## UPSKILLING: DO EMPLOYERS DEMAND GREATER SKILL WHEN WORKERS ARE PLENTIFUL?

Alicia Sasser Modestino, Northeastern University\* Daniel Shoag, Harvard University Joshua Ballance, Federal Reserve Bank of Boston

#### Abstract

Using a proprietary database of online job postings, we find that education and experience requirements rose during the Great Recession. These increases were larger in states and occupations that experienced greater increases in the supply of available workers. This finding is robust to controlling for local demand conditions and firm×job-title fixed effects as well as using a natural experiment arising from troop withdrawals as an exogenous shock to labor supply. Our results imply that the increase in unemployed workers during the Great Recession can account for 18 to 25 percent of the increase in skill requirements between 2007 and 2010.

JEL classifications: D22, E24, J23, J24, J63.

<sup>\*</sup> Corresponding Author: School of Public Policy & Urban Affairs, Northeastern University, 360 Huntington Avenue, Boston, MA 02115, (617) 373-7998 <u>a.modestino@neu.edu</u>

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#### I. Motivation: Shifting Employer Skill Requirements and Recruitment Intensity

During the slow recovery of the U.S. labor market from 2007-2012, there was a change in the Beveridge curve, or the relationship between the unemployment rate and the job vacancy rate. Following the recession, the unemployment to vacancy rate ratio was significantly higher than one would have projected from the stable pre-recession relationship (Hobjin and Sahin 2013, Diamond and Sahin 2014). Several explanations for this shift have been explored, including a mismatch between workers and vacancies across occupations and geographies, changes in the composition of job seekers.<sup>1</sup>

Although there are few empirical studies, another important factor that has been proposed to explain the shift in the Beveridge Curve during the Great Recession is a change in employer "recruitment intensity" per vacancy (Davis et al. 2012),. In this context, recruitment intensity is described as a set of actions that employers can take to influence the rate of new hires, such as changes in "advertising expenditures, screening methods, hiring standards, and the attractiveness of compensation packages" (Davis 2012). For a given vacancy-to-unemployment ratio, actions that lower the recruiting intensity per vacancy also lower the fill rate, resulting in an upward shift in the Beveridge Curve. This finding has sparked several theoretical models that endogenize this channel (Kaas and Kircher 2014, Gavazza, Mongey, and Violante 2015). Yet quantifying the magnitude of the change in recruiting intensity and why it occurs has been limited by the absence of direct measures of actions undertaken by employers (Diamond 2013, Rothstein 2012).

In this paper, we directly measure an important facet of recruitment intensity that shifted during the Great Recession, namely the skill requirements employers use to screen candidates when

<sup>&</sup>lt;sup>1</sup> This extensive debate in the economics literature sparked a numerous papers seeking to explain the apparent shift in the Beveridge Curve. See Sahin et. al. (2014), (Veracierto (2011), Barnichon and Figura (2010), Shimer (2012), Fujita and Moscarini (2013) and Hall and Schulhofer Wohl (2013), (Mukoyama, Patterson, Sahin 2014; Hagedorn et al. 2014)

filling a new vacancy. Indeed, media reports and employer surveys indicate that employer requirements increased sharply between 2007 and 2012, such that a college degree was considered a requirement for many occupations that previously required only a high school degree. This trend that has colloquially become known as "upskilling".<sup>2</sup>

Anecdotal accounts suggest that upskilling during the Great Recession was driven to some degree by a sense among employers that "[t]he recession is a wonderful opportunity to acquire top talent" when workers are more plentiful.<sup>3</sup> In contrast, as the labor market has recovered, employers report that "managers have to be much more flexible now than during the recession because there's less talent available."<sup>4</sup> These sentiments are consistent with what we find using a proprietary dataset of 36.2 million online job postings from Burning Glass Technologies (BGT). Figure 1 shows that the percentage of vacancies requiring a bachelor's degree or higher rose by more than 10 percentage points from 2007 to 2010 and then fell as labor markets recovered. A similar relationship is observed for the percentage of postings requiring four or more years of experience. Clearly, there is a strong time-series correlation between employer skill requirements and aggregate labor market slack as measured by the national unemployment rate. Yet it is still unclear the degree to which these aggregate trends reflect a *causal* shift in recruitment in intensity in response to an increase in the supply of workers.

The goal of this paper is to test the upskilling hypothesis that an increase in the supply of job searchers leads firms to raise the skill requirements in their job postings, holding all else constant. Empirically, this is challenging to measure because changes in labor market slack are often correlated with other factors that might affect skill requirements such as changes in firm

<sup>&</sup>lt;sup>2</sup> For example, according to a survey by CareerBuilder in 2013, almost one-third of employers said that: their educational requirements for employment have increased over the last five years and specifically that they are hiring more college-educated workers for positions that were previously held by high school graduates (Career Builder, 2014)." See also Rampell, Catherine. 2012. "Degree Inflation? Jobs That Newly Require B.A.'s" The New York Times, December 4.

<sup>&</sup>lt;sup>3</sup> Barry Deutsch, chief executive of Impact Hiring Solutions as quoted in Green (2009).

<sup>&</sup>lt;sup>4</sup> Similar sentiments are expressed in interviews with roughly four dozen employers in Moss, Modestino and Shoag (2017).

composition, technology, and industry demand.

To explore this hypothesis, we start by exploiting the variation in unemployment rates across states during the Great Recession. We find that employer skill requirements increased more within occupations in states experiencing greater increases in their unemployment rate. The relationship is economically important: within a six-digit detailed occupation, a 1 percentage point increase in the state unemployment rate is associated with a 0.6 percentage point increase in the fraction of employers requiring a Bachelor's degree and a 0.8 percentage point increase in the fraction of employers requiring four or more years of experience. We get similar results when examining the long-run differences as well. These OLS estimates are robust to using alternative measures of labor market slack, such as labor supply/demand ratios, and to including occupation, state, and year fixed effects and their interactions, as well as controls for the initial skill distribution and requirements. The magnitude of the correlation averaged across all of our specifications implies that the increase in the number of people looking for work during the Great Recession could potentially account for 18 percent of the total increase in education requirements and 25 percent of the experience requirements observed between 2007 and 2010.<sup>5</sup> The magnitude of the impact is somewhat smaller over the whole five-year period 2007-2012, on the order of 10 percent of the increase for education and 18 percent of the increase for experience.<sup>6</sup> To our knowledge, these findings provide some of the first empirical evidence of a shift in recruitment intensity whereby employer skill requirements are driven—in part—by the available supply of labor.<sup>7</sup>

Although this baseline relationship between rising employer requirements and the supply of

<sup>&</sup>lt;sup>5</sup> We present a more thorough overview of these back of the envelope calculations in Appendix Table B15.

<sup>&</sup>lt;sup>6</sup> This smaller magnitude over 2007-2012 is likely due to employer skill requirements reversing as the economy began to recover in some states as shown in Figure 1. For more evidence of downskilling during the recovery, see Modestino, Shoag, and Balance (2016).

<sup>&</sup>lt;sup>7</sup> A more recent paper by Hershbein and Kahn (2015) uses the same dataset of online job vacancies to study long-term structural shifts in employer skill requirements. That paper estimates the change in the requirements caused by Bartik demand shocks and finds considerable persistence. In contrast, this paper focuses on the causal identification of the portion of the increase in employer skill requirements that is related to the increased availability of workers (as opposed to demand shocks) during the business cycle.

jobless people seeking work is intriguing, the variation in the unemployment rate over the business cycle is potentially correlated with other factors. These include short-term factors such as changes in the demand for certain goods or services and credit availability as well as longer term trends such as changes in technology or other production processes that may alter the composition of employers posting vacancies and/or the types of vacancies that are posted, potentially shifting employer skill requirements.

To establish a causal relationship between changing employer skill requirements and the supply of job seekers in a location and occupation, we employ two central identification strategies. First, to account for changes in the composition of employers and/or vacancies over time, we show that upskilling occurs even **within firm**×**job-title pairs**—not just within occupations.<sup>8</sup> Our findings show greater increases in employer skill requirements in states and occupations experiencing larger increases in the unemployment rate, both within and across firm×jobtitle pairs.

For our third identification approach, we introduce an exogenous instrument for the number of searchers in an occupation-state. Specifically, we make use of a natural experiment that represents a clear shock to labor supply: the drawdown of troops from Iraq and Afghanistan between 2009 and 2012. We show that these troop withdrawals lead to an additional 200,000 to 300,000 veterans entering the U.S. domestic labor force each year and were not correlated with underlying labor market trends. Consistent with the upskilling hypothesis we find that state × occupation cells receiving larger numbers of returning veterans correspondingly experienced a greater increase in their skill requirements. We can further purge this instrument of potentially confounding correlation with contemporaneous shocks by instrumenting for a veteran's current state of residence using their state of birth. Finally, we combine the veterans-by-state of birth shock with the within firm × job-title specification to produce estimates using both approaches. These

<sup>&</sup>lt;sup>8</sup> It has been shown that firm-job-titles account for the vast majority of the variance in wages within occupations, making confounding composition changes unlikely (Marinescu and Wolthoff 2015).

relationships imply effects on the same order of magnitude as the non-IV results, confirming that an exogenous increase in the supply of job searchers leads firms to change their job posting requirements.

After expressing our main results, we briefly explore the mechanism behind this relationship and model how upskilling may be an opportunistic response to the change in the composition of job searchers during the business cycle which shifts to include a greater share of high-skilled workers during times of slack (Mueller 2015). We find suggestive evidence of this potential mechanism using skill specific labor availability measures and present new evidence on the change in the college wage premium for new hires over the business cycle.<sup>9</sup>

The finding that employer skill requirements are driven—in part—by the available supply of labor has important implications for understanding the dynamics of the labor market. We document a novel feedback mechanism between labor supply and the selectivity of vacancies that operates within occupations and is consistent with macroeconomic models of employer search decisions (Davis et al. 2012) and heterogeneous workers (Shimer 2005, Albrecht and Vrooman 2002). Importantly, we find that upskilling occurs even within firm × job-title pairs, a notion that runs counter to some of the existing approaches to modeling changes in recruitment intensity as solely a compositional effect. Moreover, a related literature has explored worker entry and mobility during recessions, particularly for college graduates. These studies typically find that workers match at lower entry wages during recessions and have less steep wage trajectories over time (e.g. Kahn 2010, Oreopoulous et al. 2012, Moscarini, 2001). We find that changes in employer requirements over the business cycle is consistent with—and even serves to reinforce—this effect.

### **II.** Data: Using Job Postings to Measure Changes in Employer Skill Requirements

To study changes in employer hiring dynamics we use a large, detailed dataset of

<sup>&</sup>lt;sup>9</sup> We also show that that the degree of unemployment-related upskilling across occupations and states is consistent with an opportunistic model. Table B13 in the online appendix shows that the impact is larger employee turnover rates are lower, when employers on-the-job training time is higher, when ages are more rigid, and when skill premiums are larger.

online job postings. Until recently, little has been written about employer job posting requirements due to a lack of detailed data. However, with the advent of online job posting and searching in the early 1990s, the collection and availability of this data has increasingly made such information available to researchers.<sup>10</sup> Over the past two decades, online vacancy data have been used by a number of researchers to study labor market dynamics (e.g., Sahin et al. 2014, Marinescu and Wolthoff 2013, Lazear and Spletzer 2012, Faberman and Mazumder 2012, Rothwell 2012, Bagues and Labini 2009, Kuhn and Skuterud 2004, Gautier, van der Berg, van Ours, and Ridder 2002).

The advantage of using online vacancy data allow analysis at a greater frequency and at more refined geographies than traditional employer surveys, such as the Job Opening and Labor Turnover Survey (JOLTS).<sup>11</sup> This is because the data are constructed from measures collected by software that parses text contained in millions of job ads posted online daily. One potential drawback is that online vacancy data only capture vacancies posted on the Internet, and may not be representative of the universe of job openings if vacancies from certain industries and occupations are less likely to be posted electronically. However, a recent report from Georgetown University estimates that between 60 and 70 percent of job postings are now posted online (Carnevale, Jayasundera, and Repnikov 2014). Other researchers have also shown that that online job ads exhibit similar trends and are closely correlated with employer surveys over time as well as across industries and occupations (also see Templin and Hirsch 2013, Ganong 2014).

The main source of online job posting data used in this paper is collected and

<sup>&</sup>lt;sup>10</sup> See Garcia, Stephanie. 2013. "History & Statistics of Job Boards." Joshua Waldman's Career Enlightenment Blog, March 6th, <u>http://careerenlightenment.com/history-statistics-of-job-boards-infographic</u>. <sup>11</sup> JOLTS is a monthly survey of employers that was developed to provide information on job openings, hires, and separations. Each month the JOLTS sample is comprised of approximately 16,000 businesses drawn from 8 million establishments represented in the Quarterly Census of Employment and Wages. The publically available data provides a measure of labor demand across broad industry classifications at the national level or overall aggregate labor demand for four quadrants of the nation. See the online appendix for further details.

aggregated by Burning Glass Technologies (BGT). BGT aggregates data with detailed information on the more than seven million current online job openings daily from over 40,000 sources including job boards, newspapers, government agencies, and employer sites.<sup>12</sup> These data are collected via a web crawling technique that uses computer programs called "spiders" to browse online job boards and other web sites and systematically text parse each job ad into usable data elements.<sup>13</sup> BGT mines over seventy job characteristics from free-text job postings including employer name, location, job-title, occupation, years of experience requested and level of education required or preferred by the employer.<sup>14</sup> BGT then codes each posting to create education and experience categories as well as occupational groupings using the 2010 Standard Occupational Classification hierarchy.<sup>15</sup>

BGT provides snapshots of the data in which vacancies are reported on a monthly basis and are pooled over the year without duplication. As such, this data is unique in allowing geographical analysis of occupation-level labor demand by education level and experience level over time. The data are available by state for detailed occupations—down to the six-digit Standard Occupation Code (SOC) level—in 2007 and 2010 and 2012.<sup>16</sup> In

<sup>&</sup>lt;sup>12</sup> See <u>http://www.burning-glass.com/realtime/</u> for more details.

<sup>&</sup>lt;sup>13</sup> The collection process employed by BGT provides a robust representation of hiring, including job activity posted by small employers. The process follows a fixed schedule, "spidering" a pre-determined basket of websites that is carefully monitored and updated to include the most current and complete set of online postings. BGT has developed algorithms to eliminate duplicate ads for the same job posted on both an employer website as well as a large job board by identifying a series of identically parsed variables across job ads such as location, employer, and job-title. In addition, to avoid large fluctuations over time, BGT places more weight on large job boards than individual employer sites which are updated less frequently. In addition, their Labor/Insight analytical tool enables us to access the underlying job postings to validate many of the important components of this data source including timeframes, de-duplication, and aggregation.

<sup>&</sup>lt;sup>14</sup> Note that the BGT data do not contain any information on the duration of the vacancy, how many applications a vacancy received, nor whether a vacancy was filled.

<sup>&</sup>lt;sup>15</sup> Carnevale, Jayasundera, and Repnikov (2014) audited a sample of job postings in the BGT database and compared them to the actual text of the postings. They concluded that the BGT coding for occupation, education, experience was accurate at least 80 percent of the time. Given that BGT has made improvements to their coding algorithms since the version of the data studied by Carnevale, Jayasundera, and Repnikov, it's likely that the accuracy of our sample is even higher. In addition, although BGT regularly improves the algorithms that are used to clean job-titles and employer names, categorize job postings by occupation and industry and extract additional information from text such as location and other skills requested, they apply these algorithms retroactively to the complete historical database of postings. Thus we are not concerned about changes over time in how the data are coded. See the online appendix for details.

<sup>&</sup>lt;sup>16</sup> No data are available for 2008 and 2009. This is the main reason for using three year differences (from 2007-2010) although we also show estimates over the whole five-year period.

total, our data represent roughly 36.2 million vacancies across these three years.

Though we use the Burning-Glass data primarily as a dependent variable (meaning that random noise does not bias our regressions), it is important to understand the coverage patterns for interpreting the results. We explore this issue in detail in the online data appendix, and other authors have also tested the robustness of these data (Carnevale, Jayasundera, and Repnikov 2014, Rothwell 2014, Hershbein and Kahn 2018). In the online appendix, we provide several tables and figures comparing the representativeness of the BGT data over time to both national (JOLTS) and state (Minnesota) employer job vacancy surveys by industry and occupation. Despite the differences in the sampling of the BGT data compared to these survey based measures, the industry and occupation distributions are quite similar and are consistent over time.<sup>17</sup> Finally, we also make use of specifications that draw on a panel of employers and job-titles over time which eliminates any potential changes in the sample composition or construction.

### A. Changes in Employer Skill Requirements

We construct several measures of employer skill requirements based on the education and experience fields parsed from the online advertisement. Table 1 provides descriptive statistics for the dependent variables constructed from the BGT data for the various samples we use in our identification strategies. Our first identification strategy controls for state and occupation fixed effects and makes use of the total sample of 36.2 million job postings, aggregated into state/occupation/year cells. On average, there are roughly 500 to 600 postings for a given state x occupation cell in each year (2007, 2010, and 2012). It should be noted that these data exhibit a considerable amount of variation given the different employment levels of these occupations, even at the state-occupation-

<sup>&</sup>lt;sup>17</sup> The largest deviations show that the BGT data tend to slightly over-represent industries such as finance and insurance, health care and social assistance, and educational services and slightly under-represent food services, public administration/government, and construction. Similarly, occupations such as computer and mathematical, management, and business and financial are slightly over-represented while occupations such as food preparation and serving, healthcare support, and transportation and material moving are slightly under-represented.

year level. The number of underlying observations available to construct some cells varies from as few as one posting to as many as 60,000 postings. To ensure that our dependent variables are capturing meaningful differences over time and accurately represent the state of the labor market, we drop observations with fewer than 15 total postings in a given cell which corresponds to eliminating the bottom 5 percent of the sample.<sup>18</sup> In addition, since we are analyzing changes in the fraction of postings requiring a particular skill, we weight the observations by the occupation's share of total openings in the state in a given time period in all regressions. This ensures that our results are not driven by outlier occupations with few underlying postings, and that the regressions are not dominated solely by large states.

We have constructed two primary dependent variables by state, occupation and year that measure the share of job postings along two dimensions of skill; educational attainment and years of experience. The BGT education categories range from the share of postings with no education requirement to the share requesting a graduate or professional degree and all levels in-between.<sup>19</sup> Required experience is measured continuously, although the vast majority of postings concentrate around round numbers of ½ year increments. We choose as our primary dependent variables the share of postings requiring a bachelor's degree or greater and the share of postings requiring 4+ years of experience.<sup>20</sup> Prior to the Great Recession, roughly 13 percent of postings requested a Bachelor's degree or higher in 2007 whereas 8 percent of postings requested 4 or more years of experience. Employer

<sup>19</sup> For education, some job postings in our sample express both a minimum ("required") and maximum ("preferred") requested educational qualification. For example, approximately 12 percent of job postings specify both a bachelor's and graduate degree in the original job posting. We created two measures of requested educational qualifications: one identifying the minimum educational qualification requested and the other using the maximum. The results in all of our specifications are qualitatively similar for both measures. In the paper, we use the maximum requested education qualification for the specifications presented which biases against our finding a significant increase in qualifications over time.

<sup>&</sup>lt;sup>18</sup> These basic results are robust to the various weighting schemes we have used such as weighting observations by the minimum total openings in both periods and dropping observations for which there are fewer than 75 openings for a given occupation/state cell in either period from our sample.

<sup>&</sup>lt;sup>20</sup> As a robustness check we also present specifications in the online appendix that use the other skill levels and find results consistent with the upskilling hypothesis. See Table B3 in the online appendix.

requirements along both dimensions of skill changed over time, with most of the increase occurring between 2007 and 2010 during the height of the Great Recession.

We also make use of two other samples to implement our second identification strategy that controls for firm and job-title fixed effects. The first is a sample of BGT job postings that identify employer names, representing roughly half of the total sample (17.3 million postings).<sup>21</sup> The second is a panel of firm-job-title-state observations over the three years eliminates any variation due to changes in firm composition or job-title composition.<sup>22</sup> The summary statistics for both of these alternate samples show upskilling trends that are similar to when we aggregate the data into state-occupation cells.

# B. Changes in Labor Market Slack

Our basic empirical strategy is to explore the relationship between changes in employer skill requirements and changes in local labor market conditions over time. To do this, we use two primary measures of labor market slack. The first measure is the state unemployment rate as reported by the Bureau of Labor Statistics. The second measure is a labor supply/demand ratio that varies within both state and broad occupation group. This measure is modeled on the Conference Board's Labor Supply/Demand Ratio for their Help Wanted Online dataset and is the ratio of the number of unemployed individuals relative to the number of job postings for a given state and occupation group. The numerator is estimated using data on unemployed individuals by state and six broad occupation groups from the American Community Survey (ACS).<sup>23</sup> The denominator is calculated using the number of BGT job postings by state and broad occupation group. In

<sup>&</sup>lt;sup>22</sup> Table A4 in the online appendix compares the industry and occupation distributions for the panel sample to that of the full sample with no missing data. Although certain industries and occupations account for a greater share of postings, there is no significant difference in the distributions across the two samples.

<sup>&</sup>lt;sup>23</sup> These broad groups consist of Management and business/financial (SOC 11–13), Professional & related (SOC 15–29), Services (SOC 31–39), Sales and office (SOC 41–43), Construction and maintenance (SOC 45–49), Production and transportation (SOC 51–53). This occupational division is used by Help Wanted Online when reporting sub-state vacancy measures and is very similar to the major occupational level of detail in Current Population Survey.

the online appendix we show that the HWOL supply/demand measure reported by the Conference Board is highly correlated with the BGT measure that we construct and provides similar results when used in both of our specifications.<sup>24</sup>

## C. Changes in Veteran Labor Supply

As a source of exogenous variation in the number of searchers, we make use of a natural experiment resulting from the large increase in the post 9/11 veteran labor force following troop withdrawals from Iraq and Afghanistan. The U.S. began withdrawing these troops in 2009 and by September 2012 approximately 1.6 million veterans had returned home and left active duty (Bilmes 2013). Less than one quarter of veterans separating from the military during this period were disabled or retired and more than half had applied for unemployment benefits (Department of Veterans Affairs 2015). As of 2010, the national unemployment rate for post-9/11 veterans who had recently served in Iraq or Afghanistan was 14.3 percent compared to 11.4 percent for veterans serving in other locations and only 9.4 percent for nonveterans (Bureau of Labor Statistics 2010) Moreover, returning veterans are attractive job candidates with practical training, hands-on experience, well-developed teamwork and leadership skills, and even higher educational attainment than the compared to the civilian population.<sup>25</sup>

To capture the change in veteran labor supply over this period, we use the ACS to

<sup>&</sup>lt;sup>24</sup> We acknowledge that a large share of hires come from job-to-job transitions, and that this form of hiring varies more over the business cycle. If this variation comes from differential changes in the number of applications sent, our unemployment based measures might not be good proxies for the application scaling. While it would also be interesting to quantify the impact of job applications directly, we do not have access to such data.

<sup>&</sup>lt;sup>25</sup> The educational attainment of post-911 veterans is higher than that of the non-veteran population with a significantly lower share of high school dropouts and high school graduates with no college, a significantly higher share of individuals with some college or an associate's degree, and similar shares of individuals with a bachelor's degree or higher (The U.S. Joint Economic Committee Democratic Staff 2014). This is true even prior to separating from the military and taking advantage of educational benefits to attend college. Practically all active duty (98 percent) and Selected Reserve enlisted accessions (96 percent) had a high school diploma or equivalent, well above civilian youth proportions (81 percent of 18-24 year-olds). In addition, given that most officers are required to possess at least a baccalaureate college degree upon or soon after commissioning, 94 percent of active duty officer accessions and 96 percent of the officer corps were degree holders (Office of the Under Secretary of Defense, Personnel and Readiness 2006).

estimate the change in the number of post-9/11 veterans in the labor force at the state level each year from 2007 through 2012. Table 2 shows that during this period, an additional 200,000 to 300,000 post 9/11 veterans joined the U.S. labor force each year. Moreover, these returning veterans were concentrated in certain locations and detailed occupations, providing a sizeable exogenous shock to the supply of skilled job searchers per posting in select markets. Figure 2 demonstrates that the changes in the post-9/11 veteran population relative to the number of job postings varied considerably across the U.S. with some states receiving a disproportionate share of the veteran withdrawal.

We also used the ACS to estimate veteran concentration within an occupation as the occupation's share of veteran employment.<sup>26</sup> Veteran employment is concentrated among a select group of occupations that typically make use of the specialized skill set that comes from serving in the military. These military-specific occupations include protective services such as police officers and sheriffs, security guards, and fire fighters as well as operations specialists such as aircraft mechanics, logisticians, and computer support specialists.<sup>27</sup> This variation across states, occupations, and years creates a natural experiment from which we can measure the response of skill requirements to increases in labor supply. For example, Figure 3 shows that logisticians—an occupation with a high concentration of veteran employment— experienced significant upskilling whereas dental hygienists—an occupation with few veterans—did not.

To more formally capture this targeted impact of the increase in the supply of post 9/11 veterans on the labor market, we construct four measures of changes in the supply of labor across state-occupation-year cells as reported in Table 2. Three of these measures are broadly similar. The first measure is simply the log difference in the number of post-9/11

<sup>&</sup>lt;sup>26</sup> These occupation shares are calculated using ACS 3yr 2007 PUMS to reflect pre-recession trends.

<sup>&</sup>lt;sup>27</sup> See Figure A5 in the online appendix for more detail on the share of veterans by occupation.

veterans in the state labor force, as reported in the ACS Summary Files, multiplied by the occupation's share of veterans. One drawback to this measure is that the 1-year ACS was not designed to measure high frequency changes in the number of post-9/11 veterans at the state level. As a result, the changes we measure are noisy and thus our estimates are subject to attenuation bias. An alternative approach is to take the log difference in the number of post-9/11 veterans at the national level and create state level variation by multiplying this change by a state's average share of the post- 9/11 veteran labor force measured over time. This approach is similar in spirit to the "initial immigrant share" method used by Card (2009) and others to study the impact of migrants.

Of course, the residence of veterans following the drawdown in Iraq and Afghanistan is potentially endogenous, as veterans can choose to migrate to better employment opportunities. This is particularly relevant during the period we are studying at the height of the Great Recession. To address this issue, we once again construct an allocation-based measure based on the national change in post-9/11 veterans. This time, however, instead of allocating veterans based on that state's current residents, we allocate them based on the veterans' share by **state of birth.** This measure of location is truly exogenous, as veteran state of birth from several decades ago is not correlated with changes in the current state of the labor market today. Yet, places where many veterans were born do receive a larger labor supply shock as many veterans return home.

Finally, to make the veterans analysis parallel to the baseline estimates, we construct a veteran supply/demand measure similar to the overall labor supply measure described above and is the ratio of the number of returning veterans relative to the number of job postings for a given state and occupation group. The numerator is constructed by multiplying the national change in the number of post-9/11 veterans by each occupation group's veteran's share and each states' share of veteran's birthplace. The denominator

remains unchanged.

D. Control Variables

We also employ additional covariates to control for omitted factors.<sup>28</sup> To account for heterogeneity in the pre-existing pool of skilled labor available to employers, our baseline controls include the share of the state population with a bachelor's degree in 2000 and the average age of the state population in 2000 for the education and experience specifications respectively. We also include a control for the initial share of openings requiring a particular skill in 2007 (i.e. the 2007 share requesting a bachelor's degree or 4 or more years of experience respectively) to account for heterogeneity across state×occupation bins.

#### **III. Empirical Approach**

We seek to explore the upskilling dynamic by measuring the degree to which the observed increase in employer skill requirements is related to the supply of job seekers. There is considerable heterogeneity in the level of required skill and labor availability across places and occupations, so we elect to use a stacked difference specification, similar to the one used in Autor, Dorn, and Hanson (2013) and Acemoglu and Restrepo (2016). Therefore we estimate the basic relationship between changes in employer skill requirements and changes in the degree of labor market slack using the following specification:

$$\Delta S_{i,\sigma,t} = \alpha + \beta \times \Delta U_{i,\sigma,t} + X_{i,\sigma,t} + \tau_t + \varepsilon_{i,\sigma,t} \quad (1)$$

Where for occupation *i*, in state  $\sigma$  over time period *t*:

 $\Delta S_{i\sigma t}$  = percentage point change in skill requirements (either education or experience)  $\Delta U_{i\sigma t}$  = change in the labor availability measure (either the change in the state unemployment rate, the supply/demand index , or the veteran's shock)

<sup>&</sup>lt;sup>28</sup> See the data appendix for more detailed information on these covariates.

 $X_{i\sigma t}$  = vector of control variables and fixed effects related to occupation or state characteristics

 $\tau_t$  = time period dummy to capture changes in the general composition of vacancies

The coefficient of interest in equation (1) is  $\beta$  which measures the increase in skill requirements related to changes in the availability of labor. A positive and significant  $\beta$  suggests that employers are upskilling education and experience requirements in response to an increase in the supply of job searchers in a particular state and occupation.

In the above regression equation, we examine changes in employer requirements across occupations and locations over time. For the specifications that use the baseline labor market measures, the identifying assumption is that the Great Recession affected some states more than others, allowing us to exploit the variation in local labor markets across states and time periods. Our controls ( $X_{i\sigma t}$ ) are used to gauge whether the relationship can be explained by pre-existing trends by state and occupation. For the specifications that use the veteran supply shocks, the identifying assumption is that the timing of the drawdown and the veteran's state of residence or birthplace was uncorrelated with underlying trends in state×occupation level skill requirements.

Equation (1) tests the upskilling hypothesis at the state×occupation level. This allows for more reliable data construction of our skill measures based on the all of the job posting data and also imposes a more representative weighting scheme that is not dominated by states or occupations with a greater number of postings. However, one potential limitation of this approach is that it ignores changes in the composition of firms and jobs that are potentially driven by factors other than the supply of job searchers such as changes in technology and industry demand. It also cannot account for changes in the representativeness of the BGT data over time.

We address concerns over changes in employer composition and data quality over time by focusing on within firm×job-title changes. We do this using the following specification for both our baseline and veteran labor availability measures:

$$S_{fj,\sigma,t} = \alpha + \beta \times U_{i\sigma t} + X_{fj,\sigma,t} + \tau_t + \varepsilon_{fj,\sigma t}$$
(2)

where for firm-job-title pair fj, in state  $\sigma$  over time period t:

 $S_{fj,\sigma,t}$  = a dummy variable for requiring a particular skill (either education or experience)  $U_{i\sigma t}$  = the labor availability measure (either the in the state unemployment rate, the supply/demand index , or the veteran's shock)

 $X_{fj,\sigma,t}$  = vector of control variables and fixed effects (including a fixed effect for each firm×job-title-state pair)

 $\tau_t$  = time period dummy to capture changes in the general composition of vacancies By focusing on within firm×job-title effects, these specifications remove the possibility that the observed upskilling relationship is due to changes in the composition of employers or job-titles postings observed in the data. The downside to this specification is that roughly half of the BGT postings do not include employer names and therefore are dropped in this specification. Since the panel is unbalanced, we perform these regressions in levels. The presence of the firm- job-title fixed effects, though, effectively make this a comparison of the skill requirements for the same job at the same employer over time.

Our second identification strategy controls for firm and job-title fixed effects and relies on those BGT jobs postings that identify employer names which represents roughly half of the total sample (17.3 million postings).<sup>29</sup> As discussed above, Burning Glass takes great pains to eliminate duplicate postings (for example, not counting the same job posted on two websites as two jobs). Occasionally, though, the data show an extremely large

<sup>&</sup>lt;sup>29</sup> Fortunately, the job-title is always populated for each posting so that observations can be categorized by occupation. However the employer name is only populated for about half of the observations. This is because employers also post on job boards where they do not necessarily list the firm name.

number of observations for the same firm×job-title×state pair in a given month. We address this in two ways. First, in our cross-sectional sample, we eliminate extreme duplicates with more than 50 observations for a given firm×job-title×state×year×month (less than one percent of the full sample with no missing data). Second, to better approximate the representative weights of the baseline specification and to more conservative about potentially overweighting heavy posters, we also construct a panel of firm×job-title×state×year level and taking the mean of the education and experience requirements. This panel has the advantage of eliminating variation due to changes in firm composition or job-title composition and weights each firm×job-title×state×year equally.<sup>30</sup> As a robustness check, Table B7 in the online appendix we replicate our firm×job-title results using the Minnesota Job Vacancy Survey.

### IV. Results

## A. Baseline OLS Specifications

We begin by running regressions of the form described above in Equation (1) where a larger  $\beta$  indicates that skill requirements rose more within detailed occupations in states experiencing a greater increase in the unemployment rate. Of course, it would be naïve to infer causality solely from these relationships, given the potential for serious omitted variable bias. Still, establishing the baseline correlations is useful for comparison purposes.

<sup>&</sup>lt;sup>30</sup> To give one a sense of the kind of variation that our specification is identified from, Table A5 in the online appendix provides a side-by-side example of changing skill requirements by occupation for two states: New Hampshire which had a peak unemployment rate of only 5.9 percent in 2010 versus Rhode Island which had a peak unemployment rate of 11.2 percent that same year. Detailed occupations that increased education requirements more sharply in Rhode Island versus New Hampshire during the Great Recession include various types of managers, compliance officers, medical and clinical laboratory technicians, medical assistants, childcare workers, residential advisors, food prep and retail supervisory positions, legal secretaries, and data entry keyers. Those that upskilled experience requirements more sharply included various managers, claims adjusters, compliance officers, information security analysts, actuaries, mental health and substance abuse workers, public relations specialists, pharmacists, chefs and head cooks, retail supervisory positions, and metal and plastic workers.

Table 3 reports the results of these initial regressions for our baseline labor supply measures and our primary dependent variables; the share of postings requiring a BA or greater and the share of postings requiring 4+ years of experience.<sup>31</sup> Standard errors for all regressions are clustered at the state level. Column (1) regresses the change in skill requirements on the change in the state unemployment rate and the BGT supply/demand ratio (the ratio of the number of unemployed to the number of postings by state and occupation) including only occupation×year fixed effects. Because the regression is specified in differences, this effectively allows for differential nonlinear trends in skills across occupations... The estimates in column (2) include our baseline set of controls, which have an extremely small impact on the coefficient of interest. Column 3 allows for differential trends in skills across locations by including state fixed effects, and Column 4 also allows for differential trends for each state×occupation pair. The coefficients are larger with these controls, but remain in the confidence intervals of the original specification. In all specifications,  $\beta$  is positive and statistically significant, indicating that there was an increase in the share of jobs requiring skilled workers across education and experience measures in response to the greater availability of workers.

To give one a sense of the magnitude of this relationship, Figure 4 plots the change in employer requirements versus the change in the unemployment rate by state for all state/occupation cells. Our baseline estimates indicate that within a six-digit detailed occupation, a 1 percentage point increase in the state unemployment rate is associated with a 0.64 percentage point increase in the fraction of employers requiring a Bachelor's degree and a 0.84 percentage point increase in the fraction of employers requiring four or more years of experience.

How large is this effect in terms of economic importance? In the context of the

<sup>&</sup>lt;sup>31</sup> Table B3 in the online appendix reports results for each education and experience category separately.

most recent downturn, our results imply that the nationwide increase in unemployment rates between 2007 and 2010 raised education requirements within occupations by 3.2 percentage points and raised experience requirements by 4.2 percentage points respectively. Relative to the observed increases in skill requirements reported in Table 1 during this period, our estimates suggest that changes in employer skill requirements due to the business cycle can account for up to 30 percent of the total increase for education and nearly 50 percent of the increase for experience.<sup>32</sup>

# B. Within Firm × Job-Title Specifications

As discussed earlier, another potential worry is that there were non-random changes in employer composition and data quality over time. Over the course of the Great Recession, the composition of employers as well as the types of jobs posted may have changed as industries suffered differential declines in employment, possibly causing the demand for low-skill labor to be procyclical. In addition, our primary data source begins in 2007 and the data collection mechanism may have changed over time in a way that was correlated with the labor market, even if the filtering algorithms were applied consistently.

To explore this, we look at changes in employer requirements within an individual firm and job-title pair over time using data from BGT on individual postings.<sup>33</sup> Again, we do this using both the change in the state unemployment rate and the change in the BGT supply/demand ratio as measures of labor availability.

Table 4 provides estimates of upskilling for both the cross-sectional sample eliminating extreme duplicates as well as the collapsed panel sample.<sup>34</sup> As with the OLS specifications, standard errors for all regressions are clustered at the state level. For both education and

<sup>&</sup>lt;sup>32</sup> Other specifications imply smaller shares. See Table B15 in the online appendix.

<sup>&</sup>lt;sup>33</sup> As a robustness check, Table XX in the online appendix replicates our firm-job-title results using the Minnesota Job Vacancy Survey.

<sup>&</sup>lt;sup>34</sup> Recall that the panel sample job-title collapses postings by firm-job-title-state–year pairing taking the mean of the job-title education or experience requirement. This effectively assign the same weight to every firm- job-title pairing, similar to the approach used when aggregating by state×occupation cells.

experience requirements we find positive and significant results using both samples discussed above—even when controlling for **the same job-title at the same employer in the same state**. Columns (1) and (3) only control for year and firm×job-title while columns (2) and (4) include fixed effects by year and firm×job-title×state cells. When controlling for firm×job-title pairs in a particular state, we find that a percentage point increase in the state unemployment rate raises the share of jobs postings requiring a Bachelor's degree by 0.505 percentage points and the share of job postings requiring four or more years of experience by 0.483 percentage points.

The firm×job-title estimates in Table 4 are not dis-similar from those found in Table 3. However, as we have previously discussed, the two specifications weight occupations and states differently making it difficult to make direct comparisons. We address this by providing additional estimates that re-weight each firm×job-title×state pair in our panel sample using the state×occupation weighting scheme from our OLS regressions. This reweighting procedure does indeed produce coefficients that are quite similar across the two sets of results despite being estimated using different samples and levels of aggregation.

Finally, we also include several robustness checks in the online appendix table by substituting HWOL for the BGT supply/demand ratio, estimating the five-year change over the entire period 2007-2012, and using the Minnesota Job Vacancy Survey—all of which produce results that are similar in magnitude or even stronger.<sup>35</sup>

#### C. Veteran Supply Shock Specifications

As a source of exogenous variation to the availability of skilled workers, we make use of a natural experiment resulting from the large increase in the post-9/11 veteran labor force following troop withdrawals from Iraq and Afghanistan. Before using these measures, we first need to establish the validity of this instrument as an exogenous shock

<sup>&</sup>lt;sup>35</sup> See Tables B5-B7 in the online appendix for more details on these results.

to the number of job seekers. With this identification technique, we are investigating whether occupation×state pairs receiving a greater number of returning veterans in a period saw greater contemporaneous increases in the skill requirements listed in their job postings.

The concern, however, is that the return of these veterans was potentially correlated with underlying trends or other factors shifting skill requirements. While the timing of the drawdown from Iraq and Afghanistan was unlikely to be correlated with these cross-sectional trends, it is possible for the location of veterans to be correlated with potential confounders if chosen endogenously. Therefore, for half of our measures, we allocate post-9/11 veterans to their state of birth as a proxy for their true state of residence. Further, the richness of the data lets us test whether the correlation between these veteran shocks and rising skill requirements can be accounted for by trends at the state, occupation, or state×occupation level. We can even test whether this correlation exists within individual firm×job-title pairings.

While it seems unlikely that the troop drawdowns were correlated with trends in skill requirements in veteran-specific occupations and locations where post-9/11 veterans were born, we check whether the veteran supply shock is correlated with other plausible confounders. Table 5 shows no correlation between the each of our constructed veteran shock measures and prior period trends in wage and employment trends.<sup>36</sup> Furthermore, the veteran shock (in either year) is not correlated with the initial level of skill requirements in postings or in the population (see Table B8 in the online appendix). These robustness checks, combined with the lack of an easy to articulate omitted variable bias problem, further reinforces our confidence in this identification strategy.

Using our different measures of the veteran supply shock, panel A of Table 6

<sup>&</sup>lt;sup>36</sup> Table B10 in the online appendix also shows no correlation between the vet shock measures and short term wage trends.

demonstrates that there is a strong, significant and positive relationship between the sharp increase in the supply of returning veterans and the rise in employer skill requirements for both education and experience. Moreover, controlling for state fixed effects—which we alternately do in the columns—does not have a large impact on these results, suggesting that we are not picking up some hidden, underlying state-level trend.<sup>37</sup> As expected and explained above, we tend to get more precise estimates when we use national estimates of the number of returning veterans allocated by state of residence as well as state of birth. The implied magnitudes suggest that a 1 standard deviation increase in the supply of veterans increases the share of postings requiring a bachelor's degree and the share requiring 4+ years of experience by roughly 1.3 percentage points.

How do these results compare to the OLS results described in previous sections? To create a more directly analogous measure, we construct a veteran-specific supply/demand ratio. The numerator is estimated by taking the change in the number of veterans (measured by state of birth) and multiplying by the broad occupation group's veteran share. We then divide by the total number of postings in each broad occupation group within the state to create a BGT supply/demand ratio for post-9/11 veterans.<sup>38</sup> As seen in the first row in Panel B, changes in this measure again strongly correlate with upskilling for both education and experience requirements. The implied magnitude is quite similar to the results in Panel A; a 1 standard deviation increase in the supply of veterans is associated with a 0.76 percentage point increase in the share of postings requiring a bachelor's degree or greater and a 1 percentage point increase in the share requiring 4+ years of experience.

This veteran supply and demand measure can also be used as an instrument for the

<sup>&</sup>lt;sup>37</sup> The online appendix contains specifications that include state×occupation fixed effects as well, effectively allowing for a trend at the state×occupation level as well as specifications without the baseline controls.

<sup>&</sup>lt;sup>38</sup> To eliminate outliers due to noise in the denominator in small occupations and states we drop the bottom and top 5% of values from our constructed supply/demand measures.

aggregate BGT supply/demand measure used in Table 2. This instrument captures information about both the number of searchers and the demand by occupation and state. As such, it has sufficient power to surpass traditional weak instrument benchmarks as shown by the first stage F-statistics reported at the bottom of Panel B (Stock and Yogo 2005). These IV estimates—again using the change in the supply of veterans by *state of birth* – are if anything larger than those reported in Table 3. Moreover, Table B12 in the online appendix also provides a robustness check accounting for the endogeneity of labor force participation among returning veterans and reports results that are very similar, if not stronger, than those using our unadjusted veteran supply shock measures.<sup>39</sup>

Finally, in Panel C of Table 5 we combine both the within firm×job-title approach with the veteran shock analysis. To do this, we use construct measures of the log of the number of veterans multiplied by the post-9/11 veterans share at the occupation level that are analogous to those used above.<sup>40</sup> We then regress these measures on skill requirements for job postings controlling for year and firm×job-title×state fixed effects which effectively compares upskilling within firm×job-title×state groupings that received veteran shocks of different magnitudes. The coefficients in Panel C are very similar in magnitude to those in Panel A, confirming that opportunistic upskilling occurs within individual firm×job-titles even when using an exogenous shock to labor availability.

Of course, the veteran supply shocks matter most for certain occupations and locations, which may not be representative along certain dimensions. Still, the fact that our natural experiment provides similar results to the baseline OLS regressions using the business cycle variation as well as the within firm×job-title specifications strongly suggests

<sup>&</sup>lt;sup>39</sup> Table B12 reports results using an estimate of only veterans in the labor force (excluding non-participants) as well as only non-disabled veterans. We are concerned, though, about the potential endogeneity of this margin (see Autor, Duggan, and Lyle 2016) and hence use only the unscaled versions here.

<sup>&</sup>lt;sup>40</sup> To do this, we need to exclude rare firm× job-title pairs that are assigned to multiple occupation codes.

a causal link between rising employer skill requirements and the increased supply of available workers.

### Mechanism

There are several reasons firms may decide to raise skill requirements when confronted with an increase in the supply of job seekers. One intuitive possibility is that firms have a higher likelihood of finding a skilled worker for a mid- or low- skilled position when the unemployment rate is high. This intuition is consistent with the fact that the number of available high-skilled job seekers per vacancy is strongly correlated with the overall unemployment rate as the composition of the pool of unemployed workers becomes more skilled during recessions (Mueller 2015).<sup>41</sup> It is also consistent with the fact that the college wage premium for new hires is strongly pro-cyclical making it more likely that a high-skilled worker will accept a job offer for a mid- or low-skilled position.<sup>42</sup>

To understand this mechanism, we very briefly sketch an illustrative partialequilibrium model. We start by assuming there are a fixed number of firms each posting a vacancy V, that generates a payout,  $\theta$ , equal to 1 when filled by a low skilled worker and  $\theta$ >1 when filled by a high skilled worker.<sup>43</sup> These firms face an applicant pool L divided between a small fraction of high-skilled applicants  $\gamma$  and a large fraction of low-skilled applicants (1-  $\gamma$ ).<sup>44</sup> High skilled applicants only search for jobs with skill requirements, and hence, employers must choose between posting a vacancy with a minimum skill requirement and accepting a low-skill worker. Each employer has a stochastic cost *c* of

<sup>&</sup>lt;sup>41</sup> See Figure B2 in the online appendix

<sup>&</sup>lt;sup>42</sup> See Figure B3 in the online appendix. As far as we can tell, prior work has only looked at the aggregate premium, not the premium for new hires, which is relevant here. See the online appendix for details regarding how we calculate the college wage premium for new hires using the multi-month matched CPS sample based on a matching algorithm similar to that proposed by Madrian and Lefgren (1999).

<sup>&</sup>lt;sup>43</sup> This could be replaced with a variable, but not perfectly elastic, supply of vacancies. While free entry (and flexible wages) are appealing modeling conventions for long run phenomenon, this model is meant to parallel the short run relationships captured in our empirical work.

<sup>&</sup>lt;sup>44</sup> We assume that search intensity is roughly constant which seems reasonable given empirical estimates large ranges of labor market tightness (Shimer 2004).

leaving the vacancy unfilled which is drawn from a uniform density distribution. Firms also vary in the exogenous turnover rate 1- $\delta$  of their employment relationships, and in the urgency for new hires to begin working modeled via their discount rate 1- $\rho$ .

To motivate the problem, we assume that high skilled applications are uncoordinated or allocated across vacancies randomly, making the number of applications a Poisson random variable. Each period, the odds that a vacancy receives at least one high skilled applicant is given by  $(1 - e^{-\frac{\gamma L}{V}})$ , which is increasing in the number of total applicants L. For simplicity, we'll assume that for the range of L considered, there are sufficiently many low skilled workers that firms can match with certainty when not posting a requirement. In this environment, firms face a single decision; whether to accept a low skilled worker in the event of not matching a high skilled worker or whether to keep searching. The value of a firm is given by

$$V = -c + \left(1 - e^{-\frac{\gamma L}{V}}\right)\frac{\theta}{1 - \delta\rho} + e^{-\frac{\gamma L}{V}}max\left\{\rho V, \frac{1}{1 - \delta\rho}\right\}$$

It is straightforward to show that, in this environment, firms' decisions follow a cutoff rule  $c^*$  in their costs of maintaining a vacancy. Employers with costs below the cutoff post minimum skill requirements and employers with costs above the cutoff do not. Since costs are drawn from a uniform distribution, (when scaled) this is equivalent to the fraction of employers posting vacancies with skill requirements. Thus the fraction of firms that wait for a high skilled worker is increasing in the number of unemployed (L) and, in particular, in the number of high skilled job searchers  $\gamma L$ .<sup>45</sup>

To test whether or not this intuition about the composition of available workers is

<sup>&</sup>lt;sup>45</sup> In the model, the sensitivity of the share of vacancies with a skill requirement with respect to unemployment is given by  $\frac{dc^*}{dL} = \frac{\gamma}{V} e^{-\frac{\gamma L}{V}} \left(\frac{\theta - 1}{1 - \delta \rho}\right)$ . From here it's easy to see that upskilling will be stronger when turnover and urgency are low and when the skill premium is high. Similarly, upskilling in this model is likely to be strong when wages are more rigid. Table B13 in the online appendix demonstrates that these comparative statics are indeed borne out in the data.

borne out in the data, we construct several proxies of labor availability by skill group at the state level using the ACS. Specifically, we measure unemployment rates at the state level separately for those with and without a BA (our proxy for education) and also for those over and under 35 (our proxy for experience). We also measure the *share* of the unemployed with by education and experience, and construct supply/demand measures using the number of unemployed by education and experience.

Table 7 shows that the intuition from the model matches the patterns we see in the data. In columns (1)-(2) and (6)-(7) we regress changes in experience and education requirements on unemployment rates for workers with and without a college degree respectively and for "seasoned" and "unseasoned" workers (over and under 35). We find that the change in skill requirements is driven by the unemployment of more highly skilled workers, with the unemployment rate for unskilled workers coming in insignificant and close to zero. In columns (3), (4), and (8) we show that the share of unemployed workers that are skilled (analogous to  $\gamma$ ) is also correlated with upskilling requirements for both education and experience. Finally, in columns (5) and (9) we test the measure most closely related to our model and show that the supply/demand ratio for skilled workers is also strongly tied to upskilling.

While we do not think our results rule out other mechanism such as random searching, we think the evidence does suggest opportunistic upskilling is likely to be operating on some level such that employers respond to the increased odds of matching with a high skilled job searcher. However, while we have a solid instrument for the overall number of searchers, we do not have a similar experiment to separate high and low skilled searchers.

However, the evidence presented here is also consistent with qualitative data from employer interviews that we conducted with firms represented in the BGT data. To better understand the mechanism behind our findings, we interviewed local employers in several

industries including manufacturing, healthcare, and finance to find out why their firm had upskilled certain jobs during the Great Recession. During our interviews, we primarily focused on entry level jobs for which the firm did the most hiring with an emphasis on "middle-skill" jobs that typically require some vocational or post-secondary training but less than a Bachelor's degree. There was definitely a sense among employers that they could recruit a better candidate during the weak economy compared to the current labor market in which they see the same number of candidates but that the quality of the candidates has decreased. For example, one recruiter reported "I remember [during the recession], the Big 4 [accounting firms] laid off thousands of people.... I couldn't buy a job for those people. You had to walk on water to get a job… you had to be in the top 10% in school and in your Big 4 ratings… now, it's so hard to find people-- all those requirements are gone" (Modestino, Moss, and Shoag 2017).

# Conclusion

The persistent weakness of the U.S. labor market following the Great Recession continues to puzzle both researchers and policymakers alike. On the one hand, employers reported difficulty finding skilled workers to fill open positions, suggesting the potential for some degree of labor market mismatch across industry, occupation, or geography. Yet on the other, economists find that the lack of real wage growth observed even within industries and occupations with relatively strong demand suggests little role for labor market mismatch. More recently, the literature has explored the possibility that a decrease in "recruitment intensity" per vacancy during the recession may have led to an upward shift in the Beveridge Curve such that a higher vacancy rate prevailed for a given unemployment rate during much of the recent recovery (Davis et al 2012).

Yet to date the application of this theory has been limited by the absence of direct

measures of recruiting intensity across employers. In this paper, we measure one channel along which recruitment intensity may have shifted during the Great Recession—in the skill requirements employers use to screen candidates when filling a new vacancy-and find evidence of opportunistic upskilling. Using data from online job vacancy postings, we find that employer requirements rise for both education and experience when job seekers are more plentiful—even when controlling for year, occupation, and state fixed effects among other covariates. This pattern is found using multiple measures of labor availability and is robust to using both online job vacancy data as well as that from a state-level employer survey. Moreover, we find that unemployment-related upskilling occurs even within firm×job-title pairs, suggesting that changes in recruitment intensity do not simply reflect a shift in the composition of employers or the positions that they seek to fill. We also use a natural experiment based on troop withdrawals from Iraq and Afghanistan as a source of exogenous variation in the availability of skilled workers and find a similar pattern of employer upskilling, even within firm×job-title pairs. Finally, we provide a simple model motivating one possible channel for employer upskilling that operates through the changing composition of the pool of unemployed workers and find suggestive evidence to support this mechanism.

The finding that weaker labor markets lead to rising job posting requirements has important implications for models in labor and macroeconomics that are aimed at explaining the dynamics of the labor market during recessions. In particular, we are able to document a novel feedback mechanism between labor supply and the selectivity of vacancies that may be relevant for macroeconomic models with heterogeneous workers and welfare analysis. Our back-of-the-envelope calculations averaged across all of our specifications implies that the employer upskilling during the Great Recession could potentially account for 18 percent of the total increase in education requirements and 25

percent of the increase in experience requirements observed between 2007 and 2010 with somewhat smaller impacts over the whole five-year period 2007-2012. To our knowledge, these findings provide some of the first empirical evidence of a shift in recruitment intensity whereby employer skill requirements are driven—in part—by the available supply of labor.

Given that our estimates do not account for most of the change in skill requirements, we recognize that opportunistic upskilling in response to the increased availability of job searchers is only one of the forces explaining the rise in skill requirements over the period we study. For example, prior research has demonstrated that changes over the business cycle are subtle and complicated because both cyclical and structural factors can interact (Jaimovich and Siu 2014; Charles Hurst, and Notowidigdo 2016). Hershbein and Kahn (2018) find supporting evidence of this, showing that the change in employer demand for skill responds persistently to local industry demand shocks that appear to be related to technological and capital changes that permanently affect the demand for education and experience. We believe this work complements our findings by measuring the degree to which structural forces are driving employer upskilling compared to the estimates that we present in this paper capturing employer responses to the business cycle. Still, by demonstrating that employer upskilling is associated with opportunistic hiring when labor market are slack, we provide important evidence that at least some of what is labeled as "structural mismatch" is at least partially cyclical and likely to revert.

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Figure 1. Relationship between Changes in Employer Requirements and Labor Supply

Source: Authors' analysis using data from Burning Glass Technologies, 2007, 2010–2014.

Source: Author's analysis of data from Burning Glass Technologies; state unemployment rates collected from the Bureau of Labor Statistics.



Figure 2. Change in Post-9/11 Veterans in the Labor Force per Job Posting, 2007-2012.

*Notes:* Authors calculations comparing the ratio of the number of post-9/11 veterans to the number of job postings by state for 2007 versus 2012. The number of post-9/11 veterans in the labor force by state are estimated using the 1 year American Community Survey from the PUMS for 2007 and 2012. The number of job postings by state is estimated from data provided by Burning Glass Technologies for 2007 and 2012.



Figure 3. Relationship Between Employer Skill Requirements and Veteran Supply Shock, 2007-2012.

*Notes:* Figures are binned scatterplots showing the baseline relationship between the percentage point change in employer requirements requesting four or more years of experience and the change in the veteran labor supply. Veteran labor supply is measured as the log change in the number of post-9/11 veterans in the labor force by state using the 1 year American Community Survey from the PUMS for 2007 and 2012. The share of employers requesting four or more years of experience is estimated from data provided by Burning Glass Technologies for 2007 and 2012.



Figure 4. Relationship Between Changes in Employer Requirements and Labor Market Slack

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Notes: Figures are binned scatterplots showing the baseline relationship between the percentage point change in employer requirements and change in labor supply (the BGT labor supply/demand ratio or percentage point change in the state unemployment rate).

Pa	nel A. Employer Skil	ll Requirements			
	2007	2010	2012	∆ <b>2007-2010</b>	∆ <b>2010-2012</b>
All postings aggregated into detailed occupation X state cells					
Number of observations	18,694.00	19,470.00	18,970.00	18,694.00	18,970.00
Total number of job postings					
Mean	634.40	516.73	625.19	-97.46	95.49
Standard deviation	1,977.38	1,701.25	2,052.94	579.56	497.86
Mean percent of job postings requesting:					
Bachelor's degree or higher	12.93	22.43	24.95	9.83	2.34
Four or more years of experience	8.40	14.17	14.97	6.04	0.72
All postings with non-missing firm names and job-titles					
Total number of job postings	5,684,530.00	4,441,522.00	6,973,321.00	-1,243,008.00	1,288,791.00
Percent of job postings requesting:					
Bachelor's degree or higher	23.23	33.38	34.42	10.15	1.04
Four or more years of experience	14.02	22.59	21.34	8.56	-1.25
Panel of employer-job title-state observations					
Total number of job postings	506,914.00	295,783.00	474,884.00	-211,131.00	179,101.00
Percent of job postings requesting:					
Bachelor's degree or higher	20.98	31.07	31.85	10.09	0.78
Four or more years of experience	11.30	17.33	16.89	6.03	-0.44
	Panel B. Labor Ma	arket Slack			
State unemployment rate					
Mean	4.43	9.07	7.59	4.64	-1.5
Standard deviation	0.87	1.95	1.61	1.51	0.76
BGT labor supply/demand ratio					
Mean	12.82	19.27	12.77	4.21	-4.33
Standard deviation	14.63	18.09	11.64	5.44	5.73

Table 1.	Summary	V Statistics f	for Empl	over Skill Re	quirements ar	nd Labor	Market Slack
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*Note:* All employer skill requirements are constructed using job posting data from Burning Glass Technologies. The sample by detailed occupation X state includes observations for 6-digit Standard Occupation Code (SOC) by state cells containing at least 15 total postings. The sample by firm X job-title excludes postings located in Washington D.C., Guam, and Puerto Rico or missing state fips code, employer name, or job title and having more than 100 postings for the same firm-job title-state within a year. The state unemployment rate is the annual rate reported by the Bureau of Labor Statistics. The labor supply/demand ratios are annual, state-level measures for the average number of unemployed persons per BGT job posting within six, broad occupation groups. See the data appendix for further details on sample and variable construction.

Panel A: Annual Change in Post-9/11 Veteran Population, 2006-2012										
Year	Number of	of Post 9/11	Veterans	YOY Change						
	in t	he Labor Fo	rce							
2006		1,504,807								
2007		1,537,363		32,556						
2008		1,559,495		22,132						
2009		1,619,193		59,698						
2010		1,927,541		308,348						
2011		2,126,179		198,638						
2012		2,330,987		204,808						
P	anel B: Co	nstructed Ve	eteran Supp	oly Shocks						
		Δ2	007-10			∆ <b>2010–12</b>				
	Mean	SD	Min	Max	Mean	SD	Min	Max		
$\Delta$ Log Raw Post 9/11 Vets × Occ Vet Share	0.3022	0.1379	-0.0682	0.6469	0.2440	0.1420	-0.1608	0.8052		
$\Delta$ Log Post 9/11 Vets × State Vet Share × Occ Vet Share										
(Allocated By Residence)	0.7567	1.8045	0.0000	66.16	0.6359	1.5128	0.0000	55.59		
$\Delta$ Log Post 9/11 Vets × State Vet Share × Occ Vet Share										
(Allocated By State of Birth)	0.7683	1.7782	0.0000	68.26	0.6451	1.4889	0.0000	57.35		
$\Delta$ BGT Supply /Demand Ratio for Post 9/11 Vets										
(By State of Birth)	0.1863	0.5284	-1.5770	1.6864	0.0405	0.5608	-1.5638	1.7363		

 Table 2. Summary Statistics for Veteran Supply Shock Measures

*Note:* Panel A reports the change in the number of post-9/11 veterans in the labor force at the state level each year from 2007 through 2012 are reported by the American Community Survey (ACS) Summary Files. Panel B reports four measures of changes in the supply of labor across state-occupation-year cells constructed from the ACS. The first measure is simply the log difference in the number of post-9/11 veterans in the state labor force, as reported in the ACS Summary Files, multiplied by the occupation's share of veterans. Veteran concentration within an occupation is calculated as the occupation's share of veteran employment estimated from the 2007 ACS 3-year estimates from IPUMS-USA. The second measure is the log difference in the number of post-9/11 veterans at the national level multiplied by a state's average share of the post- 9/11 veteran labor force allocated by state of residence in each year as calculated from the ACS. The third measure is the log difference in the number of post-9/11 veterans at the of bith in each year as calculated from the ACS. The fourth measure is a veteran supply/demand ratio where the numerator is constructed by multiplying the national change in the number of post-9/11 veterans by each broad occupation group's veteran's share and each states' share of veteran's birthplace and the denominator is the number of postings for a given state and broad occupation group.

	(1)	(2)	(3)	(4)
	Percentage Poi	nt Change in the Share of Po	ostings Requesting a Bachelo	r's Degree or Higher
$\Delta$ State Unemployment Rate	0.698 ***	0.636 ***	0.907 ***	0.904 ***
	(0.225)	(0.203)	(0.244)	(0.243)
△ BGT Labor Supply/Demand Ratio	0.125 ***	0.100 ***	0.105 ***	0.172 ***
	(0.0278)	(0.0310)	(0.0361)	(0.0472)
	Percentage Poin	nt Change in the Share of Po	stings Requesting 4 or More	Years of Experience
$\Delta$ State Unemployment Rate	0.837 ***	0.837 ***	0.960 ***	0.959 ***
	(0.143)	(0.135)	(0.172)	(0.171)
Δ BGT Labor Supply/Demand Ratio	0.174 ***	0.173 ***	0.151 ***	0.247 ***
	(0.0284)	(0.0263)	(0.0410)	(0.0525)
Baseline Controls	No	Yes	Yes	Yes
Occ x Year Fixed Effects	Yes	Yes	Yes	Yes
State Fixed Effects	No	No	Yes	Yes
State x Occupation Fixed Effects	No	No	No	No

Table 3. Relationship Between Changes in Employer Skill Requirements and Changes in Labor Market Slack, 2007-2012

*Note:* Baseline controls include the initial (2007) share of postings requiring the skill measured, the change in the number of total postings 2007-2012 as a share of total employment in 2000, and the share of the state population with a Bachelor's Degree or greater in 2000 (for Panel A) or the average age of the population in 2000 (for Panel B). Observations are occupation X state cells containing at least 15 job postings (for both years over which the change is measured) and are weighted by the occupation's share of each state's total postings. Standard errors (in parentheses) are clustered by state. \* p<0.10, \*\* p<0.05, \*\*\* p<0.01.

	(1)	(2)	(3)	(4)	(5)	(6)		
	Share	e of Postings Request	ing	Share of Postings Requesting				
	a Bach	elor's Degree or Gre	eater	4 or More Years of Experience				
Cross-sectional sample (N= 17,099,373)								
State Unemployment Rate	0.156 **	0.318 *		0.106 **	0.257 *			
	(0.074)	(0.176)		(0.045)	(0.133)			
BGT Labor Supply/Demand Ratio	0.056 **	0.079 ***		0.044 **	0.075 ***			
	(0.026)	(0.021)		(0.019)	(0.023)			
Panel sample of repeated observations (N=1,277,581)								
State Unemployment Rate	0.235 **	0.505 **	0.726 ***	0.204 **	0.483 ***	0.765 ***		
	(0.120)	(0.195)	(0.240)	(0.175)	(0.153)	(0.166)		
BGT Labor Supply/Demand Ratio	0.103 ***	0.113 ***	0.082 **	0.096 ***	0.106 ***	0.099 **		
	(0.000)	(0.027)	(0.045)	(0.031)	(0.029)	(0.035)		
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes		
Firm x Job-Title Fixed Effects	Yes	No	No	Yes	No	No		
Firm x Job-Title x State Fixed Effects	No	Yes	Yes	No	Yes	Yes		
Using Occupation x State weights from OLS specifications	No	No	Yes	No	No	Yes		

Table 4. Relationship Between Changes in Employer Skill Requirements and Changes in Labor Market Slack, Using within Firm x Job Title Variation

*Note:* Cross-sectional sample is restricted to observations not missing FIPS codes; eliminating DC, Guam, and Puerto Rico, not missing employer name, not missing job title, and eliminating observations with more than 50 duplicate postings for the same firm-job title-state within a month-year. Panel sample of repeated observations excludes observations that do not repeat across years with the same employer, job-title and state. See the online appendix for construction of variables. Regressions using the BGT supply/demand ratios also include state x occ fixed effects analogous to Table 2. Standard errors (in parentheses) are clustered by state. \* p<0.10, \*\* p<0.05, \*\*\* p<0.01.

Tuble Ct Explore	ing correlatio	in Detween v	eterun Shoen		i chub ut the	State Occup	ation Bever			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
				Log Change	e from 2002-2	007 in State-	Occupation:			
	Median Ho	ourly Wage	Mean Ho	urly Wage	Median An	nual Wages	Mean Ann	ual Wages	Total En	ployment
A Lee Dest 0/11 Wetenesse her State or Ose Wet Share	0.00511*	0.000177	0.00294	0.00122	0.00417	0.000500	0.00211	0.00101	0.00445	0.0179
$\Delta$ Log Post 9/11 Veterans by State x Occ Vet Share	-0.00511*	-0.0001//	-0.00384	0.00122	-0.0041/	0.000588	-0.00311	0.00181	0.00445	-0.01/8
	(0.00277)	(0.00330)	(0.00248)	(0.00308)	(0.00276)	(0.00323)	(0.00244)	(0.00298)	(0.00934)	(0.0108)
$\Delta$ Log Post 9/11 Veterans by State x Occ Vet Share x State										
Vet Share	0.00102	0.00127	0.000383	0.000540	0.00145	0.00179	0.000661	0.000873	-0.000361	-0.000846
(Allocated by State of Residence)	(0.00154)	(0.00183)	(0.00163)	(0.00193)	(0.00153)	(0.00182)	(0.00161)	(0, 00190)	(0.00311)	(0.00378)
	(0.00101)	(0.00100)	(0.00102)	(0.001)0)	(0.00100)	(0.0010_)	(0.00101)	(0.001)0)	(0.00011)	(0.00070)
$\Delta$ Log Post 9/11 Veterans by State x Occ Vet Share x State										
Vet Share	-6.20e-06	9.67e-05	-0.00105	-0.00111	0.000498	0.000699	-0.000702	-0.000698	-0.00548	-0.00703
(Allocated by State of Birth)	(0.00114)	(0.00135)	(0.00114)	(0.00135)	(0.00114)	(0.00135)	(0.00113)	(0.00133)	(0.00470)	(0.00567)
(	()	(	()	()	()	()	(	()	()	()
$\Delta$ BGT Supply/Demand Ratio for Post-9/11 Veterans	0.00470	0.00488	0.00212	0.00485	0.00550	0.00366	0.00275	0.00381	-0.0220*	-0.00955
(Allocated by State of Birth)	(0.00643)	(0.00610)	(0.00594)	(0.00550)	(0.00623)	(0.00579)	(0.00576)	(0.00521)	(0.0119)	(0.0111)
· - ·	. ,				. ,					. ,
Veteran Shock From	2007-2010	2010-2012	2007-2010	2010-2012	2007-2010	2010-2012	2007-2010	2010-2012	2007-2010	2010-2012
Observations	15,380	15,634	15,598	15,863	16,267	16,564	16,486	16,794	16,106	16,368

*Note:* This table explores the relationship between state-occupation level wage and employment trends in the BLS Occupational Employment Statistic (OES) and the veterans shock. Since the veterans shock is time varying, but the pre-trend is not, we run each period separately. To mimic the 5-year period used in our baseline regressions, we explore wage trends in the five years prior to the shock. As in the baseline specifications, observations are State  $\times$  Occupation cells containing at least 15 job posting (for both years over which the change is measured) and are weighted by the occupation's share of each state's total postings. Standard errors (in parentheses) clustered by state. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

	(1)	(2)	(3)	(4)			
	Change in the Shar	e of Postings Requesting	Change in the Share	of Postings Requesting			
Panel A: OLS Estimates Using Veteran Supply Shock	a Bachelor's	Degree or Higher	4 or More Yea	irs of Experience			
$\Delta$ Log Post 9/11 Veterans by State x Occ Vet Share	1.382 *	1.59 *	1.674 *	1.58 *			
	(0.771)	(0.857)	(0.844)	(0.905)			
$\Delta$ Log Post 9/11 Veterans by State x Occ Vet Share x State Vet Share	0.421 **	0.364 ***	0.696 ***	0.469 ***			
(Allocated by State of Residence)	(0.167)	(0.0964)	(0.160)	(0.106)			
$\Delta$ Log Post 9/11 Veterans by State x Occ Vet Share x State Vet Share	0.477 **	0.312 ***	0.564 ***	0.392 ***			
(Allocated by State of Birth)	(0.193)	(0.0914)	(0.132)	(0.0976)			
Baseline Controls	Yes	Yes	Yes	Yes			
Occupation, Year Fixed Effects	Yes	Yes	Yes	Yes			
State Fixed Effects	No	Yes	No	Yes			
	Change in the Shar	e of Postings Requesting	Change in the Share of Postings Requesting				
Panel B: IV Estimates Using Veteran Supply Shock	a Bachelor's	Degree or Higher	4 or More Years of Experience				
Δ BGT Supply/Demand Ratio for Post-9/11 Veterans	1.38 ***	1.317 **	1.84 ***	1.823 ***			
(Allocated by State of Birth)	(0.514)	(0.621)	(0.506)	(0.646)			
△ BGT Supply/Demand Ratio	0.498 ***	0.544 **	0.582 ***	0.645 ***			
IV with $\Delta$ BGT Supply/Demand Ratio for Post-9/11 Veterans (Allocated by State of Birth)	(0.153)	(0.204)	(0.142)	(0.208)			
First Stage F-Statistic (for A BGT Supply/Demand Ratio)	16.4	21.7	16.4	21.7			
Baseline Controls	Yes	Yes	Yes	Yes			
Occupation. Year Fixed Effects	Yes	Yes	Yes	Yes			
State Fixed Effects	No	Yes	No	Yes			
	Change in the Shar	e of Postings Requesting	Change in the Share	of Postings Requesting			
Panel C: Firm-Job Title Estimates for Veteran Supply Shock	a Bachelor's	Degree or Higher	4 or More Yea	irs of Experience			
Log Post 9/11 Veterans in ACS x Occ Vet Share	0.478	**	0.886	***			
-	(0.237)		(0.244)				
Log Post 9/11 Veterans Allocated by Avg State Vet Share x Occ Vet Share	0.773	***	1.221	***			
(Allocated by State of Residence)	(0.207)		(0.324)				
Log Post 9/11 Veterans Allocated by Avg State Vet Share x Occ Vet Share	0.758	***	1.201	***			
(Allocated by State of Birth)	(0.204)		(0.319)				
Year Fixed Effects	Yes		Yes				
Firm x Job-Title x State Fixed Effects	Yes		Yes				

 Table 6. Relationship Between Changes in Employer Skill Requirements and Veteran Supply Shock

*Note:* The first two panels use the same occupation × state sample as Table 2 while the third panel uses the same firm×job title sample as Table 3. Panels A and C use three alternative measures of the veteran supply shock. Panel B uses two supply and demand measures similar to those found in Table 2 to create comparable IV estimates. See the text and online data appendix for details on samples, baseline controls, and variable construction. First stage F-statistics demonstrating the absence of weak instrument bias are reported for these IV regressions. The firm×job title sample differs from Table 4 in that it eliminates any firm × job title pair that gets coded to more than one occupation. This makes it possible to use the occupation level veteran shocks. Standard errors (in parentheses) clustered by state. \* p<0.05, \*\*\* p<0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
	Ch	ange in the S	Share of Pos	tings Requesti	ng	Change in the Share of Postings Requesting				
		a Bachel	or's Degree	or Greater		4	4 or More Years of Experience			
Change in Unemployment Rate for BA+	0.985***	0.940**								
	(0.273)	(0.391)								
Change in Unemployment Rate for <ba< td=""><td></td><td>0.0363</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></ba<>		0.0363								
		(0.200)								
Change in Share Unemployed with BA+			0.133	0.287*						
			(0.160)	(0.156)						
Change in BGT Supply/Demand Rate Using BA+					1.656***					
					(0.430)					
Change in Unemployment Rate 35+						0.837***	0.868***			
						(0.138)	(0.201)			
Change in Unemployment Rate <35							-0.0291			
							(0.154)			
Change in Share of Unemployed 35+								0.0862*		
								(0.0465)		
Change in BGT Supply/Demand Rate Using 35+									0.563***	
									(0.0916)	
									<u> </u>	
Baseline Controls	Х	Х	Х	Х	Х	Х	Х	Х	Х	
Occ-Year Fixed Effects	Х	Х	Х	Х	Х	Х	Х	Х	Х	
Sample	Baseline	Baseline	Baseline	Exclude ND	Baseline	Baseline	Baseline	Baseline	Baseline	
Observations	40,276	40,276	40,276	39,827	40,276	40,276	40,276	40,276	40,276	
R-squared	0.655	0.655	0.650	0.655	0.656	0.613	0.613	0.599	0.615	

Table 7. Relationship Between Changes in Employer Skill Requirements and Composition of Unemployed

*Note:* The education specific measures were estimated using micro-data from the American Community Survey and the age specific unemployment rates as reported by the BLS Expanded State Employment Demographic Data. Sample is restricted to observations are occupation X state cells containing at least 15 job postings (for both years over which the change is measured) and are weighted by the occupation's share of each state's total postings, except column (4) which also drops observations in North Dakota. Standard errors (in parentheses) are clustered by state. \* p<0.10, \*\* p<0.05, \*\*\* p<0.01.