQ is simply the ratio between the top and all other rows.

We summarize our findings related to the LQ calculations graphically. **Figure 6 Panel A** 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 a similar level 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 job postings for a 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 the entire market. Social skills are thus general -- a skill that is demanded across ads for most majors.

Figure 7 plots the LQs for all majors and the 11 skill composites. Majors are listed in ascending order by the sum across skills of the absolute deviation of the LQs from one.[11] Business, Economics, and General Engineering have a skill profile that is 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 different than 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

[11] The ranking of majors using sum(abs(LQ-1)) and sum((LQ-1)^2) is very similar; correlation = 0.96.

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 over-represented on job postings with nursing majors: 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 Customer Service 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 under-represented.

D. Alternative Measures of Skill Specificity and Comparison to Prior Work

We now examine two alternative measures of the skill specificity of college majors. **Figure 8** compares our skill composite measure to the dissimilarity index measure. The dissimilarity metric captures the differences between each major and all job ads nationally along the entire vector of 9,000 skills, which incorporates more information about less frequent, possibly more specialized, skills.

The two metrics produce similar rankings of specificity across majors. The R-squared from the unweighted bivariate regression between major rankings of the two indices is 0.37 (0.53 weighted by major size) and is similar if the metric itself (rather than the rank) is used as the outcome (**Appendix Table A7**). This strong correspondence comes from the fact that most of the variation in the dissimilarity index comes from variation in the 1,000 most frequent skills, which are the ones that enter our LQ-based index.

Figure 9 compares our skill composite measures to a measure of the occupational concentration of college majors, the percent of recent college graduates accounted for by the top five most frequent occupations (for a given major) in the ACS. There is a much weaker correlation between rankings based on this metric and our skill index, though the correlation is much stronger when majors are weighted by size (R-squared = 0.469, **Appendix Table A7**).

Other scholars have constructed similar measures of major specificity, primarily relying on major-occupational linkages and earnings premia across majors. Leighton and Speer construct a Gini coefficient of wage premia across occupations. The idea being that majors whose wage premia is highly occupation-dependent are likely providing more specialized skills. **Appendix Table A8** compares the most/least specific majors using our two skill-based metrics to those published by Leighton and Speer

(2020).[12] A few majors appear on multiple lists, most notably Nursing and Education (most specific) and Mathematics (most general).

V. Geographic Variation in Skill Demand

The prior analysis demonstrated substantial variation in skill demand across major fields, aggregated across all years and levels of geography. However, the universality and granularity of the BGT data enable us to analyze variation in skill demand across space for specific majors. 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.

Figure 10 contrasts skill demand in low- and high-wage areas overall and for three specific majors. We use county-level data from a variety of sources for the years 2010 and 2017, aggregated to Metro and Micropolitan Statistical Areas. We subset our initial geographic analysis to the 381 Metro Areas (MSAs). We then divide MSAs using an unweighted median split on the MSA average of real earnings per capita for workers aged 15 and above. Within each MSA category (i.e., above median is high-wage), we calculate the share of job postings for each major that demand each skill composite. Across almost all skill categories, ads in high-wage MSAs have a higher demand for skill. This is particularly true for software skills, where ads in high-wage MSAs are 10 percentage points more likely to demand them. Cognitive and social skill demand is also greater in high-wage MSAs. Interestingly, the cross-area variability is much greater for Business (among the most general majors) and Sociology (moderate generality) than for Nursing (most specific). The skill profile expected of Nursing majors is nearly identical across MSAs. This is not surprising given standardization in job tasks across places due to national credentialing/testing of the nursing occupation.

Business majors in high-wage MSAs have greater expectations for social, cognitive, and software skills than those in low-wage MSAs. Employers in high-wage MSAs expect greater levels of writing, social, and software skills among Sociology majors than in low-wage MSAs. These differences likely reflect the different types of jobs students enter across areas, even within the same major fields. The concentration of cognitive, social, and software skills in high-wage MSAs is consistent with recent empirical work that found large variation in skill content across areas for the same occupation (Deming & Kahn, 2018). It is thus possible that undergraduate business and sociology programs must provide different sets of skills in different areas, though our wage analysis below suggests that this skill variation across areas is not necessarily reflected in market compensation.

[12] Li Linde Shimao (2021) construct a "Major Complexity Index" from major-occupation flows, but this measures vertical differentiation in the skill level required of majors rather than the extent of specificity per se.

To observe a broader set of locales, we map variation in major-specific skill demand for all of the 900+ micropolitan and metropolitan statistical regions. **Figure 11** depicts regional variation in shares of job postings listing business majors that seek cognitive skills. Regions with darker shading have larger shares of business ads that demand cognitive skills. We highlight a handful of places to emphasize intriguing features of this variation. First, contrast Jasper, Indiana and London, Kentucky. Both locations have similar quantities of job postings with 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. Second, beam down to Roswell, NM and Andrews, TX. These locales differ in both the quantity of job postings listing 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 that for Customer Service skills. Place accounts for only 3%-11% of the cross-cell variation in skill demand. Remaining, unexplained variation in skill demand is substantial -- rising to 50% for Organizational and Communication Skills, respectively.

VI. Skill Demand and Earnings

Is this variation consequential? **Figure 5** demonstrated the substantial wage variation across majors and areas. **Figure 12** plots the average of hourly earnings for prime-aged, non-enrolled, full-time business majors in each of the 381 metropolitan statistical regions. We adjust means for differences in average earnings across statistical regions and thus they reflect geographic deviations in wages for business majors, relative to the national average of hourly earnings.[13] Overall, average wages differ widely even after taking into account differences across place that reflect cost of living and local amenities.

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 of adjusted log hourly earnings in Andrews, TX (\$43.70) is 7.5% higher than in Roswell, NM, matching the relatively higher demand for cognitive skills.

[13] We regress hourly earnings on CBSA fixed effects and take the mean of the residual in each major by CBSA cell. We then add back the national mean.

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 among college graduates in major k in MSA j from the ACS, and $PctSkill_{sjk}$ is a vector of skill requirements in the major-MSA cell measured by the share of ads posted in the BGT that list each skill. The coefficient β_s divided by 10 indicates the approximate hourly earnings change associated with a 10% 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.[14]

We report results from our preferred specification in **Panel A** of **Table 5**. The first model includes only the 11 skill measures and reports the raw correlation between skill 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% 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 occupations associated with these characteristics that are also lower-paid. Collectively the 11 skill composites explain 34% of the wage variation across MSA-major cells and are collectively statistically significant at a 1% level (F-test = 18, 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 particular 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, 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 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

[14] Though we mostly focus on weighted regressions, we also estimated models without weights so that each major-msa combination receives the same weight. Unweighted estimates are generally consistent with weighted estimates, with a few exceptions we discuss.

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) includes major fixed effects, absorbing any systematic pay differences across majors that occur in all labor markets. Major fixed effects 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 a bundle of skill composites. Once major and MSA are accounted for, the remaining variation in skill demand measured by the skill composites explains relatively little additional wage variation (F-test = 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 -- a 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 correlate 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 to various changes in specification. We only report specifications that include MSA fixed effects, analogous to specifications (2) and (3). Specifications (4) and (5) adjust income at the individual level for 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 income for workers less than 35 years old, to better reflect the earnings experiences of recent college graduates. The broad patterns hold across all three of these alternative specifications: skill demand can explain a significant share of the cross-cell wage variation, but most of this can be accounted for by major-specific effects. Cross-area variation in skill demand within majors, as documented in Figures 10 and 11, does not correlate with earnings.

This finding stands in stark contrast to that of Deming and Kahn (2018), who find that local employer skill demands predict wages across areas, even after controlling for occupation and other confounders. Both Social and Cognitive skills in particular have minimal association with major premia, but are associated with area-specific occupational wage premia. This suggests caution in interpreting occupations as 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 is a closer representation of the skills employers perceive different majors to embody. Differences in skill demand within majors may happen at a much more granular level than the level of aggregation captured by our skill composites.[15]

VII. Conclusion

In this paper, we provide a comprehensive description of the skill content 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 individuals acquire skills. 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 first develop measures of skill and major specificity inspired by the logic of location quotients (LQs) from the literature on industry concentration. Our measures of skill and major specificity complement and extend recent developments in this space (e.g., Leighton & Speer, 2020) by focusing on 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.

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.

We also use information on earnings by major from the ACS to characterize associations between majors, skill demand, and earnings across locations. We show that there is substantial variation across space in average earnings by major. Despite the fact that we also document sizable variation in skill demand that cannot be explained by major or geographic location, we find little evidence that such remaining variation meaningfully correlates with variation in earnings. This suggests that majors can be generally conceptualized as bundles of skills that are fairly transportable across areas. However, recall that we use skill composites as our measures of skill demand. Thus, we leave open the possibility that a more fine-grained categorization of skills could uncover components of that unexplained variation that may have more predictive power within major and across place, in terms of earnings. Insights about such dimensions of skill demand could provide pathways for institutions of higher education to differentiate skill sets with which they equip particular majors.

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[15] One caveat to this conclusion is that we measure the flow of skill demand in the form of new postings whereas wages are measured by the stock of jobs, though our results hold when we examine only younger workers (age < 35).

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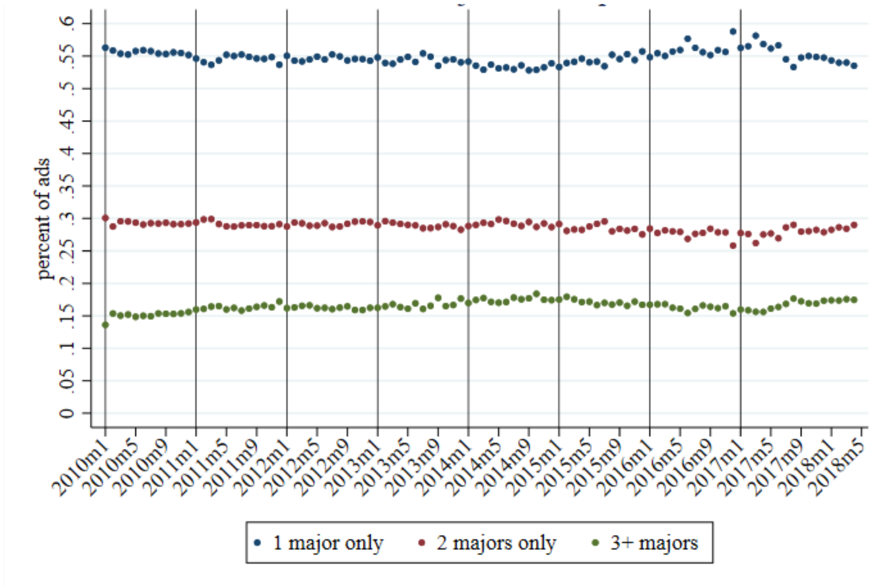
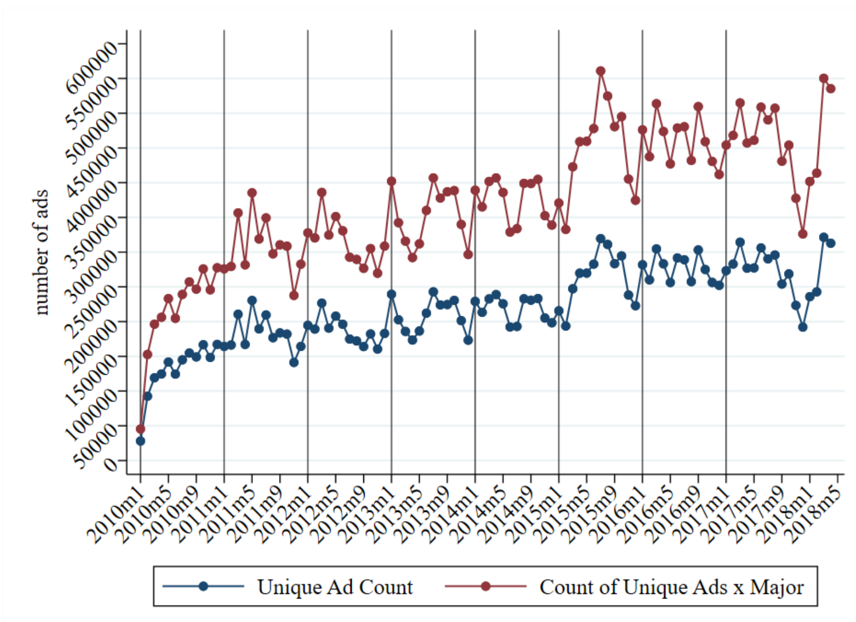
Figure 1. Number of Job Ads and Majors Over Time

A. Number of Majors Listed Per Ad



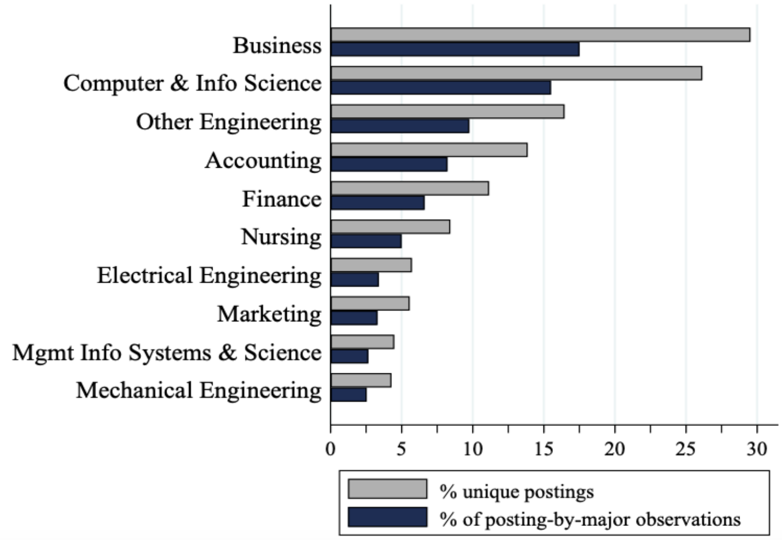
B. Unique Ads and AdsXMajors



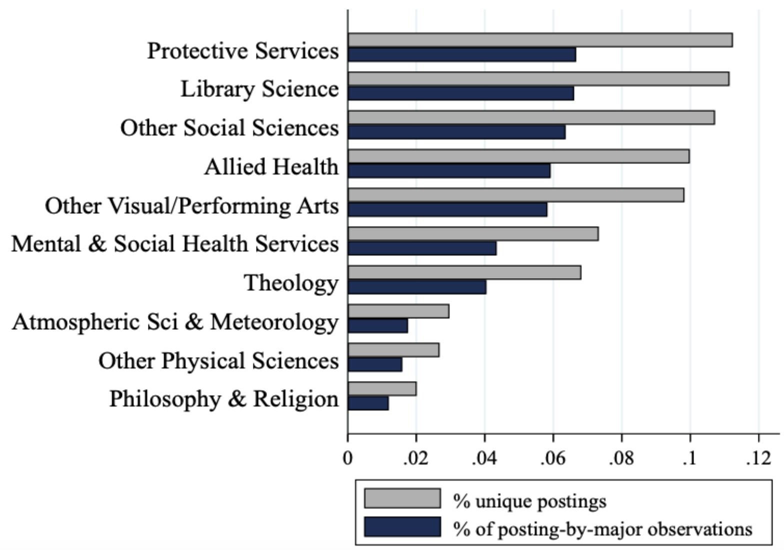
Notes: Sample includes all job ads that list 16 years of education, at least one skill, and at least one major between January 2010 and May 2018.

Figure 2. Most and Least Frequently Demanded Majors

A. Most Frequently Listed Majors

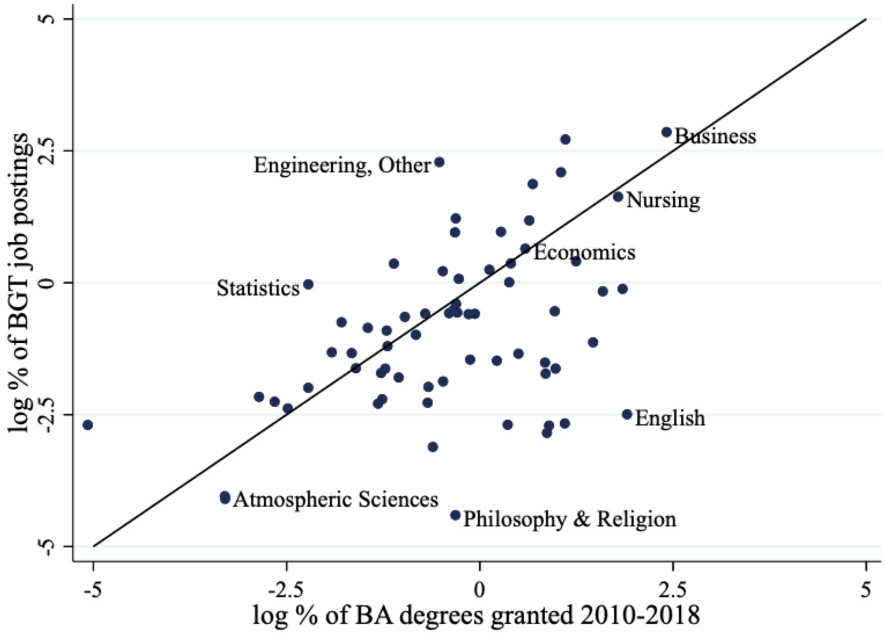


B. Least Frequently Listed Majors



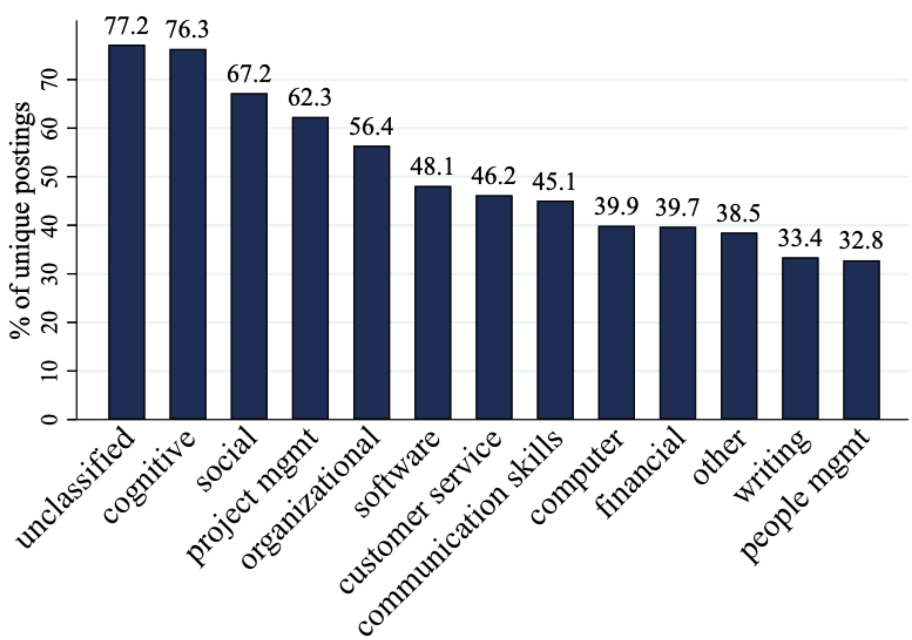
Notes: Sample includes all job ads that list 16 years of education, at least one skill, and at least one major from January 2010 to May 2018.

Figure 3. Comparison between Major Share in Ads vs. BA Completions



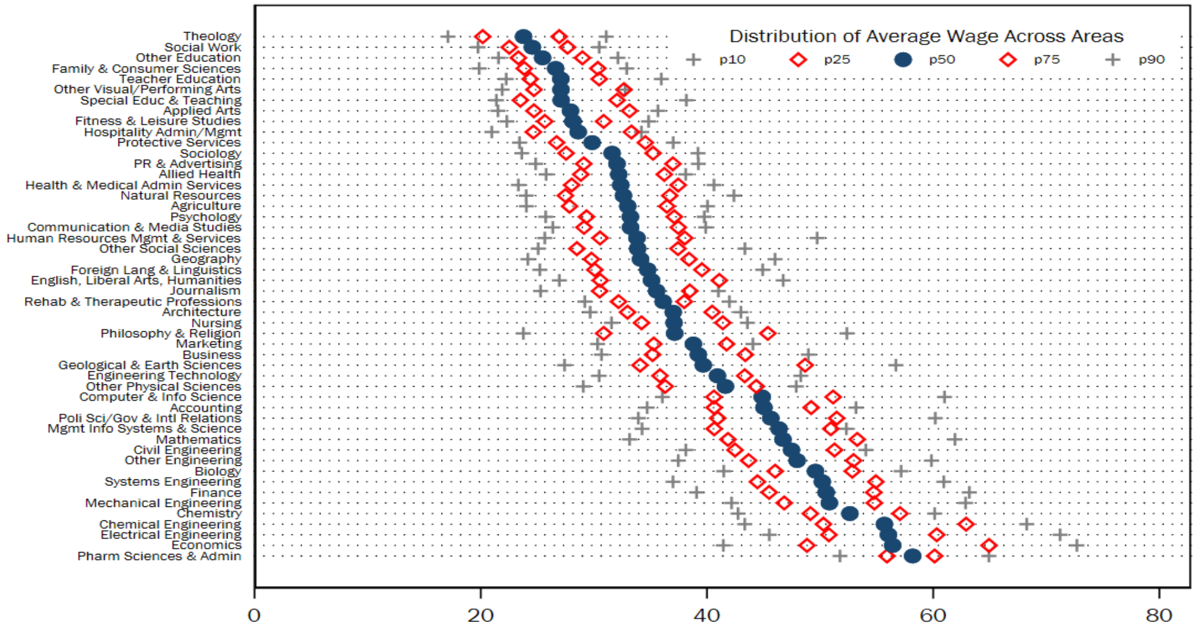
Notes: Figure plots the log percentage of BGT job postings listing each major against the log percentage of degrees granted (from IPEDs data) in years 2010-2018.

Figure 4. 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 12 skill composites constructed from the top 1000 most frequent skills. "Communication skills" is included in the "Social" composite. "Unclassified" is the share of ads containing a skill outside the top 1000 most frequent. Only 0.2% of postings list none of our 12 composites (excluding "unclassified"). Across job postings, the mean and median number of composite skills listed is six.

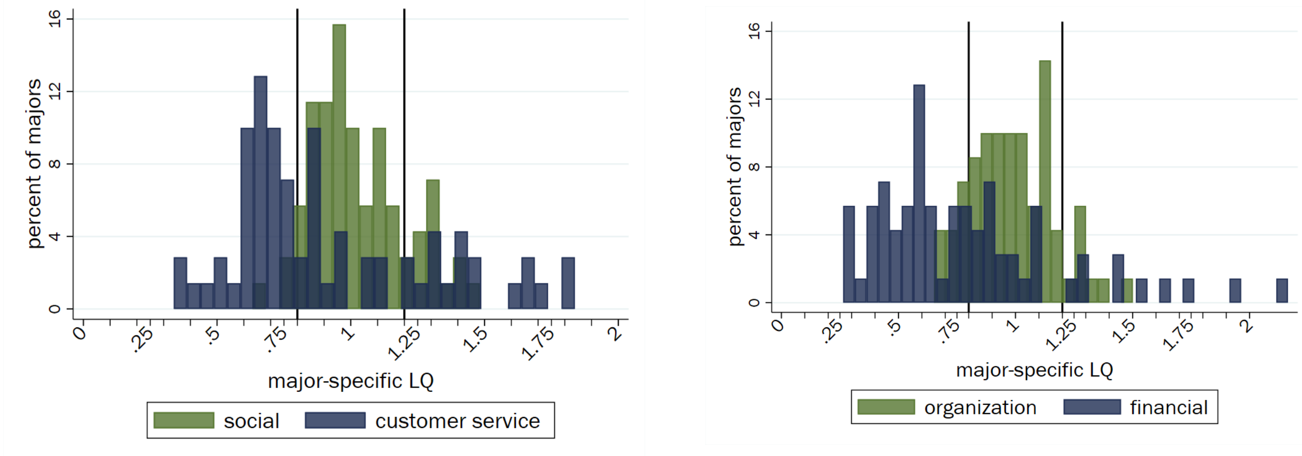
Figure 5. Distribution of Average Wage Across Majors and Areas



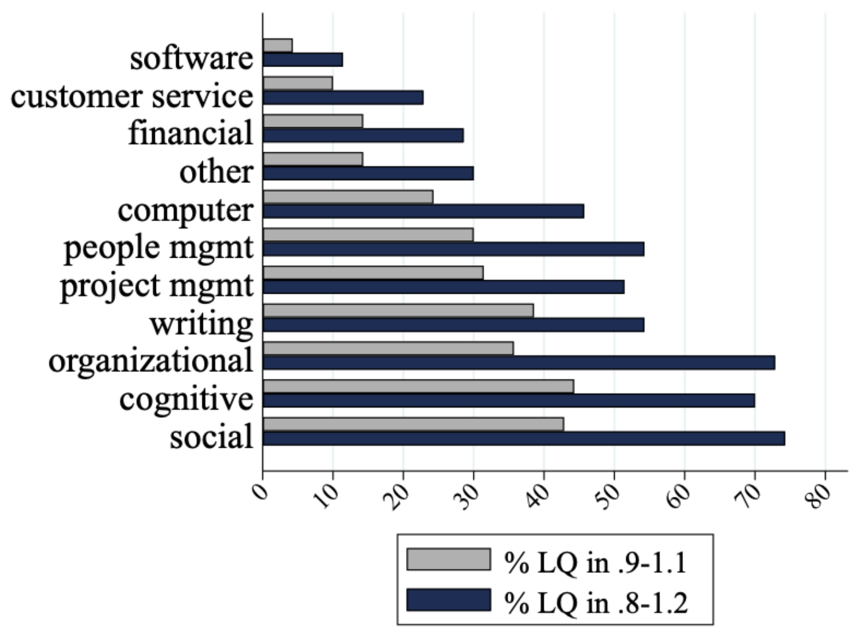
Notes: Mean hourly wages for each Major-MSA cell in the US are computed from the American Community Survey 2009-2018. Sample includes only full-time, full-year prime-age workers with a bachelor's degree. Figure includes 50 of the 71 majors with estimates in at least 600 areas.

Figure 6. Distribution of of Skill Concentration Across Majors

A. Full Distribution for Four Skills

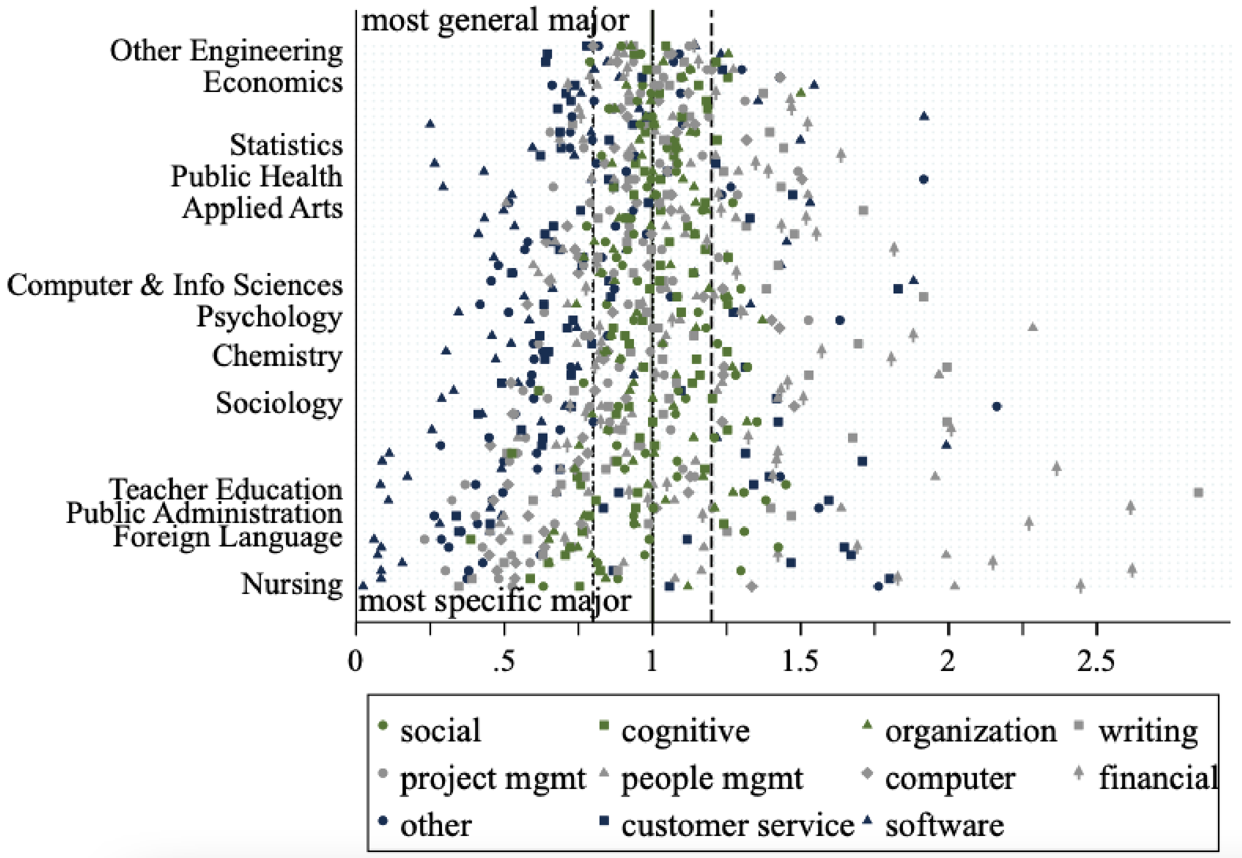


B. Skills Ranked by Specificity to Major



Notes: Panel A plots the distribution of location quotients (LQ) across all 71 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.

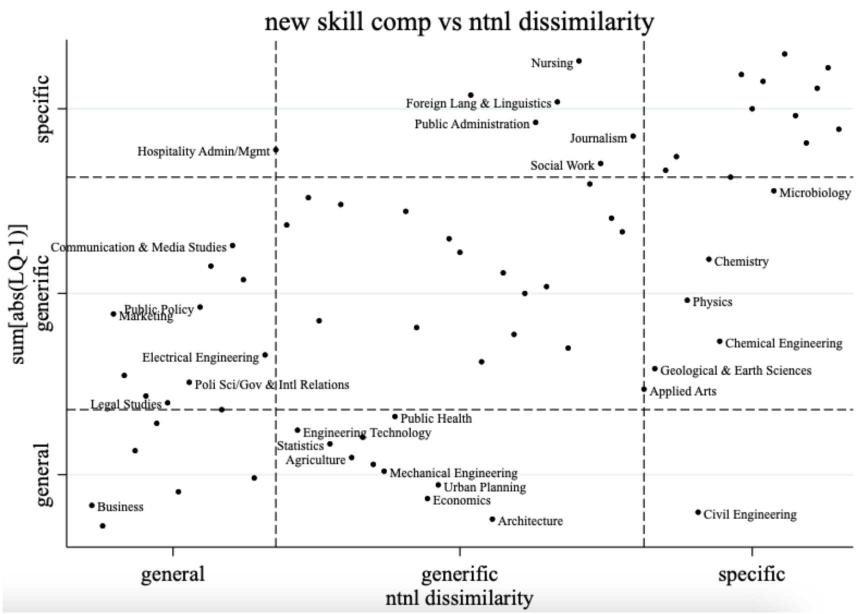
Figure 7. Skill Concentration For All Majors



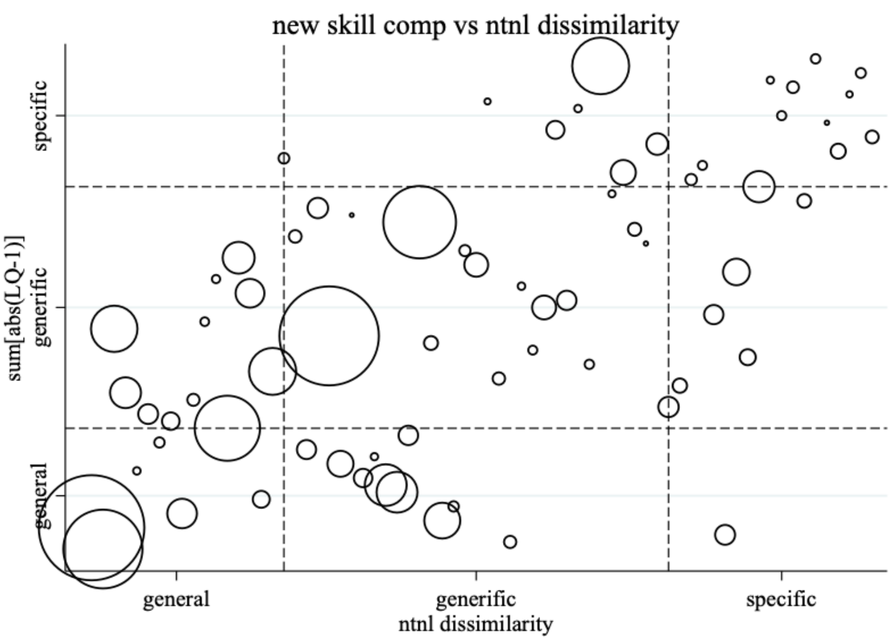
Notes: Figure plots the location quotients (LQ) for 11 skill clusters for 70 majors. An LQ greater than 1 indicates that ads with a given major are more likely to seek the skill than ads overall. An LQ less than 1 indicates that ads with the major are less likely to seek the skill than ads overall.

Figure 8. Skill Composite vs. Similarity Index Measure of Concentration

A. Unweighted

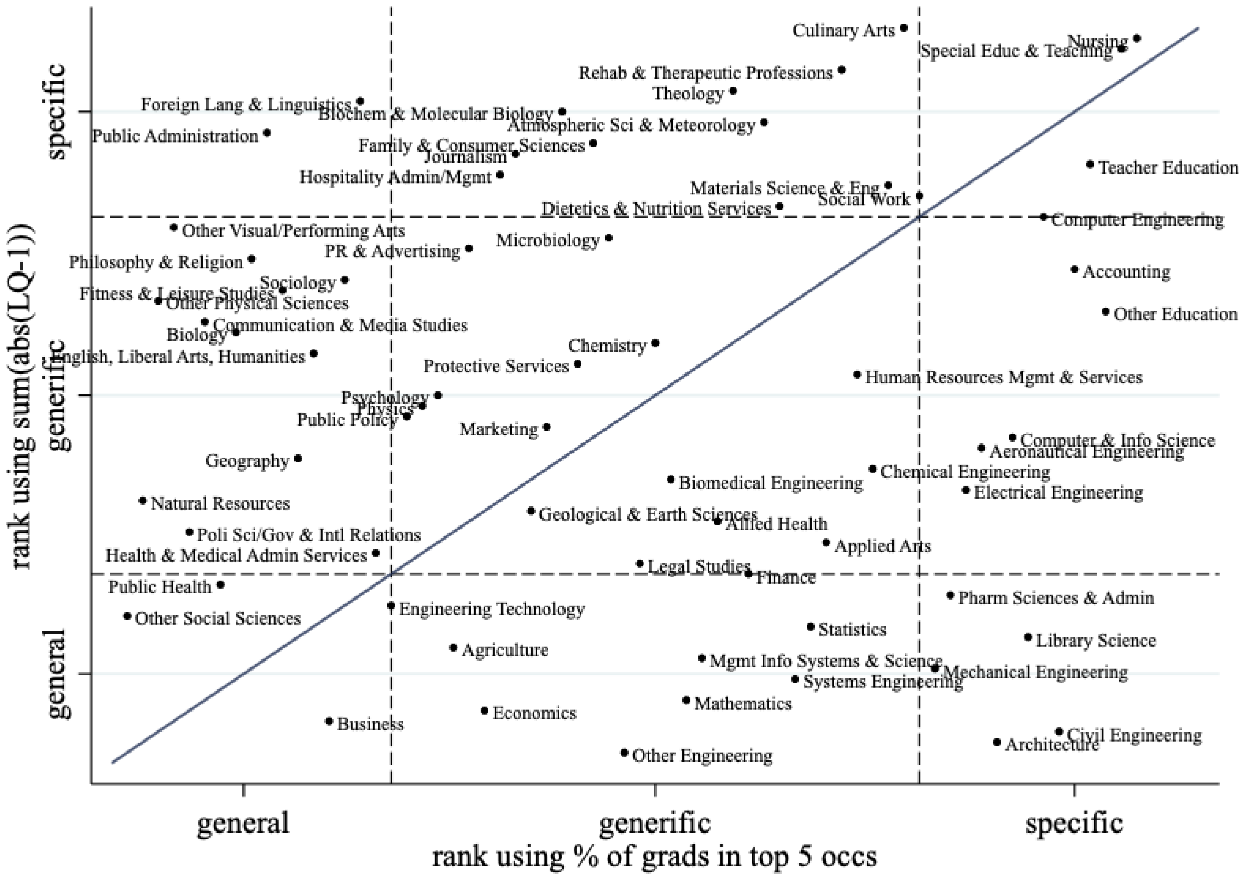


B. Weighted by Number of Job Ads



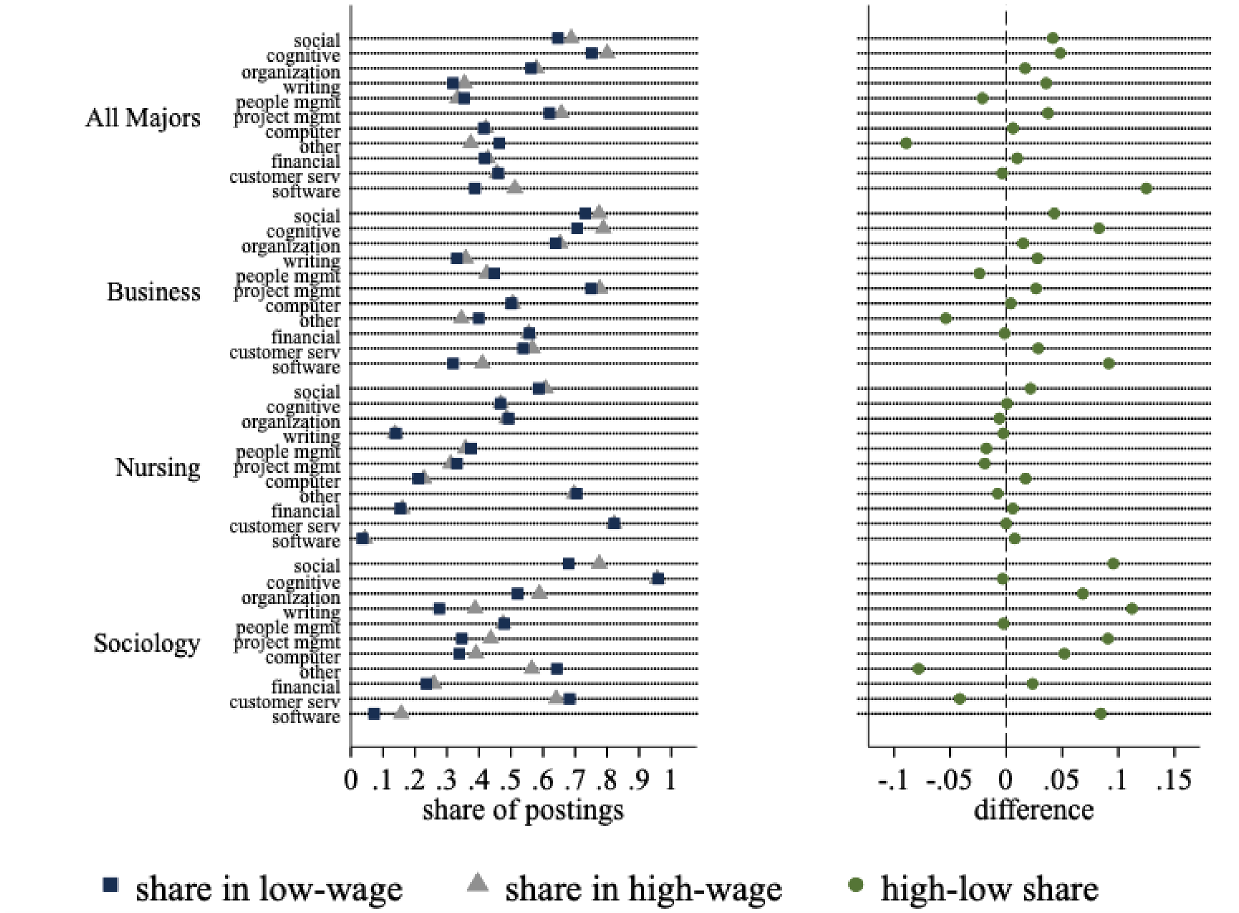
Notes: Figure plots the rank of 70 majors using two different measures of skill similarity. The y-axis plots the rank of majors from general (rank=1) to specific (rank=70). Majors are ranked according to the sum of the absolute deviation of the major's 11 LQs, from 1: sum(abs(LQ-1)). The X-axis plots the rank of each major using the cosine similarity measure constructed using the top 9000 most frequent skills. In panel A majors are unweighted and in Panel B the circle size represents the number of job postings for the major.

Figure 9. Skill Similarity Index vs. Occupational Measure of Concentration



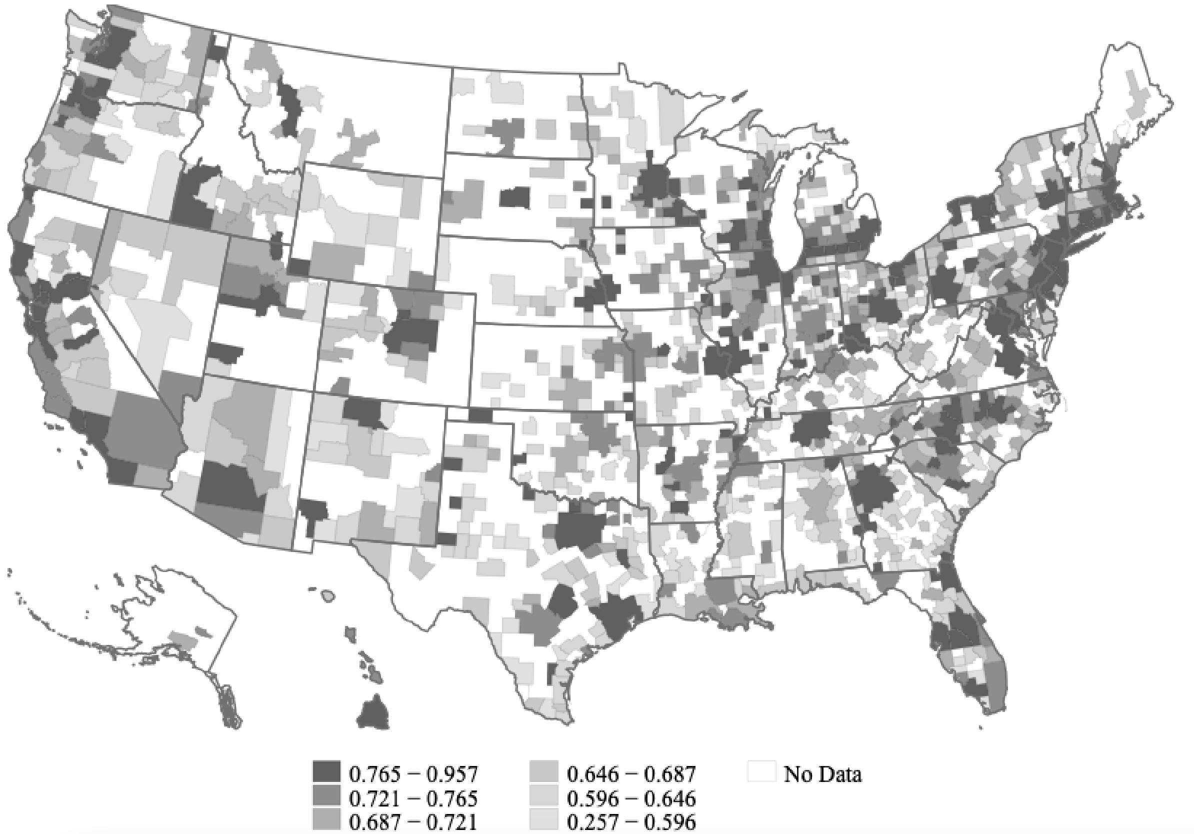
Notes: Figure plots the rank of 70 majors using two different measures of skill similarity. The y-axis plots the rank of majors from general (rank=1) to specific (rank=70). Majors are ranked according to the sum of the absolute decorations of the major's 11 LQs from 1: sum(abs(LQ-1)). The X-axis plots the rank of each major using the percent of recent college graduates found in the top five most frequent occupations for the major as measured in the American Community Survey (ACS). Majors with a lower percent of recent graduates in the top 5 occupations are considered more general.

Figure 10. Skill Demand by MSA Average Wage



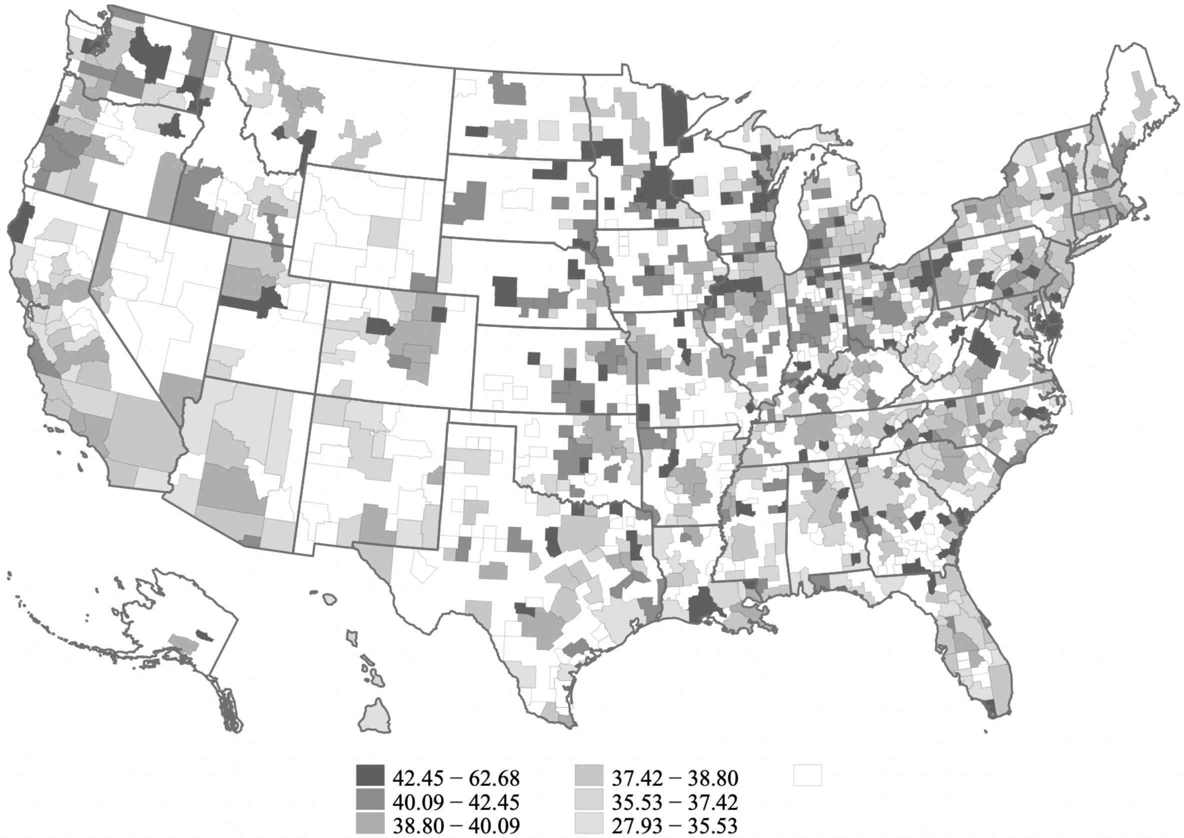
Notes: Plotted is the percent of job-posting-by-major observations in low-wage and high-wage MSAs that demand each skill. MSAs are divided into low- and high-wage using an unweighted median split on the real earnings for workers.

Figure 11. Variation in Cognitive Skill Demand Across MSAs, Business Majors



Notes: Figure plots the share of a metro or micro statistical area’s job postings that list Business majors and also list cognitive skills.

Figure 12. Variation in Earnings Across MSAs, Business Majors



Notes: Figure plots mean hourly earnings for business majors in each metro and micro statistical area. The means are adjusted for differences in average earnings across areas and reflect statistical-area deviations in earnings for Business majors, relative to the national average of hourly earnings. We regress hourly earnings on metro area fixed effects and take the mean of the residual in each major-by-metro-area cell. We then add back the national mean before plotting.

Table 1. Occupational Distribution by Sample

	Sample			
	At least 1 skill	**Education = 16**	**1 Skill and Education = 16**	**Analysis** Educ = 16 At least 1 skill At least 1 major
Count of unique ads	148,000,000	41,959,120	41,593,924	21,973,951
Count of unique ad-major (4-digit CIP)	165,832,822	57,035,270	56,633,854	37,055,416
% of original sample remaining		28.35%	28.10%	14.85%
Occupation				
soc_11 (Management)	11.92%	21.21%	21.23%	20.94%
soc_13 (Business/Financial)	6.80%	13.14%	13.20%	13.71%
soc_15 (Computer/Math)	11.85%	20.37%	20.48%	23.78%
soc_17 (Architecture/Engineering)	3.22%	5.96%	5.97%	8.63%
soc_19 (Life/Physical/Social Science)	1.03%	1.56%	1.57%	1.93%
soc_21 (Community/Social Service)	1.09%	1.41%	1.39%	1.43%
soc_23 (Legal)	0.87%	0.42%	0.42%	0.28%
soc_25 (Education/Training/Library)	2.52%	2.39%	2.37%	1.36%
soc_27 (Arts/Design/Entertainment)	2.42%	2.49%	2.49%	2.19%
soc_29 (Healthcare Practitioners)	12.24%	9.82%	9.61%	11.71%
soc_31 (Healthcare Support)	2.06%	0.01%	0.01%	0.01%
soc_33 (Protective Service)	0.99%	0.41%	0.40%	0.26%
soc_35 (Food Prep/Serving)	3.24%	0.28%	0.28%	0.27%
soc_37 (Building/Cleaning/Maintenance)	1.11%	0.07%	0.07%	0.04%
soc_39 (Personal Care)	1.75%	0.36%	0.35%	0.26%
soc_41 (Sales)	12.03%	9.25%	9.30%	4.71%
soc_43 (Office/Admin Support)	10.17%	5.31%	5.33%	3.40%
soc_45 (Farming/Fishing/Forestry)	0.06%	0.03%	0.03%	0.03%
soc_47 (Construction/Extraction)	0.98%	0.11%	0.11%	0.13%
soc_49 (Installation/Maintenance/Repair)	3.00%	0.37%	0.37%	0.31%
soc_51 (Production)	2.45%	0.75%	0.75%	0.61%
soc_53 (Transportation/Material Moving)	4.51%	0.20%	0.20%	0.11%
soc_55 (Military)	0.07%	0.03%	0.03%	0.03%
soc_na	3.61%	4.04%	4.02%	3.90%
Sample Restrictions				
Year >= 2010	Y	Y	Y	Y
At least one skill	Y	N	Y	Y
Seeking Bachelor's Degree	N	Y	Y	Y
At least one major	N	N	N	Y

Source: Authors' analysis of Burning Glass Technologies (BGT) job postings data.

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	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%
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%
Geography	4507	82%	62%	50%	61%	72%	35%	41%	20%	50%	20%	42%	31%	97%
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.

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 serv	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
Comm skill (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 varation 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		Age <35	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Share of ads requiring									
Cognitive skills	0.399***	0.223*	-1.00E-05	0.259**	-0.00793	0.271***	0.0002	0.0554	-0.007
	(0.142)	(0.117)	(0.026)	(0.117)	(0.029)	(0.078)	(0.013)	(0.105)	(0.025)
Computer skills	-0.253**	-0.0658	-0.0540***	-0.0202	-0.0687***	-0.0408	-0.0143	-0.130**	-0.0693***
	(0.106)	(0.070)	(0.016)	(0.060)	(0.017)	(0.046)	(0.015)	(0.060)	(0.019)
Customer skills	0.0809	0.0432	0.0291	0.125	0.0257	-0.03	0.0152	0.144*	0.0201
	(0.110)	(0.089)	(0.023)	(0.078)	(0.022)	(0.066)	(0.013)	(0.081)	(0.024)
Financial skills	0.303***	0.235***	-0.00855	0.158**	-0.0102	0.0506	-0.010	0.188***	0.00877
	(0.079)	(0.069)	(0.024)	(0.066)	(0.023)	(0.062)	(0.016)	(0.067)	(0.022)
Organizational skills	-0.187	-0.269**	-0.00845	-0.258***	-0.0139	-0.176***	-0.0115	-0.282***	-0.00354
	(0.113)	(0.108)	(0.016)	(0.094)	(0.016)	(0.038)	(0.013)	(0.106)	(0.022)
People managment skills	-0.609***	-0.489***	-0.0184	-0.345***	-0.0147	-0.178***	0.00603	-0.278***	0.00614
	(0.146)	(0.130)	(0.032)	(0.095)	(0.033)	(0.055)	(0.015)	(0.093)	(0.025)
Project management skills	0.401***	0.375***	0.0206	0.207**	0.00502	0.280***	0.0187	0.324***	0.00384
	(0.112)	(0.093)	(0.024)	(0.080)	(0.025)	(0.073)	(0.016)	(0.091)	(0.024)
Social skills	-0.317**	-0.477***	0.00794	-0.365***	0.0156	-0.193***	0.00396	-0.442***	-0.00115
	(0.146)	(0.119)	(0.019)	(0.104)	(0.019)	(0.051)	(0.016)	(0.113)	(0.019)
Software skills	0.02	-0.0372	0.018	-0.0955	0.0245	0.0405	0.00346	0.115	-0.0054
	(0.115)	(0.101)	(0.023)	(0.085)	(0.024)	(0.060)	(0.018)	(0.096)	(0.022)
Writing skills	0.000129	-0.0546	-0.00841	-0.0417	0.000973	-0.114***	0.0119	-0.102	-0.0249*
	(0.112)	(0.102)	(0.022)	(0.088)	(0.021)	(0.037)	(0.015)	(0.095)	(0.015)
Other skills (top 1000)	-0.102	-0.0478	-0.0486*	0.0114	-0.0503*	-0.0333	-0.0312**	-0.0556	-0.0482*
	(0.115)	(0.100)	(0.025)	(0.099)	(0.030)	(0.056)	(0.015)	(0.088)	(0.029)
Constant	3.648***	3.908***	3.665***	3.789***	3.668***	3.458***	3.474***	3.632***	3.377***
	(0.169)	(0.146)	(0.040)	(0.150)	(0.047)	(0.088)	(0.018)	(0.142)	(0.041)
Observations	22,151	22,151	22,151	22,151	22,151	22,151	22,151	19,480	19,480
R-squared	0.342	0.621	0.87	0.588	0.83	0.228	0.466	0.587	0.806
Age restriction	25-54	25-54	25-54	25-54	25-54	25-54	25-54	23-34	23-34
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 FE	NO	NO	YES	NO	YES	NO	YES	NO	YES
MSA FE	NO	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
F-test p-value	0.000	0.000	0.004	0.000	0.009	0.000	0.014	0.000	0.015

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

Note: Sample is 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.

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

	1	**2**	**3**	**4**	**5**	**6**
model SS	13905.9	15951.1	16375.7	25664.3	26931.3	30577.7
residual SS	87210.5	85165.3	84740.6	75452.1	74185.1	70538.6
total SS	101116.4	101116.4	101116.4	101116.4	101116.4	101116.4
R-squared	0.1375	0.1577	0.1619	0.2538	0.2663	0.3024
adjusted R-squared	0.1340	0.1543	0.1585	0.2498	0.2615	0.2835
basline 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	1641	1643	1652	2152	2651	10702
number of skill dummies	0	0	0	500	999	9050
N	405,748	405,748	405,748	405,748	405,748	405,748

Note: The dependent variable is an indicator for whether or not a job posting lists at least one college major. The sample is 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
soc6	504	9664.59	191.52***
naics	96	1141.07	55.54***
internship	1	109.92	509.33**
year x month	99	46.9	2.18***
metro- / micro- statistical area	940	491.67	4.39***

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. 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, Advertisin	2602	Biochemistry, Biophysics and Mol	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 Meteo	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 C	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	0.671
Microsoft Excel	0.464	Child Development	0.456	Editing	0.621
Research	0.328	Child Care	0.432	Communication Skills	0.508
Planning	0.254	Organizational Skills	0.308	Creativity	0.411
Project Management	0.183	Lesson Planning	0.256	Social Media	0.395
Writing	0.18	Teamwork / Collaboration	0.166	Research	0.322
Analytical Skills	0.16	Budgeting	0.114	Teamwork / Collaboration	0.295
SQL	0.158	Research	0.111	Organizational Skills	0.265
Data Analysis	0.117	Bilingual	0.098	Detail-Oriented	0.251
N ads	607,518	N ads	97,314		220,491

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

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%
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%
Hospitality Admin/Mgmt	5209	59%	74%	75%	68%	9%	64%	47%	61%	27%	65%	41%	54%	62%

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%
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	0.573	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	0.320	0.474	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.

Source: Authors' analysis of BGT job postings and ACS data.

Table A8. Comparison of Major Rankings by Measure of Specificity

	LQ-based rank	*Cosine-based rank*	Gini-based rank
Most specific	Culinary Arts	Family & Consumer Sciences	Primary/General Education
(top 10)	Nursing	Special Education & Teaching	Secondary Education
	Special Education & Teaching	Mental & Social Health Services	Nursing
	Allied Health	Teacher Education	Medical Tech
	Rehab & Therapeutic Professions	Atmospheric Science & Meteorology	Computer Programming
	Mental & Social Health Services	Culinary Arts	Other Med/Health Services
	Theology	Microbiology	Finance
	Foreign Language & Linguistics	Rehab & Therapeutic Professions	Precision Production/Industrial Arts
	Biochem & Molecular Biology	Biochem & Molecular Biology	Commerical Art and Design
	Atmospheric Science & Meteorology	Allied Health	Marketing
Most general	Other Engineering	Business	Music/Speech/Drama
(top 10)	Architecture	Other Engineering	Other Social Sciences
	Civil Engineering	Marketing	Philosophy/Religion
	Business	Other Allied Health	Environmental Studies
	Economics	Library Science	Psychology
	Mathematics	Health & Medical Admin Services	Accounting
	Urban Planning	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
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

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
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.

Appendix A. Defining Major Categories

To aggregate the almost 400 four-digit major 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), and Chiropractic (5101), Dentistry (5104).

For the remaining two-digit categories, we calculate the total number of job postings shared among the four-digit majors composing 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 including 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 that has 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 include 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 composite ([# of ads w/ skill=s & majorcat=c]/[# of ads w/ majorcat=c]) on a sub-sample of our data. We then use the proportions to calculate a measure of cosine similarity,[1] and for a given major look at the other majors that are most similar in skills according to the cosine similarity. 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, Systems Science and Theory (3006) was aggregated into Management Information Systems and Science (5298), Museology/Museum Studies (3014) was aggregated into Library Science (2500), and Behavioral Sciences (3017) was aggregated into Psychology (4200).

Appendix B. Constructing Skill Composites

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

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 (organization) skills, which was initially defined as keywords "organized, detail oriented, multitasking, time management, meeting deadlines, energetic" and as a result missed the very common skills of "Multi-tasking", "Organizational Skills" and "Detail-Oriented."

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.

[1] The specific formula is (insert formula) where i and j index majors, and x_ia is the proportion of ads with major i and skill a, x_ja is the proportion of ads with major j and skill a.

We map the 1,000 most frequent individual skills listed on job postings that demand a bachelor's degree to 12 skill categories as follows. First, for each individual skill, two different individuals on the research team independently coded the skill as falling into one of 12 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 skill composite for the 40 most frequently listed skills.

Skill Composite Definitions

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

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

Appendix 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 how our results change (or not) if we use the keywords displayed in Table 2 to identify skill composites.

A. Coverage

For all composites except software and people management, the percent of ads with the skill increases. 0.2% of postings don't list 1 of our 12 NEW composites. The figure before was about 4% (but for only 8 composites). Keyword approach only captured 400/1000 top most frequent skills, while our current approach classifies all 1000. Preferred composites are now mutually exclusive: before we had about 200 individual skills that fell into more than one composite (70% of these have software=1, 30% have customer service = 1, 30% have people management = 1, 30% have cognitive = 1).

The composites now also differ a lot in how many individual skills they capture. Previously, character (organization) only had 3 skills "Time management", "meeting deadlines" and "energetic". This is because of how the keywords were coded - "multi-tasking", "prioritizing tasks", and "organizational skills" are now captured. But now some of the most common skills are classified as "organizational skills"

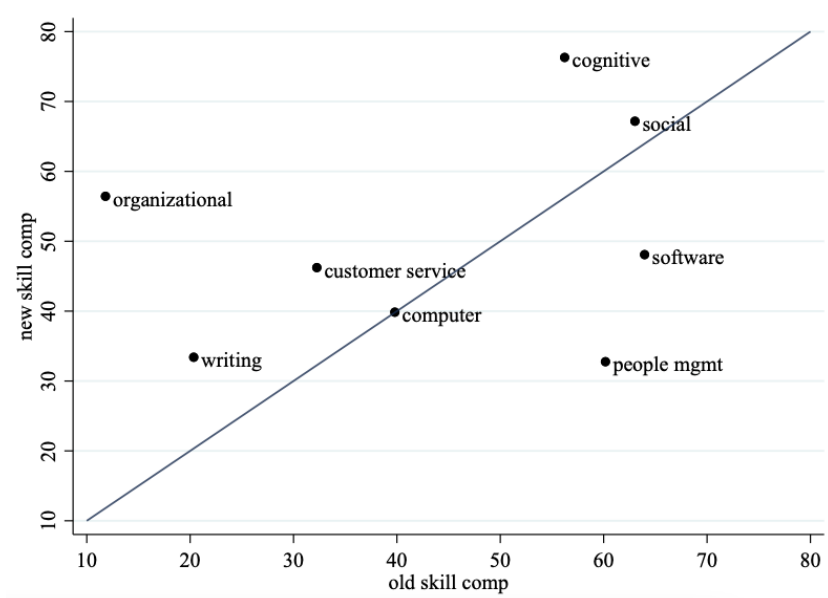
		Hand coded	Key word		
skillcomp_v2	skillcomp_v2_name	Count of skills in top 1000 most frequent	Count of skills overall	Count of skills in top 1000 most frequent	Count of skills overall

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 classified as possessing each skill composite using the two different classification approaches.

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

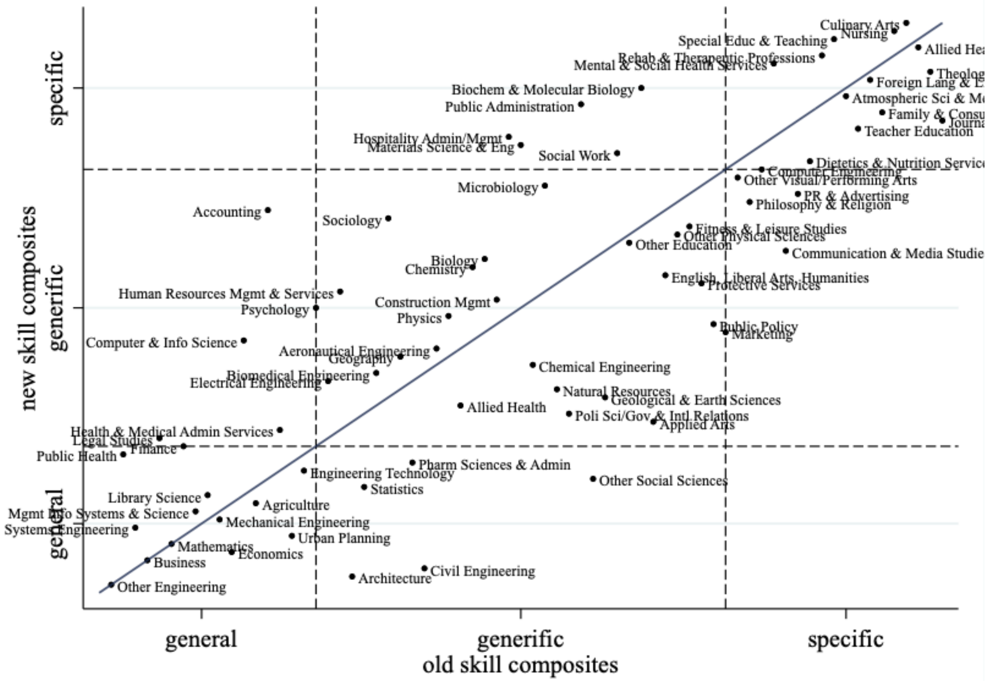


C. Characterization of Major Skill Concentration

Figure A2 compares our classification of major skill concentration between the two methods for classifying skills into composites. 50/70 majors stay in the same broad category when shifting from a key-word to top1000 approach to cluster definition. Some majors stay general (left bottom quadrant; N=13), stay "generific" (middle middle; N=23), and stay specific (right top; N=14), using General = rank 1-18 and Specific = rank 52-70. There is a symmetric movement of majors becoming more general and majors becoming more specific. Ten majors become more specific: either move from general to generic (left middle quadrant e.g. Accounting, Computer & Info Sciences), or move from generific to specific (top middle quadrant e.g. Social Work, Public Administration). Ten majors become more general: either move from specific to generific (right middle quadrant e.g. Philosophy, Communications & Media Studies) or from generific to general (bottom middle quadrant e.g. Architecture, Other Social Sciences)

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

A. Rank Correlation



B. Measure of Skill Specificity