



# College majors and skills: Evidence from the universe of online job ads<sup>☆</sup>

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## ABSTRACT

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

## I. Introduction

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

different majors play a large role in explaining earnings heterogeneity among college graduates. Somewhat surprisingly, however, there is little work that systematically characterizes the skills employers associate with college majors and their relation to differences in earnings.<sup>1</sup>

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

We measure the skills employers associate with particular majors using job vacancy data obtained from Burning Glass Technologies

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<sup>1</sup> In contrast, recent research has documented the importance of skill heterogeneity between and within occupations in explaining spatial wage variation (Deming & Kahn, 2018). But because occupation reflects post-labor-market selection, the role of pre-market skill acquisition as captured by college major remains underexplored.

(BGT), comprising the near universe of online job ads from 2010 to 2018.<sup>2</sup> A unique feature of this data source—beyond its scale and universality—is the inclusion of information on majors, detailed skills, locations, and occupations, which permits us to characterize demand along these dimensions. In contrast to previous studies that document skill-major linkages mediated through occupation (Altonji et al., 2014; Long et al., 2015), the job postings data allow us to measure skill-major linkages at the individual job level. Moreover, this information precedes the employment choices of individuals, and is thus a more proximate and direct signal of skill demand independent of occupational sorting.

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

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

Our analysis reveals marked differences in the skills associated with different majors. First, some skills—even composites—are concentrated within a small subset of majors whereas others are near universal. Employers demand social and organizational skills at similar rates across all majors, but customer service and financial skills appear specialized to relatively few majors. Second, we find that some *majors* are more typical of overall skill demand than others. For example, average skill demand for Business, Economics, and General Engineering majors accords reasonably closely with the average skill demand across all majors. Nursing, Education, and Foreign Language, on the other hand, are more specific, with job ads requesting skills demanded relatively infrequently in other majors. Common classification systems based on college curricula (such as the Classification of Instructional Programs, or CIP) may therefore fail to reflect salient dimensions of difference (or commonality) across fields of study. Together these results imply that employers view majors as meaningfully encompassing different skill bundles.

We further corroborate this premise through an analysis of earnings variation across majors and places. We use BGT data to measure skill demand for each combination of major and metropolitan statistical area (MSA), and we use American Community Survey (ACS) data to measure mean wages. We find that major—rather than MSA—accounts for the bulk of the variation in skill demand across MSA-major cells. Nevertheless, remaining within-major, cross-area variation in skill demand could play a role in explaining the appreciable differences in earnings for

the same major across areas. However, we find that this is not the case. We show that cross-major differences in skill profiles explain the vast majority of wage variation across major-MSA cells. Major fixed effects greatly diminish the capacity of the skill composites to predict earnings, and cross-area skill differences within majors have only a weak relationship with major earnings premia across areas. This finding strengthens our conclusion that majors can be conceptualized as portable bundles of skills.

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

A second strand of literature looks at whether majors are general versus specialized, which has implications for their returns over the lifecycle. Prior work has examined the benefits of a general versus specialized curriculum in the labor market (Hanushek et al., 2017; Deming and Noray, 2020; Martin, 2022). Several papers do this by quantifying the link between majors and occupations (e.g., Altonji et al., 2012; Li et al., 2021; Ransom and Phipps, 2017) or via variation in major premia across occupations (Kinsler and Pavan, 2015; Leighton and Speer, 2020). Our approach abstracts from concerns about selection of college graduates into occupations by using information from job ads prior to employment and realized earnings. Thus, we look at the specific skills associated with each major as perceived by employers and view our approach as complementary to these occupation-based approaches. Our description of the skills employers associate with college majors illustrates one source of the large returns to college major (e.g., Arcidiacono, 2004; Kirkeboen et al., 2016; Andrews et al., 2017; Martin, 2022) as well as differences in the costs of producing them (Hemelt et al., 2021).

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

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

## II. Data and samples

### A Job ad data

We use the near universe of all online job ads posted in the United

<sup>2</sup> In 2021, after we acquired the data, Burning Glass Technologies merged with EMSI, a similar firm, and the company is now known as Lightcast.

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

<sup>4</sup> Indeed, geographic heterogeneity in the sorting of majors into occupations, and the mechanisms behind it, are promising areas for further research.

States from 2010 to 2018, obtained from Burning Glass Technologies (BGT or Burning Glass).<sup>5</sup> BGT scours about 40,000 online job boards and company websites to aggregate job postings, parse and deduplicate them into a systematic, machine-readable form, and create labor market analytic products. The data contain detailed information on over 70 standardized fields including occupation, geography, skill requirements, education and experience demands, and firm identifiers. There are over 15,000 individual skills standardized from the open text in each job posting. Our data cover the United States and contain approximately 153 million individual job postings.

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

## B Sample

We restrict to job postings that list at least one skill, require exactly 16 years of education (i.e., a bachelor's degree), and list at least one college major. Just over half of the job postings that demand 16 years of education and at least one skill also explicitly list at least one college major.<sup>7</sup> These education and skill requirements leave 12.8% of the original 153 million job postings. Most of our analyses also restrict the sample to ads posted in metropolitan statistical areas (MSAs), reducing the analytic sample to about 18.5 million unique job postings.<sup>8</sup> We exclude ads specifically targeting workers with graduate education as we are interested in measuring the association between undergraduate majors and skills. Most job postings require 0–5 years of experience, which is more relevant for individuals prior to graduate education.

Given the large reduction in the sample size after imposing these restrictions, one might worry that the types of job postings in our restricted sample differ from the set of all job postings. [Table 1](#) compares the occupational composition of job postings in our analytic sample to two larger samples. Differences are mostly due to the bachelor's education requirement. It is well documented that typical job tasks performed in occupations that employ workers with less formal education differ from those that employ workers with more formal education (e.g., [Acemoglu and Autor, 2011](#)). The higher concentration of job postings in Management (22% vs. 12%) and Business (15% vs. 7%) occupations in

<sup>5</sup> Several recent papers have used BGT data to study cross-sectional skill demand ([Deming & Kahn, 2018](#); [Brüning & Mangeol, 2020](#); [Aleksieva et al., 2021](#)), cyclical and structural changes in skill or labor demand ([Hershbein & Kahn, 2018](#); [Modestino, Shoag, & Ballance, 2016](#); [Modestino, Shoag, & Ballance, 2020](#); [Forsythe et al., 2020](#)), and labor market concentration ([Azar et al., 2020](#)).

<sup>6</sup> See online Appendix A of [Hershbein and Kahn \(2018\)](#).

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

<sup>8</sup> The vast majority of postings are from metropolitan statistical areas, so this restriction drops only about 5% of the “education 16” sample with at least one major (around 1,000,000 postings).

**Table 1**  
Occupational distribution by sample.

	Sample				
	All Postings	At least 1 skill	Educ = 16 At least 1 skill	Educ = 16 At least 1 skill 1 major	Analysis Educ = 16 At least 1 skill At least 1 major In Metro CBSAs
	(1)	(2)	(3)	(4)	(5)
Count of unique ads (millions)	153.0	148.0	35.9	19.5	18.5
Count of unique ad-major (4-digit CIP; millions)				32.8	31.2
% of original sample remaining		96.71%	23.48%	12.76%	12.07%
Experience level (years)			3.391	3.649	3.682
<b>Occup. (SOC Code)</b>					
Management (11)	11.70%	11.92%	22.22%	21.93%	21.84%
Business/Financial (13)	6.64%	6.80%	14.30%	14.82%	15.02%
Computer/Math (15)	11.54%	11.85%	22.13%	25.23%	25.83%
Architecture/Engineering (17)	3.15%	3.22%	6.70%	9.50%	9.26%
Life/Physical/Social Science (19)	1.00%	1.03%	1.69%	2.04%	1.97%
Community/Social Service (21)	1.09%	1.09%	1.38%	1.40%	1.28%
Legal (23)	0.85%	0.87%	0.41%	0.25%	0.26%
Education/Training/Library (25)	2.49%	2.52%	2.48%	1.31%	1.25%
Arts/Design/Entertainment (27)	2.37%	2.42%	2.53%	2.29%	2.32%
Healthcare Practitioners (29)	12.27%	12.24%	7.58%	8.21%	8.01%
Healthcare Support (31)	2.03%	2.06%	0.01%	0.01%	0.01%
Protective Service (33)	1.00%	0.99%	0.33%	0.22%	0.21%
Food Prep/Serving (35)	3.38%	3.24%	0.24%	0.23%	0.23%
Building/Cleaning/Maintenance (37)	1.11%	1.11%	0.06%	0.04%	0.04%
Personal Care (39)	1.75%	1.75%	0.27%	0.21%	0.20%
Sales (41)	11.76%	12.03%	8.20%	4.37%	4.38%
Office/Admin Support (43)	9.96%	10.17%	4.28%	3.02%	3.02%
Farming/Fishing/Forestry (45)	0.06%	0.06%	0.02%	0.02%	0.02%
Construction/Extraction (47)	0.97%	0.98%	0.09%	0.11%	0.11%
Installation/Maintenance/Repair (49)	2.94%	3.00%	0.31%	0.27%	0.25%
Production (51)	2.45%	2.45%	0.64%	0.56%	0.52%
Transportation/Material Moving (53)	5.81%	4.51%	0.14%	0.09%	0.09%
Military (55)	0.07%	0.07%	0.03%	0.02%	0.02%
Missing (0)	3.61%	3.61%	3.93%	3.84%	3.85%

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

our analytic sample relative to all job postings concurs with this stylized fact. Analogously, the full sample of ads has a higher proportion of job postings in Food Prep (3.38% vs. 0.23%), Building Cleaning and Maintenance (1.11% vs. 0.04%), Sales occupations (11.76% vs. 4.38%), and Office & Administrative Support (9.96% vs. 3.02%).

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

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

### C College majors

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

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

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

degrees granted according to the Integrated Postsecondary Education Data System (IPEDS). Because we want our categorization of majors to reflect the fields that students at four-year institutions encounter when making choices about paths of study, we use the CIP coding hierarchy wherever possible and combine majors that tend to appear in ads together or that require similar sets of skills (as indicated in the job ads).<sup>11</sup>

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

Since the college majors listed on these job postings have received little scrutiny, an important but open question is how major-specific demand measured in these job postings relates to the composition of bachelor's degrees granted or supplied over time. Appendix Fig. A1 compares the distribution of majors listed on job postings in the BGT data to the distribution of degrees granted for the same majors in the U. S. from years 2010–2018 using IPEDS data. Majors for which the share of job postings is proportional to the share of degrees granted should fall on the 45-degree line, majors overrepresented (underrepresented) in the BGT data will fall above (below) the 45-degree line. Some majors, including Nursing and Economics, have demand that is proportional to the number of degrees awarded for the major. Engineering and Statistics, however, are overrepresented in the BGT data relative to degrees granted, whereas Philosophy and Religion, Atmospheric Sciences, and English are underrepresented.<sup>12</sup> This discrepancy likely reflects a disconnect between the supply and demand for specific college majors, an important topic beyond the scope of this current paper, rather than an issue with the representativeness of the job postings data itself.

### D Categorizing skills

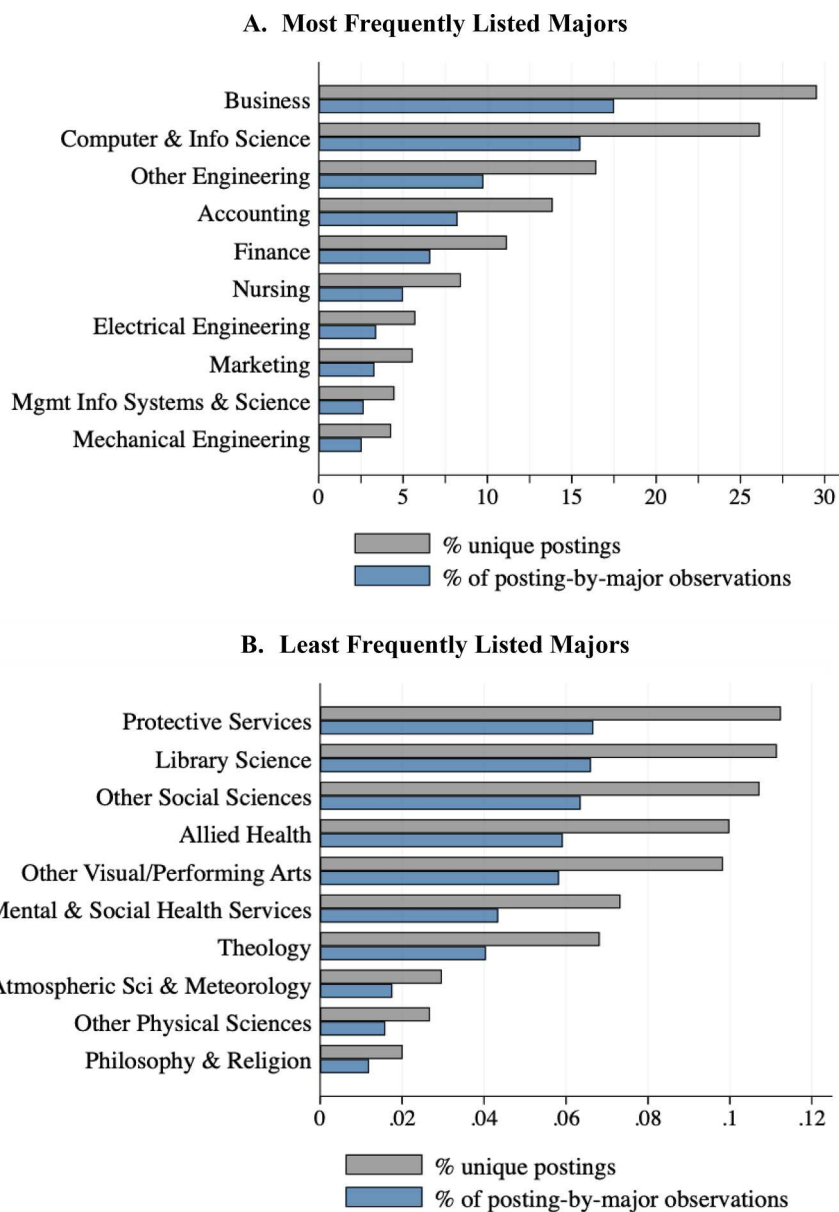
Burning Glass parses over 15,000 individual skills from the job postings. As is common practice in previous studies using BGT data to categorize skill demand in the labor market (Deming and Kahn, 2018; Hershbein and Kahn, 2018), we do not empirically distinguish between skills—a worker's endowment of capabilities—and tasks—a unit of work activity that produces goods and services. Although the literature separates these theoretically (Acemoglu and Autor, 2011), in practice employers do not always clearly differentiate between them in job postings, and thus we consider all these proficiencies to be “skills.”

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

This approach provides a few benefits over the application of the keyword approach from Deming and Kahn (2018) or Hershbein and

<sup>11</sup> Appendix B describes our process for aggregating college majors. Appendix Table A3 reports the complete list of major groups.

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



**Fig. 1.** Most and least frequently demanded majors, A. Most frequently listed majors, B. Least frequently listed majors.  
*Notes:* Figure plots the percentage of Burning Glass job postings listing each major. Sample includes all job ads posted between January 2010 and May 2018 in metropolitan statistical areas that list 16 years of required education, at least one skill, and at least one major.

Kahn (2018).<sup>13</sup> First, some of the most frequently listed individual skills are not captured by any skill composite using the keyword approach. Examples include planning (appears on 20% of postings), organizational skills (16%), detail-oriented (12%), scheduling (12%), building effective relationships (11%), creativity (10%), troubleshooting (6%) and multi-tasking (8%). Second, the keyword approach can result in the misclassification of some broad groups of skills. For example, the composite “people management” includes the keyword “management” and thus captures a wide variety of general management activities that do

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

not specifically pertain to managing people, including account management, pain management, and operations management. Similarly, underwriting is also included in the writing composite using the keyword approach, even though that skill is quite distinct.

Table 2 provides a description of each of the 11 categories along with the most frequent skills in each category.<sup>14</sup> The final column lists the words used to define these categories based on the keyword approach. Our resulting skill composites are mutually exclusive at the skill level—that is, a detailed skill maps to at most one composite—but a given job posting can have multiple skill composites. Fig. 2 shows the share of all ads containing a skill falling in each of the 11 categories. “Cognitive”

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

**Table 2**  
Skill composite definition and examples.

Skill	Definition	# skills in top 1,000	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	

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

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

### E Inferring desired skills from co-listing with majors

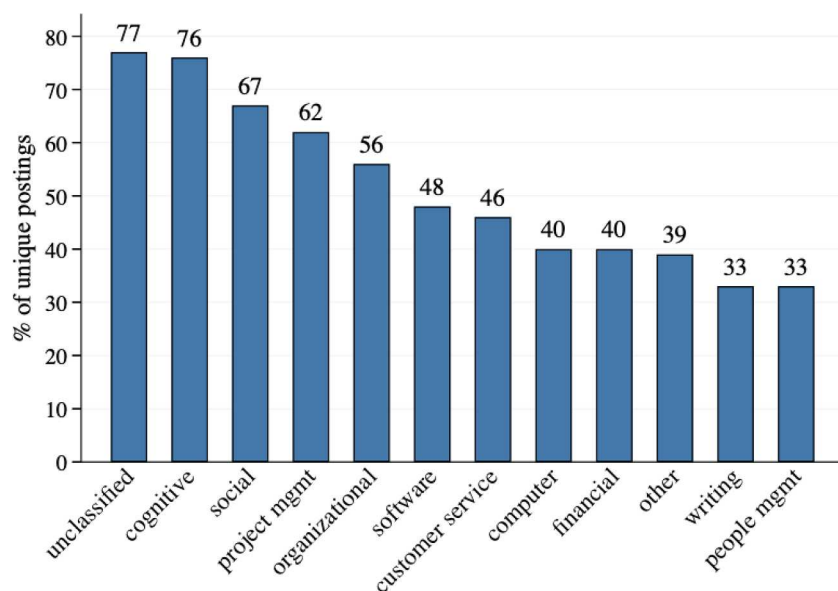
Our approach assumes that employers list all appropriate skills alongside majors, instead of listing majors in place of desired (or

assumed) skills.<sup>16</sup> If employers choose to list a desired major instead of listing the constituent skills, then our metrics will understate the importance of these core skills to a given major. This does not seem to be the case; the most frequent skills appearing alongside majors tend to be core skills required by the jobs that graduates with these majors tend to enter (Appendix Table A5).<sup>17</sup> 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. Furthermore, when we look at ads for individual

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

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

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



**Fig. 2.** Skill composites: percentage of unique job postings containing skill composite.

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

occupations, the listed skills tend to be similar regardless of whether a major is listed or not. For example, the top 10 most frequently listed skills on job postings that denote the occupation “Managers, All Others” are nearly identical between postings that list a major and those that do not, as are the shares of postings listing each of these skills. This conclusion generally holds for other occupations we examined, including Healthcare and Social Workers, Computer Programmers, Accountants and Auditors, Mechanical Engineers, and Registered Nurses.

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

Hence, we conclude that employers do not simply list majors as a substitute for listing the skills they seek in job applicants.<sup>18</sup> 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.<sup>19</sup> The benefits of listing additional information on a posting, even when this additional information is closely related to other material already on the postings (e.g., Teacher Education major and “teaching” skill), appear to exceed the costs.

While job postings illustrate differences in the *types* of skills associated with each major, we are unable to infer differences in the *level* of skill demanded within each type; wage information attached to the ads is uncommon in our sample and likely not representative. Two positions both seeking applicants with “writing” skills may require quite different

levels of this skill (e.g., jobs for Journalism majors require more advanced writing skills relative to jobs for other majors). Furthermore, the composite skills we construct also likely mask differences in skill intensity that may be reflected in the detailed set of skills. In either case, to the extent we understate differences in the intensity of skill demand across majors, the large cross-major differences documented below are likely conservative.

A final consideration is that students of varying levels of general ability sort into different majors (Paglin and Rufolo, 1990; Arcidiacono, 2004). Skills stated in job ads may thus reflect employers’ perceptions of student sorting, perceptions of human capital accumulation, or both. We do not take a stand on this distinction; either interpretation reflects employers’ views of the skills they *perceive* applicants from each major to possess. Moreover, employer skill demand may not exactly match (but likely correlates with) the skills graduates actually possess. Understanding this correlation, as well as measuring intensity of skill level from job ads, are important directions for further research.

## F Earnings by major

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

We construct hourly earnings by dividing annual earnings by the product of weeks worked during the past 12 months and usual hours worked per week. We adjust earnings for inflation to 2019 dollars using the Personal Consumption Expenditures (PCE) deflator from the Bureau of Economic Analysis (BEA). In our analyses, we use two versions of real hourly earnings. The first is the log of raw mean hourly earnings in the major-MSA cell. For the second, we regression-adjust for compositional differences across majors. Specifically, we regress the log of hourly earnings at the individual level on indicators for female, Black, and

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

<sup>19</sup> Online postings are likely to be quite different from print job ads in this regard.

Hispanic, as well as a quartic in potential experience, and we then take the mean of the residuals within each major-MSA cell.<sup>20</sup> Fig. 3 shows substantial geographic variation both across and within majors in the mean hourly wage of full-time, full-year, prime-aged workers in the United States. We later assess the extent to which this variation can be explained by differences in the skill content across and within majors.

### III. Skills associated with college majors

Table 3 reports the share of ads listing each of the skill clusters separately for a handful of majors, along with the minimum and maximum share across 70 different majors.<sup>21</sup> There is a substantial range across fields for many of these skill aggregates. For instance, the share of ads desiring specific software skills ranges from less than 4% for Nursing to (unsurprisingly) nearly all job ads in Computer Science. Project management skills are sought in nearly all job ads for Public Health majors but rarely for jobs seeking Education or Foreign Language majors. People management is rarely desired on job ads associated with Accounting majors, but appears on more than half of ads targeting Public Administration majors. Because “communication skills” constitute such a large share of the “social skills” composite, we separately report statistics for this skill.

#### 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:

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

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

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

To recover the desirable properties of LQs, we make a few adjust-

ments. First, we redefine the total count of job postings ( $N$ ) as the total number of job-posting-by-major observations ( $\hat{N}$ ) so that  $\sum_m N_m = \hat{N}$ .

Second, we analogously redefine the total count of unique job postings with skill  $s$ ,  $N_s$ , to be the total of job-posting-by-major observations that list skill  $s$  (that is,  $\hat{N}_s$ ), so that  $\hat{N}_s = \sum_m N_{ms}$ . With these changes, the adjusted LQ for a dyad of major  $m$  and skill  $s$  is:

$$\widehat{LQ}_{ms} = \frac{(N_{ms}/N_m)}{(\hat{N}_s/\hat{N})} = \frac{(N_{ms}/\hat{N}_s)}{(N_m/\hat{N})} \quad (2)$$

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

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

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

The cosine similarity and LQ measures of skill concentration provide complementary information. The former measures how similar a given major is to the broad set of jobs based on nearly the entire skill vector, which includes many infrequent and specific skills. In contrast, the latter focuses on similarity based on the large clusters of the most common skills. The LQ-based measure also permits us to characterize skill differences across majors along a tractable number of dimensions. We assess the empirical correspondence between these two measures in a subsequent section.

#### B Skill specificity of college majors based on location quotient

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

We summarize our findings from the LQ calculations graphically. Panel A of Fig. 4 plots the distribution of LQs across majors for four skill composites. Social and organizational skills have a large number of major-specific LQs that are clustered around 1, indicating that most majors require similar levels of these skills. Customer service and

<sup>20</sup> In both cases we employ sample weights when aggregating to major-MSA cells.

<sup>21</sup> Full results for all 70 majors are in Appendix Table A6.

<sup>22</sup> We narrow our focus from the complete set of 15,000 skills to the roughly 9,000 skills found on at least 0.001% of all job postings.



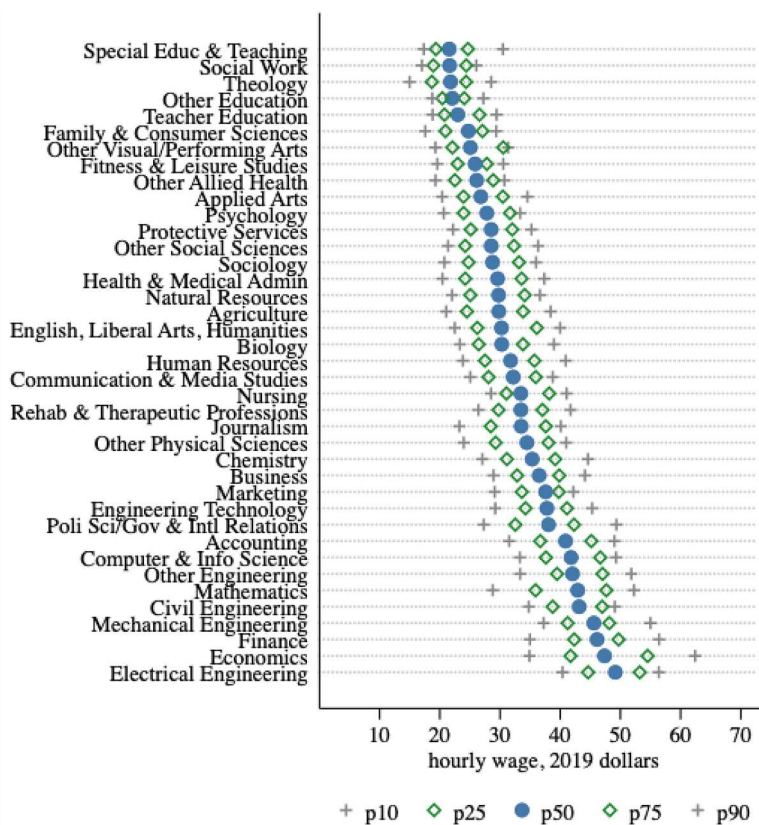


Fig. 3. Distribution of average wage across majors and areas.

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

financial skills are more varied; some majors are associated with very high levels of those skills (such as Social Work and Construction Management, respectively) and others very low (Atmospheric Science and Theology). Panel B combines the LQs into a single index—the share of the LQs that are within narrow bounds around 1—which measures the specificity of skills to majors. For a given skill, if most majors have an LQ around 1, then the demand for that skill is not particularly concentrated among any subset of majors. Most majors have an LQ for social skills near 1 because most majors have the same fraction of ads demanding social skills as does the entire market. Social skills are thus general—a skill that is demanded across ads for most majors. In contrast, Financial and Customer Service skills are specific.

Fig. 5 plots the LQs for all majors and the 11 skill composites. Majors are ordered according to the degree of overlap between a major’s skill demand and national demand. For each skill composite, we measure the absolute deviation of the major’s LQ from 1, and then sum the absolute deviations across all skills for a major.<sup>23</sup> For some majors, including Business, Economics, and General Engineering, the measure is very small, suggesting that they have a skill profile similar to that of the broader job market: LQs fall close to 1 for all skill aggregates. These majors can be thought of as “general” majors in the sense that they are associated with skills that are demanded by a large number and wide variety of jobs in the college-educated labor market.

Majors towards the bottom are *specialized* (i.e., “specific” majors) in

<sup>23</sup> Specifically, for each major, the measure is  $\sum(\text{abs}(\text{LQ}-1))$  where the sum is taken across skill composites within a major. We also order majors using the sum of squared deviations  $\sum((\text{LQ}-1)^2)$ . The ranking of majors based on the two measures is highly correlated (0.96).

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

Majors in the middle (“generic” majors), such as Computer Science and Psychology, have a skill profile broadly reflective of the national one, but with a few skill categories that are particularly over- or underrepresented.<sup>24</sup>

These results are robust, when calculating the LQ denominator, to including postings that demand 16 years of education but do not list a major. Our main measure compares the share of each major’s postings that list each skill to the percentage of all job postings with a college

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

**Table 3**  
Share of ads for selected majors indicating demand for each skill composite.

Major	Cognitive	Social	Project Mngt	Organizational	Software	Customer Service	Computer	Financial	Writing	People Mngt	Comm. (subset of Social)
All postings	80%	68%	65%	58%	50%	46%	42%	43%	35%	33%	46%
Journalism	76%	90%	44%	74%	34%	40%	47%	21%	100%	26%	51%
Computer Science	82%	65%	70%	50%	94%	39%	27%	19%	36%	29%	47%
Teacher Education	60%	99%	24%	57%	4%	61%	22%	17%	24%	34%	28%
Mech. Engineering	94%	58%	72%	51%	48%	31%	38%	37%	30%	25%	43%
Foreign Language	61%	90%	30%	39%	23%	16%	27%	15%	44%	17%	28%
Humanities	73%	84%	40%	60%	26%	36%	44%	26%	60%	25%	44%
Biology	91%	61%	54%	51%	24%	29%	35%	26%	36%	27%	41%
Public Administration	75%	69%	79%	70%	23%	38%	43%	67%	49%	55%	36%
Economics	100%	75%	68%	64%	45%	44%	60%	61%	39%	30%	52%
Sociology	96%	76%	42%	58%	14%	65%	38%	26%	37%	48%	34%
Public Health	77%	74%	98%	58%	22%	48%	44%	39%	44%	43%	46%
Nursing	47%	60%	31%	49%	4%	82%	23%	16%	14%	36%	30%
Accounting	73%	61%	52%	62%	35%	33%	62%	92%	30%	28%	46%
Business	78%	77%	77%	65%	40%	56%	51%	56%	36%	43%	53%
Minimum	31%	43%	15%	38%	1%	15%	19%	11%	12%	16%	20%
Maximum	100%	99%	100%	87%	100%	84%	63%	92%	100%	76%	63%
Mean	79%	70%	56%	57%	33%	42%	38%	34%	38%	34%	42%
Standard Deviation	15%	12%	19%	10%	24%	17%	12%	17%	14%	12%	9%

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

major that list each skill. However, it is possible that the postings that do not explicitly list a college major are searching for workers with any form of disciplinary training. If so, then the skill demand on these postings represents the skills employers expect the average college graduate to possess. To assess this, we reconstruct the LQ measures with all postings that demand exactly 16 years of education (irrespective of whether a major is listed) in the denominator.<sup>25</sup> The ranking of college majors is almost identical to our preferred specification ( $R^2 > 0.95$ ).

### C Measuring specificity with all skills

We also compare our LQ-based measure to the cosine similarity measure. The cosine similarity metric captures the similarities between each major and all job ads nationally along the vector of 9,000 skills, which incorporates more information about less frequent, possibly more specialized, skills. **Appendix Fig. A2** shows that the two metrics produce broadly similar rankings of specificity across majors. The R-squared from the bivariate regression between major rankings of the two indices is 0.37 when majors are equally weighted and 0.53 when majors are weighted by the number of ads; the association is similar if we compare the metric itself, rather than the rank (**Appendix Table A7**). This strong correspondence reflects the fact that most of the variation in the cosine similarity measure comes from variation in the 1,000 most frequent skills ( $R^2 = 0.90$ ), which are the ones that enter our LQ-based index.<sup>26</sup>

**Appendix Fig. A3** plots the similarity of skill demand between each

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

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

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

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

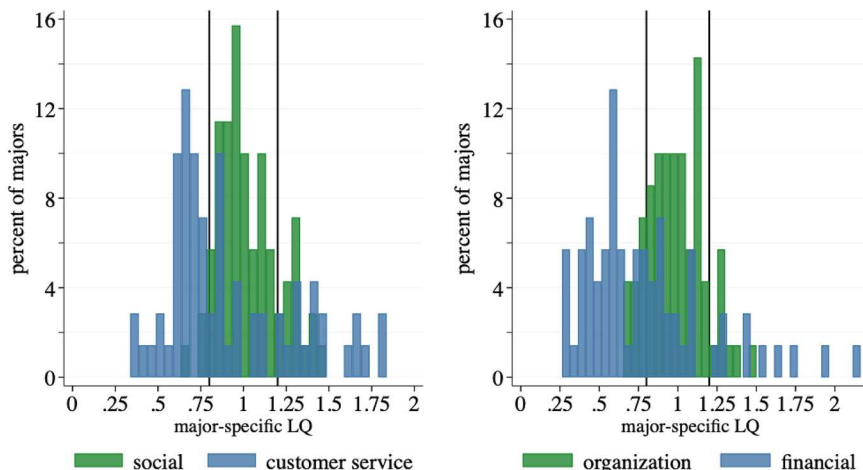
### D Comparison to prior work on college major specificity

Our measure of college major specificity complements those constructed by other scholars, which primarily rely on major-occupational linkages and earnings premia across majors. **Fig. 6** compares our measure to one based on the occupational concentration of college majors, specifically the share of recent college graduates with a given major represented in the top five most frequent occupations in the ACS. There is a moderate correlation between major rankings when cells are weighted by the number of ads (0.47), but minimal correlation when they are unweighted (0.004), suggesting that inferences about specialization are more robust for more common majors.<sup>27</sup>

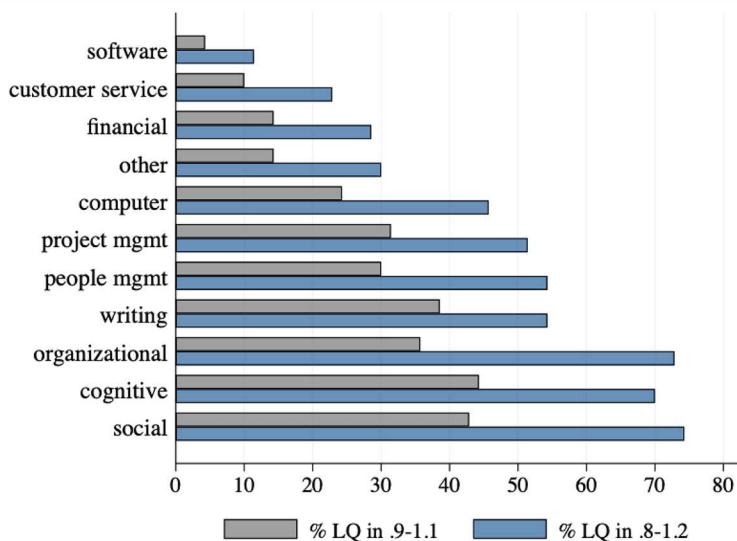
Leighton and Speer (2020) construct a Gini coefficient of wage

<sup>27</sup> Appendix Table A7 presents correlations between all of the specificity measures we construct.

**A. Full Distribution for Four Skill Composites**



**B. Skills Ranked by Specificity to Major**



**Fig. 4.** Distribution of skill concentration across majors, A. Full distribution for four skill composites, B. Skills ranked by specificity to major.

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

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

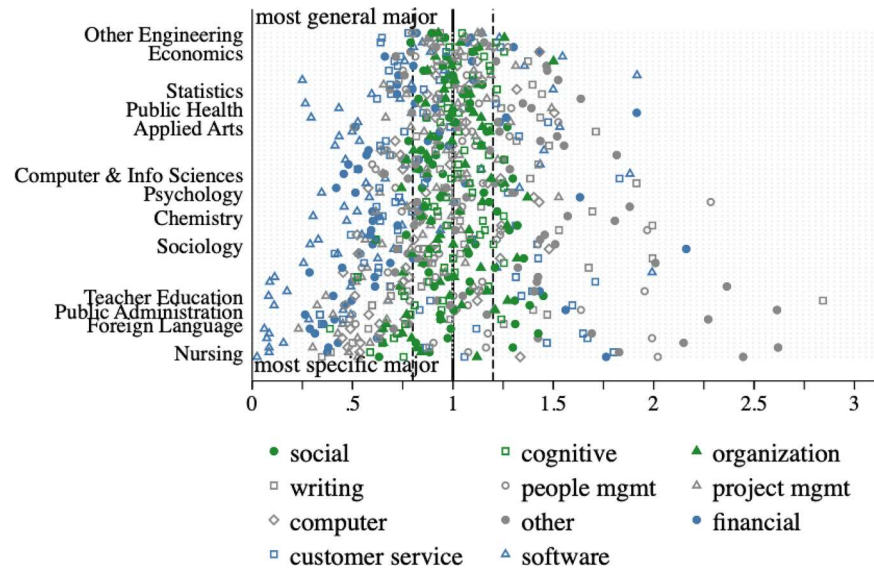
Thus, there is a correspondence between which majors are considered general or specific when skills are measured based on employers’ perceptions as expressed on job postings and when they are implicitly measured based on realized occupational sorting. Our measure of specificity, which is based on the arguably more primal skill demand, additionally permits investigation of specific mechanisms that likely contribute to major wage premia—particularly related to the role of heterogeneous demand on the basis of geography.

**IV. Skill variation across areas and earnings variability**

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

**A Geographic variation in skill demand**

As an example of what the granularity of our data allows, [Fig. 7](#) depicts variation across the more than 900 U.S. micropolitan and metropolitan statistical areas in the share of job postings for Business majors that seek cognitive skills. Areas with grayer shading have larger shares of Business major ads that demand cognitive skills. Contrast, for instance, Jasper, Indiana and London, Kentucky. Both locations have



**Fig. 5.** 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. Skill composites indicated by green markers are considered more general skills, skill composites indicated by blue markers are specific and skills indicated by gray markers are generic.

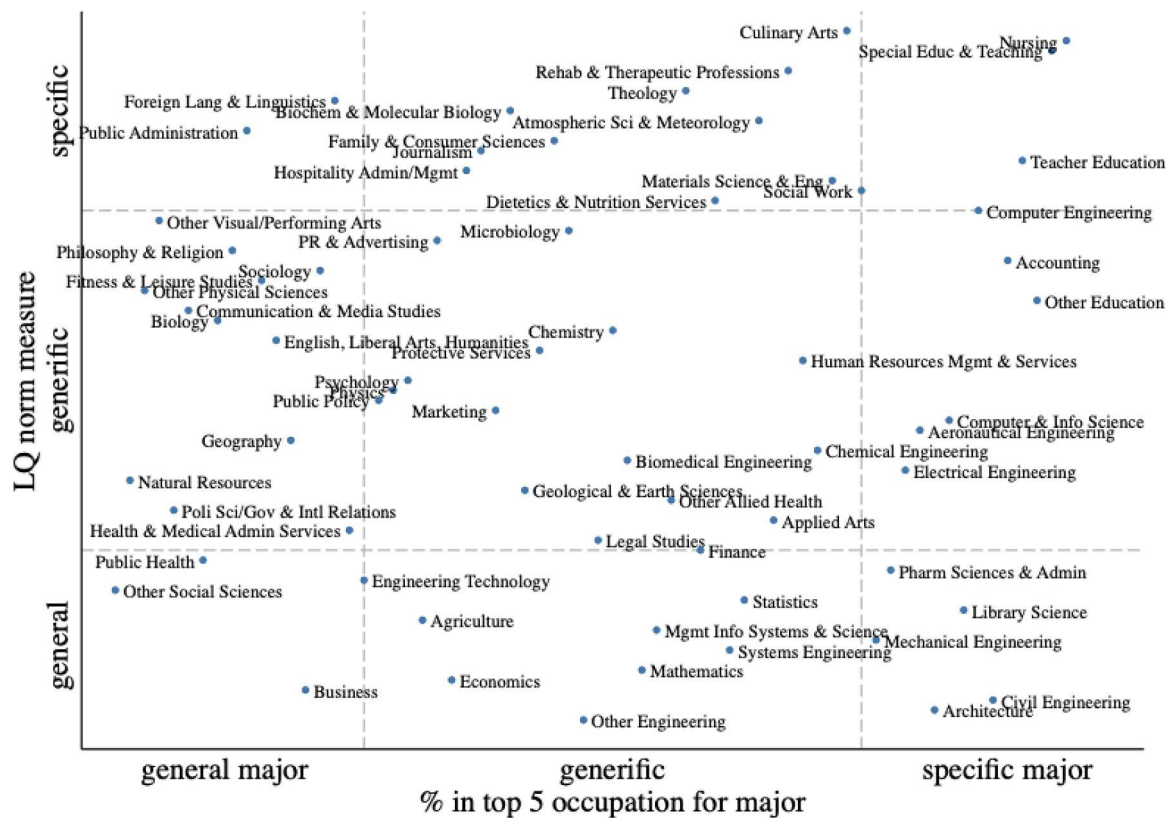


Fig. 6. Skill similarity index vs. occupational measure of concentration.

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), according to the sum of the absolute deviation of the major’s 11 LQs from 1: that is,  $\sum(\text{abs}(\text{LQ}-1))$ . The x-axis plots the rank of each major using the percentage of recent college graduates found in the five most frequent occupations for the major as measured in the American Community Survey (ACS). Majors with a lower percentage of recent graduates in the top five occupations are considered more general. Correlation = 0.469 (weighted by number of job postings) and 0.004 (unweighted).

similar quantities of job postings for Business majors (~500–700 job postings throughout our sample period). However, in Jasper, roughly 82% of job postings for Business majors demand cognitive skills compared to only 46% in London. Even though these two localities are only a 3–4 hour drive apart, employers in these areas demand very different skills from Business majors. Next, beam down to Roswell, New Mexico and nearby Andrews, Texas. These locales differ in both the quantity of job postings that list Business majors and the percentage of those job postings that demand cognitive skills.

Table 4 quantifies the amount of variation in skill demand captured by majors and places. Specifically, we construct over 15,000 major-MSA cells containing the share of ads seeking each skill composite; we then regress these shares for each composite on a set of fixed effects for majors, MSAs, or both.<sup>28</sup> We find majors alone account for the vast majority of the variation across cells—indeed, major accounts for over 90% of the variation in the demand for software and financial skills, and three-quarters for people management skills.<sup>29</sup> Geography by itself accounts for only 5–20% of the cross-cell variation in skill demand. When both sets of fixed effects are included, R-squareds are slightly less than the sum of when each set of fixed effects is included separately,

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

<sup>29</sup> If we weight cells using ACS person weights instead of the number of job ads, we find that major still explains the vast majority of the variation, although unexplained variation is about 50% larger.

indicating only modest correlation between majors and MSAs. However, there remains some unexplained variation, especially for organizational (24%) and communication (29%) skills. This remaining variation could reflect differences in the occupation or industry mix across places, as well as differences in employer characteristics.

### B Skill demand and earnings

Is this variation consequential in terms of wages? Fig. 3 showed substantial wage variation across majors and areas, and we now examine whether such differentials are (descriptively) associated with differences in skill demand. Returning to the previous examples, in Jasper, IN, the average adjusted hourly earnings among Business majors is \$44.30, which is about 5% higher than the adjusted hourly earnings of \$41.90 in London, KY, a place where employers demand relatively less cognitive skill of Business majors. The average adjusted hourly earnings in Andrews, TX (\$43.70) are 7.5% higher than in Roswell, NM, also consistent with a greater demand for cognitive skills.

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

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

where  $Y_{jk}$  is the log of mean hourly earnings (2019 dollars) among college graduates in MSA  $j$  with major  $k$  from the ACS, and  $PctSkill_{sjk}$  is a vector of skill demand in the MSA-major cell measured by the share of

ads that list each skill. The coefficient  $\beta_s$  indicates the approximate  $[(e^{\beta_s} - 1) \times 100]$  percent change in hourly earnings associated with a 100-percentage-point increase in the share of job ads requiring the skill. The inclusion of MSA ( $\gamma_j$ ) or major ( $\delta_k$ ) fixed effects isolates the association between skills and earnings that occurs within MSAs and majors, respectively. We weight each observation by the number of employed people in each cell using person weights from the ACS.<sup>30</sup>

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

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

Finally, specification (3) adds major fixed effects, absorbing any systematic pay differences across majors that occur in all labor markets. Fixed effects for majors explain a considerable share of the variation in cross-cell wages and greatly diminish the predictive power of the individual skill composites. Once we account for MSA and major, the remaining variation in skill demand measured by the skill composites explains relatively little additional wage variation (with the partial  $R^2 = 0.001$ ). As Table 4 showed, this is not because there is no remaining variation in skill demand within majors across areas, but its level does not systematically correlate with earnings. The only remaining statistically significant skill-wage correlation is that demand for basic computer skills is associated with lower wages. This association is small in magnitude: a 10-percentage-point increase in the share of ads desiring basic computer skills is associated with a 0.5% decrease in average wage. Taken in aggregate, these patterns suggest that majors can be thought of as portable bundles of skill composites.

**Panel B of Table 5** demonstrates the robustness of these results. We report only specifications that include MSA fixed effects, analogous to specifications (2) and (3) in **Panel A**. Specifications (4) and (5) adjust wages for individual-level demographics (age, sex, race, and a quartic in potential experience) before aggregating up to the MSA-major cell level. Specifications (6) and (7) weight each cell equally. Specifications (8) and (9) compute cell-level wages for workers under the age of 35 to

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

better reflect the wages of recent college graduates. The final two specifications, (10) and (11), restrict analysis to skills derived from job ads that require no more than minimal work experience in order to reflect entry-level skill demand among college graduates. Across all specifications, results are similar and the qualitative picture does not change. This suggests that the skill-wage relationship we document is not driven by demographics, density of majors, age profiles, or demand for experience by major.<sup>31</sup> The broad patterns hold: skill demand can explain an appreciable share of the cross-cell wage variation, but most of this can be accounted for by major-specific effects. Cross-area variation in composite skill demand within majors, as illustrated in Fig. 7, does not correlate with earnings. A caveat, however, is that this analysis is silent about whether variation in *detailed* skills within majors across places—as opposed to skill composites—relates to earnings.

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

## V. Conclusion

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

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

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

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

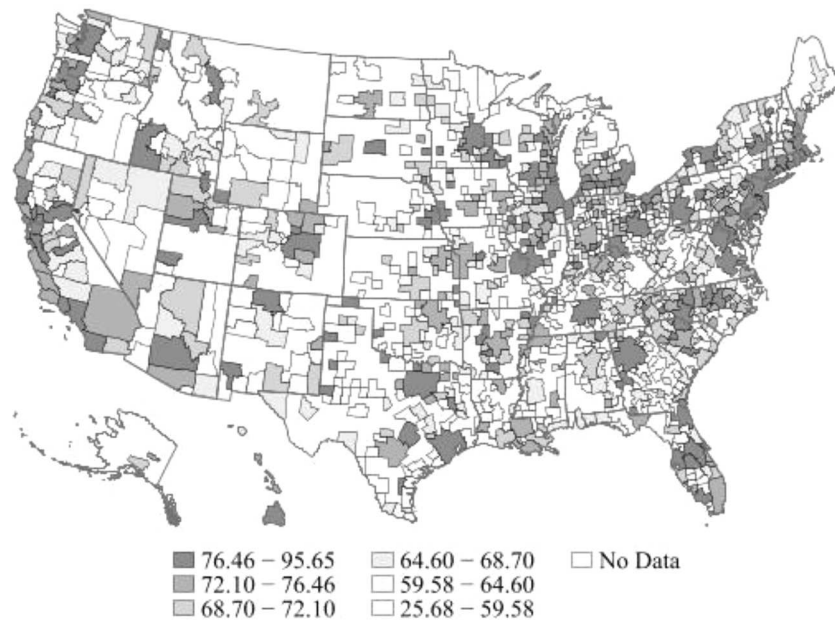


Fig. 7. Variation in cognitive skill demand across MSAs, business majors.

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

**Table 4**  
Fraction of variation in skill content explained by major and place.

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

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

We use data from the near universe of online job postings over the period 2010–2018 to develop measures of skill and major specificity based on location quotients (LQs) as well as measures based on cosine similarity to capture high-dimensional vectors of skills. These measures of skill and major specificity complement and extend recent developments in this space (e.g., Leighton and Speer 2020; Li et al., 2021) by focusing on specific skill demand manifested in job ads, thereby allowing us to compute such measures based on information that precedes the employment choices of individuals, a more proximate and direct signal of skill demand independent of occupational sorting.

We find that some majors such as Business and Engineering are general due to the fact that demand for most of their component skills is neither under- nor over-concentrated among job ads listing those majors. Other majors, such as Nursing, are more specific because they are

closely associated with skills that are not widely sought in the labor market for college graduates.

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

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

<sup>34</sup> Understanding major-specific wage premia in relation to detailed skills is a fruitful area for future research.

**Table 5**  
Relationship between skills and MSA-major average earnings.

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

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



## Data availability

The job posting data we use are proprietary but can be purchased from the company now known as Lightcast; we can share our code upon request with interested researchers.

## Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.labeco.2023.102429](https://doi.org/10.1016/j.labeco.2023.102429).

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