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Downskilling: Changes in Employer Skill Requirements over the Business Cycle

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Using a novel database of 82.5 million online job postings, we show that employer skill requirements fell as the labor market improved from 2010 to 2014. We find that a 1 percentage point reduction in the local unemployment rate is associated with a roughly 0.27 percentage point reduction in the fraction of jobs requiring at least a bachelor's degree and a roughly 0.23 percentage point reduction in the fraction requiring five or more years of experience. This pattern is established using multiple measures of labor availability, is bolstered by similar trends along heretofore unmeasured dimensions of skill, and even occurs within firm-job title pairs. We further confirm the causal effect of labor market tightening on skill requirements using a natural experiment based on the fracking boom in the United States as an exogenous shock to the local labor supply in tradable, non-fracking industries. These industries are not plausibly affected by local demand shocks or natural gas extraction technology, but still show fewer skill requirements in response to tighter labor markets. Our results imply this labor market-induced *downskilling* reversed much of the cyclical increase in education and experience requirements that occurred during the Great Recession.

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I. Introduction: Secular versus Cyclical Shifts in Skill Requirements

The persistent weakness of the U.S. labor market during the period following the Great Recession remains poorly understood. As of 2012, two years after the official end of the Great Recession, the unemployment rate still hovered around 8 percent, despite employers reporting more vacant positions. This shift in the relationship between unemployment and vacancies, known as the Beveridge curve, has highlighted the need to focus not just on the number of vacancies, but on their composition and skill requirements as well (Diamond and Sahin 2014).

A number of explanations for this shift have been proposed, with potentially different policy implications. In particular, some have interpreted the shift as deterioration in the matching/hiring process in the economy, such that idle workers may be seeking employment in sectors different from those where the available jobs are. For example, Sahin et al. (2014) measure the degree of mismatch between vacancies and workers across occupations and geographies and find that mismatch can potentially account for one-third of the increase in the unemployment rate during the Great Recession. Yet the lack of wage growth observed even within industries and occupations with relatively strong demand in the United States would suggest little or no role for labor market mismatch. This observation has prompted others to explore the importance of the composition of the workforce and the motivation of job seekers, in seeking to explain recent movements in the Beveridge curve (Veracierto 2011; Barnichon and Figura 2010; Shimer 2012; Fujita and Moscarini 2015; Hall and Schulhofer-Wohl 2015; Mukoyama, Patterson, Sahin 2014; Hagedorn et al. 2014).

More recently, the literature has focused on a third potential factor contributing to this observed shift in the Beveridge Curve—namely, a decrease in "recruitment intensity" per vacancy during recession, whereby employers engage in behavior that can influence the rate of new hires (Davis, Faberman, and Haltiwanger 2012). This behavior can be described as a set of actions that employers can take to affect recruitment intensity, such as changes in advertising expenditures, screening methods, hiring standards, and compensation. For a given vacancy-to-unemployment ratio, a lower recruiting intensity per vacancy would serve to lower the job fill rate, resulting in an upward shift in the Beveridge Curve, such as that observed after the Great

Recession. Yet to date there has been limited evidence of direct measures of recruitment intensity across employers (Diamond 2013, Rothstein 2012).

We directly measure an important channel along which recruitment intensity may have shifted during the Great Recession—the skill requirements employers use to screen candidates when filling a new vacancy. Indeed, media reports and employer surveys indicate that employer requirements increased sharply during the Great Recession so that a college degree is now required for a number of occupations that previously required only a high school degree.[1] Previous work examining this dynamic found that employers raised education and experience requirements within occupations, and even within firm and job titles (Modestino, Shoag, and Ballance 2014, Hershbein and Kahn 2016). This growth in skill levels within occupations has colloquially become known as *upskilling.* [2]

This massive increase in required skills raised concerns that the U.S. labor market faced a structural and persistent mismatch between workers' skills and firms' needs. Here and in Modestino, Shoag, and Ballance (2014), we argue that a significant portion of this increase in employer skill requirements reflects strategic or *opportunistic*[3] upskilling, whereby firms used slack labor markets as an opportunity to hire more skilled workers, potentially increasing productivity. Rather than mismatch causing unemployment, we claim that a significant portion of the observed changes in skill requirements during the Great Recession resulted from employers' response to loose labor markets. What we could not observe in that analysis, however, was the behavior of skill requirements as the labor market improved or tightened.

In this paper, we build on our earlier study of the Great Recession, with an analysis of skill trends during the subsequent recovery. Demonstrating this relationship is crucial for a number of reasons. First, falling skill requirements during the recovery provide important

[1] For example, according to a survey by CareerBuilder in 2013, almost one-third of employers said that their educational requirements for employment had increased over the last five years and specifically that they were hiring more college-educated workers for positions previously held by high school graduates (CareerBuilder 2014).

[2] See "Degree Inflation? Jobs That Newly Require B.A.s," by Catherine Rampell in the *New York Times* of December 4, 2012.

[3] We use this term in the sense used by biologists, to mean "take advantage of favorable conditions." We do not use it to convey value judgments.

confirmatory evidence that the upskilling observed during the Great Recession was indeed opportunistic to some degree. Using the post-recession data, we can more convincingly identify this effect and make use of new natural experiments giving rise to exogenous shocks to the labor supply during the recovery. Second, even if skill requirements initially rose due to cyclical labor market slack, it is not immediately clear that they would revert during a recovery. Labor markets are prone to hysteresis, and what began as a short-term response to labor market conditions may have become a more permanent trend. Finally, the symmetry or asymmetry of the response allows us to evaluate the importance of proposed mechanisms that might matter more in recessions than in recoveries.

To do this, we use a newly updated, comprehensive dataset of 82.5 million online job vacancy postings from Burning Glass Technologies (BGT). This job-level dataset covers the near-universe of electronic posts across the entire United States. More importantly, this new dataset covers the entire recovery period of the Great Recession from 2010 through 2014, allowing us to test the relationship between employer job requirements and the availability of workers during a period of declining labor market slack.

These data paint a fascinating picture of skill requirements over time. As is evident in Figure 1, during the recovery there has been a considerable reversal of the upskilling. For example, 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 five or more years of experience. Of course, these aggregate trends could be misleading, so we use the richness of the BGT data to analyze the relationship between the degree of labor market slack and employer requirements for education and experience at the local level. We do this using a variety of controls for occupational trends and local economic conditions. We find that a 1 percentage point reduction in the local unemployment rate is associated with a 0.27 percentage point reduction in the fraction of jobs requiring a bachelor's degree and a 0.23 percentage point reduction in the fraction of jobs requiring five or more years of experience. This effect is present even within firm-job title-county pairs. We also see similar trends in heretofore un-measurable dimensions of skill, such as leadership, project planning, and software skills, in data recently made available by Burning Glass Technologies.

Ultimately, the magnitude of this *downskilling* relationship during the recovery period is very similar in magnitude to the upskilling relationship we documented for the Great Recession. Our results imply that labor market-induced downskilling reversed as much as 20 percent of the total increase in skill requirements that took place during the Great Recession, essentially reversing much of the upskilling that was related to the business cycle during that period.

To better identify this effect, we turn to a natural experiment based on the hydraulic fracturing or "fracking" boom in the United States as an exogenous shock to local labor supply.[4] Between 2007 and 2011, natural gas production increased by nearly one-third as a result of the discovery of large shale deposits and adoption of fracking techniques for extraction, leading to large increases in employment in that industry in a number of counties where such deposits were located. Although fracking undoubtedly affected the types of positions needed in the natural gas industry, many tradable industries, like agriculture, manufacturing, and timber, were not directly affected by this new technology. Moreover, these tradable industries—by virtue of being tradable—are unlikely to have been affected by local demand conditions. Therefore, for these industries, fracking represents an exogenous tightening in their local labor market. We find that both within and across individual firm-job titles, jobs experiencing an exogenous tightening of their labor markets cut education and experience requirements. The IV-implied coefficients are similar to the coefficients found in our OLS regressions.

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, revealing a feedback mechanism between labor supply and the selectivity of vacancies that operates within occupations. Such a feedback mechanism between the selectivity of vacancies and labor supply is consistent with macroeconomic models of employer search decisions and heterogeneous workers (Shimer 2005, Albrecht and Vrooman 2002) and provides evidence

[4] Fracking is the process of drilling and injecting fluid into the ground at a high pressure in order to fracture shale rocks to release natural gas inside.

supporting several theoretical models that endogenize this channel (Kaas and Kircher 2015 Mongey, Violante, and Gavazza 2014). Similarly, 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 (for example, Kahn 2010, Oreopoulous, Wachter, and Heisz 2012, Moscarini 2001). Indeed, the persistence of low wages for jobs that begin when labor markets are slack has been related to jobs that offer less possibility of human capital accumulation (Okun 1973, Gibbons and Waldman 2006, Schmieder and Von Wachter 2010). We find that changes in employer requirements over the business cycle are consistent with—and even serve to reinforce—this effect.

Finally, our findings inform the debate regarding the nature of unemployment in the United States, which some have interpreted as deterioration in the matching/hiring process in the economy. Numerous media reports and employer surveys have suggested that a lack of skilled workers has made it difficult to fill jobs that are in high demand during the economic recovery, leading to slower than expected improvement in the labor market.[5] Yet the economics literature has largely concluded that the weak labor market is mostly not a result of skills mismatch or other structural factors, but instead due to weak aggregate demand that increased unemployment across worker types, industry sectors, and occupation groups (Ghayad and Dickens 2012, Daly et al. 2012, Lazear and Spletzer 2012, Rothwell 2012, Carnevale, Jayasundera, and Cheah 2012, Sahin et al. 2014, Cappelli 2014, Osterman and Weaver 2014). Our results indicate that as much as 20 percent of the observed increase in skill requirements within detailed occupations is correlated with the business cycle and subject to reversion as the labor market tightens, suggesting that a significant portion of what is sometimes labeled structural mismatch unemployment is actually cyclical. This finding sheds light on the recent shift in the

[5] *Bloomberg Business*, "Companies Say 3 Million Unfilled Positions in Skill Crisis: Jobs," July 25, 2012. Kathleen Madigan, "How Some Companies Are Bridging the Skills Gap," *Wall Street Journal*, May 15, 2014. Kathleen Madigan, "Skills Shortage Is the Worst Since 2006, Small-Business Survey Says," *Wall Street Journal*, March 10, 2015. "Boiling Point? The Skills Gap in U.S. Manufacturing," Deloitte and Manufacturing Institute, 2011. "Closing the Gap: 2012 Skills Survey of North Carolina Employers," Workforce Development Boards of NC, 2012. "Skilled Trades Remain Hardest Job to Fill in U.S. for Fourth Consecutive Year," Manpower Group, 2013.

Beveridge curve, providing some of the first direct evidence that recruitment intensity varies over the business cycle.

The relationship between employer job requirements and the state of the labor market is relevant for policymakers as well. Our results indicate that the demand for skilled workers is perhaps more dynamic and responsive to labor market conditions than previously thought, with employers acting strategically to fill positions with higher-skilled workers during periods of slack labor markets. To the degree that changes in employer requirements vary with the business cycle, it is possible that, during slack times, those with less experience and lower levels of education will have longer spells of unemployment regardless of their industy and occupation.

The paper proceeds as follows. Section II lays out a theoretical framework and model to explore why employer upskilling and downskilling might be related to the business cycle. Sections III and IV describe our empirical approach and the unique features of the online job vacancy dataset used in our estimation. Section V reports the baseline relationship between employer skill requirements and the business cycle, as well as several robustness tests for alternate interpretations, including evidence from our natural experiment related to the fracking boom. Section VI concludes.

II. Theoretical Framework: Measuring Shifts along the Labor Demand Curve

In this section, we describe a conceptual framework in which employers set skill requirements for their vacancies in the short run, based on the availability of workers. Because we focus on relatively short horizon changes, our framework treats wages, the distribution of skills in the population, and the number of firms, as fixed. In the long run, all of these features of the labor market adjust to achieve a new equilibrium, and thus our framework should be thought of as describing the dynamics of skill requirements along a transition path.

We begin by assuming that there are a fixed number of firms, indexed by j, in each market i (conceptually, a location-occupation pair), each posting a vacancy V_{ij}. Employers choose between posting a vacancy with a skill requirement and searching for a high-skilled worker or accepting a low-skilled applicant. These firms face an applicant pool U_i divided between a small fraction of high-skilled applicants γ_i and a large fraction of low-skilled applicants (1- γ_i). We normalize the value of filling a vacancy with a low-skilled worker to be equal to 1 and set the value of filling a vacancy with a high-skilled worker equal to θ_i>1. Each employer *j* has a stochastic cost c_{ij}, drawn from a uniform density distribution, of leaving the vacancy unfilled. Firms are assumed to have a constant discount rate ρ each period.

To motivate the problem, we assume that, within a market, applicants are uncoordinated or are allocated randomly across vacancies with skill requirements, making the number of applicants a Poisson random variable. Each period, the odds that a vacancy receives at least one high-skilled applicant is given by $\left(1 - e^{\frac{-\gamma_i U_i}{V_i}}\right)$, which is increasing in the number of total applicants U_i. For simplicity, we assume that, for the range of U_i considered, there are sufficient low-skilled workers so that firms can match low-skilled workers with certainty. Note that this matching probability depends on the *number* of high-skilled workers per vacancy $\frac{\gamma_i U_i}{V_i}$, not the ratio of high-to-low-skilled job seekers.

Firms face a single decision of whether to accept a low-skilled worker in the event of not matching with a high-skilled worker, or whether to keep searching. The decision to keep searching is comparable to a firm's requiring a bachelor's degree or greater work experience. The value function of firm *i* can be written as:

$$V_{ij}(\theta_i, \rho_i, c_j, U, V) = max\left\{-c_j + \left(1 - e^{\frac{-\gamma_i U_i}{V_i}}\right)\frac{\theta_i}{1-\rho} + e^{\frac{-\gamma_i U_i}{V_i}}\rho V_{ij}, \frac{1}{1-\rho}\right\}.$$

Given this problem, firms' decisions follow a cutoff rule in their vacancy posting costs c_{ij}^*. 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, c_{ij}^* (when scaled) is also the fraction of employers posting vacancies with skill requirements. The fraction of firms that wait for a high-skilled worker $F(c_{ij}^*)$ is increasing in the size of the applicant pool U_i and in the fraction of high-skilled workers γ_i.

The decision rule depends on the number of high-skilled applicants per posting$\frac{\gamma_i U_i}{V_i}$. We can therefore write the change in the fraction of employers posting vacancies with skill requirements in an occupation-location labor market as

$$\Delta c_i^* = \alpha \times \Delta\theta + \beta \times \Delta \frac{\gamma_i U_i}{V_i} + \varepsilon_i \ ,$$

where α measures the structural change in the relative value of hiring a high- versus low-skilled worker (as measured at the national level), and β measures the cyclical component, whereby labor markets with more slack raise the probability of hiring a high-skilled worker. It is this coefficient that corresponds to our empirical notion of upskilling

Unfortunately, in our empirical work, we typically cannot measure directly the increase in the number of skilled searchers per vacancy in a market. The U.S. Bureau of Labor Statistics provides information on U_i but not on $\gamma_i U_i$ at the relevant geographies. Therefore, we measure the impact of changes in this number using two different measures as proxies. First, given the strong correlation between the number of skilled workers per posting and the overall unemployment rate (as shown in Figure 2) at higher levels, we use the county unemployment rate for all workers as a benchmark. Second, we also construct a supply/demand ratio of the number of unemployed individuals in the county divided by the number of postings. This ratio serves as a proxy for the independent variable of interest as described in the model above.

There are many reasons to believe that the proxy measures we are able to construct empirically, based on the overall unemployment rate, are meaningful measures of the supply of skilled workers per posting over time. As mentioned above, at the national level, Figure 2 shows a strong correlation between changes in this number and changes in aggregate unemployment. Similarly, the correlation between the unemployment rate of college workers and the unemployment rate of all civilian workers is 0.95.[6] Using the one-year American Community Survey (ACS) to calculate unemployment rates by state separately for college and non-college workers over this period, we find that changes in these two rates have a correlation coefficient of 0.94 at the state level. Therefore, it is likely that the increases in the aggregate

[6] Calculated from 1992 to 2016, the entire available series on the Federal Reserve Bank of St. Louis FRED tool.

unemployment rate that we use are a good proxy for the increase in high-skilled searchers. Finally we show that alternative proxies we create at the state level using micro data from the ACS to capture changes in $\gamma_{\mathrm{i}} U_i$ generate very similar results.[7] The sum weight of this evidence suggests that our measures, based on the county unemployment rate, do a good job of capturing variation in the number of high-skilled applicants in a market.

With this motivating model and empirical operationalization in mind, it becomes clear that changes in employer skill requirements and the unemployment rate are jointly, endogenously determined. For example, local demand shocks could differentially affect the demand for low-skilled workers, independent of supply, thereby affecting the composition of vacancies within occupations. Alternatively, upskilling may be driven by ongoing secular increases in employer demand for skilled workers, such as changes in technology or production.

Thus, the goal in our empirical strategy below will be to carefully measure movements along the labor demand curve rather than shifts in the demand curve. For these reasons, we employ a number of identification strategies to determine the degree to which the observed decrease in employer skill requirements is related to the degree of labor market slack. We turn to this discussion in the next section.

III. Empirical Approach

We seek to explore this dynamic by measuring the degree to which the observed decrease in employer skill requirements is related to the degree of labor market slack during the recovery. During the Great Recession, county unemployment rates increased by 4.8 percentage

[7] In Appendix Table A1, we construct several measures of skill-specific labor supply using micro data from the American Community Survey at the state-year level. We create four measures based on these categories: the ratio of skilled to unskilled unemployment (corresponding to γ), the unemployment rates for skilled and unskilled workers, and a supply and demand index equal to the overall change in unemployment multiplied by the baseline county share of skilled workers. We find that: (1) movements in the composition γ are positively correlated with upskilling, although they are less important than the high-skilled unemployment rate in predicting these changes, (2) high-skilled unemployment strongly predicts upskilling, and conditional on this rate, low-skilled unemployment has a zero or even negative impact, and (3) the implied magnitudes closely resemble our baseline results. For example, a 1 standard deviation increase in the overall unemployment rate is associated with a 0.67 percentage point increase in the share of jobs needing a college degree. A 1 standard deviation increase in the unemployment rate for college grads, at the state level, is associated with a virtually identical increase of 0.61 percentage point. These three findings all conform to the predictions of our model and support the idea that our baseline measures, based on overall unemployment rates, are successfully capturing variation in the availability of high-skilled job seekers.

points on average between 2007 and 2010 and subsequently fell by 3.3 percentage points between 2010 and 2014 during the recovery.[8] Although there was considerable improvement in labor market conditions during the recovery period, the reversion was less than complete, with fewer than 15 percent of U.S. counties having returned to their pre-recession levels of unemployment. Nevertheless, the recovery period between 2010 and 2014 can provide an early test of whether the upskilling relationship observed during the Great Recession has exhibited any reversion.

Using the variation in county labor markets over time, we initially estimate the basic OLS relationship between changes in employer skill requirements and changes in the degree of labor market slack, using the following specification:

$$\Delta \textit{ Share of Vacancies Requiring Skill } S_{i\,j\,t} = \alpha + \beta \Delta UR_{jt} + \gamma X_{i,j,t} + \tau_t + e_{ijt}\,, \qquad (1)$$

where, for occupation i, in county j, over time period t:

ΔS_{ijt} = percentage point change in skill requirements (either education or experience)

ΔUR_{jt} = percentage point change in the county unemployment rate

X_{it} = vector of control variables related to occupation characteristics

τ_t = time period dummy to capture changes in the general composition of vacancies.

Equation (1) is similar to the specification we used in our earlier paper on the Great Recession, which examined the change over the three-year period from 2007 through 2010.[9] For comparison purposes, here we pool two periods of changes during the recovery: changes from 2010 to 2012 and changes from 2012 to 2014, where τ is a dummy for the earlier period.[10] As before, the coefficient of interest is β, the change in skill requirements related to changes in the business cycle. A large and positive β indicates downskilling in requirements on the part of employers as the unemployment rate decreases. In contrast, an insignificant coefficient suggests that changes in skill requirements do not exhibit such a reversal during the recovery period. We take the former to be evidence that the prior upskilling observed during the Great Recession

[8] Local Area Unemployment Statistics, Bureau of Labor Statistics, http://www.bls.gov/lau/

[9] No data are available from Burning Glass Technologies during the intervening years 2008 and 2009.

[10] We also provide in Table A.2 for the period 2010–2014, annual estimates, which yield results very similar to our two-year changes.

was related to employer attempts to capitalize on weak labor markets by selecting workers with more education or experience.

In the above regression, we examine changes in employer requirements across occupations and locations over time. The key identifying assumption is that different parts of the country recovered at different rates from the Great Recession, allowing us to exploit the variation in local labor markets across counties and time periods. Although the specification above may indicate a positive correlation between changes in employer requirements for skill and the availability of skilled labor, we still need to address two econometric concerns to reliably establish a causal relationship. First, changes in the availability of skilled workers across locations and occupations are likely to be related to demand shocks, and reliable estimates require tests to control for aggregate conditions. To address this possibility, we use the variation within locations across broad occupation groups in order to include state fixed effects to control for local demand conditions.

Second, although online job postings had increased in frequency by the end of the Great Recession, the BGT data collection mechanism may have changed over time, as well as the types of jobs being posted online.[11] We address concerns over changes in employer composition and data quality over time by focusing on changes *within* firm-job title pairs during the recovery. Previous research has shown that most of the variation in posted wages and in the experience and education level of applicants is explained by job titles (Marinescu and Wolthoff 2015). Thus, controlling for job title by firm demonstrates that employers decrease requirements for the same job title in response to the declining availability of workers.

Finally, it may still be the case that relying on the variation during the recovery period of the business cycle as the primary source of identification could lead to biased results, given that the unemployment rate is correlated with other factors at the firm level, such as product demand and access to credit. We need a general test to eliminate the possibility of omitted variable bias. Thus, we further make use of a natural experiment that represents a clear shock to labor supply: the 2007–2011 fracking boom in oil and natural gas production, which boosted

[11] Although Burning Glass Technologies consistently applies the same filtering and de-duplication algorithm across years, even retroactively as improvements are made, the number of sources scraped may have evolved over time.

wages and attracted workers, creating labor shortages in *unrelated* industries in nearby locations.[12]

The timing of this sudden surge in natural gas production was driven by the discovery of new techniques for extracting natural gas from the Marcellus Shale formation along the eastern coast of the United States. This discovery was clearly unrelated to local economic conditions. As a result, however, various regions of the country experienced a boom in production, raising the demand for workers. Many traded industries in these locations, like agriculture and manufacturing, were not directly affected by fracking technology. Moreover, as traded industries, they were not directly impacted by changes in local demand. Nevertheless, they experienced worker shortages during this period. We demonstrate that county-occupation cells in these areas correspondingly experienced a significant *decrease* in their skill requirements, as workers were lured away by the fracking industry.

IV. Data: Using Job Vacancy Data to Measure Changes in Employer Skill Requirements

To date, 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 these data have increasingly made such information available to researchers.[13] Data on a variety of vacancy characteristics are collected by software that parses the text contained in millions of job ads posted online and are increasingly being used by researchers to study labor market dynamics (for example, Sahin et al. 2014; Marinescu and Wolthoff 2015; Lazear and Spletzer 2012; Faberman and Mazumder 2012; Rothwell 2012; Bagues and Labini 2009; Kuhn and Skuterud 2004; Gautier et al. 2002).

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[12] See the July 12, 2012 *New York Times* article, "In Oil Boom, a Housing Shortage and Other Issues," by Kate Galbraith.

[13] The first online job listings were posted on Usenet, CareerMosaic, and Monster during 1990–1994. Between 1995 and 1997, additional job boards were launched (for example, Craigslist), newspaper job listings began to appear online, and CareerCast, began scraping and aggregating online job postings. Major changes took place in the years 1998 and 1999, as the job boards industry consolidated and a few key players emerged (for example, Monster, Career Builder, Jobsonline). After the dot-com bust, niche job boards proliferated between 2000 and 2002 for marketing, medical, sales, and accounting jobs. Between 2003 and 2007, the industry matured and experienced significant growth with the launch of LinkedIn and aggregators such as Top USA Jobs, indeed, and simply hired (see Stephanie Garcia's infographic, "History & Statistics of Job Boards," and Joshua Waldman's Career Enlightenment Blog, March 6th, 2013: http://careerenlightenment.com/history-statistics-of-job-boards-infographic).

These 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). Although online vacancy postings do not capture all job openings, a recent report from Georgetown University estimates that between 60 and 70 percent of job vacancies are now posted online (Carnevale, Jayasundera, and Repnikov 2012). Moreover, online job ads—including data aggregated by Burning Glass Technologies—exhibit similar trends and are closely correlated with employer surveys over time (Templin and Hirsch 2013, Ganong 2014).

A. Constructing Labor Market Measures at the County Level

Our basic empirical strategy is to explore the relationship between changes in employer skill requirements and changes in local labor market conditions during the Great Recession and subsequent recovery. Table 1 reports descriptive statistics for two alternative measures we have assembled to capture the variation in the availability of labor across counties. Our initial measure of labor market slack is the change in the annual county unemployment rate as reported by the Bureau of Labor Statistics from the Local Area Unemployment Statistics (LAUS). Although these rates are partly model based, they represent a consistent measure of labor market slack across counties over time. As a robustness check, we also create a second measure, modeled on the Conference Board's Labor Supply/Demand Ratio, which represents the number of unemployed individuals relative to the number of vacancies posted for six broad occupation groups.[14] Both measures of slack are used in regressions to establish the robustness of our result.

As discussed in Section II, we would ideally like to construct direct measures of the number of high-skilled applicants per vacancy by county, year, and occupation. Unfortunately, the data to construct such measures are unavailable. Still, for the reasons laid out above, the two measures we describe here, which are based on the total number of unemployed job seekers, are strong proxies for the number of unemployed high-skilled job seekers.

B. Constructing Employer Skill Requirements from Job Vacancy Data

[14] The BGT Labor Supply/Demand Ratio is constructed using a methodology established by the Help Wanted OnLine Labor/Supply Demand Index. This ratio is calculated by dividing the number of unemployed individuals reported by the American Community Survey by the number of job postings reported by Burning Glass Technologies (BGT) at the county level for six broad occupation groups.

The data used in this paper are collected by Burning Glass Technologies (BGT), one of the leading vendors of online job posting data. BGT collects detailed information daily on the more than 7 million current online job openings from over 40,000 sources, including job boards, newspapers, government agencies, and employer sites.[15] The 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. BGT mines over 70 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, as well as other dimensions of skill.[16]

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 predetermined 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 and 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 on individual employer sites, which are updated less frequently.[17]

In the database provided by BGT, a snapshot of vacancies is reported on a monthly basis, and these are pooled over the year without duplication. This dataset is unique in allowing geographical analysis of occupation-level labor demand for a variety of skills, including education and experience over time. Using the entire universe of job vacancies collected by BGT, we construct several measures of employer skill requirements, based on the education and experience fields parsed from the online advertisement. The data are available for detailed occupation by Standard Occupation Code (SOC) down to the three-digit level and can be drawn

[15] See http://www.burning-glass.com/realtime/ for more details.

[16] Note that the BGT data do not contain any information on the duration of the vacancy, how many applications a vacancy received, or whether a vacancy was filled.

[17] BGT has also provided access to their Labor/Insight analytical tool that 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.

for arbitrarily small geographies for 2007 and 2010 through 2014.[18] In total, our data represent roughly 82.5 million vacancies for these years.

Table 1 provides descriptive statistics for the dependent variables constructed from the BGT data by county/occupation/year cells. On average, there are roughly 250 to 450 postings for a given cell each year, with fewer postings observed during the height of the Great Recession in 2010. It should be noted that these data exhibit considerable variation, given the different employment levels of these occupations, even at the county x occupation x year level. The number of underlying observations available to construct some cells varies from as few as one posting to as many as 40,000 postings at this level of disaggregation. 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 county x occupation x year cell. 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 job postings in the county in a given period. This ensures that our results are not driven by outlier occupations with few underlying postings.

We constructed a range of dependent variables by county, occupation, and year that measure the percentage point change in the share of online job postings along two dimensions of skill: educational attainment and years of experience. Employer requirements along both dimensions of skill are changing over time, with the majority of the decrease in the time frame of our analysis having occurred between 2012 and 2014, during the recovery period. Our education categories of interest are defined as follows: the share of postings with some education requirement, the share requiring an associate's degree or greater, and the share requesting a bachelor's degree or higher. Experience is similarly defined as some experience requested, two or more years requested, and five or more years requested.

We also employ additional information, collected from the original text of the advertisement, on the skills listed in each job posting. Specifically, BGT parses each skill listed in the posting and classifies it as baseline (for example, generic skills such as leadership, project planning, and development), specialized (for example, information security), or software (for

[18] No data are available for 2008 and 2009.

example, Adobe Dreamweaver). From this, we construct the share of postings requiring each type of skill. Interestingly, these more-detailed skill requirements exhibit the same downskilling trend as the trend of the education and experience requirements.

We also construct two additional measures to control for heterogeneity across occupations. The first is the initial share of openings requiring a particular skill in the baseline year; this measure is used to account for the variation in the initial level of skill required across occupations within a state. The second is the percentage change in total job postings over the period; this measure is used to control for the degree of turnover across occupations during the recovery.

V. Results

We begin our analysis by examining the aggregate trends in the BGT job posting data. The two panels in Figure 1 show the trend over time in the national unemployment rate compared with the percentage of jobs requiring a bachelor's degree and five years of prior experience, respectively. As is evident in the graphs, there is a strong time-series correlation with aggregate labor market slack. Both measures of employer requirements rose during the Great Recession and then fell as the labor market recovered. There is clear evidence of downskilling in these aggregate data, with the fraction of jobs requiring these skills falling significantly during the recovery period from 2010 through 2014.

Of course, this correlation at the aggregate level is not necessarily causal. The BGT data collection mechanism may have changed over time, as may the types of jobs being posted online. As discussed above, we explore whether there is a decrease in the education or experience requirements for job postings within a narrowly defined occupation and whether this decrease is linked to the declining availability of skilled workers. Specifically, we begin by running regressions of the form described above in Equation (1). Recall that the relationship of interest is β, the increase in skill requirements related to changes in the degree of labor market slack. A large and positive β indicates that skill requirements fell more within occupations in counties that experienced falling unemployment. Of course, it would be naïve to infer causality from these relationships, given the potential for serious omitted variable bias. Still, investigating the baseline correlations is useful for comparison purposes.

A. Basic OLS Relationships

Table 2 reports the results of these initial regressions for each BGT measure of employer requirements of education and experience levels. In all specifications for our categorical skill measures, β is positive and statistically significant, indicating that there was a decrease in the share of jobs requiring skilled workers across education and experience measures as the local unemployment rate fell. The basic economic relationships show that a 1 percentage point reduction in the local unemployment rate is associated with a 0.21 percentage point reduction in the fraction of jobs requiring a bachelor's degree and a 0.19 percentage point reduction in the fraction requiring five or more years of experience. Similarly, using our Labor Supply/Demand Ratio, a decrease of one unemployed worker per posting is associated with a 0.33 percentage point decline in the fraction of jobs requiring a BA and a 0.14 percentage point change in the fraction requiring five or more years of experience.

These basic correlations are robust to baseline controls for simple intuitive covariates that capture differences across county-occupation cells. Occupations may have different initial skill requirements and county labor markets may differ in the availability of the skill categories we examine. In addition, county-occupation cells are likely to have different trends in job posting during the recovery, and these cells may also differ in their coverage rates in the BGT dataset. In Table 3, we show that the relationship between employer requirements and the degree of labor market slack is robust to including these baseline covariates as well as occupational fixed effects.[19] Thus, it is unlikely that our results are driven by changes over time in the composition of postings or the BGT data collection method.

Using both of these labor market measures, Figure 4 shows that tightening labor markets are associated with falling skill requirements at the county-occupation level. These relationships are robust and show clear evidence of downskilling. In fact, they look only at situations in which the labor market is weakly growing tighter. Note that these figures display the effect of

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[19] These baseline controls include the initial share of employers requiring each skill in 2010 and the change in total postings between 2010 and 2014.

labor market slack, while controlling for both time fixed and occupation fixed effects, both of which control for confounding trends in postings across occupations at the three-digit level.

B. Accounting for Local Demand Shocks

While these relationships are compelling, these regressions are still open to non-causal interpretations as well. For example, changing skill requirements and local labor market trends might be driven by some local form of technological process. Alternatively, changes in requirements might be driven by changes in job posting practices over time. The correlation between unemployment rates and skill in recovering labor markets might then be spurious.

To control for local demand shocks and technology trends, we add controls for state fixed effects into our previous regressions. These effectively allow state-specific trends in the level of skill requirements over our relatively short period. Despite the addition of state fixed effects in Table 4, we still see a positive and significant relationship of virtually the same magnitude between changes in employer requirements and tighter labor market conditions. Thus, even controlling for differences in the state of the local economy, local labor supply decreases remain correlated with falling employer skill requirements. Our estimates indicate that a 1 percentage point decrease in the state unemployment rate lowers the share of jobs requiring a bachelor's degree by 0.28 percentage point and reduces the fraction of openings requiring five or more years of experience by 0.23 percentage point.

How large is this effect in the context of the previous upskilling observed during the Great Recession? Table 5 compares the relationship between changes in employer requirements and labor market slack over the recession (2007–2010) and recovery (2010–2014) periods. The magnitude of the coefficients is remarkably similar, indicating that the strength of the relationship between employer requirements and labor market slack is fairly symmetric.

However, given that the labor market has not fully recovered, we do not find a complete reversion of the unemployment-induced upskilling in requirements observed during the Great Recession. Our results from the period of the Great Recession imply that the earlier increase in unemployment rates between 2007 and 2010 raised employer requirements within occupations by 1 percentage point for education and by 0.58 percentage point for experience. 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 roughly 20 percent of the *total* cross-sectional increase across counties in education and experience requirements during the Great Recession. During the recovery, our estimates imply that the decrease in unemployment rates between 2010 and 2014 reduced education requirements within occupations by 0.91 percentage point and lowered experience requirements by 0.75 percentage point. Thus, while the reversion in experience requirements related to the business cycle is complete, the reversion related to education remains in progress.

C. Controlling for Changes in Employer Composition and Data Quality over Time

As discussed earlier, we also need to worry about 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. One quite remarkable feature of our data is that we are able not only to explore outcomes for aggregate conditions at the local level, but also to track outcomes for individual positions. Previous research has shown that most of the variation in posted wages and in the experience and education level of applicants is explained by job titles (Marinescu and Wolthoff 2015). Thus, controlling for job title by firm demonstrates that employers decrease requirements for the same job title in response to the declining availability of workers.

In Table 6 we use the BGT postings-level data to explore the impact of local labor market conditions on skill requirements during the recovery within firm-job title pairs.[20] We then regress a dummy variable for whether the posting requires a bachelor's degree or alternately five or more years of experience, controlling for firm-job, title-county fixed effects as well as individual year dummies. Again, we cluster by county to account for correlation within counties across postings and over time. The resulting coefficients are remarkably close to the aggregate estimates. A 1 percentage point decrease in the unemployment rate makes a posting 0.2 percentage point less likely to require either type of skill requirement.

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[20] To do this, we limit the data to observations with codeable job and employer titles. We also exclude unique, firm-job title-county pairs to ease the computation. In the end we are left with roughly 20 million observations.

To examine further whether the downskilling pattern observed for education and experience requirements reflects changes in job posting practices, we make use of additional data on additional baseline, specialized, and software skills that employers requested, as collected from the advertisement. Using these three measures as well as a measure of any skill requested, Table 7 demonstrates that in all specifications of our categorical skill measures the relationship is positive and statistically significant, indicating that there was a decrease in the share of jobs requiring skilled workers across all types of skills measures as the unemployment rate fell. The degree of reversion is strongest for baseline skills, with a 1 percentage point reduction in the local unemployment rate associated with a 0.74 percentage point reduction in the fraction of jobs requiring baseline skills such as project management and leadership. In contrast, the degree of reversion is smaller for both specialized and software skills that would require more formal or time-consuming training.[21] Figure 5 further documents that tightening labor markets are associated with falling categorical skill requirements at the county-occupation level. Note that these figures display the effect of labor market slack, while controlling for our baseline controls as well as for occupation and state fixed effects in order to eliminate the potential of a confounding change in the BGT data construction.

D. Local Demand Shocks and Identification from a Natural Experiment

As a source of exogenous variation, we make use of a natural experiment resulting from the boom in natural gas production associated with hydraulic fracturing, or "fracking." Figure 6 shows that advances in fracking and horizontal drilling technologies, combined with discoveries of large shale gas deposits, greatly increased the scope of U.S. natural gas production in recent years, boosting natural gas production by 27 percent between 2007 and 2011. Using data from the USDA on county-level natural gas production over this period, we explore changing skill requirements, using the geographic dispersion in counties experiencing this boom in production, as shown in Figure 7.

Specifically, we focus on tradable industries that were not affected by fracking directly, including agriculture, timber, metal-based mining, and manufacturing. For these industries,

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[21] Moreover, data on the average number of skills requested per posting show similar downskilling trends, further evidence that postings do not simply list an ever-increasing number of skills over time.

fracking-related increases in the demand for local labor are a relatively exogenous shock to their local labor supply. The production in these industries is not driven by local demand, and these industries do not use fracking in production. As a result, differential changes in skill requirements in these industries in natural gas vs. non-natural gas counties are likely to be related to an exogenous shock to labor supply, providing sufficient variation to explore downskilling. A list of these industries is reported in the notes to Table 8.

Using posting-level data for these regressions, Table 8 demonstrates that a strong relationship exists between increases in natural gas production and falling education and experience requirements in non-fracking, traded industries.[22] A 1 billion cubic foot increase in production is associated with a 0.03 to 0.06 percentage point increase in the probability of a job needing a bachelor's degree or five or more years of experience. This is true conditional on county fixed effects (Columns 1–2) and even within firm-job title pairs (Columns 3–4). This is strong evidence of a causal effect, even within jobs, of downskilling at work. Among counties producing any natural gas in 2007, the standard deviation of the increase from 2007 to 2011 was 67 billion barrels. This implies that a 1 standard deviation larger increase was associated with a 2 percentage point increase in the share of postings requiring at least a college degree and a 1.3 percentage point increase in the share requiring five or more years of experience.

However, many counties do not produce any natural gas, so natural gas production is skewed with a long right tail across counties. To ensure that we are not driven by outliers, we recode natural gas production as a dummy variable for increases above 50 billion cubic feet in columns 5 and 6. At today's market prices, this represents an increase in production of roughly \$600 million. Roughly 1.25 percent of counties experienced a change this large between 2007 and 2011. Again, this dummy is also tightly linked to changes in skill requirements.

Finally, we use natural gas production to instrument for local unemployment, as shown in columns 7 and 8. We get moderate first-stage F statistics, demonstrating that natural gas production has sufficient power to identify the impact of changes in local unemployment rates. Again, we find coefficients that are very similar to those in the aggregate regressions reported

[22] To do this, we code each posting with a dummy outcome variable (needs BA/ needs 5). We then regress these postings data, limited to those industries in 2007 and 2011, on local unemployment rates and fixed effects for time and county.

earlier using the business cycle variation across counties over time. A 1 percentage point fall in the local unemployment rate is associated with a roughly 0.1 percentage point fall in the probability that a local, non-fracking, tradable job requires a bachelor's degree or five or more years of experience. The magnitude is somewhat smaller, but still comparable, to our OLS estimates.

VI. Conclusion

After the Great Recession, Catherine Rampell of the *New York Times* wrote, "employers are increasingly requiring a bachelor's degree for positions that didn't used to require baccalaureate education. A college degree, in other words, is becoming the new high school diploma: the minimum credential required to get even the most basic, entry-level job."[23] This perception was correct *at that moment*, and indeed our data show that skill requirements in vacancy postings increased dramatically from 2007 through 2010.

The discussion regarding these changes, though, frequently missed the possibility that this increase in employer skill requirements might reverse when the labor market recovered. In this paper, we demonstrate that this was indeed the case. Our estimates indicate that a 1 percentage point decrease in the state unemployment rate lowers the share of jobs requiring a bachelor's degree by 0.28 percentage point and reduces the fraction of openings requiring five or more years of experience by 0.23 percentage point. Moreover, the magnitude of the coefficients is remarkably similar to those estimated for the increase in employer skill requirements during the Great Recession, indicating that the strength of the relationship between employer requirements and labor market slack is fairly symmetric over the business cycle. However, given that the labor market has not fully recovered, we do not find a complete reversion of the unemployment-induced upskilling in requirements observed during the Great Recession.

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[23] "The college degree has become the new high school degree" *New York Times* (9/9/14).

Moreover, the downskilling trend is well identified. We find that the decrease in employer requirements for skill between 2010 and 2014 was greater in locations that experienced a steeper decline in unemployment. This drop is evident even conditional on controls for occupation-specific trends and local economic conditions. Downskilling is also evident within firm-job title pairs, indicating decreases in skill requirements for the same job over time and eliminating the possibility that our results are driven by changes in the composition of vacancies. Moreover, we find a similar pattern of downskilling for heretofore un-measurable dimensions of skill, with larger declines in baseline skills such as leadership and project planning compared with specialized skills and software skills that might require more formal or time-intensive training. Finally, using natural-gas production as an instrument for labor market tightness in tradable industries, we find that this downskilling can be causally linked to worker availability. Tradable industries like manufacturing and agriculture, which are not impacted by fracking directly or by local demand shocks, reduced skill and experience requirements when their labor markets tightened, even within firm-job titles.

This demonstration of downskilling in vacancy postings, the first to our knowledge, is important for many reasons. It better identifies the dynamic nature of employer skill requirements and it establishes that movements in these requirements will, at least in part, revert with the labor market. The relationship between employer job requirements and the state of the labor market is relevant for policymakers as well. Our results indicate that the demand for skilled workers is dynamic and responsive to labor market conditions, with employers acting strategically to fill positions with higher-skilled workers during a period of slack labor markets. To the degree that changes in employer requirements vary with the business cycle, it is possible that during slack times those with less experience and lower levels of education will have longer spells of unemployment, regardless of their industry and occupation. It also cautions against targeting high-frequency changes in labor market posting requirements *within occupations* in designing training programs, since these requirements may revert during recoveries. However, shifts in demand across occupations might be less cyclical than changes in the employer requirements studied in this paper. Therefore, real-time labor market information on changes in the number and share of job vacancies across occupations may in fact be quite useful in determining which training programs should receive funding.

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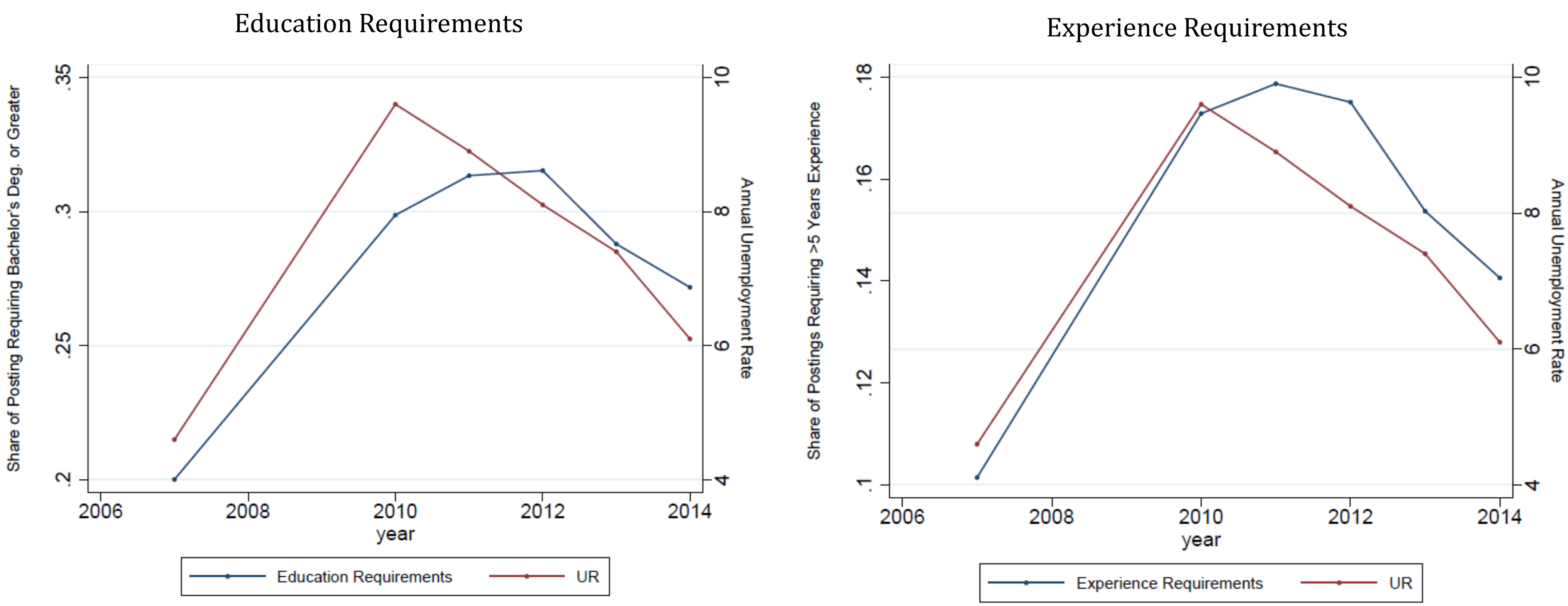
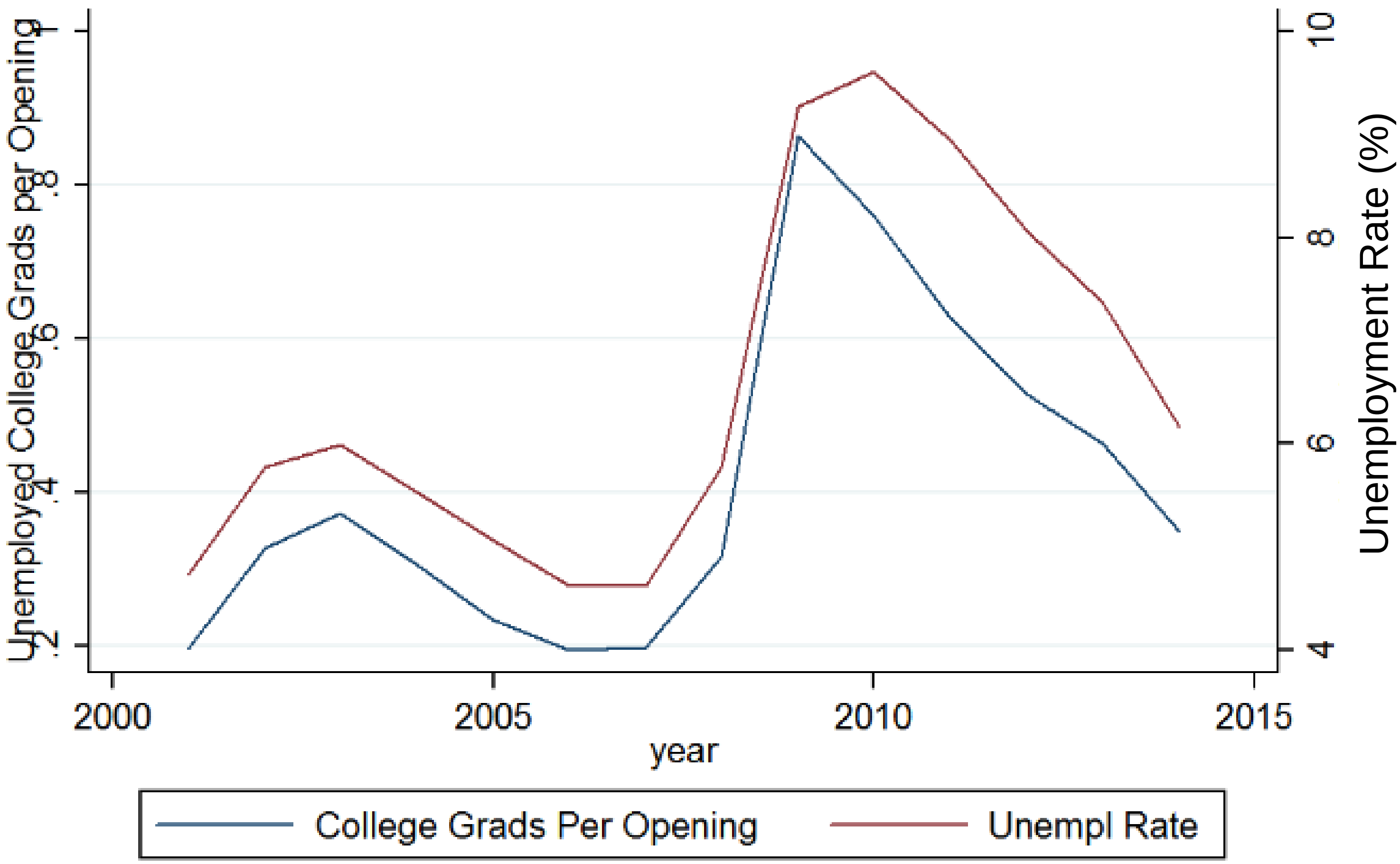
Figure 1. Relationship between Changes in Employer Requirements and Labor Market Slack, 2007–2014



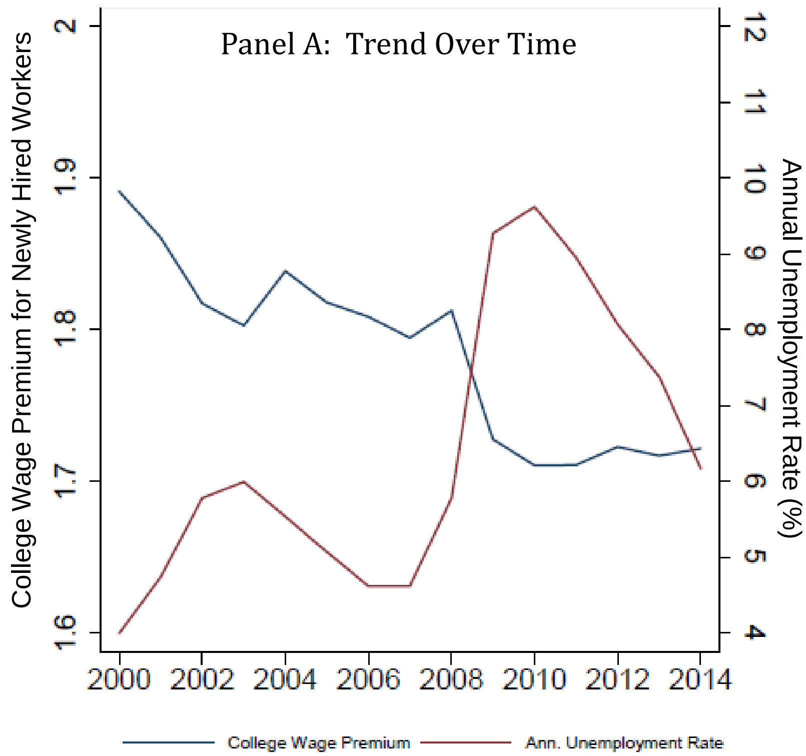
Notes: Authors' analysis using the unemployment rate as reported by the Bureau of Labor Statistics and data on job postings from Burning Glass Technologies, 2007–2014.

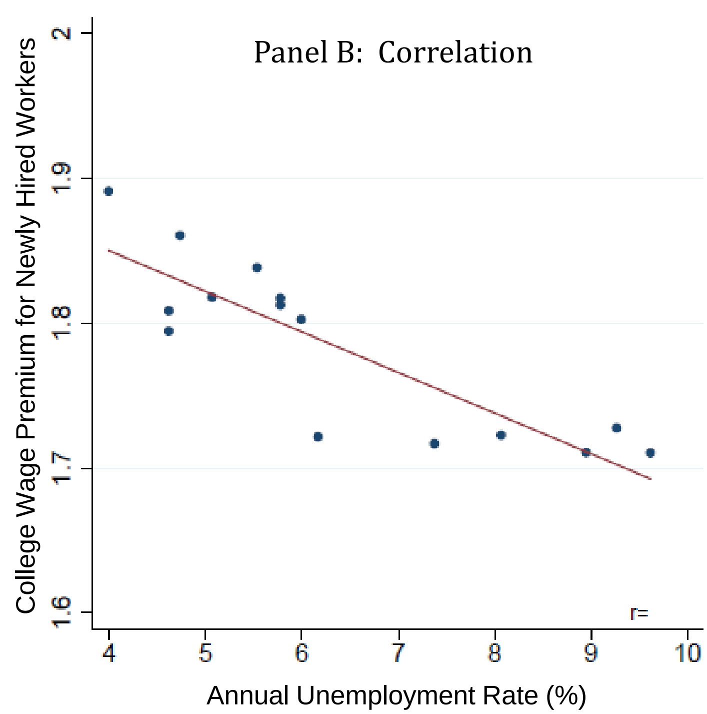
Figure 2. Correlation between Skilled Workers Per Posting and the Unemployment Rate, 2000–2014



Notes: The unemployment rate is the annual rate for the United States as reported by the Bureau of Labor Statistics. The number of unemployed college graduates per opening is calculated by dividing the number of college graduates by the number of job openings each year for the United States. The number of college graduates is calculated from the Current Population Survey. The number of job openings is the average over the 12 months of the year as reported by the Job Openings and Labor Turnover Survey collected by the Bureau of Labor Statistics.

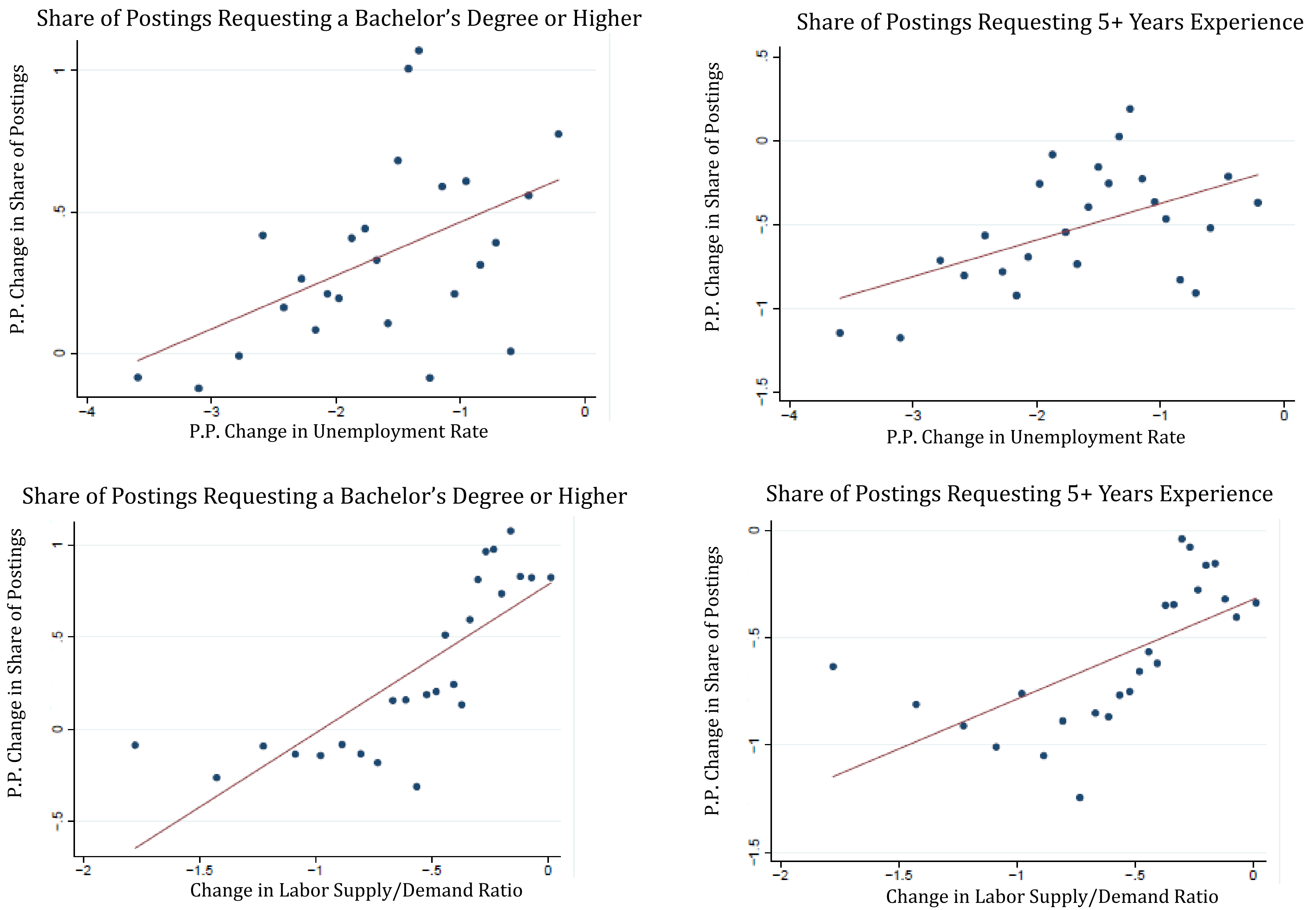
Figure 3. Relationship between the College Wage Premium for New Hires and the Unemployment Rate





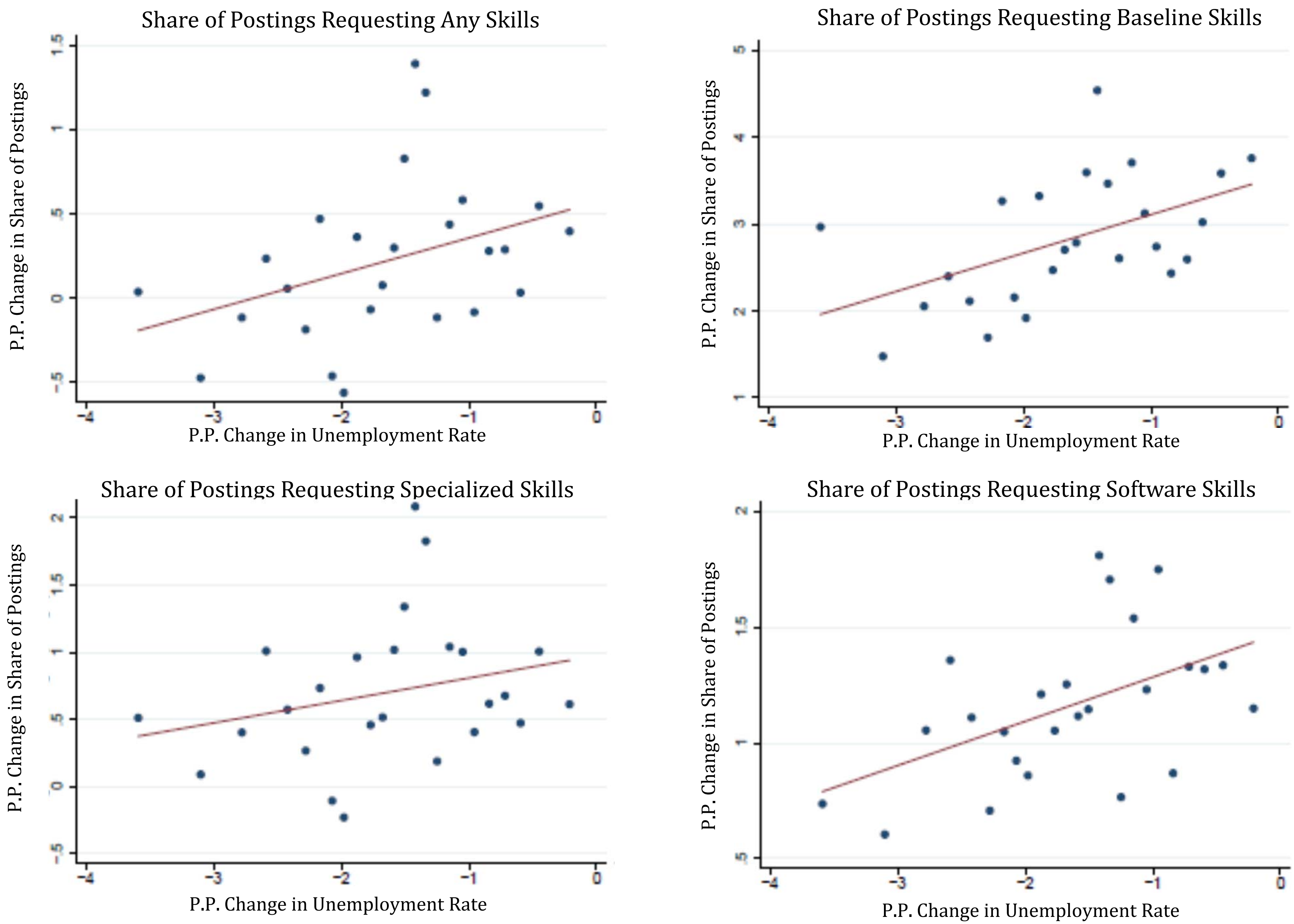
Notes: Authors' calculations using the unemployment rate as reported by the Bureau of Labor Statistics and data on new hires from the Current Population Survey (CPS). The college wage premium for new hires as the ratio of hourly earnings for college relative to high school workers using a multi-month matched CPS sample and a matching algorithm similar to that proposed by Madrian and Lefgren (1999).

Figure 4. Relationship between Changes in Employer Requirements and Labor Market Slack, 2010–2014



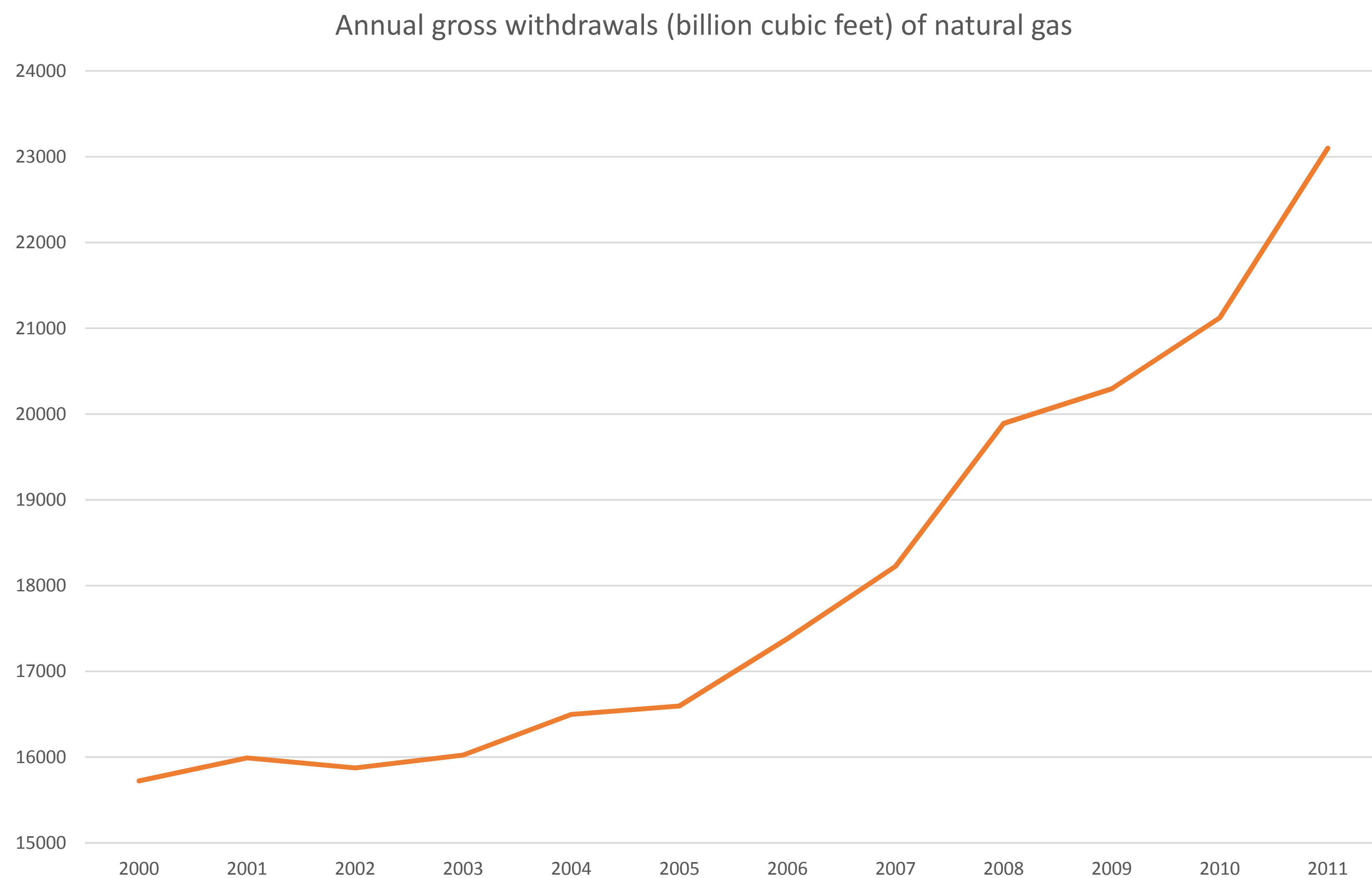
Notes: Authors' analysis using data from Burning Glass Technologies. The figure is a binned scatter plot (N=100) based on observations of county x 3-digit occupation cells.

Figure 5. Relationship between Changes in Employer Skills Requested and Labor Market Slack, 2010–2014



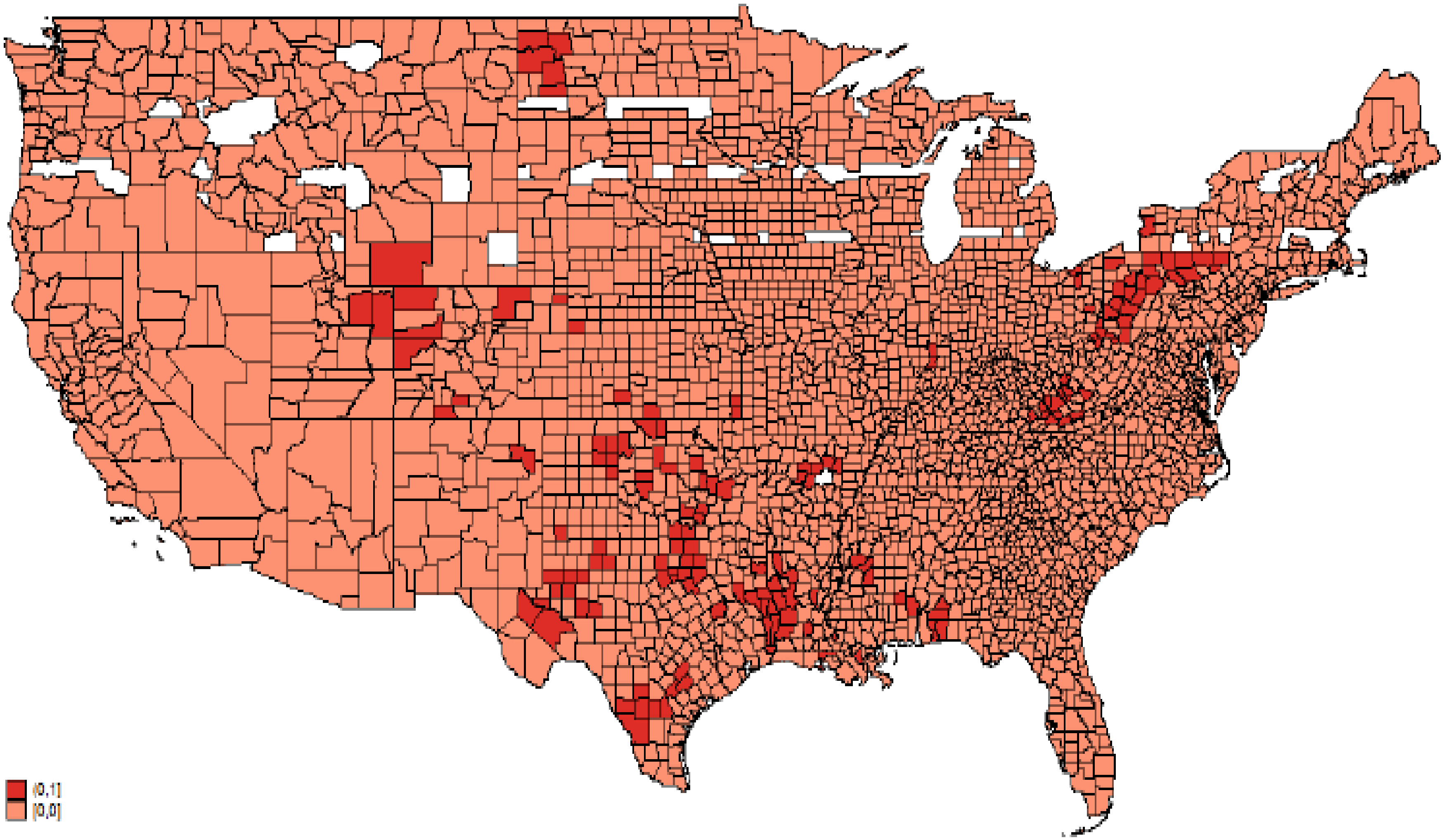
Notes: Authors' analysis using data from Burning Glass Technologies. The figure is a binned scatter plot (N=100) based on observations of county x 3-digit occupation cells.

Figure 6. Trend in Natural Gas Production, 2000–2011



Notes: Authors' calculations using data reported by the USDA Economic Research Service. http://www.ers.usda.gov/data-products/county-level-oil-and-gas-production-in-the-us.aspx

Figure 7. County-level Variation in Change in Natural Gas Production, 2007–2011



Notes: USDA Economic Research Service. http://www.ers.usda.gov/data-products/county-level-oil-and-gas-production-in-the-us.aspx. Darker shading represents counties where natural gas production exceeds 1 billion cubic feet.

Table 1. Summary Statistics

	2007	2010	2012	2014	Δ2007–2010	Δ2010–2012	Δ2012–2014
Measures of Labor Market Slack							
County Unemployment Rate	4.56	9.30	7.82	6.01	4.76	-1.48	-1.81
	(1.370)	(2.550)	(2.260)	(1.800)	(1.710)	(0.970)	(0.830)
BGT Labor Supply / Demand Ratio	0.87	1.96	1.46	0.67	1.14	-0.51	-0.78
	(0.660)	(1.430)	(1.170)	(0.470)	(1.060)	(0.800)	(0.820)
Employer Education, Experience, and Skill Requirements							
Total Number of Job Posting Ads	266.76	254.60	292.39	445.51	-32.38	38.06	152.85
	(1154.960)	(1120.670)	(1172.430)	(1618.050)	(314.630)	(295.630)	(584.700)
Share of Job Posting Ads Requesting:							
Any Educational Requirement	25.87	42.97	47.46	46.47	16.93	4.51	-0.98
	(14.310)	(19.000)	(19.470)	(19.290)	(18.210)	(15.500)	(15.120)
An Associate's Degree or Greater	15.10	23.22	25.06	23.57	7.78	1.86	-1.48
	(14.980)	(22.330)	(23.460)	(22.630)	(14.610)	(10.800)	(10.570)
A Bachelor's Degree or Greater	13.43	20.07	21.59	20.12	6.34	1.53	-1.45
	(14.510)	(21.520)	(22.560)	(21.720)	(13.880)	(10.040)	(9.810)
Share of Job Posting Ads Requiring:							
Any Experience	25.59	42.69	44.19	40.26	16.71	1.52	-3.93
	(13.670)	(18.480)	(18.710)	(17.680)	(17.880)	(15.110)	(13.810)
Two or More Years of Experience	18.24	29.30	30.34	27.08	10.64	1.05	-3.25
	(13.130)	(19.170)	(19.620)	(18.110)	(15.120)	(12.120)	(11.590)
Five or More Years of Experience	6.87	10.67	11.04	9.63	3.59	0.38	-1.41
	(7.710)	(11.890)	(12.100)	(10.980)	(9.420)	(7.900)	(7.410)
Share of Job Posting Ads Requiring:							
Any Skills	65.92	84.99	88.44	85.57	18.88	3.47	-2.87
	(19.120)	(14.990)	(13.330)	(14.800)	(15.330)	(9.400)	(9.850)
Baseline Skills	32.79	57.76	64.48	63.44	24.66	6.73	-1.03
	(18.490)	(22.150)	(21.500)	(20.520)	(17.850)	(14.120)	(13.990)
Specialized Skills	60.57	78.87	83.74	80.54	17.95	4.90	-3.20
	(19.800)	(16.730)	(15.190)	(16.230)	(15.830)	(10.710)	(10.700)
Software Skills	10.77	18.46	21.28	20.88	7.33	2.84	-0.39
	(11.630)	(16.980)	(17.960)	(16.990)	(11.720)	(10.480)	(10.280)
Number of Observations	35,220	35,220	35,261	35,210	35,220	35,261	35,210

Source: Authors' analysis using data from the U.S. Bureau of Labor Statistics and Burning Glass Technologies.

Notes: Means are reported with standard deviations in parentheses below. Observations are county x 3-digit Standard Occupation Code (SOC) cells containing at least 15 total postings in each year. The last three columns are summary statistics for the change in these measures by time period and represent the estimation sample for the baseline relationships. County unemployment rates are as reported by the Bureau of Labor Statistics Local Area Unemployment Statistics program: http://www.bls.gov/lau/ . The BGT Labor Supply/Demand Ratio is constructed using a methodology established by the Help Wanted OnLine Labor/Supply Demand Index. This ratio is calculated by dividing the number of unemployed individuals as reported by the American Community Survey by the number of job postings as reported by Burning Glass Technologies (BGT) at the county level for six broad occupation groups. All job posting data, including employer education, experience, and skill requirements, are calculated using data from Burning Glass Technologies.

Table 2. Changes in Employer Requirements and Labor Market Slack during Recovery, 2010–2014

Panel A: Education Qualifications

Percentage Point Change in the Share of Postings Requesting:

	Any Education Level	Associate's Degree or Greater	Bachelor's Degree or Greater
	(1)	(2)	(3)
Δ County UR	0.374 **	0.254 ***	0.214 ***
	(0.170)	(0.076)	(0.066)
R^2	0.032	0.024	0.022
Number of Observations	70,471	70,471	70,471
Δ BGT Labor Supply/Demand Ratio	1.117 ***	0.369 ***	0.327 ***
	(0.188)	(0.098)	(0.083)
R^2	0.035	0.025	0.023
Number of Observations	70,471	70,471	70,471

Panel B: Experience Qualifications

Percentage Point Change in the Share of Postings Requesting:

	Any Experience Level	2 or More Years of Experience	5 or More Years of Experience
Δ County UR	1.177 ***	0.662 ***	0.191 ***
	(0.158)	(0.110)	(0.063)
R^2	0.039	0.034	0.014
Number of Observations	70,471	70,471	70,471
Δ BGT Labor Supply/Demand Ratio	1.283 ***	0.684 ***	0.137 ***
	(0.174)	(0.112)	(0.055)
R^2	0.039	0.034	0.014
Number of Observations	70,471	70,471	70,471

Source: Authors' analysis using data from Burning Glass Technologies.

Notes: Observations are county x 3-digit Standard Occupation Code (SOC) cells containing at least 15 total postings in each year. See notes to Table 1 for construction of variables. All specifications include a control for differences between the two time periods, 2010–2012 and 2012–2014. Observations are weighted by the occupation's share of each county's total postings. Standard errors (in parentheses) are clustered by county. * p<0.10, ** p<0.05, *** p<0.01.

Table 3. Changes in Employer Requirements and Labor Market Slack During Recovery, Controlling for Occupation Fixed Effects

	P.P. Change in the Share of Postings Requesting: a Bachelor's Degree or Greater				P.P. Change in the Share of Postings Requesting: 5 or More Years of Experience			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ County UR	0.242 ***	0.331 ***			0.196 ***	0.192 ***		
	(0.064)	(0.066)			(0.059)	(0.059)		
Δ BGT Labor Supply/Demand Ratio			0.317 ***	0.444 ***			0.216 ***	0.259 ***
			(0.083)	(0.091)			(0.053)	(0.055)
Baseline Controls	X	X	X	X	X	X	X	X
Occupation Fixed Effects		X		X		X		X
R^2	0.035	0.123	0.035	0.123	0.062	0.124	0.062	0.125
Number of Observations	70,471	70,471	70,471	70,471	70,471	70,471	70,471	70,471

Source: Authors' analysis using data from Burning Glass Technologies.

Notes: Observations are county x 3-digit Standard Occupation Code (SOC) cells containing at least 15 total postings in each year. See notes to Table 1 for construction of variables. Baseline controls include the initial (2010) share of postings requiring the skill measured as well as the change in the number of total postings, 2010–2014, as a share of total employment in 2010. All specifications include a control for differences between the two time periods, 2010–2012 and 2012–2014. Observations are weighted by the occupation's share of each county's total postings. Standard errors (in parentheses) are clustered by county. * p<0.10, ** p<0.05, *** p<0.01.

Table 4. Changes in Employer Requirements and Labor Market Slack During Recovery, Controlling for State Fixed Effects

	P.P. Change in the Share of Postings Requesting: a Bachelor's Degree or Greater				P.P. Change in the Share of Postings Requesting: 5 or More Years of Experience			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ County UR	0.331 ***	0.277 ***			0.192 ***	0.226 **		
	(0.066)	(0.088)			(0.059)	(0.086)		
Δ BGT Labor Supply/Demand Ratio			0.444 ***	0.351 ***			0.259 ***	0.230 ***
			(0.091)	(0.093)			(0.055)	(0.059)
Baseline Controls	X	X	X	X	X	X	X	X
Occupation Fixed Effects	X	X	X	X	X	X	X	X
State Fixed Effects		X		X		X		X
R^2	0.123	0.128	0.123	0.128	0.124	0.129	0.125	0.127
Number of Observations	70,471	70,471	70,471	70,471	70,471	70,471	70,471	70,471

Source: Authors' analysis using data from Burning Glass Technologies.

Notes: Observations are county x 3-digit Standard Occupation Code (SOC) cells containing at least 15 total postings in each year. See notes to Table 1 for construction of variables. Baseline controls include the initial (2010) share of postings requiring the skill measured as well as the change in the number of total postings, 2010–2014, as a share of total employment in 2010. All specifications include a control for differences between the two time periods, 2010–2012 and 2012–2014. Observations are weighted by the occupation's share of each county's total postings. Standard errors (in parentheses) are clustered by county. * p<0.10, ** p<0.05, *** p<0.01.

Table 5. Changes in Employer Requirements and Labor Market Slack, Recession (2007–2010) versus Recovery (2010–2014) Period

	P.P. Change in the Share of Postings Requesting: a Bachelor's Degree or Greater				P.P. Change in the Share of Postings Requesting: 5 or More Years of Experience			
	2007–2010	2010–2014	2007–2010	2010–2014	2007–2010	2010–2014	2007–2010	2010–2014
Δ County UR	0.225 ***	0.277 ***			0.121 **	0.226 **		
	(0.081)	(0.088)			(0.056)	(0.086)		
Δ BGT Labor Supply/Demand Ratio			0.767 ***	0.351 ***			0.470 ***	0.230 ***
			(0.107)	(0.093)			(0.072)	(0.059)
Baseline Controls	X	X	X	X	X	X	X	X
Occupation Fixed Effects	X	X	X	X	X	X	X	X
State Fixed Effects	X	X	X	X	X	X	X	X
R^2	0.721	0.128	0.723	0.128	0.700	0.129	0.702	0.127
Number of Observations	35,220	70,471	35,220	70,471	35,220	70,471	35,220	70,471

Source: Authors' analysis using data from Burning Glass Technologies.

Notes: : Regressions on 2010–2014 replicate results form Table 4. Regressions from 2007–2010 use the same specification on data from the Great Recession. See notes to Table 4 for more details. Sample excludes county/occupation cells with fewer than 15 postings in either period for which the change is measured. Observations are weighted by the occupation's share of each county's total postings. Standard errors (in parentheses) are clustered by county. * p<0.10, ** p<0.05, *** p<0.01. Observations are county x 3-digit Standard Occupation Code (SOC) cells containing at least 15 total postings in each year. Observations are weighted by the occupation's share of each county's total postings. Standard errors (in parentheses) are clustered by county. * p<0.10, ** p<0.05, *** p<0.01.

Table 6. Changes in Employer Requirements and Labor Market Slack During Recovery, Within Firm-Job Title

	Posting Requires a Bachelor's Degree or Greater		Posting Requires 5 or More Years of Experience	
	(1)	(2)	(3)	(4)
County UR	0.166**	0.217**	0.151***	0.201***
	(0.070)	(0.089)	(0.042)	(0.054)
Firm-Job Title- County Fixed Effects	X	X	X	X
Year Fixed Effects	X	X	X	X
Years included in sample	2010–2014	2010, 2012,2014	2010–2014	2010, 2012,2014
R^2	0.869	0.884	0.857	0.872
Number of Observations	19,930,641	10,498,538	19,930,641	10,498,538

Source: Authors' analysis using data from Burning Glass Technologies.

Notes: We limit the data to those with codeable firm names and job titles. We further omit unique, firm-job title-county pairs, as those yield no additional information with these fixed effects. Standard errors (in parentheses) are clustered by county. * p<0.10, ** p<0.05, *** p<0.01.

Table 7. Changes in Employer Requirements and Labor Market Slack During Recovery, By Type of Skills Requested

Percentage Point Change in the Share of Postings Requesting:	Any Skills	Baseline Skills	Specialized Skills	Software Skills
	(1)	(2)	(3)	(4)
Δ County UR	0.340 **	0.705 ***	0.385 ***	0.185 *
	(0.119)	(0.176)	(0.126)	(0.099)
Δ BGT Labor Supply/Demand Ratio	0.661 ***	1.255 ***	0.816 ***	0.387 ***
	(0.107)	(0.181)	(0.117)	(0.090)
Baseline Controls	X	X	X	X
Occupation Fixed Effects	X	X	X	X
State Fixed Effects	X	X	X	X
Number of Observations	70,471	70,471	70,471	70,471

Source: Authors' analysis using data from Burning Glass Technologies.

Notes: Observations are county x 3-digit Standard Occupation Code (SOC) cells containing at least 15 total postings in each year. See notes to Table 1 for construction of variables. Baseline controls include the initial (2010) share of postings requiring the skill measured as well as the change in the number of total postings, 2010–2014, as a share of total employment in 2010. All specifications include a control for differences between the two time periods, 2010–2012 and 2012–2014. Observations are weighted by the occupation's share of each county's total postings. Standard errors (in parentheses) are clustered by county. * p<0.10, ** p<0.05, *** p<0.01.

Table 8. Relationship between Changes in Employer Requirements and Natural Gas Labor Supply Shocks

	Percentage Point Change in the Share of Postings Requesting:							
	5 Or More Years of Experience	Bachelor's Degree or Greater	5 Or More Years of Experience	Bachelor's Degree or Greater	5 Or More Years of Experience	Bachelor's Degree or Greater	5 Or More Years of Experience	Bachelor's Degree or Greater
	1	2	3	4	5	6	7	8
Gas Production (in Billion Cubic Feet)	-.0003147***	-.0002033***	-.000628***	-.0004248****				
	(.0000277)	(.0000213)	(.000037)	(.0000241)				
Dummy (Δ Gas Prod >50 Billion Cubic Feet)					-.1321177***	-.0889454 ***		
					(.0130302)	(.0072097)		
Unemployment Rate (Instrumented with Gas Prod)							0.1233698***	0.0796979***
							(.043173)	(.027079)
First Stage F-Statistic								
Fixed Effect	County	County	Firm-Job Title	Firm-Job Title	County	County	County	County
Observations	1,957,304	1,957,304	602,854	602,854	1,957,304	1,957,304	1,957,304	1,957,304
R-squared	0.0535	0.0425	0.8489	0.821	0.0535	0.0425	0.0213	0.026
Number of Counties	2,738	2,738	2,228	2,966	2,738	2,738	2,738	2,738

Sources: Authors' analysis using data on employer requirements from Burning Glass Technologies. County-level gas production data from the USDA Economic Research Service. http://www.ers.usda.gov/data-products/county-level-oil-and-gas-production-in-the-us.aspx.

Notes: All specifications control for year dummies (2007 versus 2011). The dummy variable in specifications 3 and 4 takes a value of 0 in all 2007 observations, and 1 in counties whose production rose more than 50 billion cubic feet. We marked the following industries as tradable and non-fracking for this table: NAICS code less than 210000, NAICS codes between 212111 and 221330 (excluding 213111 and 213113), and NAICS codes from 311111 to 339999. Standard errors (in parentheses) are clustered by county.

Table A1. Changes in Employer Requirements and Labor Market Slack During Recovery, Accounting for Composition of the Unemployed

Panel A: Education Qualifications

	Percentage Point Change in the Share of Postings Requesting: a Bachelor's Degree or Greater				
	(1)	(2)	(3)	(4)	(5)
Share of Unemployed that are College Graduates	0.114***		0.058		
	(0.046)		(.053)		
Unemployment Rate for College Graduates		0.494***	0.364*	0.676***	
		(.168)	(.193)	(.205)	
Unemployment Rate for Non-College Graduates				-0.221*	
				(.116)	
BGT Supply/Demand Ratio * Share of Population that are College Graduates					0.199***
					(.453)
R^2	0.022	0.022	0.022	0.023	0.023
Number of Observations	70,482	70,482	70,482	70,482	68,925

Panel B: Experience Qualifications

	Percentage Point Change in the Share of Postings Requesting: 5 or More Years of Experience				
	(1)	(2)	(3)	(4)	(5)
Share of Unemployed that are Over Age 35 Years	0.019		-0.021		
	(0.026)		(.023)		
Unemployment Rate for Workers Over Age 35 Years		0.312***	0.370***	0.355**	
		(.113)	(.093)	(.142)	
Unemployment Rate for Under Age 35 Years				-0.057	
				(.076)	
BGT Supply/Demand Ratio * Share of Population Over Age 35 Years					0.289***
					(0.106)
R^2	0.014	0.014	0.014	0.014	0.014
Number of Observations	70,482	70,482	70,482	70,482	68,925

Source: Authors' analysis using data from Burning Glass Technologies.

Notes: In Panel A, we classify workers as skilled or unskilled based on whether or not they have a college degree. In Panel B, we indirectly determine work experience by classifying workers older than 35 as skilled. Observations are county x 3-digit Standard Occupation Code (SOC) cells containing at least 15 total postings in each year. All specifications include a control for differences between the two time periods, 2010–2012 and 2012–2014. Sample excludes county/occupation cells with fewer than 15 postings in either period for which the change is measured. Observations are weighted by the occupation's share of each county's total postings. Standard errors (in parentheses) are clustered by county. * p<0.10, ** p<0.05, *** p<0.01.

Table A2. Relationship between Employer Requirements and Labor Market Slack During Recovery, Fixed Effects Panel by Year 2010–2014

	P.P. Change in the Share of Postings Requesting: a Bachelor's Degree or Greater		P.P. Change in the Share of Postings Requesting: 5 or More Years of Experience	
	(1)	(2)	(3)	(4)
Δ County UR	0.147 **		0.102 **	
	(0.059)		(0.048)	
Δ BGT Labor Supply/Demand Ratio		0.326 ***		0.120 **
		(0.075)		(0.052)
County x Occupation Fixed Effects	X	X	X	X
Year Fixed Effects	X	X	X	X
R^2	0.927	0.927	0.845	0.845
Number of Observations	176,389	176,389	176,389	176,389

Source: Authors' analysis using data from Burning Glass Technologies.

Notes: Observations are county x 3-digit Standard Occupation Code (SOC) cells containing at least 15 total postings in each year. See notes to Table 1 for the construction of variables. Specifications include data for each year 2010–2014. Observations are weighted by the occupation's share of each county's total postings. Standard errors (in parentheses) are clustered by county. * p<0.10, ** p<0.05, *** p<0.01.