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What skills do employers seek in graduates? Using online job posting data to support policy and practice in higher education

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WHAT SKILLS DO EMPLOYERS SEEK IN GRADUATES? USING ONLINE JOB POSTING DATA TO SUPPORT POLICY AND PRACTICE IN HIGHER EDUCATION

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Abstract

Employers increasingly reach job seekers through online job postings, particularly for jobs requiring a higher education qualification. Job postings available online provide a rich source of real-time and detailed data on the qualifications and skills sought by employers across industries, occupations and locations. Using a sample of over 9 million job postings in four US states (Ohio, Texas, Virginia and Washington), this paper explores three questions. How does employer demand for graduate skills vary geographically, within and among occupations? For graduates in a general study field without a dedicated career vocational pathway, like sociology, what occupational clusters show evidence of employer demand, and what skills are sought? Given the high demand in the field of information and communications technology (ICT), are employers looking for ICT specialists open to hiring graduates from study fields other than ICT?

We find evidence of variation in occupational demand, and to some extent in skill demand, within occupational clusters across the four states. We identify three occupational clusters where sociology graduates are in most demand, with distinct skill profiles. We also find that, when filling ICT positions, a notable share of employers considers recruiting graduates from other fields of study while requiring those graduates have the right technical transferable skills.

Job posting data, we conclude, hold promise to complement existing labour market information systems and aid educators and policy makers in aligning labour demand and educational offerings. If analysed and disseminated effectively, such data could also assist students and workers in making learning and career decisions, for instance by identifying opportunities to build their own non-traditional path into high-demand, high-paying ICT occupations.

Résumé

Les employeurs sont de plus en plus nombreux à publier leurs offres d’emploi en ligne, notamment pour les emplois hautement qualifiés. Les offres d’emploi diffusées en ligne offrent une mine d’informations détaillées et en temps réel sur les diplômes et les compétences recherchés par les employeurs en fonction des secteurs d’activité, des professions et des zones géographiques. En s’appuyant sur un échantillon de plus de 9 millions d’offres d’emploi dans quatre États américains (Ohio, Texas, Virginie et Washington), ce rapport vise à répondre à trois questions : quelles sont les variations régionales de la demande de diplômés, au sein d’une même profession et d’une profession à l’autre ? Pour les diplômés d’une filière générale (sociologie) n’ayant pas suivi de formation professionnelle spécialisée, quels sont les groupes de professions pour lesquels on observe une demande de la part des employeurs, et quelles sont les compétences recherchées ? Les employeurs recherchant des spécialistes en technologies de l’information et de la communication (TIC), un domaine en forte demande, sont-ils ouverts à des diplômés provenant d’autres filières ?

Des éléments attestent d'une variation, entre les quatre États, dans la demande enregistrée au niveau des professions et, dans une certaine mesure, dans la demande de compétences constatée dans les groupes de professions. Nous avons recensé trois groupes de professions où les diplômés en sociologie sont les plus demandés, avec des profils de compétences distincts. Nous avons également constaté que, pour pourvoir les postes vacants dans le domaine des TIC, une proportion notable des employeurs envisagent la possibilité de recruter des diplômés d'autres filières, en imposant toutefois à ces derniers d'être dotés des compétences techniques transférables requises.

En conclusion, il ressort de notre étude que les données issues des offres d'emplois en ligne pourraient apporter un complément aux systèmes d'information existants sur le marché du travail, et aider les spécialistes de l'éducation et les responsables de l'action publique à aligner l'offre de formations sur la demande de main-d'œuvre. Si elles sont analysées et diffusées avec efficacité, ces données pourraient aussi aider les étudiants et les travailleurs à prendre des décisions éclairées quant à leurs études et à leur carrière, par exemple en identifiant les possibilités d'accéder, en construisant leur propre parcours de formation, à des emplois en forte demande et offrant une rémunération élevée dans le secteur des TIC.

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1. Introduction

1.1. Objectives and research questions

This Working Paper forms part of the OECD Higher Education Policy team's programme of work on the labour market relevance and outcomes of higher education. The paper offers an exploratory analysis of large-scale online job posting data using over 9 million job postings in four US states – Ohio, Texas, Virginia and Washington – with two main objectives. First, it aims to shed light on the skills employers in these states look for in higher education graduates, with particular attention paid to transferable skills, defined as skills that are not specific to a job or occupation but can be used across jobs and occupations. These findings may be read jointly with the report *Labour Market Relevance and Outcomes of Higher Education in Four US States: Ohio, Texas, Virginia and Washington*, which provides an assessment of the alignment of higher education systems and labour markets in those four states and state-specific recommendations to improve alignment (OECD, 2020[1]). This Working Paper also offers insights into the potential value online job posting data may have to answer questions of interest to higher education stakeholders.

This Working Paper aims to address the following questions:

- How does the current employer demand for different types of higher education qualifications and skills vary by occupational cluster in the four US states? In particular, what is the employer demand by occupational group for transferable skills such as cognitive, socio-emotional and technical skills, compared to job-specific skills?
- How can job posting data shed light on the potential career trajectories of students and graduates from fields of study not directly connected to specific occupations?
- How can job posting data be used to identify the range of graduate profiles that employers look for in their hiring processes in the ICT sector, where the number of ICT graduates is insufficient to meet growing labour market demand?

This paper demonstrates that "big data" in the form of online job postings can be a valuable tool in addressing these questions. Timely information on the qualifications and skills needed to succeed in the labour market is important for higher education students and graduates, policy makers, higher education leaders and others who are working to strengthen the links between higher education and the labour market. However, this information is difficult to obtain from traditional sources such as job vacancy survey data or employer surveys about skill needs. The former often lack granularity to identify skills needed, and the latter are expensive to conduct on a large scale.

Online job posting data, properly analysed, can complement traditional sources of labour market information. The data's key benefits are derived from their real-time availability, large size, and the rich information they contain. This includes detailed information on job characteristics such as occupation, industry, job tasks and location of the employer, as well as on the educational level, credentials and skills required of applicants. As job posting data provide information on the skill profile employers seek in addition to formal education and training requirements, these data can help policy makers and institutional leaders fund and design educational offerings that meet skill needs, contributing to the alignment of labour supply and demand. At the present time, while some US states have begun using job posting data to analyse their labour market, big data sources are not systematically used as part of states' labour market information (LMI) systems (OECD, 2020[1]). There seems to be scope for greater integration of these data sources into existing LMI systems, and for greater use of these data by policy makers and educators to support the development of labour market relevant education and training. In addition, these data have the potential to help students better plan their study pathway and to help graduates better match themselves to available job opportunities.

After briefly discussing the literature on employer skill demand and changes in occupational tasks in Section 1.2, we introduce the Burning Glass Technologies (BGT) dataset[1] and its benefits and limitations, then outline our sample construction in Section 2. In Section 3, we present the skills framework developed to support the analysis, which aims to delineate the demand for job-specific skills and for different types of transferable skills, namely cognitive, socio-emotional and technical transferable skills. While a range of techniques, including machine learning and keyword searches, hold promise to improve the efficiency of categorising skills, the approach taken in this paper allows us to categorise transferable skills with more precision. We also outline the two measures of skill demand we employ in the analysis. These quantify the demand for individual skill categories along two dimensions: (i) how widely skill categories are requested across any particular set of job postings, measured by the share of job postings that list these skill categories (prevalence), and (ii) how important is the skill category compared to other skills categories in any particular set of job postings, measured as the share of total skills they represent in the average posting (intensity).

Section 4 shows that according to these two skill measures, education requirements and skill demand vary considerably across occupations, and to some extent across states within the same occupation. Section 5 presents two analyses on graduate trajectories in the four US states under review, to demonstrate the potential for this type of data to inform higher education policy and practice, as well as the study and career choices of students and graduates. The first analysis focuses on the occupational demand for graduates with a sociology degree, as an example of a field of study with few direct connections to specific occupations. We find that 60% of the demand for this field of study in online job postings is concentrated in three occupational clusters, namely community and social service occupations; management occupations; and education, training and library occupations. The second analysis focuses on the qualifications and skill requirements contained in job postings for workers in information and communications technology (ICT) occupations. This analysis aims to shed light on whether employers looking to hire ICT specialists also consider graduates from other fields of study for these positions, and examine the skills they expect these candidates to have. Our results show that besides graduates from ICT programmes, graduates from engineering or business management, marketing, and related support services with the right technical skills are most suited to fill ICT specialist positions. Finally, Section 6 concludes and highlights areas for further analysis.

1.2. Key findings in the research literature that motivate the analysis of employer skill demand

The changes to work requirements that have taken place across many OECD countries over the past 30 years have been accompanied by three widely documented phenomena, namely the "routinisation" of jobs, job polarisation and skill-biased technological change. In the literature, routinisation refers to the automation of tasks previously performed by workers. The increased use of technology in production, for instance in the form of industrial robots, replaces human workers for tasks like organising, storing, retrieving and manipulating information (Autor, Levy and Murnane, 2003[2]). This automation of routine tasks has been

[1] While BGT offers data on several countries, we only focus on the US dataset in this report. All BGT data references are thus limited to the United States only.

identified to affect primarily middle-skill workers who thus suffer from high risks of job loss (Goos, Manning and Salomons, 2014[3]). Displaced workers then often have to make difficult transitions to jobs in high-skill professions (Bechichi et al., 2018[4]), or move into low-skill occupations. This results in job polarisation: the simultaneous hollowing out of middle-skill jobs and increase in employment at both ends of the occupational skill distribution (OECD, 2017[5]).

Numerous studies suggest that job polarisation has increased inequality in the United States over the past decades, with wages in high-skill jobs rising faster than wages in low-skill jobs (Acemoglu and Autor, 2011[6]; Autor, Katz and Kearney, 2008[7]). The literature argues that this is because a large share of low-skill jobs is concentrated in the service sector, involving manual, non-routine tasks that are difficult to automatise. High-paying jobs, on the other hand, tend to involve cognitive, non-routine tasks, and exhibit increased productivity due to the use of technology. This complementarity between high levels of skill and technology has been coined “skill-biased technological change”.

Recent research has increasingly focused on the types – in addition to levels – of skills in demand in the labour market, with a particular emphasis on transferable skills that may help individuals move between jobs and occupations during their careers. Besides increasing returns to cognitive skills, socio-emotional skills are becoming more important as computers substitute for non-interactive tasks. Several papers provide evidence of complementarities between cognitive and socio-emotional skills, showing that the interaction of both types of skills generates a positive return in addition to the return to each type of skill (e.g. (Weinberger, 2014[8]; Deming, 2017[9]; Deming and Kahn, 2018[10])). Our skill demand analysis thus pays particular attention to cognitive and socio-emotional skills, along with other transferable skills.

A number of studies have used BGT data to analyse recent changes in employer skill demand. One key result is the observation of an increase in demand for qualifications and skills in occupations that previously advertised lower job requirements, such as level of studies or years of experience, and that demanded fewer specific skill requirements (Modestino, Shoag and Ballance, 2019[11]). This development is particularly notable for ICT skills, which results in computer scientists being in higher demand, but also results in higher ICT skill requirements for non-computer scientists (Restuccia, Liu and Williams, 2017[12]). The increase in demand for education credentials is particularly pronounced in occupations that lack good alternatives for identifying skill proficiency (Modestino, Shoag and Ballance, 2019[11]). Conversely, occupations with either strict licencing requirements, training programmes that are recognised and trusted by employers, measurable skill standards, or a combination thereof (e.g. respiratory therapists or radiology technicians) do not tend to exhibit this trend of increased demand for education credentials (Burning Glass Technologies, 2014[13]). The increased demand for higher qualifications and skill requirements suggests the importance of obtaining higher education qualifications and in-demand skills, and in signalling these effectively to employers.

The demand for digital skills is growing rapidly. For example, a BGT analysis shows a disproportionately fast growth in the number of middle-skill jobs demanding digital skills, and that these jobs also advertise a higher wage, on average, compared to middle-skill jobs without digital requirements (Burning Glass Technologies, 2017[14]). Based on the analysis of job requirements, the study finds that digital skills range from basic software proficiency, programming and social media skills, to occupation-specific digital skills, and that acquiring relevant digital skills can serve as a career advancement tool into middle- and high-skill jobs for workers who have previously worked in lower-skill jobs. On the other hand, jobs without any digital skill requirements are concentrated in few industries, such as transportation or construction. The increasing importance of digital skills for middleand high-skill jobs provides another reason to focus our analysis on transferable skills, which include digital skills.

2. Burning Glass Technologies data and sample selection

2.1. Data collection methods and representativeness

2.1.1. The Burning Glass Technologies database

The BGT database consists of information taken from online **job postings** (see Box 2.1 for a definition). For this, BGT collects job postings from over 40 000 distinct job boards and company websites, using **web-scraping** techniques. They then **de-duplicate** vacancies that appear on multiple websites to obtain unique job postings. The text of every unique, advertised position is **parsed**, categorising the job postings into a set of variables where the relevant information is available in the advertisement. For instance, retrieved information may contain geographic location, occupation, industry, required skills, and required education and experience levels. Figure 2.1 presents an example of a job posting being categorised into several variables. Some of the variables in the BGT database, such as occupation and location, are standardised using official classifications from the country the job posting is from, making it easy to link these data to other datasets. For a more detailed description of BGT's data collection process, see Carnevale, Jayasundera and Repnikov (2014[15]).

Box 2.1. Key terms

Job postings vs. job openings

Job postings or job advertisements are published job offers. When either term is used in this paper, unless stated otherwise, it refers only to job postings or advertisements published online, as the BGT database only contains these job postings. Job openings or job vacancies, on the other hand, are "real" openings, where a firm is looking to hire someone for the advertised position. A job opening or vacancy may be published or not. Job openings are the true measure of labour market demand, which we would like to study. As a proxy, we analyse online job postings detected by BGT.

Web-scraping

Web-scraping refers to the process through which data is extracted from websites, which is typically performed in an automated way. BGT "captures" (i.e. detects or accesses) as many job postings published online as possible and collects information from these postings.

De-duplication

The process of eliminating duplicates when job postings appear on multiple websites. For instance, if BGT finds the same job posting on a company website as well as an online job board, the second posting is deleted so that the posting appears in the database only once.

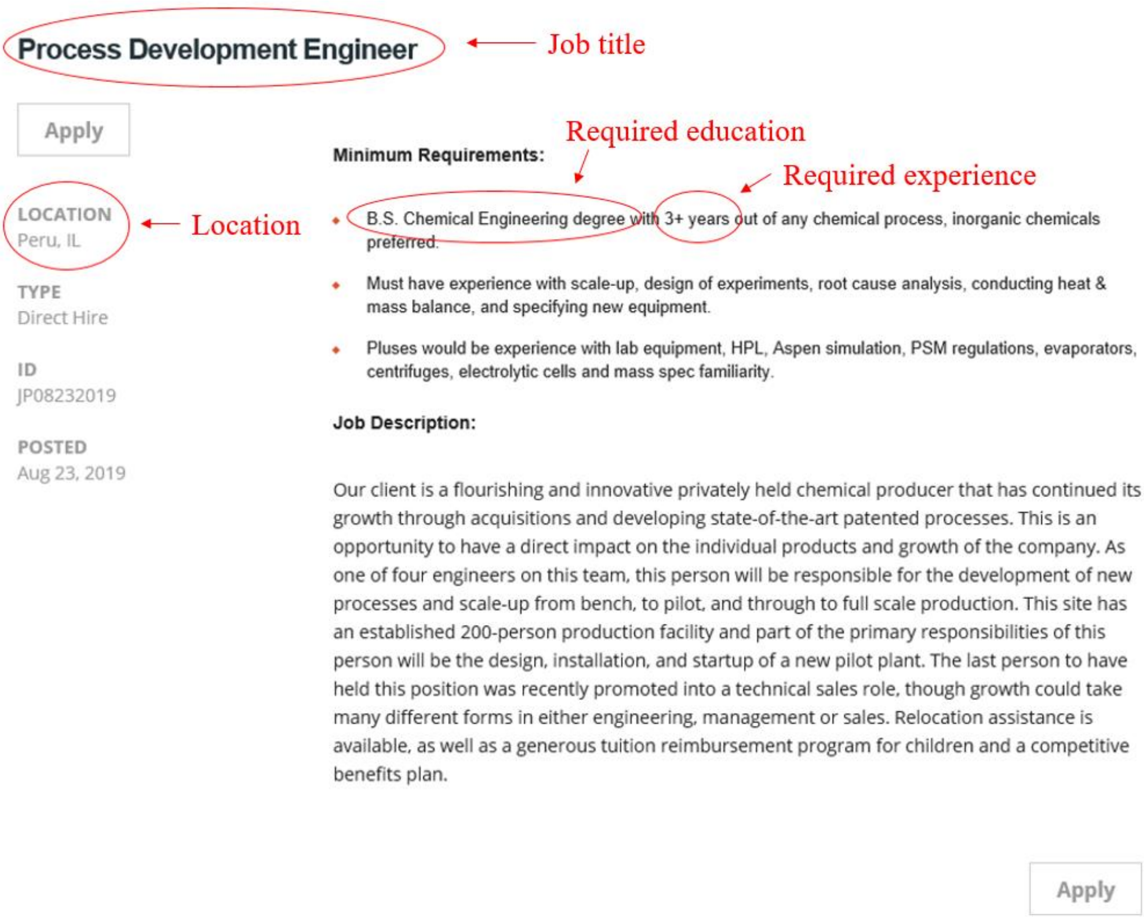
Text parsing

Text parsing refers to the process through which machines "read" the job postings, identifying relevant information such as the job title, occupation, education and skill requirements, when these are mentioned in the text. Text parsing allows for translation of plain text in the job postings to a set of variables in the database. An example of some of the information that has been extracted with this method is given in Figure 2.1.

Algorithm

A finite set of instructions to solve a problem or to conduct a computation, typically carried out by a computer. BGT uses algorithms to direct the machines to find job postings online and to categorise their information.

Figure 2.1. An example of a web-scraped job posting



Source: Burning Glass Technologies, (n.d.[16]), "Labor Insight™ Real-Time Labor Market Information Tool," https://www.burning-glass.com/products/labor-insight/ (accessed 13 October 2019).

BGT scans the internet every day and finds around 3.4 million unique active postings in the United States at any given time. They estimate that 85% of all **job openings** in the United States are posted online (Burning Glass Technologies, 2020[17]); while Carnevale, Jayasundera and Repnikov (2014[15]) estimated in 2014 that 60-70% of all job openings were posted online. For job openings with a bachelor's requirement or higher, the latter estimate that over 80% are published online. One likely reason for the difference in estimates is the time of publication. As companies have increased their online presence over the past years, so has their tendency to advertise job postings online (McKinsey Global Institute, 2015[18]). Thus, more recent data from online sources are likely to have a higher coverage of all job postings, on- and offline. Moreover, BGT's search **algorithms** have improved, meaning the share of job postings they capture out of all online job postings has grown over time. To account for this increase in the number of job postings available in the

BGT database, we only study relative changes over time, controlling for the absolute number of postings per year.

The accuracy of the data we analyse does not only depend on BGT's ability to capture relevant job postings, but also on how accurately the information contained in the postings is categorised into variables. BGT's ability to parse a posting correctly, that is for the machine to "understand" the information in the posting, has been tested (Carnevale, Jayasundera and Repnikov, 2014[15]). When education requirements were included in the job advertisement, BGT identified them correctly 85% of the time. This means that in 15 out of 100 postings with education requirements, the information stored in the BGT database is false, as the machine was unable to correctly "read" the education requirement from the plain text job posting. Geographical variables, skills, occupation title, and two-digit occupation codes are classified at a greater than 80% accuracy. The share drops to 73% for the most granular occupation classification (6-digit occupational clusters in the 2010 US Standard Occupational Classification (SOC) system). Carnevale, Jayasundera and Repnikov (2014[15]) explain this difference by the fact that BGT derives occupations from the job title when the occupation is not explicitly stated in the job advertisement. This is more difficult to do at a greater level of granularity. To ensure the highest level of representativeness possible, we refrain from analysing employer demand in narrowly defined occupations. Instead, we keep occupations at the most aggregate, two-digit SOC level in our analysis, where parsing accuracy is highest (over 80%).

Information listed in job postings must be interpreted carefully. Job advertisements often include skills that are required but difficult to find among applicants. For instance, positions in hospitality or customer service more often request basic mathematical skills in their postings compared to all occupations, whereas ICT positions often emphasise soft skills (Burning Glass Technologies, 2015[19]). This suggests that caution should be used in interpreting the intention of employers in including certain skills in postings – it may reflect both the importance of these skills for the position and the expected difficulty of finding workers with these skills. While all skills posted are either important for the job or scarce among applicants, other skills not explicitly mentioned might still be necessary for successful applicants to have.

2.1.2. Advantages

The key advantage of the BGT data is their size and level of detail. They cover a wide range of vacancy sources and comprise a rich set of information from each job posting. Each advertisement can be categorised into over 70 variables. The combination of the size and granularity of the data makes it possible to study labour demand variations at a very detailed level, such as within occupations and small regions. This is usually not possible with traditional survey-based data, due to much smaller sample sizes.

The data also permit the analysis of recent changes in job characteristics, such as job tasks as well as qualification and skill requirements. Traditional vacancy data typically provide little information on the job's task content or on required qualifications and skills for candidates. These details are sometimes supplemented by information sources on occupational job tasks, such as the US Occupational Information Network (O*NET)[2], but the occupational descriptions are not updated as frequently and are derived from job

[2] The O*NET programme describes the activities and tasks performed in an occupation as well as the knowledge, skills, and abilities required to carry these out. The occupations follow the United States' Standard Occupational Classification system (National Center for O*NET Development, n.d.[28]).

characteristics of the whole workforce[3] rather than from the expectations of current employers engaged in hiring. When job tasks within occupations change over time requiring workers to have different or higher levels of skills, this likely becomes apparent in the skill requirements for recent hires before affecting the whole workforce of that occupation. Thus, small or early changes in a job's characteristics can be observed more precisely in the BGT data than in databases like O*NET. Lastly, labour force surveys may serve to analyse changes in the supply of qualifications and skills, but not their demand. The BGT dataset hence presents a complementary data source to existing ones, and is particularly suited to analyse recent developments in labour demand.

Additionally, online job postings are becoming increasingly informative. Not only are data collection methods and parsing algorithms improving over time, job postings themselves are also becoming increasingly descriptive. Hershbein and Kahn (2018[20]) found that in 2015, vacancies were 12% more likely to include educational and experience requirements and certain cognitive skills than in 2007.

BGT data are relatively representative for occupational analysis, especially for later years. Hershbein and Kahn (2018[20]) studied BGT's representativeness across occupations in the United States by comparing it to Current Population Survey's (CPS) new jobs data. Using the share of new job postings by occupation to compare it to the share of new jobs by occupation in the CPS data, they find that any differences between the two have remained stable over time or have slightly decreased since 2007. The largest deviations in 2007 are for computer and mathematical occupations, at 11-percentage points overrepresentation in the BGT data, and for construction, where job advertisements in the BGT data are underrepresented by 7 percentage points.

Carnevale, Jayasundera and Repnikov (2014[15]) compare the BGT online job advertisements to job openings and new hires in the US Job Openings and Turnover Survey (JOLTS) from a previous time period (i.e. lagging the JOLTS data). They find that BGT online job advertisements and JOLTS openings and new hires follow a similar trend. This result becomes even stronger when we consider that JOLTS data and BGT measure slightly different things. While BGT data capture as many new online job postings as possible every day, JOLTS data capture labour demand in a random sample of establishments at a certain day every month, potentially repeating vacancies if they have not been filled within a month.

2.1.3. Limitations

While the trend in the BGT data matches JOLTS data rather well, the BGT data have been found to be more volatile, meaning that the BGT data fluctuate more around their average value (Carnevale, Jayasundera and Repnikov, 2014[15]). This means that the BGT data are less reliable when only looking at a short period of time. To deal with the relatively high volatility of the BGT data and to avoid seasonality, we aggregate the data by year.

Since not all vacancies are published online, the BGT data cannot represent all job openings. While the occupational distribution and the change in the number of published job advertisements matches other representative data sources well, this is not the case for all variables. Carnevale, Jayasundera and Repnikov (2014[15]) estimate that 80-90% of job postings in the United States that require at least a bachelor's degree can be found online, whereas only 40-60% of advertisements requiring a high school degree are posted online. This share is lowest for openings seeking associate's degree holders, at 30-40%. In line

[3] Every year around 100 out of 974 occupations are updated though surveys of job incumbents and occupational experts (National Center for O*NET Development, n.d.[29]).

with this, BGT states that jobs in small businesses as well as lower-income and lower-skill jobs are underrepresented in the BGT dataset (Burning Glass Technologies, 2020[17]). For the purpose of our analysis of labour demand for higher education graduates, most job postings can be found online, with the exception of job advertisements seeking associate's degree holders. A lower relative number of online job postings is not a problem in itself, given the size of the dataset. However, if the postings that are published online differ from those that are only accessible offline along the dimensions we study (occupational distribution, skill demand, or geographical location, for instance), then we will obtain biased results. This bias is small when the data cover a high share of job postings and when the difference in the variables we study is small between postings that are online and those that are not.

Another limiting factor is that not all postings contain information on all variables, which means that we do not have information on the demand for qualifications and skills for every posting. We cannot differentiate whether an employer did not have any requirements, did not provide the information in the job advertisement but implicitly demands it, infers qualifications or skills from other requirements (e.g. a higher education degree might be demanded to ensure a certain level of critical thinking), or whether BGT's algorithms did not pick up the information. For instance, only half of all postings in the BGT database from 2010-18 specified education requirements, but this does not necessarily mean that all other jobs could be carried out without formal education. While it is possible to infer educational requirements from other job postings in the same job category through an imputation method (Hershbein and Kahn, 2018[20]), we restrict the analysis to those observations that explicitly mention a higher education requirement. The potential bias arising from this decision is mitigated by the fact that the probability to post an educational requirement is highest for jobs in which workers typically have higher education (Hershbein and Kahn, 2018[20]).

Another challenge is that the heterogeneity of workers and firms' search behaviour may create a bias. For instance, if certain industries are less likely to post job advertisements online, their lower frequency of postings could be misinterpreted as lack of labour demand. Similarly, if some groups of workers send out more unsolicited applications, firms might post fewer job advertisements for these types of workers. Moreover, some firms might advertise one job but actually recruit several applicants, or they might not employ anyone at all. This could happen, for instance, when employers plan to hire at a later date but wish to make an early assessment of the potential candidate pool (Carnevale, Jayasundera and Repnikov, 2014[15]). In addition, individual jobs differ in their hiring and separation rates. For instance, different occupations within the same firm may have different recruitment cycles. Equally, a position in the same occupation might have a higher turnover across different industries. In relation to the average firm, Davis et al. (2009[21]) find that growing firms (and similarly, growing industries or occupations) are overrepresented in job posting data.

While the data present considerable benefits and opportunities in assessing detailed labour demand, it is important to keep in mind that the BGT dataset does not cover all job openings, and those that are included do not always explicitly specify all relevant information. By studying *relative* differences in the demand for qualifications and skills across states, occupations, and time, we avoid a bias arising from these factors as long as they affect the variables we study equally. However, the heterogeneity of workers and firms likely affects employers' propensity to publish job advertisements online and the extent to which they explicitly demand qualifications and skills. These caveats need to be kept in mind when interpreting our results.

2.2. Sample selection

We restrict the data to the states under analysis in the OECD review *Labour Market Relevance and Outcomes of Higher Education in Four US States: Ohio, Texas, Virginia and Washington* (OECD, 2020[1]) and to the years 2010 to 2018. This gives access to nearly 29 million job postings. Although the data in our sample are not as recent as would be feasible, the time period we use aligns with that considered in the review of the four US states mentioned above and allows us to demonstrate the potential value of these data for policy and practice in higher education. We further limit the sample to job advertisements that demand an associate's degree or higher, leaving us with 9.7 million observations. In order to carry out occupational analyses, we focus on job postings that BGT was able to attribute to an occupation. This gives us a total of 9.3 million job postings, with the number of observations increasing across the period, from 580 000 in 2010 to 1.5 million in 2018.

3. Categorising skills and quantifying skill demand

BGT harmonises the skills found in the job postings. For instance, teamwork and collaboration are combined to "teamwork/collaboration", and words that have several accepted spellings are considered interchangeable. We use these harmonised skills without performing any other cleaning procedures. There are over 14 000 unique harmonised skills in our sample. The skills in the dataset range from general skills such as "communication skills" to specific skills such as "store management" or "Python." Nearly 99% of the postings in our sample contain at least one skill requirement. Of those, the median posting requires 12 skills and the average number of skills is nearly 13. BGT has developed skill categories to organise these skills. However, the BGT skill categories tend to reflect industry categorisations, such as "retail industry knowledge" and "emergency and intensive care", rather than skill or competency categories, with the exception of a limited number of transferable skill categories, such as basic and advanced ICT software.

Some analysis of BGT data only uses information about the job description, occupation and educational requirements, without analysing the skill requirements included in the postings (e.g. (Modestino, Shoag and Ballance, 2019[11])). When the skill requirements are not used, researchers have sometimes assessed skill demand by matching the occupational SOC classification as categorised by BGT with skills data from O*NET (e.g. (Beblavý et al., 2016[22])). This allows researchers to extract information on the skills typically required in a given occupation without having to categorise the thousands of skills provided in the BGT data. The limitation of this approach is that the shifts in occupational skill requirements that have not yet been captured by O*NET will not be identified. Furthermore, with this method, it is not possible to observe variation in skill requirements within an occupation across other dimensions available in BGT job postings, such as location or time. This is because the skills inferred from O*NET are the same across the United States and the O*NET typology is infrequently updated.

In studies where the skills information contained in the BGT data is used, a keyword search across all skills is often performed (e.g. (Deming and Kahn, 2018[10]; Hershbein and Macaluso, 2018[23]; Hershbein and Kahn, 2018[20])). For instance, Hershbein and Kahn (2018[20]) examine the prevalence of cognitive skill requirements in job advertisements over time by using a set of keywords to identify skills that are deemed cognitive, such as "research" and "analysis". This avoids having to classify the vast amount of skills individually, but runs the risk of capturing skills that include the keywords but have a different meaning, and misses synonyms.

We take a systematic approach to analysing the skills information included in the BGT data to obtain a comprehensive picture of the skills required of higher education graduates. For this, we develop a simple skills framework, which has the advantage of helping to categorise a large variety of skills in high-order categories, rather than only focusing on a restricted number of skills of interest.

The OECD has developed different skills frameworks in recent years for different purposes. For example, the OECD Learning Compass 2030 is a "future-oriented conceptual learning framework that supports a common understanding of the knowledge, skills, attitudes and values that are important for students" (OECD, 2019[24]). The OECD Skills for Jobs indicators focus on competencies needed at work and the alignment between the skills people have and those in demand in the labour market, while the skills framework underpinning the OECD Survey of Adult Skills (PIAAC) aims to identify skills considered to be key information-processing skills for adults to function in a modern economy.

The framework used in this Working Paper, presented in Annex A, recognises these different perspectives. It contributes to work across the OECD that focuses on helping individuals, policy makers and educational leaders better understand the alignment between the skills of individuals – in this case, the skills of higher education graduates – and those that employers seek. While the framework's primary purpose is to support a point-in-time analysis using US data from four states, its development contributes to ongoing research at the OECD and beyond to expand the use of big data for education and employment policy.

To develop the skills framework, three analysts grouped the skills into four main categories: cognitive, socio-emotional, technical transferable, or technical job-specific. The first three categories describe skills potentially applicable to a large range of jobs and occupations, whereas the latter group comprises skills that are particular to a specific job or occupation. The first three groups are those of most interest to our work, as they provide information about the various types of transferable skills demanded by employers. For this reason, we assign four to six subcategories to each of them to analyse the demand for transferable skills in greater detail. The category of job-specific skills helps assess the balance in the demand between transferable and job-specific skills.

To categorise the skills contained in BGT data, we use the job postings that are i) for jobs in the United States[4], ii) require a higher education qualification, iii) have been assigned an occupation and iv) in 2018 only. By expanding the sample from the four states to job postings from all of the United States, we reduce the influence of states with large economies, such as Texas, on the skill categorisation. Categorising skills in 2018 only enables us to focus on the skills that were recently in demand, although it may mean that the skill categorisation is less relevant for earlier years. While the data for this set of job postings contain around 14 000 unique skills, we restrict the mapping to the 564 most frequently demanded skills, which cover 75% of all skills in these job postings. This decision was based on efficiency considerations – a 70% threshold would have required categorising 425 skills, whereas to cover 80%, we would have had to assign groups to 759 skills. A group of three analysts then attributed the 564 most prevalent skills from the BGT data to one of the categories and subcategories in our framework. As an example, the mapping of a selection of cognitive skills is presented in Table 3.1 below.

[4] The data include job postings from the 50 US states and Washington DC, American Samoa, the Commonwealth of the Northern Mariana Islands, the Commonwealth of Puerto Rico, Guam, the Republic of Palau, the Republic of the Marshall Islands and the US Virgin Islands.

Table 3.1. Skills framework: Cognitive skill categories and subcategories

Cognitive skill	Standardised skills from Burning Glass Technologies
Critical thinking	Critical thinking Analytical skills Writing Research Online research
Communication	Communication skills Written communication Verbal/oral communication Oral communication Presentation skills
Decision-making	Decision-making Strategic thinking Strategic planning Strategic development Thought leadership
Problem-solving	Problem-solving Creative problem-solving
Numeracy/Quantitative reasoning	Statistical reporting Calculation Statistics Statistical analysis
Meta-cognition and ability to learn	Quick learning

The remaining 25% of skills that have not been categorised are more likely to be job-specific. The more often a skill is mentioned across all postings, the more likely it is that the skill is valued across different occupations, making it a transferable skill in our definition. To check the potential bias that our framework produces, we selected a random sample of 100 skills among the 25% of unclassified skills and found that 66 of the 100 skills are technical job-specific skills, 32 skills are technical transversal skills and 2 are socio-emotional skills. When weighting the 100 randomly drawn skills by frequency of appearance, technical job-specific skills comprise 52% of skills, technical transversal skills contain 48% of skills, and the share of socio-emotional skills drops to just over 0%. Our results will therefore underestimate the prevalence of job-specific skills, as well as technical transferable skills.

With this caveat in mind, two alternative and complementary measures of skill demand were developed to assess the demand of different skill categories: prevalence and intensity.

Skill prevalence:

The share of job postings within an occupation that require a particular skill category (e.g. socio-emotional skills). This tells us how broadly this type of skill is required in an occupation. If the share is close to 100%, the skill category is highly demanded across job postings within the occupation. A low share (close to 0%) means that most jobs in an occupation do not require the skill category. Hence, the "prevalence" refers to the prevalence of skill demand within an occupation.

A drawback of this measure is that it ignores the number of skills per posting that fall into the skill category under examination, since a job posting will count towards the share of postings requiring socio-emotional skills if at least one of the listed skills falls in that category. In other words, it does not distinguish whether the posting only requires one socio-emotional skill out of many, or if all of the skills the job posting requires fall in the category of socio-emotional skills. Moreover, an increase in the total number of skills listed per job posting will most likely increase the prevalence (the more skills are listed in an advertisement, the higher the probability that at least one skill falls into a given skill category). We therefore define a second skill measure, intensity.

Skill intensity:

The share of a particular skill category among all skill requirements for the average posting in a particular occupation. To calculate the skill intensity, we first compute the share of the skill category among all skills for every job posting, then average these shares across all postings in the particular occupation.[5] This measure assesses the relative "importance" of a skill category. A share of 100% means it is the only skill category required in the average posting, whereas a share close to 0% indicates that many other skills are necessary for the average job in an occupation.

A limit of this skill measure is that skill categories that include more facets of a similar skill will most likely exhibit a higher share by construction, since more individual skills are necessary to describe the skill set. For instance, "verbal/oral communication skills" and "written communication skills" would be considered two separate skills, although closely related, whereas "teamwork/ collaboration" has been grouped in the data as one skill and has fewer close complements. Another drawback is that the number of skills categorised as technical job-specific, for instance, is much greater than for those that are socio-emotional, making it difficult to compare skill demand across skill categories with this measure. Perhaps the biggest limitation of measuring the skill intensity is that not all skills may be needed in the same proportion on the job, but the skills are given equal weight in this measure. Thus, if a job advertisement lists many skill requirements but only a few skills are crucial, these skills will be considered less important by this measure than they might be in the perspective of the employer posting the advertisement.

4. Occupational demand in four US states

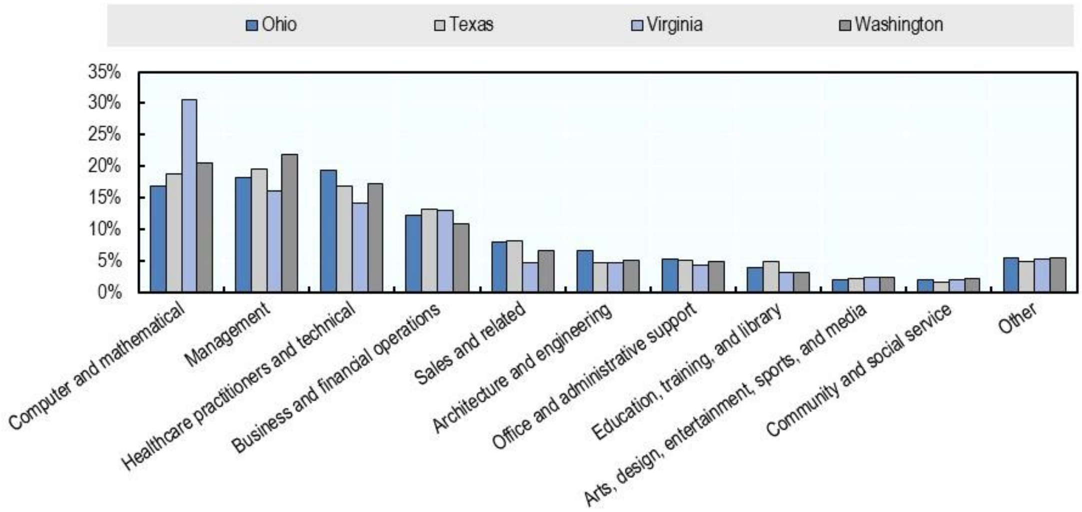
Large-scale job posting data can help assess employers' demand for education and skills over time and across a range of variables, including location and occupation, thus constituting a helpful data source to supplement existing labour market information systems. The first analysis in this Working Paper focuses on the regional and occupational differences in employer demand across four US states explored in a recent OECD review, Ohio, Texas, Virginia and Washington (OECD, 2020[1]). These four states are highly diverse from a geographic, demographic and socio-economic perspective, and therefore provide interesting comparators to explore regional variation in employer demand in a large labour market as that of the United States. Figure 4.1 shows the occupational distribution by state of job postings that demand an associate's degree or higher in 2018. This sheds light on the geographical distribution of job postings for higher education graduates by 2-digit SOC occupation, though the figure might understate the demand for occupations with

[5] The skill intensity measure excludes job postings without skill requirements (around 1% in our sample) in the average since the computation of the skill share is not possible for these postings: both numerator (skills from a given skill category) and denominator (all skills in the posting) would be zero, which is mathematically undefined.

a large share of associate's degrees, as they are underrepresented in the data compared to bachelor's degrees and higher (see Section 2.1.3). While not examined here, changes over time and within-state variation would be interesting dimensions to explore in future analysis.

Figure 4.1. Occupational distribution of online job postings requiring higher education in 2018

Percentage of jobs in the listed occupational clusters in Ohio, Texas, Virginia and Washington



Notes: The data show the occupational distribution by state of job postings that demand an associate's degree or higher in 2018. The occupations are aggregated following the 2-digit 2010 SOC codes; the ending "occupations" is omitted in the labels for brevity. The data are arranged in descending order of the number of job postings by occupational cluster across all four states. Displayed are the ten most frequently occurring occupational clusters, which make up around 95% of all postings in every state; the remaining occupational clusters are aggregated in the category "Other".
Source: Adapted from Burning Glass Technologies (2019[25]), *NOVA™ Job Feed data file*. The sample is restricted to postings in Ohio, Texas, Virginia, and Washington in 2018 that BGT could attribute to an occupation and that require an associate's degree or higher.
Data available at: https://www.oecd.org/education/higher-education-policy/EDU-Working-Paper-231-data.xlsx.

Figure 4.1 shows that while the occupational distribution of postings is similar across states overall, there are important differences such as for computer and mathematical occupations. While this occupational cluster comprises 30% of job postings in Virginia, highlighting the important role of the state's technology sector in recent employment opportunities (OECD, 2020[1]), these occupations cover between 17% and 20% of postings in the other three states. This strong difference shows important variations in the composition of labour demand across states.

In Ohio, Texas and Washington, jobs advertisements are approximately evenly distributed across the three occupational clusters concentrating most postings, namely computer and mathematical, management, and healthcare-related occupations, with shares ranging between 17% and 22% of job advertisements. In all four states, these three occupational clusters make up at least 55% of online job postings for higher education graduates. The remaining occupational clusters each have a share of 13% or less in every state.

These figures refer to the *relative* importance of main occupational clusters in the demand for higher education graduates in each economy. In *absolute* numbers, Texas has more job postings than any of the three other states for every displayed occupation, in line with the size of its economy. The data for 2018 contain 700 810 job advertisements for Texas, 311 171 for Virginia, 275 938 for Ohio, and 231 215 for Washington. It is thus important to consider that the absolute number of job postings varies by state when comparing employer demand across the four states, even if the composition within each state is relatively similar. Analysing employer demand for qualifications and skills by occupation avoids the bias that might arise from differences by occupation in the propensity of firms to post jobs online or of BGT to capture a posting. Hence, for the rest of this section, we study employer demand for education requirements and skills by occupation.

4.1. Across-state variations in education requirements by occupation

To compare employer demand across states by occupation, we examine the required level of education for the ten occupational clusters with the most online job postings (Figure 4.2). The required level of education refers to the lowest degree requirement stated in the job advertisement, i.e. if a position asks for a master's degree or a doctoral degree, the master's degree is identified as the required level of education. We find that the demand varies substantially across occupational clusters and that differences in the requirements within an occupational cluster across states exist but are often small. This does not mean that the overall demand for education requirements is the same across states, but rather differences can largely be attributed to the different occupational distributions of states.

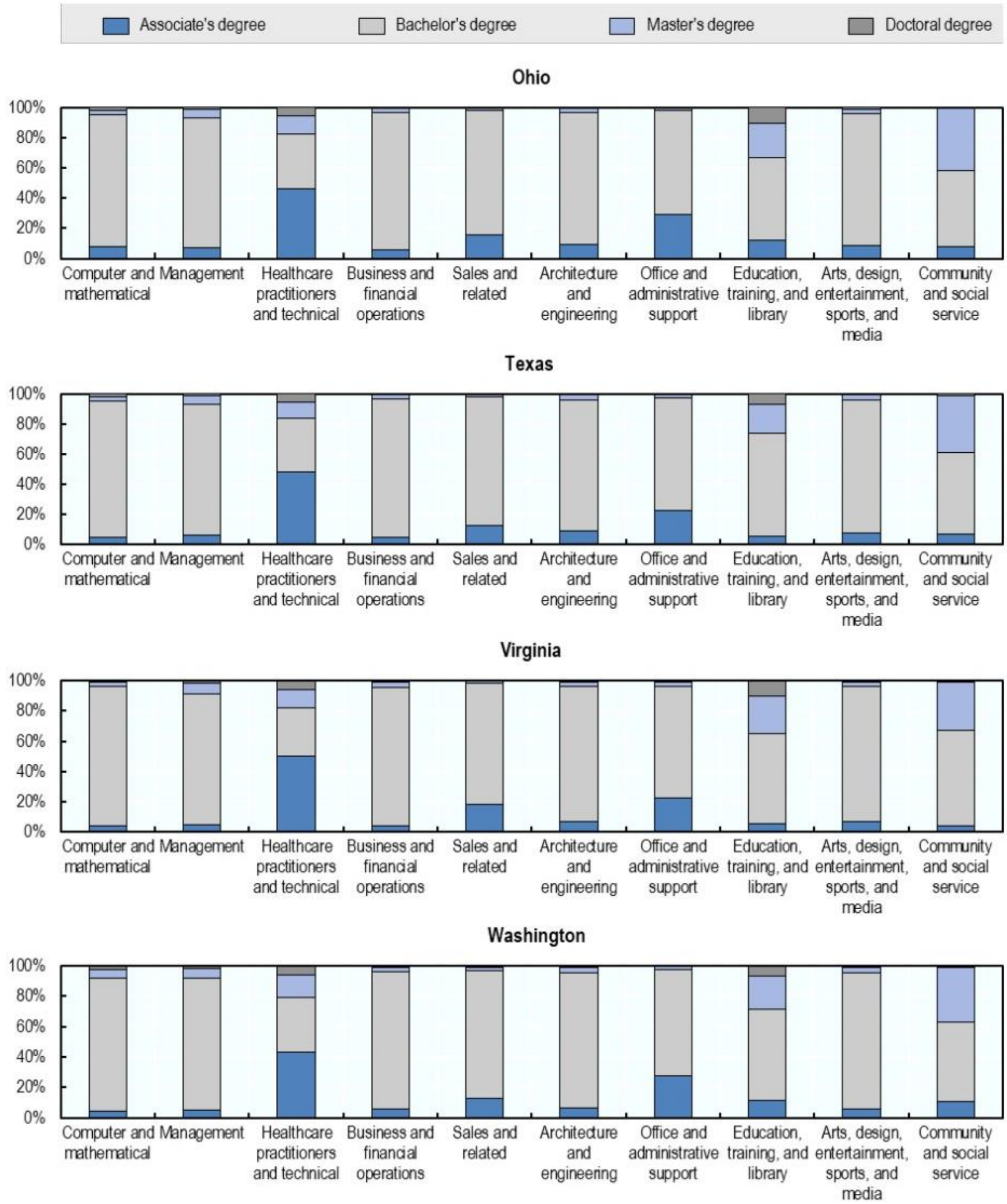
In most occupational clusters, bachelor's degrees are demanded more often than any other degree. This is particularly true for business and financial operations occupations, where the share of bachelor's degrees is highest, at over 90% for all four states. The state variation is small, with its lowest value at 91% in Ohio and Washington and reaching 92% in Texas.

The share of job postings requiring an associate's degree is typically low, which might also be due to the lower coverage of these job advertisements in the data (see Section 2.1.3). Nevertheless, an associate's degree is the minimum requirement for around half of all advertisements in healthcare practitioners and technical occupations, ranging from 43% in Washington to 50% in Virginia. Similarly, a considerable share of postings in office and administrative support occupations require an associate's degree in all four states. The share is lowest in Texas at 22% and reaches 29% in Ohio.

An important share of job postings in community and social service occupations require a master's degree, ranging from 32% of postings in Virginia to 41% in Ohio. Many job postings also require master's degrees in education, training, and library occupations, ranging from 20% in Texas to 25% in Virginia. For this occupational cluster, the share of postings with doctoral degree requirements is also important, ranging from 7% in Texas and Washington to 10% in Ohio and Virginia. The high educational requirements for education, training, and library occupations may be explained by the fact that 31% of these job postings are for postsecondary teachers.

Figure 4.2. Level of study requirements in 2018

Percentage of job posting requiring a given level of education, by occupational cluster and state



Notes: The data depict the distribution of minimum level of education requirements by occupation and state. The selected occupations are aggregated following the 2-digit 2010 SOC codes; the ending "occupations" is omitted in the labels for brevity. The data are arranged in descending order of the number of job postings by occupational cluster across all four states (the occupational cluster with most postings is on the left side of the chart displayed are the ten most frequently occurring occupational clusters, which make up around 95% of all postings in every state).

Source: Adapted from Burning Glass Technologies (2019[25]), *NOVA™ Job Feed data file*. The sample is restricted to postings in Ohio, Texas, Virginia, and Washington in 2018 that BGT could attribute to an occupation and that require an associate's degree or higher.

Data available at: https://www.oecd.org/education/higher-education-policy/EDU-Working-Paper-231-data.xlsx.

In conclusion, degree requirements vary considerably across occupational clusters as expected. While smaller, there are also variations in educational requirements within occupational clusters across states. These differences may result from a variety of factors that would warrant further exploration. These may include, for example, differences in the supply of or demand for workers suitable for a particular occupation across states, regulatory differences in certain occupations, or variation in employers' perceptions and preferences about higher education qualifications.

4.2. Differences in the skill demand across the four states for selected occupations

Computer and mathematical occupations, management occupations, and healthcare practitioners and technical occupations comprise 60% of job postings across the four states. In this section, we complement the analysis of educational demand for these occupations by studying the skills required in these job postings in detail and examining state variations.

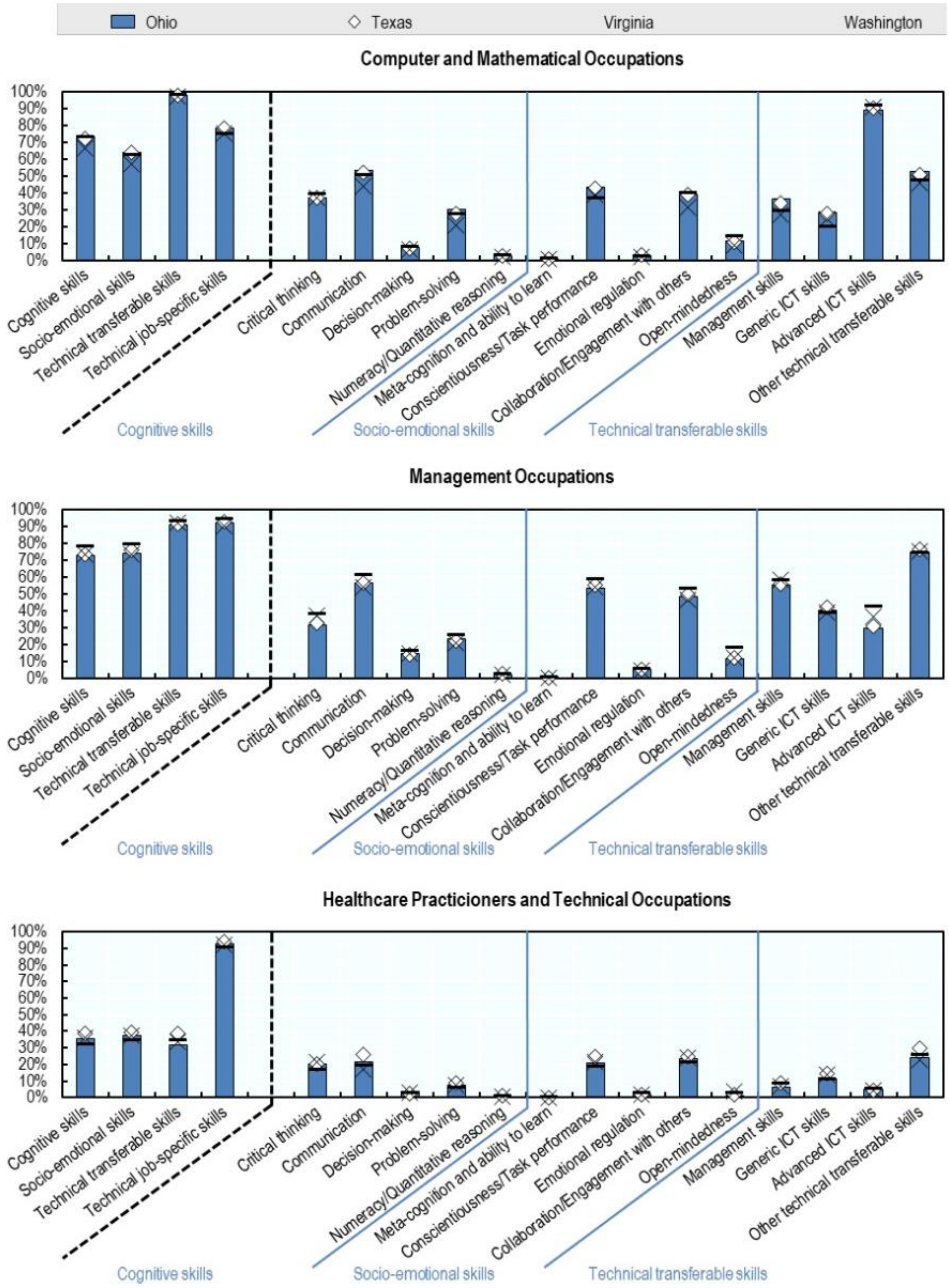
We start by exploring skill demand by state according to our two measures – prevalence and intensity. Figure 4.3 presents the prevalence of skill demand: the prevalence for the four skill categories in our framework (cognitive skills, socio-emotional skills, technical transferable skills, and job-specific skills) is indicated on the left part of the figure. The prevalence of the three transferable skill subcategories is presented to the right of the black, dashed, vertical line. Figure 4.4 presents the same information, but this time with respect to the intensity of skill demand.

Job postings in computer and mathematical occupations require transferable skills more frequently than job-specific skills. This is largely due to the fact that almost all job postings require technical transferable skills (at least 97% in every state), which is the category comprising programming languages or other software competencies. The subcategory of advanced ICT skills alone is required in 89% of job postings in that occupation in every state. However, the other transferable skill categories, namely cognitive and socio-emotional skills, are also widely required in computer and mathematical occupations. Cognitive skills are listed in many job postings, from 67% in Virginia to 73% in Ohio and Washington. Within that skill category, communication skills, critical thinking, and problem-solving skills are demanded most widely in this occupational cluster in all four states. Finally, the identification of socio-emotional skills in postings ranges from 57% in Virginia to 64% in Ohio and Texas, and is approximately ten percentage points lower than the prevalence of cognitive skills in each of the four states. Among socio-emotional skills, conscientiousness and task performance is the subcategory with the highest prevalence, followed by collaboration and engagement with others, in all states but Washington, where the order is reversed and the latter is 3% more widely demanded than the former skill subcategory.

In management occupations, technical job-specific skills and technical transferable skills are each required in at least 90% of job postings in all states. Cognitive and socio-emotional skills are also widely required in all four states, with between 73% and 79% of job postings listing skills from those categories. In all states, a slightly larger share of job postings require socio-emotional skills than cognitive skills in management occupations. The shares of postings that require skill subcategories of cognitive or socio-emotional skills resemble the prevalence observed for computer and mathematical occupations. Among technical transferable skills, the subcategory of other technical transferable skills (which includes skills such as "English" or "event planning") is demanded most widely, followed by management skills. The largest difference in management occupations between the states is the demand for advanced ICT skills, which is considerably larger in Washington (42%) than in Ohio (30%).

Figure 4.3. Prevalence of employer skill demand for selected occupations, by state

Share of job postings by occupation and state that list at least one skill from a given skill category



Notes: To the left of the black, dashed, vertical line are the four broad skill categories. The first three skill categories have subcategories, the results for which are presented to the right of the black line. The selected occupations are aggregated following the 2-digit 2010 SOC codes.

Source: Adapted from Burning Glass Technologies (2019[25]), *NOVA™ Job Feed data file*. The sample is restricted to postings in Ohio, Texas, Virginia, and Washington in 2018 that BGT could attribute to an occupation and that require an associate's degree or higher.

Data available at: https://www.oecd.org/education/higher-education-policy/EDU-Working-Paper-231-data.xlsx.

In contrast to computer and mathematical occupations and management occupations, job postings in healthcare practitioners and technical occupations almost always require job-specific skills, but infrequently identify one of the three transferable skill categories. Figure 4.3 shows that while job-specific skills are mentioned in at least 90% of postings in every state, transferable skills are listed less often, ranging from 32% for technical transferable skills in Ohio to 39% for socio-emotional skills in Texas. We see the largest variation across states for cognitive skills, which are listed in only 32% of job advertisements in Washington, but in 39% of job advertisements in Texas.

Since the prevalence measure only indicates the share of postings that list at least one skill from a given skill category, but not how many skills from that category typically are in a posting, we turn to the skill intensity measure for the three occupational clusters. Figure 4.4 displays the skill intensity measure. This measure reflects the share of a skill category among all skills in the average posting, and is calculated by (i) computing the share represented by each skill category among all skills for every job posting, and (ii) averaging these numbers across job postings within an occupation.

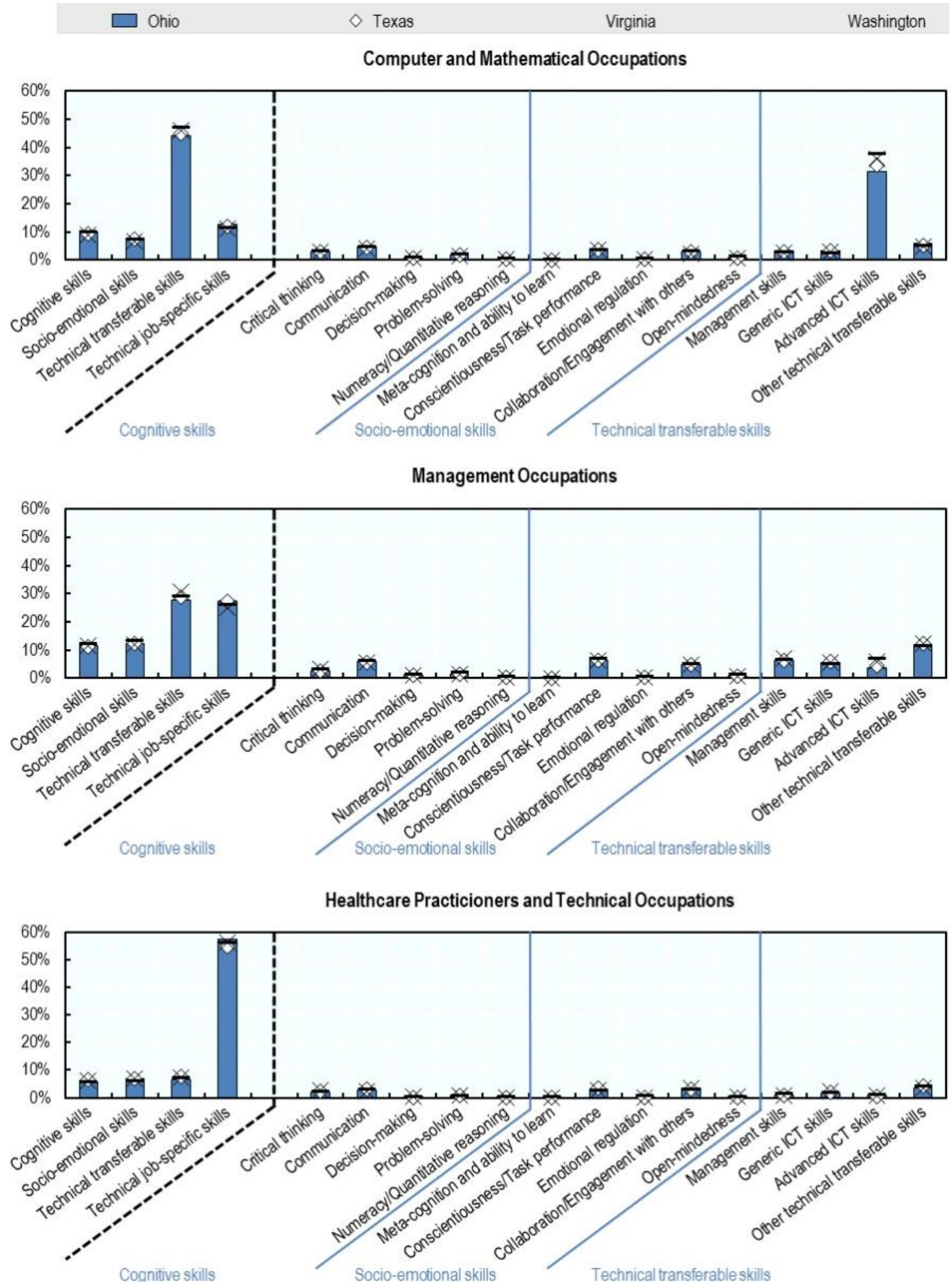
In computer and mathematical occupations, the skill shares in the average job posting underline the importance of technical transferable skills, and in particular advanced ICT skills, compared to other skills. We observe some variation between states, with advanced ICT skills representing 32% of skills in the average job posting in Ohio compared to 37% in Washington. Since almost all job postings in this occupational category list at least one advanced ICT skill across the four states, very little variation is observable on the skill prevalence measure. By contrast, the intensity measure shows some variation, suggesting that advanced ICT skills in computer and mathematical occupations are most demanded as a share of total skills in Washington. This may be an effect of the large presence of leading firms in the sector in the state (OECD, 2020[1]).

Although skills in the average job posting in management occupations are more evenly distributed across the four broad skill categories, technical transferable skills and technical job-specific skills are required more than twice as often as cognitive and socio-emotional skills in the average job posting of every state. While this may in part be explained by the greater number of skills that fall into the technical transferable skill and technical job-specific skill categories (see Section 3), the comparison across occupational clusters suggests that cognitive and socio-emotional skills play a greater role for employers in management occupations.

In healthcare practitioners and technical occupations, over half of the skills listed in the average job posting fall into the technical job-specific category in all states (55-57%). Since the probability of the unclassified skills to be job-specific is high, the true intensity of job-specific skills is likely even higher. In other words, even though a sizable share of postings mention the three transferable skill categories (Figure 4.3), these skills do not make up a large proportion of the demanded skills. Both skill measures thus highlight the importance of technical job-specific skills for healthcare practitioners and technical occupations.

Figure 4.4. Intensity of employer skill demand for selected occupations, by state

Share of a given skill category out of all skills in the average posting of an occupation and state



Notes: To the left of the black, dashed, vertical line are the four broad skill categories. The first three skill categories have subcategories, the results for which are presented to the right of the black line. The selected occupations are aggregated following the 2-digit 2010 SOC codes.

Source: Adapted from Burning Glass Technologies (2019[25]), *NOVA™ Job Feed data file*. The sample is restricted to postings in Ohio, Texas, Virginia, and Washington 2018 that BGT could attribute to an occupation and that require an associate's degree or higher.

Data available at: https://www.oecd.org/education/higher-education-policy/EDU-Working-Paper-231-data.xlsx.

Overall, employer skill demand varies substantially across occupational clusters, and across the four states within the same occupational cluster for some skill categories. The analyses demonstrate that online job posting data allow for a very detailed understanding of labour demand.

If properly integrated into labour market information systems, such data may support policy makers, higher education leaders and other stakeholders in their efforts to design education and training programme aligned with and responsive to, the needs of the labour market. In addition, if incorporated into public-facing information tools, these data could help students and graduates explore the demand for skills and qualifications by requirements relating to their own background – such as their level of education or experience – or by job characteristics – such as industry, occupation, or location. This tailored information could assist students and graduates in developing labour market relevant skills and in identifying job opportunities matching their specific profile.

5. Using job posting data to answer questions relevant to higher education: two examples

Besides generating higher education qualification and skills profiles for various types of jobs, the BGT dataset also permits the study of specific questions relevant to policy makers and leaders of educational institutions. This section presents two examples of such analyses. The first analysis focuses on the demand for graduates from sociology programmes. Graduates from sociology may be able to use their skills in a wide variety of careers. However, because career trajectories for sociologists are not clearly defined, graduates' transitions into the labour market can be more challenging than for their peers graduating from occupationally-oriented study fields with high employment demand. Sociology has been chosen as an example of fields of study where graduates may benefit from guidance about employers' skill demand to better match their qualifications and skills to opportunities in the labour market. The study of skill demand in job postings may also serve to inform prospective students in their subject choice and provide valuable information to sociology teachers about the trajectories of their graduates.

The other question we analyse using BGT data relates to the fast-growing employment demand in ICT occupations in the United States. The United States' Bureau of Labour Statistics predicted an employment growth of 12.2% for computer occupations from 2018 to 2028, compared to an average employment growth of 5.2%[6], and computer occupations are already among the occupations struggling with labour shortages. Ensuring a sufficient supply of workers that can fill these positions is thus very important. This analysis explores the qualifications, certifications and skills that might help graduates from other fields of study than ICT fill those positions. The following subsections present these two analyses.

5.1. Job opportunities for sociology graduates

To study the job opportunities for sociology graduates, we restrict the data to a subsample of job postings from the four states that demand sociologists (job postings coded by BGT as "45.11", according to the 4-digit Classification of Instructional Programs (CIP) 2010) with at least an associate's degree. Since the sample size is relatively small for this subgroup, we pool the data from 2010 to 2018 as well as across the four states, which leaves us with data from 19 192 online job postings.

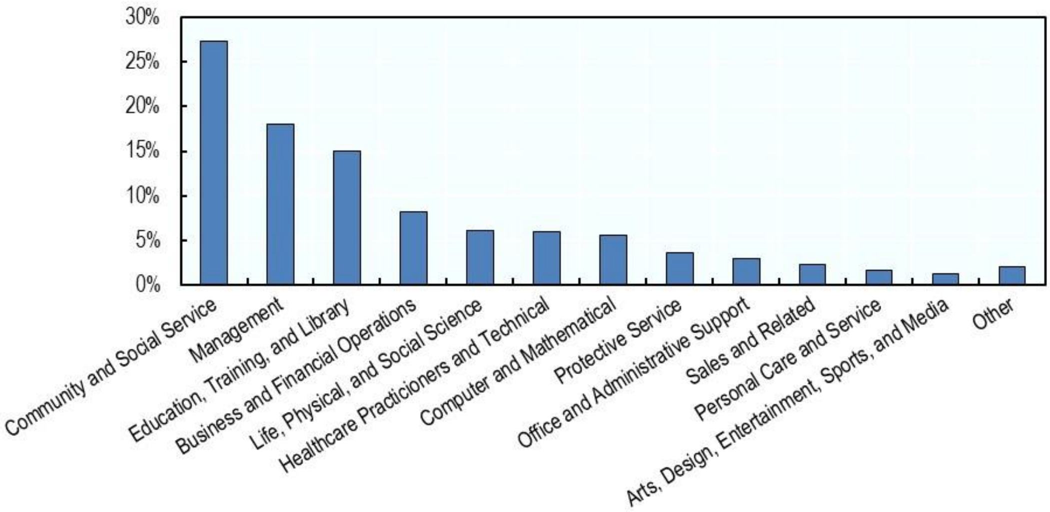
[6] Data downloaded from U.S. Bureau of Labor Statistics (2020[27]).

Sociology graduates can successfully apply to many more jobs than those that specifically mention their field. Job advertisements do not always mention all degrees that recruiters will consider, which makes the range of possible job opportunities much larger than the sample we study. Nevertheless, it is valuable to know in which occupations sociology is listed as a desired field of study where they would potentially have an advantage over candidates from other fields. In addition, the probability that the job tasks are related to sociology is arguably higher in positions that list a degree in sociology as an asset. Therefore, these type of jobs might be particularly appealing to sociology graduates.

Figure 5.1 shows that 60% of the postings that explicitly state a requirement for a sociology degree are for jobs in three occupational clusters: community and social service occupations; management occupations; and education, training, and library occupations. Community and social service occupations contain the largest share, making up 27% of postings. Management occupations follow at 18%, and education, training, and library occupations make up 15% of this demand. From the latter occupational cluster, 74% of postings are for postsecondary teachers.

Figure 5.1. Occupational distribution of the demand for sociology graduates

Percentage of job postings in each occupational category – pooled data across Ohio, Texas, Washington and Virginia (2010-18)



Notes: The chart shows the share of job postings demanding graduates from sociology from 2010 to 2018. The data are aggregated by 2-digit 2010 SOC codes; the ending "occupations" is omitted in the labels for brevity. Occupational groups that make up more than 1% of all postings are displayed; the rest are aggregated in the category "Other".

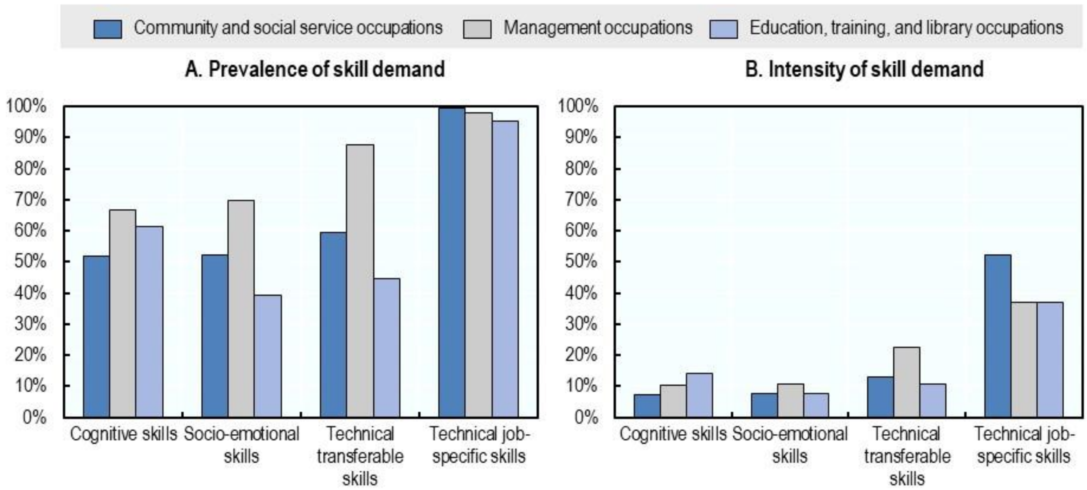
Source: Adapted from Burning Glass Technologies (2019[25]), *NOVA™ Job Feed data file*. The sample is restricted to postings in Ohio, Texas, Virginia, and Washington from 2010 to 2018 that BGT could attribute to an occupation and that require an associate's degree or higher in sociology (2010 CIP code 45.11).

Data available at: https://www.oecd.org/education/higher-education-policy/EDU-Working-Paper-231-data.xlsx.

As the top three occupational clusters requiring sociology graduates make up 60% of postings in our sample, the skill demand for these groups is examined in more detail. Since the sample size is relatively small, we restrict the analysis to the four broad skill categories. Figure 5.2 shows the results for the prevalence measure (the share of postings within an occupation requiring at least one skill from a skill category) in Panel A, and the skill intensity (the skill category as a share of all skills in the average posting) is depicted in Panel B.

Figure 5.2. Skill demand in job postings for sociology graduates, by occupation

Skill demand of selected occupations as determined by the prevalence and intensity measures – pooled data across Ohio, Texas, Virginia and Washington (2010-18)



Notes: Panel A displays the skill prevalence of the three occupational clusters (2010 SOC codes), defined as the share of job postings that list at least one skill from a given skill category. Panel B displays the skill intensity of the three occupational clusters (2010 SOC codes), defined as the share of a given skill category out of all skills in the average posting.

Source: Adapted from Burning Glass Technologies (2019[25]), *NOVA™ Job Feed data file*. The sample is restricted to postings in Ohio, Texas, Virginia, and Washington from 2010 to 2018 that BGT could attribute to an occupation and that require an associate's degree or higher in sociology (2010 CIP code 45.11).

Data available at: https://www.oecd.org/education/higher-education-policy/EDU-Working-Paper-231-data.xlsx.

Technical job-specific skills constitute the skill category most often required among the four broad skill categories. Examples for technical job-specific skills in these job postings are medical coding, teaching or social work. Their prevalence is high across all three occupational clusters, with 95 to 100% of postings requiring skills from this category (Panel A). Technical job-specific skills represent over half of all demanded skills (52%) in the average job posting in community and social service occupations, whereas they comprise 37% of skills in the average job posting in both management occupations and education, training, and library occupations (Panel B). This indicates a higher importance of technical job-specific skills for community and social service occupations compared to the two other occupational clusters. In all occupations, the demand intensity for technical job specific skills would likely be even higher if all skills from the data were categorised (see Section 3).

Cognitive skills are most widely demanded in postings for management occupations, where 67% of postings require at least one such skill, compared to 61% in education, training, and library occupations. However, when looking at the skill intensity the importance of cognitive skills reverses. We find that cognitive skills comprise 14% of the demanded skills in education, training, and library occupations, a larger share than in management occupations, where it is 10%. This suggests that the demand for cognitive skills is more concentrated in specific job postings in education, training, and library occupations, which is plausible since they aggregate a more diverse set of occupations. According to both skill measures, the demand for cognitive skills is lowest in community and social service occupations.

With respect to socio-emotional skills, postings for management occupations list these skills most often: 70% of all postings feature at least one socio-emotional skill requirement (Panel A). In the average posting for management occupations, around one out of ten skills is socio-emotional (Panel B). Community and social service occupations show the second strongest demand: 52% of job postings list at least one socio-emotional skill and, on average, they make up 8% of all skills in a job posting. For education, training, and library occupations, socio-emotional skills are least important: the skill prevalence is 39% and the skill intensity 8%.

Technical transferable skills are also most in demand in management occupations, and the difference in demand between management occupations and the two other occupation clusters is strongest for this skill category. About 88% of job postings in management occupations demand technical transferable skills, and these skills cover 23% of all skills in the average job posting. By comparison, community and social service occupations demand technical transferable skills in only 59% of all postings (Panel A) and the skill demand intensity is 13% for these skills (Panel B). The technical transferable skill demand figures are lowest for education, training, and library occupations, at 45% and 11%, respectively. The particularly high demand for technical transferable skills in management occupations likely stems from the demand for skills that have been classified as management skills, a subcategory of technical transferable skills. Examples of management skills are project management, performance management, or business acumen.

When looking at employer skill demand by occupation, we find that their skill profiles vary. The importance of technical job-specific skills is particularly high in community and social service occupations, whereas all three transferable skill categories have similar demand patterns. In education, training, and library occupations, both skill demand measures show cognitive skills as the most valued skill category among transferable skills. However, technical job-specific skills are identified even more often than cognitive skills. Management occupations show a relatively strong demand for transferable skills, in particular for technical transferable skills, which include the subcategory of management skills. Nevertheless, as for the two other occupational clusters, the prevalence and intensity are highest for skills falling in the broad category of technical job-specific skills.

The identification of occupations that show high demand for sociology graduates in online job postings, complemented by an analysis of the required skills profile in these advertisements, holds potential to guide sociology students towards occupations that match their skill profiles best, and help them recognise areas for development in their qualifications and skills. For example, the analysis shows that employers in management occupations are more likely to look for a combination of transferable skills in sociology graduates, while those in community and social work place a greater focus on job-specific technical skills. Further analysis could use a larger dataset (for instance, including all US states) to analyse the demand for skill subcategories or changes in the demand over time. Additional variables could be explored to refine the understanding of skills requirements for sociology graduates, such as experience requirements or the industry of the employer.

5.2. Alternative pathways into ICT occupations

ICT specialists are in high demand in all four states, and particularly in Washington and Virginia (OECD, 2020[1]). To meet labour demand, educational policies might aim to increase enrolment in the fields of study of computer and information sciences and support services (hereinafter ICT fields of study; they include all fields of study listed as "11" in the 2-digit CIP). However, graduates from other fields of study, if equipped with the right skills and able to demonstrate these skills to employers, might also be able to fill some of the unmet demand. We are thus interested in what higher education qualifications, certifications and skills candidates from other educational backgrounds should possess to be able to fill vacancies in computer occupations (hereinafter ICT occupations; they include all occupations listed as "15-11" in the 4-digit 2010 SOC).

We first restrict our data from the four states to those vacancies that call for an associate's degree or higher, and that have been identified by BGT as ICT occupations. This yields nearly 1.9 million postings from 2010-18, of which around 300 000 were posted in 2018. While employer demand may vary geographically (see Section 4), we aggregate occupations across all four states for this the rest of this subsection to highlight the type of analysis that can be conducted with online job posting data. Since our aim is to find graduates from fields of study other than ICT that might be capable of filling positions in ICT occupations, we subdivide the postings from 2010-18 into four groups according to their field of study requirements:

1. postings without a field of study requirement;
2. postings requiring exclusively ICT fields of study;
3. postings where either ICT or other fields of study meet the requirement;
4. postings seeking graduates from fields of study other than ICT.

Group 1 (job advertisements that do not list any information on required fields of study) comprises 41% of postings in 2018. Group 2 (postings demanding exclusively ICT fields of study) covers 24% of postings in 2018. Group 3 (ICT and other fields of study are acceptable) includes 23% of postings in 2018. Group 4 (graduates from fields of study other than ICT) represents 13% of the postings in 2018. Together, Groups 3 and 4 comprise 35% of job postings, which suggests that in ICT occupations in more than one job posting out of three, a degree in a field other than ICT is acceptable to the employer. Depending on how many employers from Group 1 accept applicants with higher education degrees in fields of study other than ICT, the share of employers willing to hire candidates with other higher education backgrounds than ICT could increase to 76%. This distribution is similar for the earlier years, 2010-17.

In the remainder of Section 5.2, we will first characterise the four different groups to gain an understanding of how similar or different the job postings are across groups, depending on the field of study required. We do so by analysing what fields of study other than ICT are frequently demanded in ICT occupations (for Groups 3 and 4), and by studying the ten most demanded skills and certifications within each of the four groups. Then, we use the skills framework developed in Section 3 to look at the prevalence and intensity of skill demand over time and to analyse recent job postings from Group 3 in more detail. We focus on Group 3 as these postings hold the greatest promise to identify the necessary skills and qualifications for graduates from other fields of study to address the excess demand for ICT specialists.

5.2.1. Characterising four groups of job postings in ICT occupations

The demand for fields of study other than ICT is highly concentrated

While more than one-third of all postings for jobs in ICT occupations contain fields of study other than ICT as job requirements in 2018, only a small range of fields of study is listed by employers in ICT occupations. Table 5.1 shows the five most frequently demanded fields of study for Groups 3 and 4 respectively. Postings from Group 3, where employers require either an ICT or a non-ICT degree, list 2.6 fields of study on average. Out of all listed fields, 43% are in ICT. The second most demanded field is engineering at 26%, followed by business, management, marketing, and related support services (20%). Mathematics and statistics make up 7% of this category, and social sciences represent 1% of the required fields of study. Combined, these five fields of study cover 97% of all fields of study demanded in job postings seeking ICT or other fields of study.

Job advertisements that require only non-ICT degrees (Group 4) list 1.7 fields of study per posting on average, which is almost one field of study less than in Group 3 postings. The listed fields of study across the two groups are very similar. Business, management, marketing and related support services, as well as engineering subjects, are demanded most often in Group 4, comprising 38% and 34% of all required degrees, respectively. Mathematics and statistics, and social sciences follow again at a much lower rate, at 8% and 5% respectively. Finally, health professions and related programmes cover 3% of all listed fields of study in job postings that do not demand a degree in ICT.

Table 5.1. Top five demanded fields of study in ICT occupations, by field of study requirement

The data are pooled across Ohio, Texas, Virginia and Washington in 2018

	Postings with ICT and other fields of study (Group 3)	Share	Postings with only fields of study other than ICT (Group 4)	Share
(1)	Computer and information sciences and support services	42.55%	Business, management, marketing, and related support services	38.14%
(2)	Engineering	26.06%	Engineering	33.61%
(3)	Business, management, marketing, and related support services	19.98%	Mathematics and statistics	7.84%
(4)	Mathematics and statistics	7.01%	Social sciences	4.98%
(5)	Social sciences	1.42%	Health professions and related programmes	2.60%
…	Other	2.98%	Other	12.84%
	2.6 fields of study per posting		**1.7 fields of study per posting**	
	69 093 postings		**38 544 postings**	

Note: The shares are calculated by counting the mentions of a field of study across all postings in a given group and dividing them by the total number of mentions of any field of study in that group.
Source: Adapted from Burning Glass Technologies (2019[25]). The sample is restricted to postings in Ohio, Texas, Virginia, and Washington in 2018 that require an associate's degree or higher and that have been identified by BGT as ICT occupations (2010 SOC code 15.11).

Table 5.1 shows that demand for non-ICT degrees is heavily concentrated in two fields. Excluding ICT degrees in Group 3, engineering and business management, marketing, and related support services make up 80% of the remaining field of studies. This figure is 72% for Group 4. Therefore, graduates equipped with qualifications in these two fields seem particularly well suited to find their way into ICT occupations.

The most frequently demanded individual skills differ based on degree requirements

In each of the four groups of job postings for ICT occupations, communication skills are the most widespread skill requirement (Table 5.2). Their share of all skills varies from 2.1%

for postings that look for ICT and other fields of study (Group 3), to 2.8% in postings requiring only non-ICT degrees (Group 4). While these numbers appear low, it means that 41% of postings across all groups list communication skills as a skill requirement.

Table 5.2. Top ten demanded skills in ICT occupations, by field of study requirement

The data are pooled across Ohio, Texas, Virginia and Washington in 2018

	Postings not listing any field of study (Group 1)	Postings with only ICT fields of study (Group 2)	Postings with ICT and other fields of study (Group 3)	Postings with only other fields of study (Group 4)
(1)	Communication Skills (2.4%)	Communication Skills (2.2%)	Communication Skills (2.1%)	Communication Skills (2.8%)
(2)	Teamwork / Collaboration (1.6%)	Software Development (1.8%)	SQL (1.5%)	Teamwork / Collaboration (1.6%)
(3)	Problem Solving (1.4%)	Java (1.8%)	Software Development (1.5%)	Problem Solving (1.4%)
(4)	Troubleshooting (1.4%)	SQL (1.7%)	Information Systems (1.4%)	Planning (1.4%)
(5)	SQL (1.3%)	Problem Solving (1.5%)	Java (1.4%)	Project Management (1.3%)
(6)	Planning (1.2%)	Teamwork / Collaboration (1.4%)	Teamwork / Collaboration (1.4%)	Research (1.3%)
(7)	Software Development (1.2%)	Troubleshooting (1.4%)	Problem Solving (1.4%)	Microsoft Excel (1.2%)
(8)	Project Management (1.1%)	Software Engineering (1.3%)	Software Engineering (1.1%)	Writing (1.1%)
(9)	Java (1.1%)	JavaScript (1.2%)	Troubleshooting (1.1%)	Microsoft Office (1.0%)
(10)	Writing (1.0%)	Linux (1.1%)	Python (1.0%)	SQL (0.9%)
…	Other (86.4%)	Other (84.7%)	Other (86.1%)	Other (85.9%)
	16.2 skills per posting*	**19.1 skills per posting***	**20.5 skills per posting***	**16.8 skills per posting***
	124 835 postings**	**72 422 postings****	**69 084 postings****	**38 513 postings****
	99.78% of postings list skills	**99.96% of postings list skills**	**99.99% of postings list at skills**	**99.92% of postings list skills**

Notes: The percentages in brackets show the share of the individual skill out of all required skills in a given group. For example, 2.4% of skills listed in job advertisements that do not mention any field of study requirement are communication skills. *The average number of skills per posting is calculated based on postings with at least one skill requirement in a given group. **The number of job postings refers to those postings that list at least one skill requirement in a given group.

Source: Adapted from Burning Glass Technologies (2019[25]). The sample is restricted to postings in Ohio, Texas, Virginia, and Washington in 2018 that require an associate's degree or higher and that have been identified by BGT as ICT occupations (2010 SOC code 15.11).

Job postings without any field of study requirement (Group 1) and those that require only non-ICT fields of study (Group 4) list a similar number of skills on average, 16.2 and 16.8, respectively; they also have seven out of ten skills in common. For both groups, the three most demanded skills are communication skills, teamwork/collaboration, and problem solving. Group 1 advertisements (no field of study) feature troubleshooting, software development, and Java in their top ten list, whereas Group 4 advertisements (non-ICT fields of study) list more generic ICT skills, namely research, Microsoft Excel, and Microsoft Office. This suggests that jobs without any mention of a particular field of study have a higher share of specialised ICT tasks on average than advertisements specifically targeting graduates from non-ICT fields of study.

Job postings demanding only ICT degrees (Group 2) and postings seeking applicants from either an ICT field or other fields (Group 3) feature more skills on average than the other groups. At 20.5 skills per job posting on average, Group 3 has the most skill requirements out of the four groups. A reason for this could be that since the potential field of study background of candidates in Group 3 is largest, the skills necessary for the job have to be defined more precisely. Postings looking only for ICT fields of study (Group 2) have slightly less skills per posting, 19.1 on average. Out of the four groups, Group 2 and Group 3 have the largest number of skills typically associated with ICT specialists, such as software engineering, Java, or software development, which is consistent with their search for ICT graduates. Since the jobs postings in Group 2 advertise positions for ICT specialists, the similarity in skill demand between Groups 2 and 3 suggests that the advertised jobs in Group 3 contain a large share of tasks typically carried out by ICT specialists.

A degree in ICT may substitute for some certification requirements

Before looking at the most frequently demanded certifications in each of the four groups, it is important to note that BGT has loosely defined the term “certification”. Certifications may include professional/industry certificates (e.g. CompTIA Security+, issued by the Computer Technology Industry Association) as well as certifications such as a security clearance.

Table 5.3 shows that in all groups except Group 2 (only ICT fields of study), around 30% of postings require at least one certification. This share is lower for Group 2, where it is 24%. Thus, a degree from an ICT field of study might substitute for some of the certification requirements; employers might expect certain skills from graduates with ICT degrees that candidates from other fields would have to prove through other certifications.

In general, the most requested certifications are very similar across the four groups. A security clearance is the most common certification in job postings from any of the four groups, ranging from 13% of all certifications in postings demanding a higher education degree in ICT (Group 2) to 20% in postings requiring either ICT or other fields of study (Group 3). Besides a security clearance, five certifications appear in all four groups and combined, they make up between 22% and 28% of all certifications demanded in these groups. These certifications are Certified Information Systems Security Professional (CISSP), Cisco Certified Network Associate (CCNA), CompTIA Security+, IT Infrastructure Library (ITIL) Certification, and Project Management Certification. Some certifications are named slightly differently but appear to be the same, such as IT Infrastructure Library (ITIL) Certification and ITIL Certification or CompTIA Security+ and Security+. If in both cases these two certifications were counted as being the same, the share of the five certifications that are required in all four groups grows even larger (23-34%, depending on the group).

Table 5.3. Demand for certifications in ICT occupations, by field of study requirement

The data are pooled across Ohio, Texas, Virginia and Washington in 2018

	Postings not listing any field of study (Group 1)	**Postings with only ICT fields of study (Group 2)**	**Postings with ICT and other fields of study (Group 3)**	**Postings with only other fields of study (Group 4)**
(1)	Security Clearance (18%)	Security Clearance (13%)	Security Clearance (17%)	Security Clearance (20%)
(2)	Certified Information Systems Security Professional (CISSP) (6%)	Certified Information Systems Security Professional (CISSP) (8%)	Certified Information Systems Security Professional (CISSP) (7%)	Project Management Certification (8%)
(3)	CompTIA Security+ (6%)	IT Infrastructure Library (ITIL) Certification (7%)	IT Infrastructure Library (ITIL) Certification (6%)	Project Management Professional (PMP) (5%)
(4)	IT Infrastructure Library (ITIL) Certification (6%)	CompTIA Security+ (6%)	Project Management Certification (5%)	Certified Information Systems Security Professional (CISSP) (5%)
(5)	Project Management Certification (5%)	Cisco Certified Network Associate (CCNA) (5%)	CompTIA Security+ (4%)	Driver's License (5%)
(6)	Cisco Certified Network Associate (CCNA) (4%)	SANS/GIAC Certification (4%)	SANS/GIAC Certification (3%)	IT Infrastructure Library (ITIL) Certification (4%)
(7)	Security+ (3%)	Security+ (3%)	Cisco Certified Network Associate (CCNA) (3%)	Certified Information Systems Auditor (CISA) (3%)
(8)	Project Management Professional (PMP) (3%)	Cisco Certified Network Professional (CCNP) (3%)	Certified Information Systems Auditor (CISA) (3%)	CompTIA Security+ (3%)
(9)	SANS/GIAC Certification (3%)	Project Management Certification (3%)	Project Management Professional (PMP) (3%)	Cisco Certified Network Associate (CCNA) (2%)
(10)	ITIL Certification (2%)	ITIL Certification (3%)	Cisco Certified Network Professional (CCNP) (3%)	ITIL Certification (2%)
…	Other (44%)	Other (46%)	Other (45%)	Other (44%)
	2.2 certifications per posting*	**2.4 certifications per posting***	**2.3 certifications per posting***	**2.0 certifications per posting***
	37 962 postings**	**17 446 postings****	**21 423 postings****	**12 172 postings****
	30% of postings list certifications	**24% of postings list certifications**	**31% of postings list certifications**	**32% of postings list certifications**

Notes: The percentages in brackets show the share of a certification out of all certifications in a given group. For example, in the group of postings that do not mention any field of study requirements, 18% of all demanded certifications are a security clearance. *The average number of certifications per posting is built based on those postings that require at least one certification in a given group. **The number of job postings refers to postings that list at least one certification requirement in a given group.

Source: Adapted from Burning Glass Technologies (2019[25]). The sample is restricted to postings in Ohio, Texas, Virginia, and Washington in 2018 that require an associate's degree or higher and that have been identified by BGT as ICT occupations (2010 SOC code 15.11).

5.2.2. Skill analysis of job postings in ICT occupations for graduates from either ICT or other fields of study

We are interested in identifying the skill and qualification profiles of higher education graduates without a degree in an ICT field of study that could help alleviate the high demand for ICT specialists. For this, we will focus on the skill demand in Group 3 as the analysis of the most frequently demanded skills (Table 5.2) suggests that employers look for similar skills in graduates who have either an ICT or non-ICT degree compared to those looking for ICT graduates only. Additionally, Table 5.3 shows that the top ten demanded certifications are very similar across all four groups, including Group 2 and Group 3. Based on the similarities in employer demand between Group 2 and Group 3, we expect the skills required in Group 3 postings to enable higher education graduates from other fields of study than ICT to fill positions with a high share of specialised ICT tasks. Moreover, by taking up a larger share of Group 3 positions (where employers consider both ICT and other fields of study), graduates from other fields of study than ICT could potentially "free up" graduates from ICT programmes for the most specialised positions (Group 2).

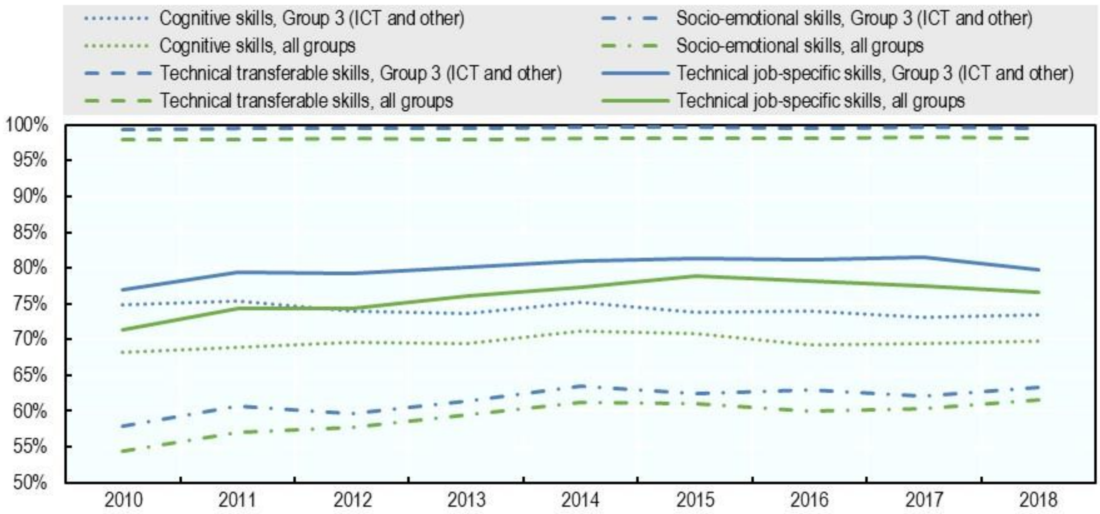
Figure 5.3 shows the evolution of skill demand in postings seeking either ICT degrees or degrees from other fields of study (Group 3) based on the prevalence measure. We rely on the broad skill categories developed in Section 3 and include postings from all four groups combined as a comparison group. The share of job postings that demand at least one skill from a skill category is larger in Group 3 than across all groups for any of the four skill categories. Technical transferable skills are by far the category of skills that is most widely requested in Group 3 job postings. Across the period 2010-18, over 99% of postings from Group 3 list one or more technical transferable skill, which is around one percentage point higher than for postings across all four groups. Technical job-specific skills are required in 80% of Group 3 postings in 2018, a 3-percentage point increase since 2010. For all groups combined, the increase over time in the number of postings requiring technical job-specific skills has been larger (5-percentage points); however, the share remains at a lower level (77%) than in Group 3 in 2018.

The absolute and relative difference in skill demand between Group 3 and all four groups combined is largest for cognitive skills, although the gap has narrowed over time, from 7- to 4-percentage points. The closing of the gap results from a small decrease in the skill prevalence of cognitive skills for job postings seeking graduates from ICT or other fields of study (Group 3), as well as from a slight rise in the skill measure across postings from all four groups.

Socio-emotional skills were required least widely in postings from both Group 3 and all four groups combined in 2010, where only about 58% and 54% of postings required one or more skills from that category respectively. While their demand remained less widespread than for other skill categories, they have experienced the largest relative increase. In Group 3, the figure rose by 5-percentage points from 58% to 63%, which constitutes a 9% increase. All four groups combined have seen an even larger relative increase of 13%, from 54% to 62% of postings demanding socio-emotional skills.

Figure 5.3. Prevalence of skill demand in job postings for ICT occupations over time, Group 3 and all groups combined

Share of postings in a given year that list at least one skill requirement from a given skill category – pooled data across Ohio, Texas, Virginia and Washington

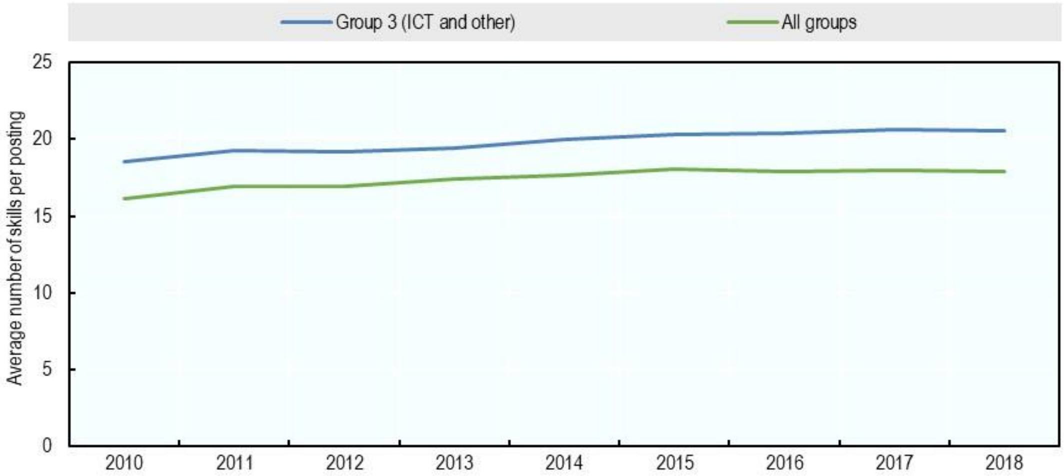


Notes: The graph depicts the skill prevalence of the broad skill categories for Group 3 (job postings in ICT occupations where higher education degrees in ICT and other fields of study meet the job requirement) and all groups combined (all job postings for higher education graduates in ICT occupations). The skill prevalence is defined as the share of postings in a given year that list at least one skill requirement from a given skill category. For example, for postings that require either a degree in ICT or other fields of study (Group 3), almost all postings required at least one technical transferable skill in 2010.
Source: Adapted from Burning Glass Technologies (2019[25]), *NOVA™ Job Feed data file*. The sample is restricted to postings in Ohio, Texas, Virginia, and Washington from 2010 to 2018 that require an associate's degree or higher and that have been identified by BGT as ICT occupations (2010 SOC code 15.11).
Data available at: https://www.oecd.org/education/higher-education-policy/EDU-Working-Paper-231-data.xlsx.

To provide context for the above analysis, we look at changes in the average number of posted skill requirements in Figure 5.4. We can expect that an increase in the average number of skills listed per posting over time increases the probability that at least one of the skills will belong to any of the skill categories. Indeed, we find an increase in the average number of skills listed from 18.5 to 20.5 for Group 3 and from 16.1 to 17.9 across all four groups. This may explain some of the increase in the prevalence measures in Figure 5.3. Moreover, the larger number of skills in Group 3 compared to all four groups might to some extent explain the higher prevalence levels for Group 3.

Figure 5.4. Average number of skills per posting in job postings for ICT occupations over time, Group 3 and all groups combined

Pooled data across Ohio, Texas, Virginia and Washington



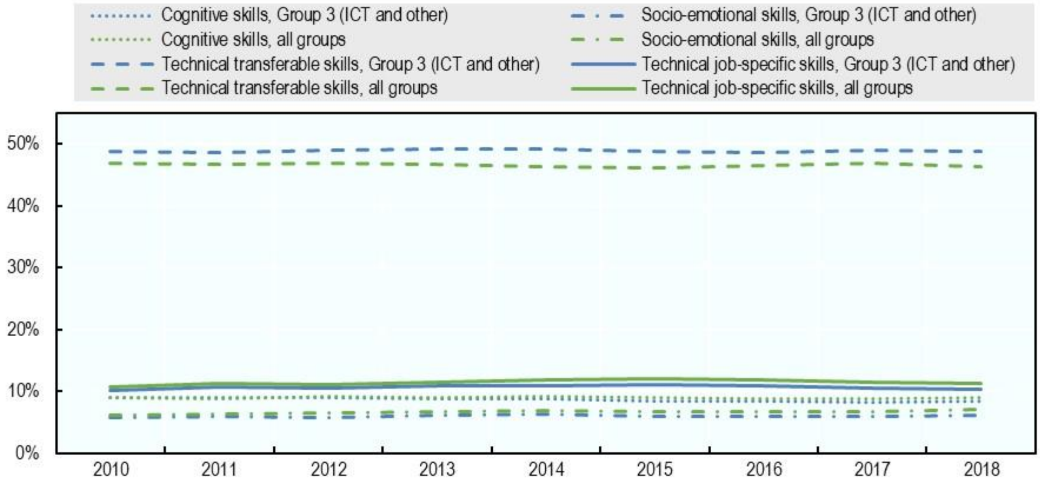
Notes: This graph shows the average number of skills demanded in Group 3 (job postings in ICT occupations where higher education degrees in ICT and other fields of study meet the job requirement), as well as in all groups (all job postings for higher education graduates in ICT occupations).
Source: Adapted from Burning Glass Technologies (2019[25]), *NOVA™ Job Feed data file*. The sample is restricted to postings in Ohio, Texas, Virginia, and Washington in 2018 that require an associate's degree or higher and that have been identified by BGT as ICT occupations (2010 SOC code 15.11).
Data available at: https://www.oecd.org/education/higher-education-policy/EDU-Working-Paper-231-data.xlsx.

We have discussed the proportion of job advertisements that demand at least one skill from a given skill category so far, and now turn to the composition of skills listed in a job posting. We therefore look at the skill demand intensity, defined as the share of a skill category among all skills in the average job posting.

The intensity measure, depicted in Figure 5.5, shows almost no change over time, suggesting that the increase in skill requirements has not altered the composition of skills in the average job advertisement. The largest difference is the variation in the share of socio-emotional skills across all four groups, which has increased from 6% to 7% over time, a nearly 16% increase. Nevertheless, when looking at the distribution of skills, we find that the skill intensity measure reinforces the importance of technical transferable skills. At around 49% in Group 3 and 47% across all groups, they make up almost half of all skills in the average job posting in any given year.

Figure 5.5. Intensity of skill demand in job postings for ICT occupations over time, Group 3 and all groups combined

Share of a skill category among all skill requirements in the average posting of a given year - The data are pooled across Ohio, Texas, Virginia and Washington



Notes: The graph depicts the skill intensity of the broad skill categories for Group 3 (job postings in ICT occupations where higher education degrees in ICT and other fields of study meet the job requirement) and all groups combined (all job postings for higher education graduates in ICT occupations). The skills intensity is defined as the share of a particular skill category among all skill requirements for the average posting in a given year. For example, for postings that require either a degree in ICT or other fields of study (Group 3), almost half of all skills listed in the average posting in 2010 were technical transferable skills. Note that the total of all four skill categories does not equal 100% as not all skills have been categorised (see Section 3).
Source: Adapted from Burning Glass Technologies (2019[25]), *NOVA™ Job Feed data file*. The sample is restricted to postings in Ohio, Texas, Virginia, and Washington in 2018 that require an associate's degree or higher and that have been identified by BGT as ICT occupations (2010 SOC code 15.11).
Data available at: https://www.oecd.org/education/higher-education-policy/EDU-Working-Paper-231-data.xlsx.

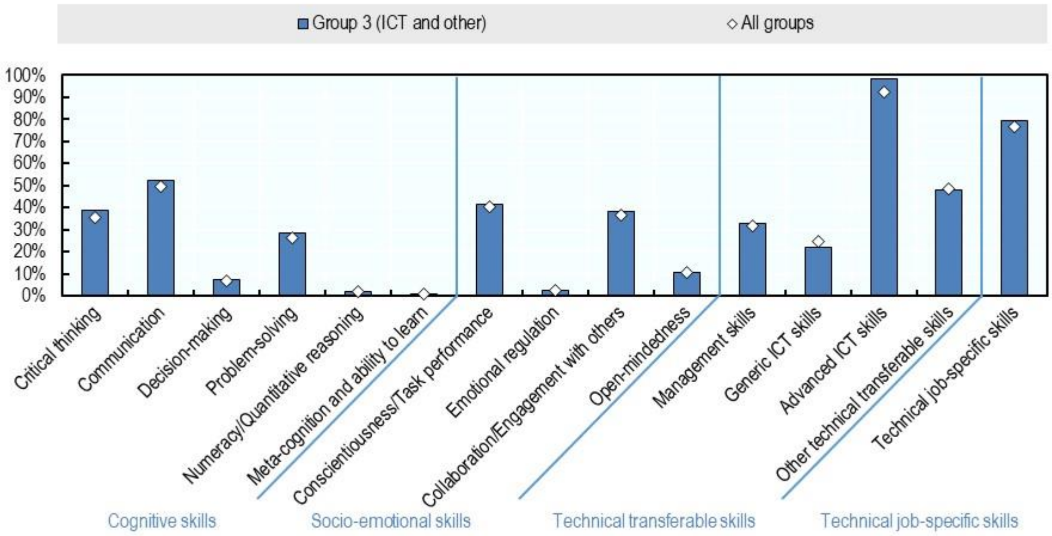
Detailed skill demand in ICT occupations for graduates from either ICT or other fields of study in 2018

Technical transferable skills are particularly important for graduates seeking employment in ICT occupations. When analysing this skill category in detail, we find that advanced ICT skills are by far the most widely required skill subcategory across job postings (Figure 5.6). Advanced ICT skills include skills such as Python, graphic design, or machine learning. Nearly all postings (98%) that list ICT and non-ICT degrees require at least one advanced ICT skill, and 93% of postings from all four groups combined do as well. Nevertheless, other technical transferable skills like "budgeting" or "event planning" are also in demand, with 48% of postings requiring at least one such skill in Group 3 and 49% of postings in all four groups combined.

Among cognitive skills, communication, critical thinking, and problem-solving are demanded most widely. Similarly, conscientiousness and task performance, as well as collaboration and engagement with others, are widely demanded socio-emotional skills. All of these skills are more prevalent across postings from Group 3 than in postings from all four groups combined.

Figure 5.6. Prevalence of skill demand in job postings for ICT occupations, Group 3 and all groups combined

Share of postings that list at least one skill requirement from a given skill category – Pooled data across Ohio, Texas, Virginia and Washington in 2018

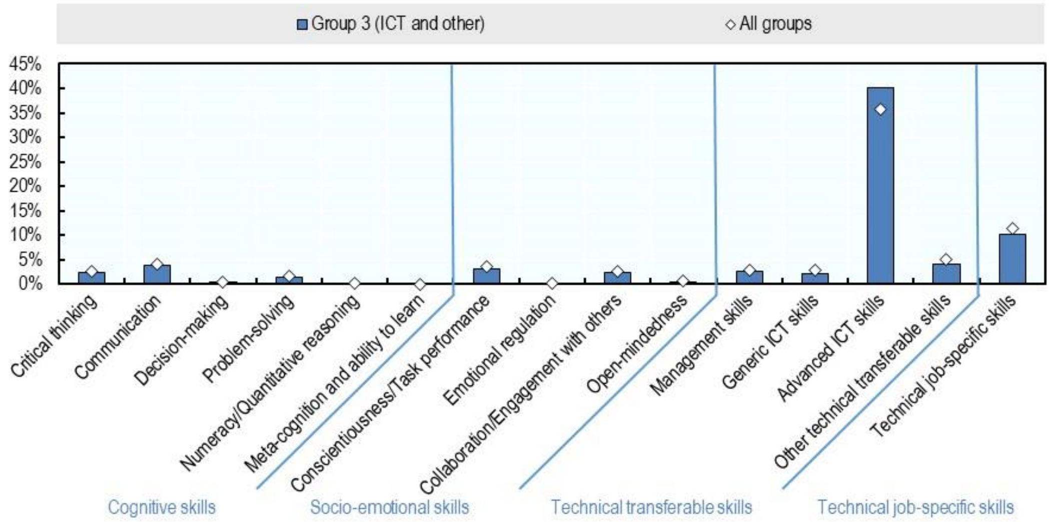


Notes: The graph depicts the skill prevalence of the skill subcategories for Group 3 (job postings in ICT occupations where higher education degrees in ICT and other fields of study meet the job requirement) and all groups combined (all job postings for higher education graduates in ICT occupations). The skill prevalence is defined as the share of postings that list at least one skill requirement from a given skill category. For example, for postings that require either a degree in ICT or other fields of study (Group 3), almost all postings required at least one advanced ICT skill in 2018.
Source: Adapted from Burning Glass Technologies (2019[25]), *NOVA™ Job Feed data file*. The sample is restricted to postings in Ohio, Texas, Virginia, and Washington in 2018 that require an associate's degree or higher and that have been identified by BGT as ICT occupations (2010 SOC code 15.11).
Data available at: https://www.oecd.org/education/higher-education-policy/EDU-Working-Paper-231-data.xlsx.

When looking at advanced ICT skills as a share of all transferable skills subcategories in our framework, their importance to employers becomes even clearer (Figure 5.7); advanced ICT skills comprise 40% of all skills in the average Group 3 posting. This is a larger share than in all four groups combined, where the same figure reaches 36%.

Figure 5.7. Intensity of skill demand in job postings for ICT occupations, Group 3 and all groups combined

Share of a skill category among all skill requirements in the average posting of a given year - The data are pooled across Ohio, Texas, Virginia and Washington in 2018



Notes: The graph depicts the skill intensity of the skill subcategories for Group 3 (job postings in ICT occupations where higher education degrees in ICT and other fields of study meet the job requirement) and all groups combined (all job postings for higher education graduates in ICT occupations). The skills intensity is defined as the share of a particular skill category among all skill requirements for the average posting. For example, for postings that require either a degree in ICT or other fields of study (Group 3), 40% of all skills listed in the average posting in 2018 were advanced ICT skills. Note that the total of all skill subcategories does not equal 100% as not all skills have been categorised (see Section 3).
Source: Adapted from Burning Glass Technologies (2019[25]), *NOVA™ Job Feed data file*. The sample is restricted to postings in Ohio, Texas, Virginia, and Washington in 2018 that require an associate's degree or higher and that have been identified by BGT as ICT occupations (2010 SOC code 15.11).
Data available at: https://www.oecd.org/education/higher-education-policy/EDU-Working-Paper-231-data.xlsx.

In conclusion, the analysis of employer job posting data for ICT occupations shows that among non-ICT fields of study, graduates from engineering, as well as from business management, marketing, and related support services, have the best chances of filling positions in ICT occupations. Without a degree in ICT, it helps to have certain certifications valued by employers to demonstrate relevant skills. In positions for which graduates from other fields might substitute ICT graduates, technical transferable skills, especially advanced ICT skills, are predominantly sought after. Not only are they listed in almost every job posting, they also make up nearly half of the skills in the average posting, and their importance has changed little over time. Effectively signalling these skills is thus key for graduates seeking to enter ICT occupations. Advanced ICT skills appear to be a particular focus of short, online courses and micro-credentials (Kato, Galán-Muros and Weko, 2020[26]), which provide an opportunity for current students and workers alike to acquire and signal these skills to employers. In future analysis, it would be interesting to study which advanced ICT skills employers require in particular, and the extent to which the demand for these skills has changed over time, for instance due to certain software becoming outdated. This information would be particularly valuable to employees since ICT skills often yield salary premia (Burning Glass Technologies, 2017[14]).

6. Conclusion and avenues for further research

This paper explored how large-scale online job posting data may be used to provide useful information for prospective and current students, graduates, higher education leaders and instructors, and policy makers about the qualifications and skills employers are looking for. Because they allow for the exploration of similarities and differences in employer demand across a multitude of variables such as geography, industry and occupation, as well as experience, education and skill requirements, this type of data makes it possible to build employer demand profiles of a more granular and up-to-date nature than previously possible. Online job postings thus provide a valuable, complementary source of information to traditional sources such as vacancy survey data or occupational descriptors like O*NET. However, it is important to bear in mind that job posting data are a proxy rather than a direct measure of employer demand and have limitations requiring careful interpretation and, ideally, that such data be considered in conjunction with other sources such as representative survey data.

The analyses conducted in this paper show that job posting data can be employed to build job profiles detailing required qualifications, certifications and skills in a range of occupations that may help graduates prepare for their future careers. The analysis of occupational demand in Ohio, Texas, Virginia and Washington shows modest, but notable, differences in skills requirements within an occupation across the four states.

Job posting data can also be used to help answer targeted questions with the potential to contribute to a better alignment of labour demand and supply. For example, by helping identify the types of occupations where graduates from academic study fields – like sociology – may be in demand, the data can help students and graduates identify skills that they may need to develop to be competitive candidates in the occupation they are interested in. Additionally, this data may help them identify potential occupations in which employers may be interested in their combination of education and skills. Educators may also value a deeper understanding of the career trajectories of graduates and of the skills typically required of graduates across occupations. By exploring the types of qualifications and skills that may be substitutes for an ICT degree, the data may help individuals from a variety of backgrounds – both current students and workers – identify opportunities to build their own non-traditional path into high-demand, high-pay ICT occupations. For instance, we find that higher education graduates from engineering or business management, marketing, and related support services with the necessary technical skills seem particularly suited to fill vacancies in ICT occupations.

From a policy perspective, these data hold promise to complement traditional labour market information systems and enhance their relevance and use. In the four states examined in this paper, governments have developed tools to provide information about the outcomes of higher education graduates, assess current and projected occupational demand, and share this information with students, graduates, institutions and the broader public. However, there is scope for more systematically and better integrating online job posting data in those systems. Exploring the ways in which this could be done – including the resources needed to analyse and disseminate online job posting data – may thus be of interest to governments, in the United States and beyond.

Annex: Skills framework and examples of skills

TRANSFERABLE SKILLS	
Cognitive	**Example skills from Burning Glass**
Critical thinking	Critical thinking Analytical skills Writing Research Online research
Communication	Communication skills Written communication Verbal/oral communication Oral communication Presentation skills
Decision-making	Decision-making Strategic thinking Strategic planning Strategic development Thought leadership
Problem-solving	Problem-solving Creative problem-solving
Numeracy/Quantitative reasoning	Statistical reporting Calculation Statistics Statistical analysis
Meta-cognition and ability to learn	Quick learner
Socio-emotional	**Example skills from Burning Glass**
Conscientiousness/Task performance	Initiative Self-starter Detail-oriented Organisational skills Time management Prioritising tasks
Emotional regulation	Positive disposition Conflict management
Collaboration/Engagement with others	Teamwork/collaboration Persuasion Public speaking Building effective relationships
Open-mindedness	Creativity

Technical transferable	Example skills from Burning Glass
Management skills	Project management Budget management Performance management Business acumen Team management
Generic ICT skills	Microsoft Office Spreadsheets Microsoft Excel Computer literacy Microsoft Word Word processing
Advanced ICT skills	SQL Software development Java Python Graphic design Machine learning
Other technical transferable skills	English Budgeting Typing On-boarding Cost estimation Event planning
JOB-SPECIFIC SKILLS	
Technical job-specific	**Example skills from Burning Glass**
Technical job-specific	Patient care Accounting Sales Procurement Repair Critical care nursing Spanish Logistics Lesson planning Risk assessment

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