BII Report

Review of Burning Glass Job-ad Data

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Introduction

Posting and searching online job-ads is ubiquitous in the U.S. labor market for both employers and job seekers. Job seekers who search online job-ads are much more likely to find work and find work faster than those who do not (Faberman & Kudlyak, 2016). In addition, the job-ads posted by employers on corporate websites and online job boards provide a source of opportunity data that has opened up new avenues for research. This technical document evaluates the feasibility of using the real-time labor market information (LMI) collected by Burning Glass Technologies to supplement survey and administrative data collected by federal and state governments. In contrast to designed and administrative data which have varying lag times between collection and dissemination and are often aggregated over broad occupation groups, the real-time job ads collected by Burning Glass Technologies are made available within a day of a job-ad being posted and provide information at a granular level that links employer skill set requirements to detailed occupations in the O*NET-SOC taxonomy[1]. In this document, the data are evaluated for use in identifying the skill sets necessary for a job in the skilled technical workforce, future work will evaluate the Burning Glass Technologies resume data in defining pathways to skilled technical workforce jobs.

This document reviews the use of the Burning Glass Technologies job-ads in academic research highlighting issues with the data and if the researchers made any attempt to validate the Burning Glass Technologies job-ads data, the validation data sources they used, and their results. It provides the results of profiling and exploratory data analyses, for both the Virginia Burning Glass Technologies job-ads data and the Virginia Open Data/Open Jobs Data[2] which is compared to the Burning Glass Technologies job-ads data. The document concludes with recommendations regarding fitness-for-use.

Burning Glass Technology

Background

Burning Glass Technologies[3] is a Boston-headquartered labor market analytics firm founded in 1999, that uses artificial intelligence technologies to collect and host a massive repository of workforce and employment data. Burning Glass collects these data primarily for commercial purposes and secondarily for research purposes. The company markets both the data as a product as well as their consulting expertise on labor market questions to

[1] The O*NET-SOC taxonomy. O*NET Resource Center. Available at https://www.onetcenter.org/taxonomy.html. (last accessed May 15, 2019)
[2] Open Data/Open Jobs https://opendata-cs-vt.github.io/ccars-jobpostings/ (last accessed August 9, 2019)
[3] Burning Glass Technologies https://www.burning-glass.com/about/faq/ (last accessed May 15, 2019)

customers across a variety of industries, education institutions, local and regional governments, recruiting and staffing agencies, and corporate firms.

Burning Glass Technologies data are collected using a web crawling technique that uses computer programs called spiders to browse approximately 50,000 online job boards, corporate websites, and other places where job ads are posted and extract more than 70 variables per advertisement to create the repository of jobs data (see Appendix B for the Burning Glass Technologies Job-ad Data Dictionary). De-duplication of the job ad is performed once at the website level, to avoid counting the same posting that recurs across multiple days, and once at the aggregate level, to eliminate the same posting advertised on multiple sites. Data has been extracted since 2007 with the exception of 2008 and 2009. Both the algorithms used to identify duplicates and scrape websites are proprietary as well as the website addresses that are scraped.

Review of Academic Literature

This review was done to alert us to issues other researchers had encountered in using the Burning Glass Technologies data for research and how they addressed them. In the end, ten articles met the final screen. The literature review located research articles that used the Burning Glass Technologies job-ads data. Academic data bases that were searched included EconLit, Social Sciences, Web of Knowledge/Web of Social Science and Humanities Library, and Education Research Complete; and the grey literature data bases. The grey literature has been defined by the Luxembourg Convention[4] on Grey Literature as "Information produced on all levels of government, academics, business and industry in electronic and print formats not controlled by commercial publishing, i.e. where publishing is not the primary activity of the body." The grey literature includes technical reports, government documents, working papers, conference proceedings, white papers, institutional repositories, blogs, and newspapers. The search engines, databases, repositories and directories of grey literature resources used for this report included Google Scholar, Registry of Open Access Repositories, and Directory of Open Access Journals. A list of academic references was also provided to us by Burning Glass Technologies. The inclusion criteria for the initial screen were articles that used 2010 to 2019 Burning Glass Technologies U.S. job-ads data and not Burning Glass Technologies dashboards like Labor Insight™, 57 articles were found in the initial screen. Of the 57 articles, only those that described one or both of their processes and results for data profiling and validation were kept. The focus of the inclusion criteria was on technical issues regarding the fitness-for-use of the data that became apparent after researchers profiled and benchmarked the Burning Glass Technologies data to other data sources for job-ad data such as government surveys or other job-ad aggregators. This review does not discuss the topics and findings of the research using Burning Glass Technologies job-ad data.

We started by looking at what these research articles reported about data profiling. Data profiling is a process for determining both the quality of the data and its fitness-for-use in addressing the research question(s); it evaluates data quality measures like duplicate observations, missing values, values outside the range of the variable, etc. (see the section on Data Profiling for more detail). In the 57 articles that were reviewed, the majority cited the work of Carnevale et al. (2014) when it came to data profiling issues (Table 1). Carnevale et al. (2014) wrote a technical report on assessing the usefulness on online job-ad data. Using 2013 Burning Glass Technologies job-ad data they estimated between 60 to 70 percent of job openings are posted online[5]. The data profiling issues they reported were missing employer name and education requirement for ~50% of the job-ads; and a bias in the representativeness of the job-ads which favored white collar jobs. A more recent article (Azar et al. 2019a) that used Burning Glass Technologies job-ad data from 2010 until the last quarter of 2016, found that 35.9% of the employer names were missing. It is common for job-ads posted by staffing companies not to disclose the employer. Overall, for variables such as state, city, occupation title, major occupation group (two-digit occupation codes), and skills, Carnevale et al. (2014) found that coding accuracy was greater than 80%. Two other articles (Rothwell 2014; Hershbein & Hollenbeck

[4] Library and Learning Commons on the Grey Literature https://bowvalleycollege.libguides.com/grey-literature (last assessed August 10, 2019)

[5] Since then, Burning Glass Technologies estimates that share has grown to roughly 85% and states: "The jobs that aren't online now are usually in small businesses (the classic example being the "help wanted" sign in the restaurant window) and union hiring halls. Lower-income, lower-skill jobs are also less likely to be posted online than higher-skill jobs." https://www.burning-glass.com/about/faq/ (last accessed May 20, 2019)

2015) that reported on data profiling issues using the same variables were in agreement with Carnevale et al. (2014) regardless of the year(s) of job-ads data used in their research (Table 1).

Only one article profiled duplicate observations. An article looking into physician assistant (PA) shortages (Morgan et al. 2017) manually checked for duplicated job-ads and in 40 ads found 3 duplicates; they also found that 23% of the jobs listed as PA were not for a PA job. In this case the PA acronym had numerous interpretations such as the abbreviation for Pennsylvania and professional association. As noted in Burke et al. (2019), Burning Glass Technologies uses the same filtering and de-duplication algorithm across years and applies any improvements to the algorithm retroactively. In the case of Morgan et al. (2017), the dual interpretation of the PA acronym was corrected by Burning Glass Technologies and retroactively applied.

Table 1. Summary of the Data Profiling Issues Researchers Found with the Burning Glass Technologies Job-ads Data

Reference	Data Description / Years	Findings
Azar, Huet-Vaughn, Marinescu, Taska, & Wachter (2019)	Job-ad data (2010-2016 Q4)	Missing Data: 39.5% of the job-ads did not report an employer
Carnevale, Jayasundera, & Repnikov (2014)	Job-ad data (2013 Q2)	Accuracy: coding for occupation, education, and experience were ≤80% accurate; for fields like state, city, occupation title, major occupation group (two-digit occupation codes), and skills accuracy is >80% Job Bias: white-collar office jobs (sales & office support, managerial & professional office, and STEM occupations) make up three out of five online job ads Missing Data: almost half of the online ads do not report an education requirement Education Bias: 30-40% of online job-ads are for workers with some college or an Associate's degree; 40-60% are for workers with a high school diploma; 80-90% are for workers with at least a Bachelor's degree
Rothwell (2014)	Job-ad data (Jan 2013-Mar 2013) Company websites in metropolitan areas	Missing Data: only 53% of the job-ads provided education requirements (55%), experience requirements (52%), salary (7%)
Hershbein & Hollenbeck (2015)	Job-ad data (2010–2013)	Missing Data: only 53% of the job-ads provided education; occupations that cluster at both the extreme high and low ends of the education spectrum are less likely to specify necessary education in postings
Morgan P, Himmerick KA, Leach B, Dieter P, & Everett C (2017)	Job-ad data (2014)	Duplicates: Burning Glass Technologies only considers a posting to be a duplicate if it is repeated within 2 months; manual targeted search for duplicates among 40 postings found 3 duplicates (7.5%); and 2 of these were for the same job that had remained posted for > 2 month Accuracy: BG location field very accurate; physician assistant (PA) job field had significant errors that resulted in 23% of postings not being for a PA job, majority of these postings were for jobs that had "PA" in the text of the advertisement, such as jobs found in Pennsylvania (abbreviated "PA") or for legal jobs that often have the suffix of "PA" (for a type of legal entity called a professional association); some values that Burning Glass Technologies had assigned for the duration of experience required were found to be inaccurate, jobs that were coded with a small integer (1, 2, 3, and 5) had accuracy >80%, but jobs that had coded for fractions of years or higher integer values were typically inaccurate

Since Burning Glass Technologies job-ad data only includes vacancies posted on-line, as opposed to federal surveys such as the Job Openings and Labor Turnover Survey (JOLTS) or state surveys which are administered to a representative sample of a target population of employers, understanding the potential biases are essential. There are many sources of potential bias:

1. Whether or not the Burning Glass Technologies job-ads data is *representative* of the population of all job vacancies in the U.S. at any time point is a function of their crawling policy and the fact that job-ads from certain occupations are less likely to be posted online, for example less-skilled jobs in the construction and service industries.

2. Whether or not the Burning Glass Technologies job-ads data is *accurate* is a function of the company's algorithm to code and canonicalize the scraped information in the ads and get rid of duplicates.

Of the 57 articles, nine benchmarked the Burning Glass Technologies data using different levels of aggregation and data sources; the data sources used in the comparisons include:

- federal surveys Job Openings and Labor Turnover Survey (JOLTS), American Community Survey (ACS), Current Population Survey (CPS), and Bureau of Labor Statistics' Occupational Employment Statistics (OES);
- state surveys from the Oregon Employment Department, Washington State Employment Security Department, and from the Boston, Minneapolis-St. Paul, Portland-Vancouver-Hillsboro, and Seattle-King County metropolitan areas;
- the not-for-profit, The Conference Board, Inc.[6], Help Wanted Online™ series (HWOL); and
- the for-profit Standard & Poor's, Compustat[7].

The remaining articles that mentioned benchmarking, referred to either the research of Hershbein and Kahn (2018) or Carnevale et al. (2014). Hershbein and Kahn (2018) evaluated the changes in skill requirements listed in vacancy postings following the 2009 Great Recession; using Burning Glass Technologies job-ads data they documented evidence of upskilling (firms demanding higher-skilled workers) when the local economy suffers a recession.

Table 2 provides the results of the benchmark review; the table lists the name of the benchmark data set, the dates of the Burning Glass Technologies used and any constraints imposed (for example, using only those job-ads with an employer name), the level of aggregation (for example, Standard Occupational Classification codes by month by state), and the results. Of the twelve benchmarking data sets, only the HWOL[8] data is collected in a similar manner to Burning Glass Technologies. The HWOL data is collected in real-time from over 28,000 different online job boards including traditional job boards, corporate boards, social media sites, and smaller job sites that serve niche markets and smaller geographic areas. The differences are that Burning Glass Technologies only measures new postings (the same posting appears only on the first month it is recorded) whereas HWOL measures new and active postings (in active postings the same job can appear in two or more consecutive months if the time to fill is more than 30 days) and unlike the Burning Glass Technologies, HWOL aggregates the total number of ads available by month. In May 7, 2019, the Conference Board announced a collaboration with Burning Glass Technologies to enhance the HWOL program[9]. Although Carnevale et al. (2014)[10] estimated that online job ads capture 60-70% of the total job openings in the labor market using 2013 Q2 Burning Glass Technologies job-ad data, Burning Glass Technologies currently estimates that number is closer to 85%. Sahin et al. (2014) report that approximately 60 percent of online job vacancies are posted on only five job boards of which Craig's list is one. Comparing the HWOL data to the Job Openings and Labor Turnover Survey (JOLTS), Cajner and Ratner[11] (2016), illustrate how the changes in online advertising prices (for example, Craigslist job postings) can lead to an underestimate of job vacancies. They estimated that when prices were raised from no fee in 2015 to $25 ($35 and $45 in larger metropolitan areas) there was a 12% decrease in the total number of HWOL ads and 22% percent fewer new HWOL ads. In the only comparison of Burning Glass Technologies to HWOL that we found in the literature, Hershbein and Hollenbeck (2015), report HWOL has greater coverage and that Burning Glass Technologies underreports vacancies in agricultural and construction relative to HWOL.

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[6] Help Wanted Online https://www.conference-board.org/data/helpwantedonline.cfm (last accessed May 15, 2019)
[7] Compustat https://www.spglobal.com/marketintelligence/en/?product=compustat-research-insight (last accessed May 10, 2019)
[8] Help Wanted Online https://www.conference-board.org/data/helpwantedonline.cfm (last accessed May 10, 2019)
[9] The Conference Board and Burning Glass Technologies Announce Help Wanted OnLine™ Collaboration https://www.burning-glass.com/blog/conference-board-burning-glass-announce-help-wanted-online-collaboration/ (last accessed September 11, 2019)
[10] In 2013 Burning Glass Technologies visited 32,000 websites and today it visits over 50,000.
[11] A Cautionary Note on the Help Wanted Online Data https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/a-cautionary-note-on-the-help-wanted-online-data-20160623.html (last accessed May 10, 2019)

Comparisons to federal surveys show that regardless of the survey, the years compared, or the aggregation level, occupations in food preparation & servicing, building grounds cleaning & maintenance, construction, production, and transportation & materials moving are all underrepresented in Burning Glass Technologies. Carnevale et al. (2014) aggregated the CPS and Burning Glass Technologies job-ads by education requirements and concluded the Burning Glass Technologies job-ads underrepresent those with some college or Associate's degree and over represents college graduates. This agrees with Clemens et al. (2018) who in a comparison to OES reported that low wage occupations are underrepresented in Burning Glass Technologies data. Hershbein and Kahn (2018) documented the occupation distributions of Burning Glass Technologies compared to CPS and OES and showed Burning Glass Technologies overrepresented occupations in computer & mathematical, management, business & financial operations, and healthcare practice & technicians. In the case of occupations in computer & mathematics Burning Glass Technologies had over four times the number of CPS and OES; also overrepresented to a lesser extent are occupations in management, healthcare practitioners & technical, business & financial operations. Rothwell (2014) used state survey data from the metropolitan areas, Boston, Minneapolis-St. Paul, Portland-Vancouver-Hillsboro, and Seattle-King County, and came to the same conclusions regarding occupation over- and under- representation as Hershbein and Kahn (2018).

Table 2. Summary of the Data Benchmarking Process Researchers Found with the Burning Glass Technologies Job-ads Data

Comparison Data Set	Reference	BGT Data Source / Years	Aggregation	Findings
Compustat	Liu & Wu (2018)	Job-ad data (2007, 2010-2016), Posting with employer name	NAIC 2-digit industry code (17)	matched Burning Glass Technologies employer names and Compustat names; Burning Glass Technologies sample represents 65% of Compustat; most underrepresented is Mining & Logging (43.3%); most over-represented is Retail Trade (79.5)
	Hershbein & Kahn (2018)	Job-ad data (2007, 2010-2015) Firms that posted in the 2010-2015 that can be matched to at least one job-ad in 2007	Publicly traded companies	matched 41% of Burning Glass Technologies job-ads to Compustat firms
Job Openings and Labor Turnover Survey (JOLTS)	Hershbein & Kahn (2018)	Job-ad data (2007, 2010-2015)	Major industry groups (15)	health & social assistance, finance & insurance, and education are overrepresented in Burning Glass Technologies; accommodation & food services, public administration/government and construction are underrepresented; most differences are small in magnitude (not quantified)
	Carnevale, Jayasundera, & Repnikov (2014)	Job-ad data (2013 Q2)	Industry (16)	education services, real estate & rental & leasing, and manufacturing are overrepresented in Burning Glass Technologies; professional & business services, transportation, warehousing & utilities are among the most consistently represented industries; job ads in the government and construction industry are among the most underrepresented; total active online job ads captured each month 60-70% of the total job openings in the labor market
	Mohnen, Berkes, & Taska (2018)	Job-ad data (2010-2016)	Industry (16) x Years (2010, 2013, 2016)/Quarterly	manufacturing, finance, education, and healthcare are overrepresented in Burning Glass Technologies; construction, accommodation & food services, government are underrepresented
	Hershbein & Hollenbeck (2015)	Job-ad data (2010–2013) Postings with listed educational requirements	Standard Occupational Classification (SOC) 2-digit codes (22)	overall trends in volume are similar, although levels vary
American Community Survey (ACS)	Mohnen, Berkes, & Taska (2018)	Job-ad data (2010-2016)	Standard Occupational Classification (SOC) 2-digit codes (22) x Years (2010, 2013, 2016)/Quarterly	business & financial, computer & mathematical, and healthcare occupations are overrepresented in Burning Glass Technologies; education, construction, and production occupations are underrepresented

Table 2. Summary of the Data Benchmarking Process Researchers Found with the Burning Glass Technologies Job-ads Data

Comparison Data Set	Reference	BGT Data Source / Years	Aggregation	Findings
	Papageorgiou (2018)	Job-ad data (Feb 2016-Apr 2016)	Occupation	95.28% of employed workers in the ACS data are working in an occupation in which there is an MSA job-ad in the Burning Glass Technologies data, suggesting that there are few occupational opportunities beyond those captured in the Burning Glass Technologies data
Minnesota Job Vacancy Survey	Modestino, Shoag, & Balance (2016)	Job-ad data (2007, 2010, and 2012)	Skills	constructed similar measures of employer skill requirements using an actual survey of employers conducted by the Minnesota Department of Labor found similar patterns to Burning Glass Technologies
Surveys from Boston, Minneapolis-St. Paul, Portland-Vancouver-Hillsboro, and Seattle-King County metropolitan areas	Rothwell (2014)	Job-ad data (2010–2013) Company websites in metropolitan areas	Standard Occupational Classification (SOC) 2-digit codes (22) x Years (2010-2013) /Quarterly	Burning Glass Technologies overrepresented computer & mathematical occupations (8.9%) and management & business (1%); BG underrepresented food preparation & serving occupations (10.1%), sales, and building & grounds cleaning & maintenance both at (3%)
Oregon Employment Department Survey	Rothwell (2014)	Job-ad data (2013) Company websites in metropolitan areas	Standard Occupational Classification (SOC) 2-digit codes (22)	correlation between the share of jobs taking 30 or more days to fill and Burning Glass Technologies median duration was 0.47
Washington State Employment Security Department Survey	Rothwell (2014)	Job-ad data (2013) Company websites in metropolitan areas	Standard Occupational Classification (SOC) 2-digit codes (22)	similar ranking between vacancy duration; from Seattle survey the 5 hardest to fill occupations were computer & mathematical, architecture & engineering, health care practitioners & technical, transportation & material moving, and personal care & service; from Burning Glass Technologies the 6 hardest to fill were education, training, & library, computer & mathematical, architecture & engineering, management, personal care & service, and health care
Help-Wanted Online Index (HWOL)	Hershbein & Hollenbeck (2015)	Job-ad data (2010–2013) Postings with listed educational requirements	Standard Occupational Classification (SOC) 2-digit codes (22) x month	HWOL provides more thorough coverage of occupations than Burning Glass Technologies; Burning Glass Technologies undercounts jobs in agriculture and construction relative to HWOL
Bureau of Labor Statistics' Occupational Employment Statistics (OES)	Clemens, Kahn, & Meer (2018)	Job-ad data (2011–2016) Postings with employer name and low wage jobs	Standard Occupational Classification (SOC) 4-digit codes x month x state	Compared Burning Glass Technologies and OES occupation shares over 6 years, low wages occupations are underrepresented in Burning Glass Technologies; few changes in the difference between the two occupation distributions overtime
	Hershbein & Kahn (2018)	Job-ad data (2007, 2010-2015)	Major occupation groups (22) using 2-digit Standard Occupational Classification codes	BG has a 4x the number of computer & mathematical occupations; management, healthcare practitioners & technical, business & financial operations, are overrepresented to lesser degrees; underrepresented in transportation & material moving, food preparation & serving related, production, and construction & extraction
Current Population Survey (CPS)	Hershbein & Kahn (2018)	Job-ad data (2007, 2010-2015)	Major occupation groups (22) using 2-digit Standard Occupational Classification codes	Burning Glass Technologies has a 4x the number of computer & mathematical jobs; management, healthcare practitioners & technical, business & financial operations, are overrepresented to lesser degrees; underrepresented in transportation & material moving, food preparation & serving related, production, and construction & extraction; changes in representativeness remained small over time (2007-2015) tendency to move in the direction of closer representativeness (not quantified)

Table 2. Summary of the Data Benchmarking Process Researchers Found with the Burning Glass Technologies Job-ads Data

Comparison Data Set	Reference	BGT Data Source / Years	Aggregation	Findings
	Carnevale, Jayasundera, & Repnikov (2014)	Job-ad data (2013 Q2)	Education (4)	BG job-ads underrepresent those with some college or Associate's degree and over represents college graduates

Virginia Open Data Open Jobs

Background

Our data discovery process located a pilot project initiated by the Commonwealth Center for Advanced Research and Statistics (CCARS) to create an open real-time data set of advertised job-ads in Virginia. This was an initiative by former Gov. Terry McAuliffe which established the (CCARS) to improve labor market, workforce, and education data. The intended use of these data was to create applications that could "help connect Virginians to job opportunities, offer insights into the needs of employers by occupation, skills, or education requirements, or create predictive models to help Virginia determine its future needs for talent!" The pilot project is no longer operating, the last posting of job-ads was in July 2017.

The comparison data set that was chosen for this study is Open Data Open Jobs (OD/OJ) collected by the Commonwealth Center for Advanced Research and Statistics because it was collected in a similar manner as the Burning Glass Technologies job-ad data but only for vacancies within Virginia. Another difference includes the fact that CCARS only scraped government websites. Although the OD/OJ data were collected over the time period June 2010 to June 2017, daily web scraping only occurred in the later months. Therefore, comparison between the Burning Glass Technologies and OD/OJ data is limited to job-ads in Virginia for the month of June 2017. Based on our literature review, this is the only validation of the Burning Glass Technologies job-ads data at the level of the job-ads, all other validations are based on aggregated data.

Unlike the Burning Glass Technologies job-ad technology which browses approximately 50,000 online "job boards, corporate websites, and other places where job ads are posted" the OD/OJ job-ad data were constructed from only three websites. The OD/OJ website acknowledged that the job-ads they collected did not cover all job openings in Virginia advertised online. The websites that were included in the OD/OJ job-ad data are:

1. A daily feed of jobs from the National Labor Exchange[12] (NLx) made available by the DirectEmployers Association, Inc.[13];
2. Job-ads in the Virginia Workforce Connection[14] made available by the Virginia Employment Commission; and
3. A feed of schema tagged jobs available through an open API built by Devis for the Veterans Job Bank[15].

All three are aggregators of job-ads. NLx is an electronic labor-exchange network, that collects job openings found on only three sources, over 25,000 corporate career websites, 50 state workforce agency job banks plus Puerto Rico, Guam, and the District of Columbia, and the federal job portal usajobs.gov. Unlike Burning Glass Technologies, NLx does not index third party sites or job boards. The indexed NLx employer community includes both DirectEmployers member companies and nonmembers who would like their jobs to appear in the NLx. The job feeds on NLx are

[12] National Labor Exchange https://usnlx.com/ (last accessed June 12, 2019)
[13] "DirectEmployers is a nonprofit Member-owned and -managed association formed in 2001 by 14 leading Fortune 500 companies searching for a way to reduce recruiting costs, while regaining ownership of their recruitment brand." https://directemployers.org/ (last accessed June 12, 2019)
[14] Virginia Workforce Connection https://www.vawc.virginia.gov/vosnet/Default.aspx (last accessed June 11, 2019)
[15] Veterans Job Bank https://nrd.gov/nrdLandingPage?term=veterans%20job%20bank (last accessed July 25, 2019)

refreshed daily, the previous day's file eliminated and replaced with a new one. No information was found on the how the Virginia Workforce Connection aggregates job-ads. The Veterans Job Bank is maintained by the National Resource Directory and federal government website that provides Veterans and transitioning Service Members with a central, online source to search for job opportunities and helps employers find qualified Veterans to fill vacancies. When last accessed on July 25th it appears the Veterans Job Bank is no longer functional.

The OD/OJ combined the job-ads from the three sites into a single data set by:

- mapping job-ads from all three sources to the job-posting schema standard;
- enriching job-ads with average wage data from the Georgetown University's Center for Education and the Workforce;
- canonicalizing job titles with assistance from Glassdoor; and
- de-duplicating the data using an algorithm to identify identical job postings.

Data Profiling

Introduction

The SDAD data profiling starts with a determination of both the quality of the data and its fitness-for-use to the project at hand. An important feature of the data profiling process is that discovered issues are only described and not actually "fixed". The appropriate fix will depend upon the specific needs of the research. If the prescribed "fix" is not appropriate, or even possible there would be no need for any action and attempting a fix at this stage could result in wasted time and effort. The data profiling metrics are described below.

- *Completeness* - completeness is a variable metric, the metric is a percentage, the number of observations that have values compared to the number of observations that "should" have values (NA (not available) are not counted as a value).
- *Value validity* - value validity is a variable metric, data elements with proper values have value validity; the metric is the percentage of data elements whose attributes possess values within the range expected for a legitimate entry (NAs are considered a valid value).
- *Consistency* - consistency is a variable metric, it is the degree of logical agreement between variable values. The rules that specify the logical relationships between the entity values are called dependency constraints. A simple example of a dependency constraint violation would be a location disagreement, a zip-code that does not agree with a state code.
- *Uniqueness* - uniqueness is a variable metric, it is the number of unique valid values that have been entered for a variable (NAs are not counted as unique values).
- *Duplication* - duplication is a data set metric, it is the degree of replication of distinct observations per observation unit type; the metric is the percentage of observations in a data set that are duplicated.

Burning Glass Technologies Job-Ad Data Description

The Social and Decision Analytics Division purchased the Burning Glass Technologies job-ad data for the years 2007, 2010-2017 after an extensive data discovery and evaluation process. Burning Glass Technologies is the only vendor who sells databases of individual job postings and resumes for research purposes. While other vendors maintain their own resume databases, products sold are typically dashboards intended for use by job recruiters or the data is aggregated prior to delivery. Burning Glass Technologies places significant effort into the maintenance of individual records in these databases, including de-duplication of job postings and resumes, de-identification of individual resumes, and extraction of key terms. In addition, variables are linked to standard codes in the industry (e.g., occupation codes, industry codes) and they have developed their own hierarchy of skill taxonomy variables.

Burning Glass Technologies job-ad data contains six separate data sets that can be linked by a unique job-ad identifier:

1. *Main* - the base table, contains 54 columns of job descriptors such as the Burning Glass Technologies Job ID, date the posting was spidered, industry classifications, educational requirements, etc.;
2. *Certifications* - a related table of certifications associated with the job (there is a row for each certificate, the 4 columns contain the Burning Glass Technologies Job ID, date the posting was spidered, minimum annual salary, and certification);
3. *CIP* - a related table of Classification of Instructional Program (CIP) codes for the field of study (there is a row for each CIP code, the 4 columns contain the Burning Glass Technologies Job ID, date the posting was spidered, minimum annual salary, and CIP code);
4. *Degree* - a related table indicating level of study (there is a row for each degree, the 4 columns contain the Burning Glass Technologies Job ID, date the posting was spidered, minimum annual salary, and degree);
5. *Major* - a related table indicating field of study using plain-text description (there is a row for each major, the 4 columns contain the Burning Glass Technologies Job ID, date the posting was spidered, salary, and standardized major);
6. *Skill* - a related table of skills associated with the job (there is a row for each skill, 9 columns contain the BGT Job ID, date the posting was spidered, minimum annual salary, skill, skill cluster, skill cluster family, is skill specialize?, is baseline skill?, is software skill?).

The full list of variables and descriptions are provided in the BGT Data Dictionary which is provided upon purchase on the data.

Burning Glass Technologies Job-ad Data Profiling Results

This section describes of the results of the Burning Glass Technologies data profiling, The following sixteen variables are profiled; the variables from the main file were selected since they align with a comparison data set described in the next section; and the variables from the skill files were chosen since the Burning Glass Technologies skills variables will be important to our future research in identifying pathways to the skilled technical workforce.

Thirteen of the variables used in the profiling are from the main file:

- bgtjobid - job identifier
- jobdate - the date the job was posted
- occfam - the major occupation family code of the job posting
- occfamname - the industry corresponding with the major occupation code
- employer - the name of the hiring company
- city - the city where the job is located
- state - the state where the job is located
- county - the county where the job is located
- fipsstate - the fipsstate code where the job is located
- fipscounty - the fipscounty code where the job is located
- fips - the whole fips code where the job is located
- lat - the latitude where the job is located
- lon - the longitude where the job is located

Three variables used in the profiling are from the skills file:

- skill - skills is a canonicalized version of a skill listed in the posting to enable improved search and categorization
- skillcluster - groupings of skills that have similar functionality, can be trained together, and/or frequently appear together in job postings

- skillclusterfamily - the most general layer of the Burning Glass Technologies skill taxonomy; each skill and skill cluster belong to exactly one family

The results of the Burning Glass Technologies data profiling are displayed in Table 3.

The two variables with the largest number of missing values are skillcluster and skillclusterfamily; these variables are part of the Burning Glass Technologies skill taxonomy. Skill clusters are groupings of skills that have similar functionality for example, Microsoft Office and Microsoft PowerPoint are skills that are in the Microsoft Office and Productivity Tools skill cluster. Skill cluster families are the most general layer of the Burning Glass Technologies skill taxonomy; for example, the skill cluster Microsoft Office and Productivity Tools is in the Information Technology skill cluster family, along with other skill clusters such as Technical Support, Basic Computer Knowledge, and Enterprise Resource Planning (ERP). Each skill and skill cluster belong to exactly one family. There are 10,631 unique skills in the 2017 Virginia job-ad data, of those, 6,464 (60.8%) have been assigned to a skill cluster and skill cluster family.

Every skill, regardless of whether or not it has a complete Burning Glass Technologies skill hierarchy designation, is categorized into one of the two Burning Glass Technologies categories, baseline skill or specialized skill. Burning Glass Technologies uses baseline or foundational skills and specialized or technical skills in lieu of the commonly used paradigm of hard and soft skills[16]. Baseline skills are those that are in high demand by almost all employers; skills demanded across multiple occupations that are not typically taught in training classes are baseline skills. Baselines skills are not just people skills such communication and troubleshooting, but also knowledge of specific software packages like Microsoft Word and Excel and foreign languages (25 different languages listed). According to Burning Glass Technologies even in the most technical career areas (such as IT, Healthcare, and Engineering) at least a quarter of the skills demanded by employers are baseline skills. Baseline skills include many soft skills, but also skills like Microsoft Word and Excel since even thought people can be formally taught to use these software packages, most learn to use them on their own. Burning Glass Technologies defines technical skills as those that can both be taught and are specific to a particular occupation or industry. For example, software programs ranging from Adobe Photoshop to RStudio may be either self-taught or learned in a formal setting, but the demand for these skills is limited to specific occupations and industries. The top ten baseline and technical skills as a percentage of the 2017 VA job-ads are displayed in Table 4.

The variable with the second largest number of missing values is employer, 21.3%. This is attributed to staffing companies that do not or are not allowed to disclose the name of the employer.

[16] The Human Factor https://www.burning-glass.com/wp-content/uploads/Human_Factor_Baseline_Skills_FINAL.pdf (last accessed August 10, 2019)

Table 3. Data Profiling for Select Variables from the Burning Glass Technologies Main and Skill Data Files

Main Data File: N=63,610 July 2017 Virginia (only)			
Variable	Completeness N / %	Value Validity N / %	Uniqueness* N
bgtjobid	63,610 / 100%	63,610 / 100%	63,610
jobdate	63,610 / 100%	63,610 / 100%	31
occfam	61,462 / 96.62%	63,610 / 100%	23
occfamname	61,462 / 96.62%	63,610 / 100%	23
employer	50,064 / 78.70%	Not Checking**	6,308
city	63,158 / 99.29%	63,610 / 100%	798
state	63,610 / 100%	63,610 / 100%	1
county	63,158 / 99.29%	63,610 / 100%	132
fipsstate	63,610 / 100%	63,610 / 100%	1
fipscounty	63,158 / 99.29%	63,610 / 100%	131
fips	63,158 / 99.29%	63,610 / 100%	131
lat	63,180 / 99.32%	63,610 / 100%	951
lon	63,180 / 99.32%	63,610 / 100%	988
Skills Data File: N=639,364 July 2017 Virginia (only)			
skill	63,5078 / 99.33%	639,364 / 100%	7,548
skillcluster	46,3878 / 72.55%	639,364 / 100%	610
skillclusterfamily	46,3878 / 72.55%	639,364 / 100%	28

*Excludes NA
**The employer value validity will be evaluated when it is being considered for use in analysis. It is not evaluated here since it is not one of the variables used in the comparison to the OD/OJ data.

Table 4. Top 10 Burning Glass Technologies (BGT) Baseline & Specialized as a Percentage of the Number* of VA Job-ads for 2017

BGT Baseline Skills	Percent	BGT Specialized Skills	Percent
Communication Skills	28.52	Customer Service	15.65
Planning	12.30	Teamwork / Collaboration	13.63
Writing	11.29	Scheduling	10.67
Problem Solving	11.07	Sales	9.68
Organizational Skill	10.97	Budgeting	7.38
Research	10.70	Project Management	7.28
Microsoft Office	10.69	Customer Contact	6.35
Microsoft Excel	10.55	Retail Industry Knowledge	5.56
Physical Abilities	9.52	Repair	5.22
Detail-Oriented	8.73	SQL	4.70

*Number of Job-ads = 699,754

Consistency was evaluated by checking to see that the city, county, fipscounty, and fips values were all located in the state of Virginia. Excluding missing values (blank or null values) all values for city, county, fipscounty, and fips are consistent with values for the state of Virginia. Duplication was evaluated in the Main data file only. Duplication was evaluated by counting the number of observations (rows) with the same value for all variables except the unique id, bgtjobid. When duplicates were evaluated using the 13 variables listed in Table 3, there were 18,431 duplicates (71.02% unduplicated); when all 52 variables are included there were no duplicates.

OD/OJ Job-ad Data Description

The OD/OJ job-ads data is a single data set with nine variables:

- rawdata_id - unique job identifier
- jobLocation_geo_latitude - the latitude where the job is located
- jobLocation_geo_longitude - the longitude where the job is located
- normalizedTitle_onetCode - the major occupation family code of the job posting
- normalizedTitle_onetName - the industry corresponding with the major occupation code
- datePosted - the date the job was posted
- experienceRequirements - text string that can include education and skill requirements, years of experience
- jobDescription - text string that can include responsibilities and skill requirements
- hiringOrg - name of the hiring organization

OD/OJ Job-ad Data Profiling Results

This section describes of the results of the OD/OJ data profiling, the results are displayed in Table 5.

Table 5. Data Profiling for Open Data Open Job Variables

N=47,908 July 2017 Virginia (only)			
Variable	Completeness N / %	Value Validity N / %	Uniqueness* N
rawdata_id	47,908 / 100%	47,908 / 100%	47,908
jobLocation_geo_latitude	47,807 / 99.79%	47,908 / 100%	126
jobLocation_geo_longitude	47,807 / 99.79%	47,908 / 100%	126
normalizedTitle_onetCode	39,639 / 82.74%	47,908 / 100%	384
normalizedTitle_onetName	39,639 / 82.74%	47,908 / 100%	384
datePosted	47,908 / 100%	47,908 / 100%	28
experienceRequirements	5,313 / 11.09%	47,908 / 100%	2,933
jobDescription	47,905 / 99.99%	47,908 / 100%	41,522
hiringOrg	47,896 / 99.97%	Not Checking**	1,400

*Excludes NA
**The employer value validity will be evaluated when it is being considered for use in analysis. It is not evaluated here since it is not one of the variables used in the comparison to the Burning Glass Technologies data.

Consistency was evaluated by plotting the latitudes and longitudes to see if the job location was in Virginia. Only three jobs were located outside Virginia; these job-ads were removed. Duplication was evaluated by counting the number of observations (rows) with the same value for all variables except the unique identifier, rawdata_id. When duplicates were evaluated using the seven remaining variables listed in Table 4, there were 3,032 duplicates (93.67% unduplicated). Duplicate observations were retained to account for the possibility of multiple openings for the same position and same employer, supported by evidence discovered during the data exploration process.

- All the duplicates have an employer and a job description, often a very detailed one.

- Half of the duplicates have an O*NET code for truck drivers. A sixth of the duplicates are missing O*NET codes, but the job description either includes the title or provides a detailed description of the position. The next two most common titles are general operations managers and wholesale sales representatives.

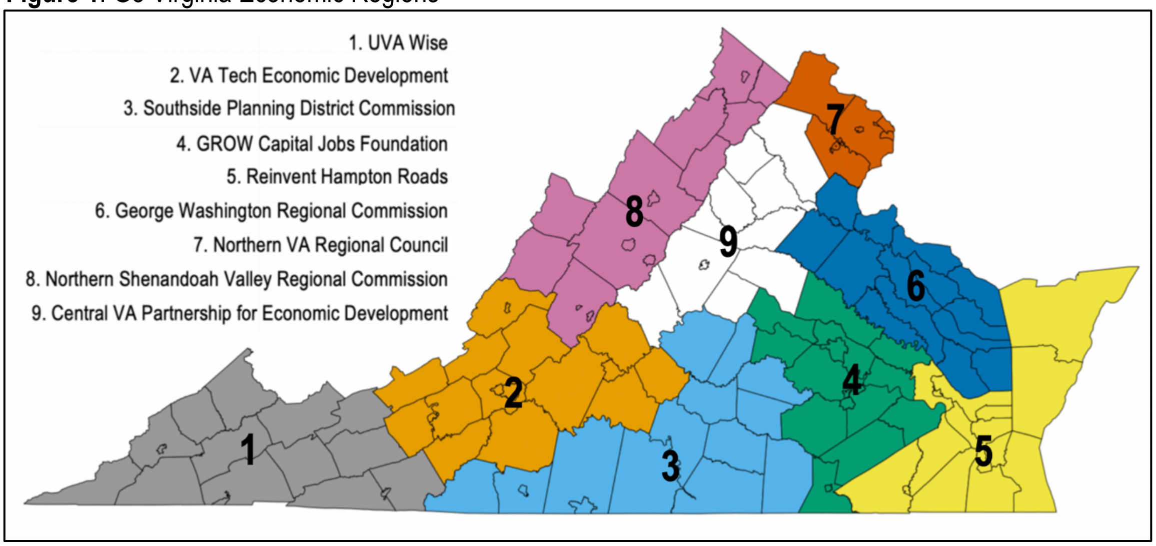
Due to the closure of the Virginia Open Jobs program, it may prove difficult to definitively draw conclusions about the duplicates one way or another. However, the rich detail of employer and job description information and the pattern of lower-level operations and sales positions supports the inclusion of these positions as multiple 'real' positions and not duplicates of existing positions.

Benchmarking Burning Glass Technologies against OD/OJ

Region Comparisons

Job-ads from July 2017 were used for the Burning Glass Technologies and OD/OJ comparisons. Comparisons between the Burning Glass Technologies and OD/OJ job-ads were made by aggregating the data by the 23 major occupations groups and the nine economic regions of Virginia as designated by GO Virginia[17]. GO Virginia is a bipartisan, business-led economic development initiative that established nine regional boundaries based on their priority industry clusters. The thought is aggregating by different industry clusters might help identify any occupation biases in the Burning Glass Technologies web scraping process. The locations of the nine economic regions are displayed in Figure 1 and the number of Burning Glass Technologies and OD/OJ job-ads by region is displayed Table 5.

Figure 1. Go Virginia Economic Regions



The number of job-ads that could be placed in a region is 63,180 (99.32%) for Burning Glass Technologies and 47,807 (99.79%) for OD/OJ. The total number of job-ads for the month of July 2017 is 24% higher for Burning Glass Technologies; this was expected since Burning Glass Technologies scraps approximately 50,000 websites and OD/OJ only three, but the three sites are aggregators of job-ads (Table 5). Despite the difference in the number of job-ads, the nine regions have similar trends (Pearson correlation coefficient = 0.996). The largest difference in job-ads between Burning Glass Technologies and OD/OJ are in Region 7 (Northern VA Regional Council) where Burning Glass Technologies had 28,690 ads and OD/OJ 20,745. Only one region had more OD/OJ job-ads than BGT, Region 2 (VA Tech Economic Development, BGT = 3,688, OD/OJ = 41,41). Due to the large difference in the number of job-ads, the counts were normalized by the total before making further comparisons. The number of job-ads by counties and cities within a region are displayed in Appendix A.

[17] Virginia Initiative for Growth and Opportunity https://govirginia.org/ (last accessed June 12, 2019)

Figure 2 compares the two methods for collecting job-ads over the nine regions. Figure 2A displays the percentage of jobs-ads by region plotting BGT against OD/OJ. The points cluster along the line of equality and indication the trends across the regions are nearly identical.

Figure 2. Burning Glass Technologies and OD/OJ Job-ad Comparisons by Region

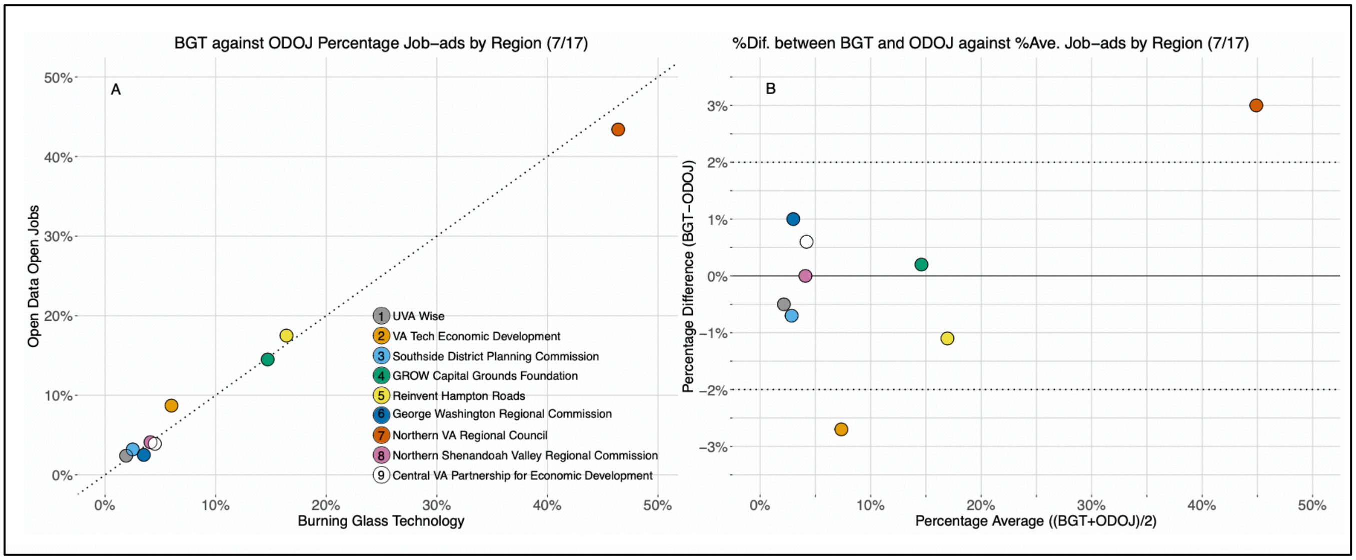


Figure 2B compares the two methods by plotting the percentage average against the percentage difference (%BGT – %OD/OJ). In this plot it is easier to assess the magnitude of disagreement by visualizing the variability as a function of the average. There is no clear association between the magnitude of the average and the magnitude of the variability. The difference varies between ±3% from the zero line of no difference. OD/OJ has a larger percentage of job-ads in Regions 1, 2, 3, and 5 which are all located in southern Virginia. The two regions with the greatest difference are 2 and 7.

Occupation Family Comparisons

Table 6. Burning Glass Technologies (BGT) and OD/OJ Comparison by GO Virginia Region

Region #. Region Name	BGT N / %	OD/OJ N / %
1. UVA Wise	1,204 / 1.9	1,132 / 2.4
2. VA Tech Economic Development	3,688 / 6.0	4,141 / 8.7
3. Southside Planning District Commission	1,547 / 2.5	1,509 / 3.2
4. GROW Capital Jobs Foundation	9,071 / 14.7	6,914 / 14.5
5. Reinvent Hampton Roads	10,126 / 16.4	8,350 / 17.5
6. George Washington Regional Commission	2,168 / 3.5	1,193 / 2.5
7. Northern VA Regional Council	28,690 / 46.4	28,690 / 46.4
8. Northern Shenandoah Valley Regional Commission	2,565 / 4.1	1,964 / 4.1
9. Central VA Partnership for Economic Development	2,807 / 4.5	1,859 / 3.9
Total	63,180	47,807

The number of job-ads that could be classified into an occupation family is 61,462 (96.62%) for Burning Glass Technologies and 39,639 (82.74%) for OD/OJ. It is not clear how this might bias the comparison. Despite this, the percentage of job-ads in the 23 occupation families have similar trends (Pearson correlation coefficient = 0.756). The largest difference in occupation families are in Computer and Mathematical job-ads (BGT – OD/OJ = 7,616) where

Burning Glass Technologies has 12,947 ads and OD/OJ 5,331; Healthcare Practitioners and Technical job-ads (BGT – OD/OJ = 4,503) where Burning Glass Technologies has 7781 ads and OD/OJ 3,278; and Sales and Related job-ads (BGT – OD/OJ = 4,095) where Burning Glass Technologies has 5,,811 ads and OD/OJ 1,716. Based on the literature review it is not unexpected that Burning Glass Technologies has an more Computer and Mathematical and Healthcare Practitioners and Technical job-ads (Hershbein & Kahn 2018; Mohnen et al. 2018; Rothwell 2014). The one occupation family where OD/OJ has more ads is the Management occupation family, (BGT – OD/OJ = –3,361), BGT has 6,450 ads and OD/OJ 9,811. This is unexpected since researchers have reported Burning Glass Technologies over represents jobs in the Management occupation family (Carnevale et al. 2014; Rothwell 2014; Hershbein & Kahn 2018).

Unlike using latitude and longitude to assign a job-ad to a region, there is a greater chance for error when assigning a job-ad to an occupation category. Errors can occur in normalizing the job title which can account for some of the differences between the two methods.

Table 7. BGT OD/OJ Comparison by Major Occupation Group

Occupation Family #. Occupation Family Name	BGT N / %	OD/OJ N / %
11. Management	6,450 / 10.5	9,811 / 24.8
13. Business and Financial	5,041 / 8.2	5,737 / 14.5
15. Computer and Mathematical	12,947 / 21.2	5,331 / 13.4
17. Architecture and Engineering	1,852 / 3.0	2,006 / 5.1
19. Life, Physical, and Social Science	623 / 1.0	220 / 0.6
21. Community and Social Service	604 / 1.0	191 / 0.5
23. Legal	291 / 0.5	88 / 0.2
25. Education, Training, and Library	1,121 / 1.8	571 / 1.4
27. Arts, Design, Entertainment, Sports, and Media	1,380 / 2.2	880 / 2.2
29. Healthcare Practitioners and Technical	7,781 / 12.7	3,278 / 8.3
31. Healthcare Support Occupations	981 / 1.6	416 / 1.0
33. Protective Service	874 / 1.4	516 / 1.3
35. Food Preparation and Serving Related	1,527 / 2.5	593 / 1.5
37. Building & Grounds Cleaning and Maintenance	579 / 0.9	243 / 0.6
39. Personal Care and Service	491 / 0.8	130 / 0.6
41. Sales and Related	5,811 / 9.5	1,716 / 4.3
43. Office and Administrative Support	5,087 / 8.3	2,861 / 7.2
45. Farming, Fishing, and Forestry	34 / 0.1	0 / 0.0
47. Construction and Extraction	611 / 1.0	306 / 0.8
49. Installation, Maintenance, and Repair	1,581 / 2.6	1,112 / 2.8
51. Production	1,087 / 1.8	397 / 1.0
53. Transportation and Material Moving	4,602 / 7.5	3,236 / 8.2
55. Military Specific	107 / 0.2	0 / 0.0
Total	61,462	39,639

Figure 3. Burning Glass Technologies and OD/OJ Job-ad Comparisons by Occupation Family

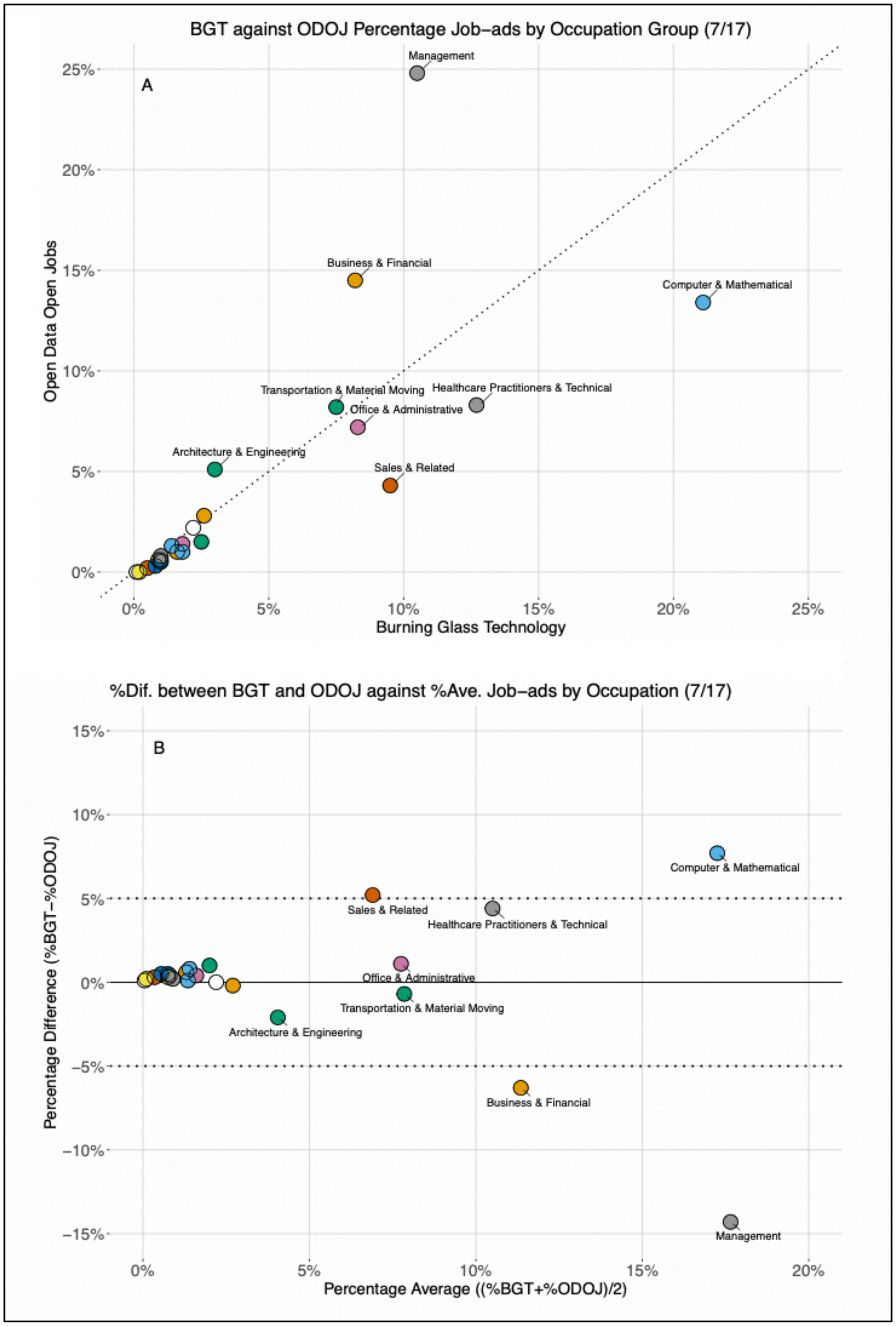


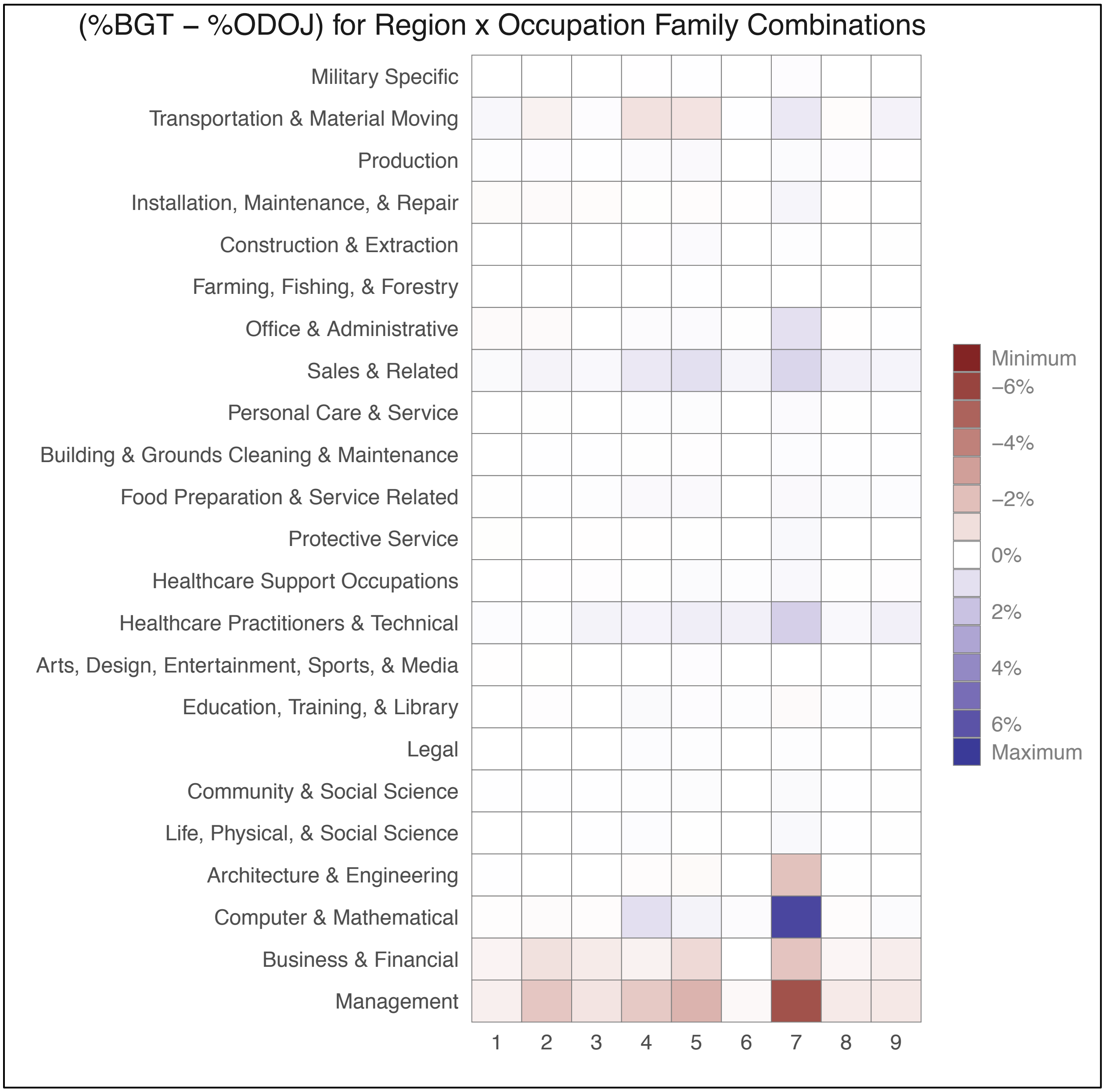
Figure 3 compares the two methods for collecting job-ads for the 23 occupations families. Figure 3A displays the percentage of jobs by occupation family plotting Burning Glass Technologies against OD/OJ. The points cluster along the line of equality for the smaller values and move away from the line for the larger values.

Figure 3B compares the two methods by plotting the percentage average against the percentage difference (%BGT – %OD/OJ). In this plot it is easier to assess the magnitude of disagreement by visualizing the variability as a function of the average. The differences vary from a low of –15% to +7%. The magnitude of the difference increases as the average increases and indication of an association. The largest difference is the over representation of management job- ads in OD/OJ and to a lesser extent computer job-ads in Burning Glass Technologies.

A heat map was constructed to look for trends in the percentage difference (%BGT – %OD/OJ) in the 207region by occupation family combinations (Figure 4). The percentage of job-ads in the 207 combinations have similar trends (Pearson correlation coefficient = 0.828). 93.72% of the differences are within ±1, leaving thirteen combinations.

Seven of the thirteen are in the Northern VA Regional Council the region with the largest number of employed, the other three regions are Reinvent Hampton Roads, GROW Capital Jobs Foundation, and VA Tech Economic Development which have the 2nd, 3rd, and 4th largest number of employed. Based on the literature review it was expected Burning Glass Technologies job-ads would over represent the Computer and Mathematical occupation family; this occurred in Northern VA Regional Council (7) and GROW Capital Jobs Foundation (4). All of the combinations where %OD/OJ > %BGT occur in the Management occupation family (4 occurrences), Business and Financial (2), and Architecture and Engineering (1) occupations. All of the combinations where %BGT > %OD/OJ occur in the Computer and Mathematical (2 occurrences), Healthcare Practitioners and Technical (1), Sales and Related (2), and Office and Administrative Support (1).

Figure 4. Heat Map of the (%BGT – %OD/OJ) for the Region by Occupation Family Combinations



Conclusions and Recommendations

Burning Glass Technologies' Virginia job-ad data was benchmarked against job-ad data collected in a similar manner by CCARS for July 2017; this was the last month CCARS web scraped job-ad data and is the most complete OD/OJ data based on our data profiling of the other months and years. Both Burning Glass Technologies and CCARS constructed their job-ad data tables from web scraped information but they used different websites; CCARS only scraped three government websites whereas Burning Glass Technologies scraped government and non-government websites. In addition, CCARS acknowledges that their job-ad data does not capture all job-ads in Virginia. Despite this, the Burning Glass Technologies and OD/OJ align across locations (r = 0.996) and occupation families (r = 0.756). This difference between the two categories could be an indication of the error involved in taking scraped information and transforming/canonicalizing it into a useable data format; there is less error in assigning a place of employment to a latitude and longitude than determining the occupation family from a job title. Even when the comparison across the 207 geographic location by occupation family combinations was made the percentage difference was less than ±1% for 194 (93.72%) of the combinations. Seven of the thirteen combinations outside this range are in Region 7, Northern VA Regional Council, which has the largest population (> 2.5 million) and number of jobs (> 1.3 million)[18] within the nine regions. Three of the remaining combinations involve the Management occupation family where the OD/OJ had more job-ads than Burning Glass Technologies in all nine regions; in particular Regions 2, 4, 5, and 7 the four regions with the largest population and number of jobs. It is not clear why the OD/OJ has more job-ads in this occupation family, whether it is error in the scraping and assignment process or can be attributed to the differences in the websites being scraped. Our analyses showed that Burning Glass Technologies job-ad data over-represents postings in the Computer & Mathematical and Healthcare Practitioners & Technical occupation families (Figure 3) which is consistent with the findings of other researchers. The over-representation in Computer & Mathematical jobs in Region 7 aligns with the revealed comparative advantage (RCA)[19] of these occupations in Region 7 (cities Alexandria, Fairfax, Falls Church, Manassas, and Manassas Park; and the counties of Arlington, Fairfax, Loudoun, and Prince William) which ranges from 1.73 to 3.88 (a value >1 indicates an advantage). It may also be attributable to the fact that not all openings are posted online reflect an actual vacancy and that anecdotal evidence suggests a small share of the ads in information technology occupations are used to collect information about the potential applicant pool (Carnevale et al. 2014).

With regard to benchmarking against government surveys, the findings across researchers is consistent: trends across occupations and years are similar to those in surveys; business & financial, computer & mathematical, and healthcare occupations are overrepresented in Burning Glass Technologies; and construction, public administration & government, mining & logging, and accommodation & food services are underrepresented. In most cases the discrepancies were not quantified, when they were, the percentage differences were less than ten. The fact that the number of employers posting job-ads online and the number of websites Burning Glass Technologies scrapes is increasing implies benchmarking should be an ongoing process in order to accurately document any biases in a changing landscape.

With regard to the fitness-for-use, to our knowledge there has not been any research on the STW that used online job postings. The concern is that since these jobs do not require a college degree and it has been reported that online job-ads are biased toward college graduates (Carnevale et al. 2014; Rothwell 2014; Hershbein & Hollenbeck 2015) STW jobs maybe underrepresented in online job-ads. Since JOLTS does not provide a breakdown by education, quantifying the bias against a survey is not possible. On average the completeness of the minimum education requirement variable is ~50 percent. Carnevale et al. (2014) used imputation methodologies to provide estimates for missing values; they concluded 40 to 60 percent of job openings for workers with a high school diploma and 30 to 40 percent of job openings for workers with some college or an Associate's degree are posted online. We recommend that additional methods for estimating the minimum education requirement be evaluated. In our work with the resume data we were able to derive a binary variable, below a Bachelor's degree / Bachelor's degree or

[18] Virginia Initiative for Growth & Opportunity Region 7 at-a-glance https://govirginia.org/regions/seven/ (last accessed August 14, 2019)
[19] DataUSA: Revealed Comparative Advantage "… a calculation used to determine what is special or unique about a certain location/occupation or location/industry combination." https://datausa.io/about/glossary/ (last accessed November 20, 2019)

above, by using related variables to increase the completeness of the minimum education variable from <50 percent to 79 percent; this should be explored with the job-ad data.

Aligning the Burning Glass Technologies data, their data dictionary, and online publications, provides insight into the definitions of the Burning Glass Technologies derived variables (for example, the skill taxonomy hierarchy, baseline, specialized, and software skills) which are an invaluable resource for understanding the skill demands of employers. The Burning Glass Technologies job-ad data in combination with their publications and the publications of non-profits, academic institutions, and government agencies that use their job-ad data for research, provide information on the non-degree credential landscape which is not available in designed and administrative data sources. At present there are no federal or state surveys or administrative data sources that approach the comprehensiveness of the Burning Glass Technologies job-ad[20]. These data address data gaps in:

1. The types of skills used on the job in STW occupations that require training beyond the high school level but not at the bachelor's level or higher.
2. The specialized skills and non-degree credentials demanded by employers for entry level STW jobs.
3. The baseline or soft skills demanded by employers.
4. The job-ad data can be linked with Burning Glass Technologies resume data by location (for example, MSA, county, state) to provide information on the skills that are demanded by employers that are not available in the current STW workforce.

[20] Leventoff, Jenna, "Measuring non-Degree Credential Attainment: 50-State Scan," Workforce Data Quality Campaign, May 2018, https://www.nationalskillscoalition.org/resources/publications/file/Measuring-Non-Degree-Credential-Attainment-50-State-Scan.pdf. (last accessed August 14, 2019)

Acronyms

ACS	American Community Survey
BGT	Burning Glass Technologies
CIP	Classification of Instructional Program
CCARS	Commonwealth Center for Advanced Research and Statistics
CPS	Current Population Survey
ERP	Enterprise Resource Planning
HWOL	Help Wanted Online Index
JOLTS	Job Openings and Labor Turnover Survey
LMI	Labor Market Information
NLx	National Labor Exchange
OES	Occupational Employment Statistics
O*NET	Occupational Information Network
OD/OJ	Open Data/Open Jobs Data
PA	Physician Assistant
RCA	Revealed Comparative Advantage
SDAD	Social Decision Analytics Division
SOC	Standard Occupational Classification
STW	Skilled Technical Workforce

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APPENDIX A

Job-ad Counts by Economic Region & County (OD/OJ > Burning Glass Technologies bolded)

Region	Region Name	County	BGT	OD/OJ
1	UVA Wise	Bland County	15	11
1	**UVA Wise**	**Bristol city**	**119**	**434**
1	UVA Wise	Buchanan County	48	15
1	UVA Wise	Carroll County	49	15
1	UVA Wise	Dickenson County	30	13
1	UVA Wise	Galax city	76	67
1	UVA Wise	Grayson County	27	15
1	UVA Wise	Lee County	60	22
1	UVA Wise	Norton city	34	34
1	UVA Wise	Russell County	51	45
1	UVA Wise	Scott County	57	24
1	UVA Wise	Smyth County	103	39
1	UVA Wise	Tazewell County	196	149
1	**UVA Wise**	**Washington County**	**51**	**87**
1	UVA Wise	Wise County	108	103
1	UVA Wise	Wythe County	180	59
2	**VT Economic Development**	**Alleghany County**	**54**	**58**
2	VT Economic Development	Amherst County	63	31
2	VT Economic Development	Appomattox County	27	10
2	VT Economic Development	Bedford County	176	103
2	VT Economic Development	Botetourt County	114	31
2	VT Economic Development	Campbell County	95	73
2	VT Economic Development	Craig County	16	NA
2	VT Economic Development	Floyd County	30	6
2	VT Economic Development	Franklin County	179	92
2	VT Economic Development	Giles County	51	29
2	**VT Economic Development**	**Lynchburg city**	**22**	**780**
2	**VT Economic Development**	**Montgomery County**	**656**	**788**
2	**VT Economic Development**	**Pulaski County**	**219**	**676**
2	VT Economic Development	Radford city	1	NA
2	VT Economic Development	Roanoke city	1574	1264
2	VT Economic Development	Roanoke County	47	18
2	VT Economic Development	Salem city	364	182
3	Southside Planning District Commission	Amelia County	20	9
3	Southside Planning District Commission	Brunswick County	58	17
3	Southside Planning District Commission	Buckingham County	27	19

Region	Region Name	County	BGT	OD/OJ
3	Southside Planning District Commission	Charlotte County	63	NA
3	Southside Planning District Commission	Cumberland County	11	7
3	**Southside Planning District Commission**	**Danville city**	**463**	**527**
3	**Southside Planning District Commission**	**Halifax County**	**119**	**407**
3	Southside Planning District Commission	Henry County	77	43
3	Southside Planning District Commission	Lunenburg County	27	16
3	Southside Planning District Commission	Martinsville city	219	149
3	Southside Planning District Commission	Mecklenburg County	162	121
3	**Southside Planning District Commission**	**Nottoway County**	**62**	**116**
3	Southside Planning District Commission	Patrick County	37	7
3	Southside Planning District Commission	Pittsylvania County	72	40
3	Southside Planning District Commission	Prince Edward County	130	31
4	GROW Capital Jobs Foundation	Charles City County	11	NA
4	GROW Capital Jobs Foundation	Chesterfield County	560	440
4	GROW Capital Jobs Foundation	Dinwiddie County	463	74
4	**GROW Capital Jobs Foundation**	**Emporia city**	**58**	**114**
4	GROW Capital Jobs Foundation	Goochland County	207	90
4	GROW Capital Jobs Foundation	Greensville County	25	5
4	GROW Capital Jobs Foundation	Hanover County	438	271
4	GROW Capital Jobs Foundation	Henrico County	707	463
4	GROW Capital Jobs Foundation	Hopewell city	110	56
4	GROW Capital Jobs Foundation	New Kent County	95	12
4	**GROW Capital Jobs Foundation**	**Petersburg city**	**8**	**276**
4	GROW Capital Jobs Foundation	Powhatan County	44	90
4	GROW Capital Jobs Foundation	Prince George County	158	132
4	GROW Capital Jobs Foundation	Richmond city	6129	4759
4	GROW Capital Jobs Foundation	Surry County	29	17
4	**GROW Capital Jobs Foundation**	**Sussex County**	**29**	**37**
5	Reinvent Hampton Roads	Accomack County	246	206
5	Reinvent Hampton Roads	Chesapeake city	1201	1131
5	**Reinvent Hampton Roads**	**Franklin city**	**86**	**176**
5	**Reinvent Hampton Roads**	**Hampton city**	**87**	**610**
5	**Reinvent Hampton Roads**	**Isle of Wight County**	**90**	**402**
5	Reinvent Hampton Roads	James City County	427	11
5	Reinvent Hampton Roads	Newport News city	2104	1777
5	Reinvent Hampton Roads	Norfolk city	2358	1230
5	Reinvent Hampton Roads	Northampton County	58	14
5	Reinvent Hampton Roads	Poquoson city	24	5

Region	Region Name	County	BGT	OD/OJ
5	Reinvent Hampton Roads	Portsmouth city	447	421
5	Reinvent Hampton Roads	Southampton County	46	12
5	Reinvent Hampton Roads	Suffolk city	328	235
5	Reinvent Hampton Roads	Virginia Beach city	2482	1656
5	**Reinvent Hampton Roads**	**Williamsburg city**	**58**	**387**
5	Reinvent Hampton Roads	York County	84	77
6	George Washington Regional Commission	Caroline County	75	36
6	George Washington Regional Commission	Essex County	77	19
6	George Washington Regional Commission	Fredericksburg city	891	511
6	George Washington Regional Commission	Gloucester County	105	85
6	George Washington Regional Commission	King and Queen County	277	5
6	**George Washington Regional Commission**	**King George County**	**73**	**156**
6	George Washington Regional Commission	King William County	47	26
6	George Washington Regional Commission	Lancaster County	42	27
6	George Washington Regional Commission	Mathews County	79	8
6	George Washington Regional Commission	Middlesex County	40	21
6	George Washington Regional Commission	Northumberland County	28	16
6	George Washington Regional Commission	Richmond County	23	9
6	George Washington Regional Commission	Spotsylvania County	49	31
6	George Washington Regional Commission	Stafford County	307	227
6	George Washington Regional Commission	Westmoreland County	55	16
7	Northern Virginia Regional Council	Alexandria city	2422	NA
7	Northern Virginia Regional Council	Arlington County	4637	3053
7	Northern Virginia Regional Council	Fairfax County	15986	11162
7	**Northern Virginia Regional Council**	**Falls Church city**	**28**	**1084**
7	Northern Virginia Regional Council	Loudoun County	3782	2655
7	Northern Virginia Regional Council	Manassas city	582	436
7	Northern Virginia Regional Council	Manassas Park city	14	NA
7	Northern Virginia Regional Council	Prince William County	1239	1216
8	Northern Shenandoah Valley Regional Commission	Augusta County	250	98
8	Northern Shenandoah Valley Regional Commission	Bath County	55	18
8	Northern Shenandoah Valley Regional Commission	Buena Vista city	21	7
8	Northern Shenandoah Valley Regional Commission	Clarke County	86	48
8	Northern Shenandoah Valley Regional Commission	Frederick County	102	25
8	Northern Shenandoah Valley Regional Commission	Harrisonburg city	446	260
8	**Northern Shenandoah Valley Regional Commission**	**Highland County**	**16**	**26**
8	Northern Shenandoah Valley Regional Commission	Lexington city	86	74
8	Northern Shenandoah Valley Regional Commission	Page County	105	54

Region	Region Name	County	BGT	OD/OJ
8	Northern Shenandoah Valley Regional Commission	Rockbridge County	40	14
8	Northern Shenandoah Valley Regional Commission	Rockingham County	261	110
8	Northern Shenandoah Valley Regional Commission	Shenandoah County	171	163
8	**Northern Shenandoah Valley Regional Commission**	**Staunton city**	**127**	**184**
8	Northern Shenandoah Valley Regional Commission	Warren County	135	98
8	Northern Shenandoah Valley Regional Commission	Waynesboro city	138	96
8	**Northern Shenandoah Valley Regional Commission**	**Winchester city**	**526**	**689**
9	Central Virginia Partnership for Economic Development	Albemarle County	87	13
9	Central Virginia Partnership for Economic Development	Charlottesville city	1320	946
9	Central Virginia Partnership for Economic Development	Culpeper County	214	175
9	Central Virginia Partnership for Economic Development	Fauquier County	447	235
9	**Central Virginia Partnership for Economic Development**	**Fluvanna County**	**57**	**367**
9	Central Virginia Partnership for Economic Development	Greene County	48	26
9	Central Virginia Partnership for Economic Development	Louisa County	99	32
9	Central Virginia Partnership for Economic Development	Madison County	64	11
9	Central Virginia Partnership for Economic Development	Nelson County	54	6
9	Central Virginia Partnership for Economic Development	Orange County	71	27
9	Central Virginia Partnership for Economic Development	Rappahannock County	346	21
NA	NA	NA	1314	NA