

# No Longer Qualified? Changes in the Supply and Demand for Skills within Occupations

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**Abstract:** Using a novel database of 159 million online job postings, we examine movements in employer skill requirements for education and specific skill sets between 2007 and 2017. We find that upskilling—both in terms requirements for a Bachelor’s degree and demands for software skills—was persistent among high-skill occupations but either temporary or non-existent among middle-skill and low-skill occupations. We also find evidence that persistent upskilling in the high-skill sector contributed to greater occupational mismatch that remained elevated during the recovery period. In contrast, labor market mismatch had largely dissipated within the low-skill and middle-skill sectors by 2017.

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## I. Introduction

Prior research indicates that employers increased education requirements within occupations during the Great Recession, a trend that has become known as “upskilling” (Modestino, Shoag, and Ballance 2019). Although roughly one-third of upskilling during the recession has been shown to be cyclical or opportunistic, as much as two-thirds of the increase appears to have persisted throughout the recovery period (Modestino, Shoag, and Ballance 2016, Hershbein and Kahn 2018). To the extent that upskilling has been persistent, unemployed workers in some occupations may no longer qualify for the positions they once held if they lack the necessary education credentials to meet these new requirements. In this paper, we provide new insights into recent changes in both education and actual skill requirements within different types of occupations and examine the implications of upskilling for labor market functioning.

Although the term mismatch often refers to imbalances in supply and demand for labor *across* occupations, skill mismatch *within* occupations can also arise if job requirements are changing over time. Skill mismatch within occupations could impair matching efficiency in just the affected occupations or, if sufficiently large or widespread, could reduce aggregate matching efficiency for the labor market as well. Recent evidence suggests that aggregate matching efficiency remains significantly below its pre-recession levels (Hall and Schulhofer-Wohl 2018), despite the unemployment rate being historically low and aggregate mismatch across occupations having almost fully abated since the recession (Burke 2015, Turrell et al. 2019).

Our main data source comes from Burning Glass Technologies and includes the near-universe of online job postings (roughly 159 million total) in the U.S. between 2007 and 2017 (excepting the years 2008 and 2009 for which no data are available). We first use these data to determine which segments of the labor market—classified as low-, middle-, or high-skill based

on the pre-recession education levels of incumbent workers—engaged in permanent versus temporary upskilling over the most recent business cycle. We find that occupations in the high-skill sector—jobs that as of 2006 were held by college graduates in a plurality of cases—were more likely to have experienced rising education requirements during the recession *and* were more likely to have maintained those higher requirements during the recovery. In contrast, occupations in the middle- and low-skill sectors largely engaged in temporary upskilling that reversed once the labor market tightened. Using the Current Population Survey, we also show that the educational distribution of new hires within occupations in the high-skill sector shifted upwards relative to existing workers, suggesting that the new education requirements imposed by employers were indeed binding.

We then use the Burning Glass data to describe changes in specific skill requirements (e.g., baseline, specialized, and software skills) within occupations in order to gain insight into what factors might have driven the changing education demands in different sectors of the labor market. We find that while the demand for software skills increased rapidly within all sectors of the labor market during the Recession, demand for these skills continued to increase during the recovery only in the high-skill sector. In contrast, the share of employers demanding baseline skills (e.g., project management) and other specialized skills (e.g., information security) increased similarly across all sectors of the labor market—rising rapidly during the Great Recession and then continuing to rise, albeit more slowly, during the recovery. This finding is consistent with anecdotal evidence that job descriptions in some industries have been revised to include new tasks requiring more advanced skills, either in response to regulation or changes in technology. For example, new regulations under the Affordable Care Act, by reducing the reimbursement rates for a host of medical procedures and services, allegedly raised the skill

requirements for nurses and physicians' assistants as services formerly rendered by doctors were pushed down the skill hierarchy.<sup>1</sup> New technology, such as additive manufacturing, may also lead to persistent upskilling as it requires workers to master computer-aided-design (CAD) software and 3D printing to produce parts formerly made using only analog technologies.<sup>2</sup> More broadly, the persistent upskilling we observe within some segments of the labor market might represent part of the longer-term phenomenon of labor market polarization, whereby automation and trade liberalization in some industries have led to a loss or transformation of middle-skill jobs while boosting demand for both low-skill and high-skill jobs.<sup>3</sup>

We further identify several dimensions along which these increased skill and education demands affected matching efficiency in the labor market. First, since most of the persistent (rather than temporary) upskilling occurred within the high-skill sector, occupational mismatch in that sector might have moved differently across the Great Recession compared with mismatch within either the middle-skill or low-skill sector. To test this hypothesis, we expand on the methodology of Şahin et al. (2014) and construct mismatch indices by skill sector, and we find that mismatch in both the low- and middle-skill sectors exhibited a sharply cyclical pattern, while mismatch within the high-skill sector exhibited a modest increase during the recession and increased further during the recovery rather than abating.

Persistent upskilling *within* certain broad occupation groups might also have contributed to aggregate mismatch. To explore this, we construct mismatch indices for major occupations at

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<sup>1</sup> See, for example, “Four Ways the ACA Affects Healthcare Staffing” at <http://www.thestaffingstream.com/2016/10/19/four-ways-the-aca-affects-healthcare-staffing/>

<sup>2</sup> See, for example, “2018 skills gap in manufacturing study” at <https://www2.deloitte.com/us/en/pages/manufacturing/articles/future-of-manufacturing-skills-gap-study.html>. However, these technologies may not as yet be widely used and indeed there is some evidence that employer claims of a skill gap might be overblown (Osterman and Weaver 2017).

<sup>3</sup> The literature on job market polarization is extensive. See Autor, Katz, and Kearney (2008), Autor and Acemoglu (2010), Autor and Dorn 2013, Holzer (2015).

the 2-digit SOC level, and compare results according to the prevalence of persistent upskilling among the minor sub-occupations at the 3-digit SOC level within it. Among major occupations consisting purely of persistent upskillers at the 3-digit level, in all but one case we observe that mismatch did not move in tandem with the business cycle, as was the case for the aggregate index. Moreover, mismatch continued to increase during the recovery, since 2010, for this group of persistent upskillers. In contrast, major occupations consisting primarily of either temporary upskillers or non-upskillers at the 3-digit level, exhibited mismatch trends that moved with the business cycle and were either a flat or declining since 2010. Together, these new empirical facts suggest that previous measures of mismatch constructed across occupations failed to capture the skills shifts occurring within occupations that may in part explain the persistent weakness of the labor market during the recovery period after the Great Recession.

Our findings contribute to the broader understanding of aggregate labor market functioning during the long recovery from the Great Recession. For example, although the unemployment rate has recently fallen to historically low levels, that has been accomplished despite the fact that aggregate matching efficiency remains below its pre-recession levels (Hall and Schulhofer-Wohl 2018). In other words, the labor market might have recovered more quickly than it actually did without the drag of lower matching efficiency. We identify one arguably structural trend within some occupations that may have contributed to the persistent decline in aggregate matching efficiency—employer upskilling. The mismatch induced by persistent upskilling *within* occupations may explain why employers consistently report difficulty in filling vacancies due to a lack of skilled workers while the empirical economics literature shows little evidence of labor market mismatch. If skill requirements increased rapidly during the business cycle, recently unemployed workers may no longer qualify for the jobs that

they previously held without additional training or skills. Retraining or skill acquisition takes time and therefore may help to explain why the Beveridge Curve continued to exhibit an elevated vacancy rate relative to the unemployment rate, even though the unemployment rate had fallen back to below its pre-recession level.

Our findings also speak to policy debates about workforce development and related educational policies, an arena which could benefit from using real-time labor market data that includes information on employer demand for specific skills. For example, the ability to distinguish between persistent versus temporary shifts in skill demands within certain occupations could help higher education institutions to identify which human capital investments are likely to have higher returns in the long-term. Such information could also be used by workforce development career counselors to develop sector-based or job-driven training in key industries as well as advise job seekers about whether their qualifications have become outdated and how best to re-train or apply their skills to another occupation (Holzer 2015).

Our results may also help reconcile recent debates about slow wage growth in the face of low unemployment and employer complaints concerning the difficulty of filling vacancies. A cursory examination of wage growth by occupation indicates that wages increased rapidly during the recovery within some of the persistent upskilling occupations and less so among the temporary upskillers, but the pattern does not hold uniformly across the board. Yet, raising the offering wage for positions that experience a sudden shift in demand for skills that are scarce might not be the most effective way to fill vacancies, at least in the short run when workers have not had the opportunity to seek out additional education and training. At present, there are only anecdotal stories of employers offering coding bootcamps (Lanahan 2019), but not much rigorous evidence on training behavior in relation to upskilling. Therefore an important question

for future research concerns whether employers who engaged in permanent upskilling were also more likely to engage in training to secure the desired skills, and whether this explains the lack of wage growth.

The paper proceeds as follows. Section II places our study within the related literature on upskilling and labor market matching efficiency. Section III describes the data and methods used to measure upskilling, matching efficiency, and mismatch. Section IV presents our results. First, we examine demand-side changes in education and skill requirements within occupations over the business cycle for different sectors of the labor market (low-, middle-, or high-skill). We then generate estimates of labor market mismatch both within skill sectors and within 2-digit occupations over the most recent business cycle. Section V concludes with a discussion of potential policy implications.

## **II. Related Literature**

Recent research suggests that changes in employer skill requirements reflect a combination of both cyclical and structural forces. On the cyclical side, Modestino, Shoag, and Ballance (2019) show that the share of jobs posting requiring a Bachelor's degree increased by 10 percentage points during the Great Recession. They estimate that about one-third of the upskilling they observed was temporary or opportunistic in response to the greater availability of workers during that period. In a subsequent paper, these same authors show that employer demand for college degrees, as well as other types of skills, fell as the labor market tightened between 2010 and 2014 (Modestino, Shoag and Balance 2016).

On the structural side, a complementary set of papers shows that up to two-thirds of the upskilling that occurred during the Great Recession was in fact persistent, or apparently structural (Hershbein and Kahn 2018, Zago 2018). Structural upskilling may also be related to

the longer-term trends of skill-biased technological change (Katz & Murphy 1992; Autor, Katz & Krueger 1998; Autor, Levy & Murnane 2003) and labor market polarization (Autor, Katz & Kearney 2008; Autor & Dorn 2008; Acemoglu & Autor 2010). In addition, both the cyclical and structural forces may be reinforcing, as recessions have been shown to induce long-term changes in the labor market (Hershbein and Kahn 2018, Charles, Hurst, & Notowidigdo 2012; Jaimovich & Siu 2012; Tuzeman & Willis 2013; Beaudry, Green, & Sand 2013).

Perhaps not coincidentally, the Beveridge Curve exhibited a significant outward shift during this same period, such that the unemployment rate appeared elevated relative to what was expected at the given vacancy rate. A large literature has since developed trying to explain this shift in the Beveridge Curve. These explanations included the role of reduced employer recruiting efforts (Davis, Faberman, and Haltiwanger 2012), increased uncertainty (Barnichon et al. 2012, Daly et al. 2012), pre-recession trends in matching efficiency (Hall and Schulhofer-Wohl 2015), extended unemployment benefits (Daly et al. 2012, Veracierto 2011, Barnichon and Figura 2010, Hagedorn et al. 2014), and cyclical fluctuations in job search effort (Mukoyama, Patterson, and Şahin 2018), among other factors.

One remaining explanation that has been repeatedly put forth by employers but has received little support from the empirical literature is that of labor market mismatch. Şahin et al. (2014) showed that mismatch between vacancies and unemployed workers across industries, occupations, and geographies increased significantly during the Great Recession, contributing to reduced matching efficiency in the aggregate and therefore to the shift in the Beveridge Curve. However, the sluggish wage growth observed during most of the recovery period seems inconsistent with the mismatch hypothesis (Rothstein 2012, Abraham 2015), and several papers have argued that weak aggregate demand offered a more convincing explanation for the outward



shift of the Beveridge Curve than did skills mismatch or other structural factors (Barlevy 2011, Lazear and Spletzer 2012, Rothwell 2012, Carnevale, Javasundera, and Cheah 2012, Diamond 2013, Diamond and Şahin 2015, Osterman and Weaver 2017). Furthermore, measures of mismatch across occupations have also recovered to pre-recession levels (Burke 2015). Nonetheless, the aggregate vacancy rate remains high relative to the (low) unemployment rate, and according to recent evidence aggregate matching efficiency remains below its pre-recession level (Hall and Schulhofer-Wohl 2015, Hobijn and Perkowski 2016).

Relatively little work has been done to study the relevance of skills mismatch *within* occupations for the recent labor market experience in the United States, and formal studies of changes in skill requirements by occupation are few in number. Using the US Department of Labor's O\*NET database, Vaisey (2006) compares the education requirements of jobs to the educational attainment of workers employed in the same jobs and finds that the average worker was overqualified for his/her job as of 2002. Liu and Grusky (2013) also find evidence that certain skill requirements measured using O\*NET—including computer skills and analytic and quantitative skills—increased within jobs since 1979, but the increases are small to modest. Although skill-biased technological change has been cited as a factor leading to increased demand for highly-educated workers relative to less-educated workers (Katz & Murphy 1992; Autor, Katz & Krueger 1998; Autor, Levy & Murnane 2003), the evidence is mixed as to whether the adoption of new technologies raises skill requirements *within* jobs (see for example Acemoglu 2002, Zicklin 1987, and Keefe 1990). More recently, Hershbein and Kahn (2018), find that the persistent upskilling observed across the Great Recession emerged as the result of routine-biased technological change that was occasioned by the recession itself.

Some researchers have questioned whether requirements listed on job vacancies are truly

binding and emphasize the problem of overqualification within occupations rather than underqualification (Cappelli 2014 and Cappelli 2015). However, occupations involving relatively high computer use, including scientific occupations and healthcare jobs, experienced large increases in wages at the upper end of the wage distribution relative to occupations involving less computer use (Bessen 2014). Similarly, states that experienced greater job polarization during the recession—a loss of routine (middle-skill) jobs in favor of both manual (low-skill) and abstract (high-skill) jobs—also experienced greater educational mismatch as evidenced by workers moving down the occupational skill ladder relative to what would be expected given their education credentials (Zago 2018). Over the longer-run, structural labor market polarization may manifest as both upskilling within some occupation classes as employers raise skill requirements, as well as educational overqualification in other occupation classes as middle-skill workers take jobs in the low-skill sector.

We build on these different literatures by describing upskilling patterns over a longer time period and decomposing them by skill sector, according to whether the job vacancies initially tended to require either low-, middle-, or high-education levels. We further identify which types of occupations engaged in structural versus temporary upskilling in their education requirements. Using the richness of the BGT data, we then examine which types of underlying skills (e.g., baseline, specialized, or software) might be driving the large and persistent increases in the demand for education. While these trends are inherently interesting, we make an important contribution to the literature by examining the implications of these changes in skill demands. We find that mismatch evolved very differently over the business cycle in the high-skill sector compared with the middle-skill and low-skill sectors, in line with differences in upskilling patterns. We also find evidence that mismatch exhibited secular (rather than cyclical) increases

within certain major occupations that exhibited persistent upskilling. Together, these new empirical facts suggest that persistent upskilling in the high-skill sector of the labor market may have exerted a drag on aggregate matching efficiency during the recovery period. Furthermore, this source of drag was obscured by most previous approaches to the measurement of mismatch.

### **III. Data and Methods**

Our primary objective is to explore the degree to which upskilling within occupations over the business cycle contributed to reduced matching efficiency in specific portions of the labor market and possibly in the aggregate. Specifically, we seek to answer the following research questions:

- How have employer education requirements increased within occupations and in which skill segments (low-, middle-, and high-skill) of the labor market? Are these skill requirements binding?
- Which skillsets are now in greater demand? Are these increases persistent or temporary?
- Does upskilling generate mismatch—within and/or across occupations? If so, can this help explain the reduced matching efficiency in certain segments of the labor market?

To test our hypotheses, we use a variety of methods drawing on multiple data sources to provide a collage of evidence from which we can draw our conclusions. Our analysis consists of two primary parts. First, we use the near-universe of online job vacancy data provided by Burning Glass Technologies to examine the demand-side changes in education and skill requirements within occupations over the business cycle, describing such changes separately for each of three skill sectors (low, middle, and high). Second, we generate estimates of occupational mismatch over the most recent business cycle, separately for each of the three skill sectors and for each of several major occupations, in order to identify linkages between upskilling and

mismatch. Along the way, we also conduct several robustness checks confirming that skill requirements appear to be binding and exploring the pattern in wage increases across occupations engaged in persistent versus temporary upskilling.

## **A. Data Sources**

### *1. Online job posting data from Burning Glass Technologies (BGT)*

Over the past two decades, online vacancy data have been used by a number of researchers to study labor market dynamics (Kuhn and Skuterud 2004; Bagues and Labini 2009; Şahin et al. 2014; Marinescu 2017). The vacancy data used in this paper is collected by Burning Glass Technologies (BGT), one of the leading vendors of online job posting data. BGT collects 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>4</sup> The data are collected via a web crawling technique to browse online job boards and other web sites and systematically text parse each job ad into usable data elements. BGT mines over seventy job characteristics from free-text job postings including employer name, location, job title, occupation, years of experience, and level of education required.<sup>5</sup>

Unlike other online job vacancy sources, BGT also parses out other dimensions of skill from the text of the job ad, allowing us to create measures of different types of skill rather than simply relying on education as a proxy. They aggregate this data by parsing each skill from a job posting and categorizing it into a canonicalized version of similarly named skills. For example, Python 3.3 and Python 2.7 are both standardized to Python. Because this process results in over 16,000 canonicalized skills, BGT then places each canonicalized skill into a broader skill cluster.

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<sup>4</sup> See <http://www.burning-glass.com/realtime/> for more details.

<sup>5</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.

For example, algebra and calculus would both be placed into the math skill cluster. These skill clusters are then aggregated up into skill families (e.g. math and science are both STEM skills). Finally, skill families are classified as either baseline skills (e.g. leadership), specialized skills (e.g., accounting), or software skills (e.g., Oracle).

BGT's data-collection process is designed to capture the most current and complete set of online postings at a given time and includes algorithms that eliminate duplicate ads for the same job vacancy. 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.<sup>6</sup> The firm applies the same filtering and de-duplication algorithm across years and applies any improvements to the algorithm retroactively to the entire history, so that the methodology is consistent throughout our dataset. Nonetheless, the number of sources scraped by BGT may have evolved over time.

The advantage of using online vacancy data is that it allows analysis at a greater frequency and at more refined geographies than traditional employer surveys, such as the Job Opening and Labor Turnover Survey (JOLTS). The BGT data are available at a monthly frequency by zip code and at the level of the six-digit Standard Occupation Code (SOC) for 2007 and 2010-2017.<sup>7</sup> 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, estimates show that as of 2012 between 60 and 70 percent of job vacancies were posted online (Carnevale, Jayasundera, and Repnikov 2012).<sup>8</sup> Other research shows that the number of online

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<sup>6</sup> 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.

<sup>7</sup> No data are available from BGT for 2008 and 2009.

<sup>8</sup> Carnevale, Jayasundera, and Repnikov (2014) audited a sample of job postings in the BGT database and found that the BGT coding for occupation, education, experience was accurate at least 80 percent of the

job ads represents a reliable predictor of actual hiring activity one quarter later (Templin and Hirsch 2013). We explore this issue further in the appendix, and other authors have also tested the robustness of these data (Rothwell 2014; Hershbein and Kahn 2018). Despite differences in the sampling frame of the BGT data compared to state and national employer job vacancy surveys, we find that the industry and occupation distributions of the different vacancies series are quite similar and that the relationships between the BGT and the survey-based series are consistent over time.<sup>9</sup>

We make use of two distinct versions of the BGT data. The main dataset is provided at the job posting level and contains detailed data on the job-title, occupation, industry, and location as well as information on requirements for education, experience, and skills. The data are pooled over the year without duplication and we observe the month in which the posting first appeared. We use this version of the data for the first part of our analysis that explores the changes in employer demands by education and detailed types of skills over time at both the 3-digit and 6-digit SOC level.

Although Figure 1 shows that the BGT data exhibit a high degree of correlation over time with the JOLTS vacancy series (0.82), the level of BGT vacancies is consistently lower. In part, this is because JOLTS includes both online and offline postings such as those posted in print, in shop windows, or within firms. In addition, the JOLTS is a survey that specifically asks the number of vacancies that are open whereas a single online job posting may represent multiple vacancies. To obtain an accurate number of vacancies over time, BGT creates a normalized

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time. This is likely an underestimate given algorithm improvements that have been retroactively and consistently applied since then.

<sup>9</sup> These comparisons show that the BGT data tend to slightly over-represent industries such as finance and slightly under-represent others such as food services. Similarly, occupations such as management are slightly over-represented while occupations such as food preparation are slightly under-represented.

(reweighted) dataset that exactly matches the monthly JOLTS vacancies by industry. We use this second version of the data when calculating the number of vacancies by occupation on the demand side to construct our mismatch indices by skill sector.

## *2. Current Population Survey*

On the labor supply side, we make extensive use of the Bureau of Labor Statistics' Current Population Survey microdata (IPUMS-CPS, Flood et al. 2018) from 2007 through 2017. In particular, to construct our mismatch indexes we use the CPS data to measure the number of unemployed workers by occupation at various levels of occupational detail (such as the 3-digit SOC and the 6-digit SOC). When estimating mismatch-related unemployment we exploit the panel dimension of the CPS data to estimate job finding rates and job destruction rates by occupation, utilizing the methodology developed by Shimer (2012). Finally, we make further use of the longitudinal data in the CPS to identify new hires by 6-digit occupation and continuing employees by 6-digit occupation. In addition, we use the CPS data to describe the relative education level of new hires to continuing employees by occupational skill sector. The details of how we construct these various measures from the CPS data are provided below and in the appendix.

## **B. Methods**

### *1. Classifying occupations by skill sector*

In several parts of our data analysis we partition the universe of occupations into three skill sectors—low-skill, middle-skill, and high-skill—and examine labor market patterns (such as upskilling or mismatch) separately by skill sector. To classify an occupation into one of the three sectors, we use the pre-recession distribution of educational attainment among incumbent workers in the occupation as measured by the three-year 2005-07 sample of the

American Community Survey (ACS). An occupation is classified as “high-skill” if at least a plurality (40 percent) of employed workers in that occupation had completed a bachelor’s degree or higher and “low-skill” if at least 40 percent of its workers had completed only high school or less. Occupations in which neither of those criteria is met are classified as “middle-skill.”<sup>10</sup> We keep these definitions fixed throughout the study period.

## *2. Measuring demand-side upskilling within occupations by skill sector*

We use the BGT data to examine demand-side changes in education and skill requirements within occupations over the most recent business cycle, for each of the low-, middle-, and high-skill sectors defined above. We are interested in whether increases in job requirements by occupation (or on average by skill sector) were either temporary—in the sense of being restricted to the recessionary period of 2007-2010—or instead persisted into the recovery period of 2010-2017. We define an occupation as having upskilled during the Great Recession if there was at least a 5 percentage point increase in the share of postings requiring a Bachelor’s degree or higher between 2007 and 2010—this threshold was the average increase in education requirements observed during this period as shown in Modestino et. al (2019). Occupations with less than a 5-percentage point increase in bachelor’s degree requirements during the recession are classified as having “no upskilling”. We further define an occupation as a “persistent upskiller” if the share of postings requiring a Bachelor’s degree declined by less than half (2.5 percentage points) during the recovery period (between 2010 and 2017). In contrast, an occupation is defined as a “temporary upskiller” if the share of postings requiring a Bachelor’s degree were reversed by more than half (2.5 percentage-points) during the recovery period. Using these upskilling definitions and the skill sector classification, we compare the

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<sup>10</sup> Note that we observe no cases in which an occupation could be placed into more than one skill category based on these criteria.



extent of persistent, temporary, and no upskilling for each 3-digit occupation within the three skill sectors.

We also examine changes in requirements for specific skills, rather than just education, as potential indicators of structural changes in the nature of the underlying job. Specifically, we compare trends in skill requirements across the recession and recovery for persistent versus temporary upskillers using a difference-in-difference analysis. In this way, we assess the degree to which permanent upskilling was associated with differential changes in the share of postings requiring skills of a given type (e.g., baseline, specialized, or software skills) We then delve further into the skills data to examine changes in the most frequently requested skill clusters within each of the baseline, specialized, and software skill categories to determine whether employers are simply seeking more of the same skills or entirely new skills are being requested.

### *3. Measuring labor market mismatch by skill sector*

Heterogeneity in upskilling behavior across the three skill sectors may have differential implications for matching efficiency by skill sector. For example, if persistent upskilling is more likely to occur within the high-skill sector relative to the low- or middle-skill sectors then we would expect the high-skill sector to exhibit different movements in mismatch over the business cycle as well as failing to dissipate in the recovery. One way to detect such differences is to measure labor market mismatch separately by skill sector over the period of interest, as mismatch offers one indication of inefficiencies in the hiring process. To do so, we extend the methodology of Şahin et al. (2014) to construct an occupational mismatch index separately for each of our three skill sectors (low-, middle-, and high-skill).

In this framework, the labor market is frictional in that a given worker is assumed to search for jobs only within a circumscribed set of occupations (in this case, within a 2-digit SOC

restricted by skill sector). Likewise, this model assumes that firms only find/hire workers who are searching within the occupation classification of their job opening. These assumptions seem more plausible for major occupation categories (such as the 2- or 3-digit SOC level) than for narrowly defined detailed (e.g., 6-digit SOC) occupations. Although some studies place mobility across occupations to be quite low, these estimates have been known to vary widely.<sup>11</sup>

Following Şahin et al. (2014), we adopt a mismatch index that quantifies the fraction of potential hires that fail to occur because of a misallocation of unemployed workers to occupations relative to the distribution of vacancies by occupation.<sup>12</sup> Here we provide a brief derivation of the mismatch index, with further details presented in the appendix. The number of hires in occupation  $i$  at time  $t$ , denoted  $h_{it}$ , is assumed to be governed by a matching process that can be represented as:

$$h_{it} = \phi_t \varphi_{it} m(u_{it}, v_{it}) = \phi_t \varphi_{it} u_{it}^{1-\delta} v_{it}^{\delta} \quad (1)$$

In the above,  $\phi_t \varphi_{it}$  represents matching efficiency in occupation  $i$  at time  $t$ , which includes both an aggregate component,  $\phi_t$ , and an occupation-specific component,  $\varphi_{it}$ . Throughout our mismatch calculations these parameters are held constant. The expression  $m(u_{it}, v_{it})$  represents an underlying matching function that follows a Cobb-Douglas form, where hires are increasing in both the number of unemployed workers searching in occupation  $i$  at time  $t$ , denoted  $u_{it}$ , and the number of vacancies in occupation  $i$  at time  $t$ , denoted  $v_{it}$ . Summing across occupations (and assuming a common matching function across them), the aggregate number of hires in the economy,  $h_t$ , can be written as:

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<sup>11</sup> For example Molloy et al. (2017) observe a 4 percent transition rate across three-digit occupations in the CPS during the 2000's, while Kambourov and Manovskii (2009) report a 21 percent transition rate across 3-digit occupations during the 1990s using the PSID.

<sup>12</sup> Mismatch can also be measured across industries. Throughout our discussion, “industries” could be substituted for “occupations” with no loss of generality.

$$h_t = \phi_t u_t^{1-\delta} v_t^\delta \left[ \sum_{i=1}^I \varphi_{it} \left( \frac{u_{it}}{u_t} \right)^{1-\delta} \left( \frac{v_{it}}{v_t} \right)^\delta \right] \quad (2)$$

In the above expression,  $u_t$  and  $v_t$  refer to the total number of unemployed and the total number of vacancies, respectively. The total number of hires at each date is optimized subject to the matching friction imposed by each occupational labor market, and taking the vector of occupation-specific vacancies as given. The planner's solution moves the unemployed across sectors to allocate more unemployed workers to markets with higher matching efficiencies and higher vacancies. The optimal number of hires is the number the planner achieves under the optimal allocation of unemployed workers to occupations for the given vectors of vacancies and matching efficiencies. Using the expression above together with the expression for the optimal number of hires (derived in the appendix), the basic mismatch index can be written as follows:

$$M_t = 1 - \frac{h_t}{h_t^*} = 1 - \sum_{i=1}^I \left( \frac{\varphi_{it}}{\bar{\varphi}_t} \right) \left( \frac{v_{it}}{v_t} \right)^\delta \left( \frac{u_{it}}{u_t} \right)^{1-\delta} \quad (3)$$

where  $\bar{\varphi}_t$  refers to a CES aggregator of the occupation-specific matching efficiencies weighted by their respective vacancy shares. The mismatch index captures the total number of hires that fail to occur under the given (inefficient) allocation of unemployed workers to occupations, as a fraction of the optimal number of hires.

We expand on the basic mismatch index by constructing measures of occupational mismatch separately by skill sector. To accomplish this we partition each major 2-digit occupation into three bins—a low-skill bin, a middle-skill bin, and a high-skill bin—based on the educational categories of each of the six-digit occupations within it.<sup>13</sup> We do this for both the

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<sup>13</sup> For example, we partition the 2-digit occupation for healthcare practitioners and technical occupations (29) into each 6-digit category within it. We then categorize each six-digit occupation as low/middle/high skill using the prior definitions based on the 2005-07 ACS. For example, ob-gyn (29-1064) is categorized as a high-skill occupation, pharmacists (29-1051) is categorized as a middle-skill occupation, and OSHA technician (29-9012) is categorized as

demand side (e.g., the number of vacancies) and the supply side (e.g., the number of unemployed). Then the mismatch index for each sector is constructed based on equation (3) above, which requires the vector of vacancy shares and unemployment shares by occupation within the given skill sector. For example, within the high-skill sector, the vacancy share for a given (skill-partitioned) 2-digit occupation represents the total number of vacancies *in the high-skill bin* within that 2-digit occupation as a share of all high-skill vacancies, and similarly for the unemployment share of a given (skill-partitioned) 2-digit occupation. If we observe elevated mismatch within the high-skill sector, that would mean that unemployed individuals in the high-skill sector are searching in the wrong high-skilled occupations (at the 2-digit level) relative to the distribution of vacancies for high-skilled occupations (at the 2-digit level).<sup>14</sup>

With some further assumptions we can use the mismatch index to develop an estimate of “mismatch unemployment,” defined by Şahin et al. (2014) as the difference between actual unemployment and the level of unemployment that would arise under zero mismatch. To calculate the counterfactual unemployment level in the absence of the occupational mismatch, we follow Şahin et al. (2014) and Shimer (2005). See the appendix for further details of the estimation of mismatch unemployment by sector.

#### *4. Estimating Mismatch Within 2-Digit Occupations*

Upskilling could also manifest itself in a shifting of vacancies *within* a major 2-digit occupational category toward jobs requiring more education and more specialized skills. Under the assumptions of the mismatch model, if workers cannot easily move across the 3-digit

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a low-skill occupation. We do this for all the six-digit occupations within healthcare practitioners and technical occupations (29). We then create separate two-digit healthcare practitioners and technical occupations for each of the high-skill sector, middle-skill sector, and low-skill sectors by aggregating the appropriate six-digit occupations within that sector. See Figure A.5 in the appendix.

<sup>14</sup> Note that unemployed individuals “belong” to the high-skill sector if their most recent employment was in a high-skill 6-digit occupation, and they are assumed to search only within the high-skill bin of the 2-digit occupation containing their most recent 6-digit occupation. See Figure A.6 in the appendix.

occupations within the 2-digit occupational category, then persistent upskilling would lead to high and persistent measures of mismatch. To test for this, we construct mismatch indices across the minor 3-digit occupations within each of the major 2-digit occupation groups, subject to data limitations.<sup>15</sup> If structural upskilling leads to an increase in mismatch within an occupation, then the mismatch index should exhibit less cyclical, and be steady or increasing during the recovery period for those 2-digit occupations which experienced exhibited a high prevalence of persistent upskilling. We determine the prevalence of persistent upskilling for a 2-digit occupation according to the share of 3-digit occupations under its umbrella that engaged in persistent upskilling.

## IV. RESULTS

### A. Demand-Side Upskilling within Occupations by Skill Sector

We know from previous research that employers increased skill requirements within occupations during the Great Recession—most notably requiring a bachelor’s degree or higher. About one-third of this upskilling was cyclical in response to the increased supply of workers and was reversed as the labor market recovered (Modestino et al 2016). However, recent research finds that as much as two-thirds of the upskilling during the recession was structural (Hershbein and Kahn 2018).

#### 1. *Educational Upskilling Within Occupations, by Skill Sector*

In this section, we exploit the detailed information in the BGT data to understand the heterogeneity in upskilling over the business cycle by skill sector. Across all occupations, just shy of 40 percent qualify as persistent upskillers, close to 19 percent were temporary upskillers, and almost 42 percent engaged in no upskilling (see Panel A of Table 1). However, persistent

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<sup>15</sup> For smaller occupations with low rates of unemployment, the CPS contained insufficient data to generate the supply side of the mismatch index.

upskilling was far more prevalent within the high-skill occupation group (82.1 percent) compared to the middle-skill (40.0 percent) and low-skill (11.6 percent) groups. In contrast, temporary upskilling was most common among middle-skill occupations (25.0 percent) and no upskilling was most likely to occur among low-skill occupations (69.8 percent). One might also want to know what share of persistently upskilling occupations was accounted for by each skill group. Splitting the data differently, Panel B of Table 1 shows that high-skill occupations were sharply overrepresented (63.9 percent) among the set of all occupations classified as persistent upskillers, whereas low-skill occupations were overrepresented among the non-upskillers (79.0 percent).

How did these upskilling patterns evolve within each skill sector over the business cycle? Panel A of Figure 2 shows the trend in education requirements for the low-, middle-, and high-skill sectors in the aggregate. Again, we find that permanent upskilling had a greater impact in the high-skill sector of the labor market. During the recession, the share of postings requiring a bachelor's degree (BA) increased across all three skill groups, although much more so for middle- and high-skill occupations. During the recovery the BA share decreased for low- and middle-skill occupations while remaining elevated and even increasing among high-skill occupations.

Although the skill and/or education requirements contained in job postings are an indicator of employer demand, the advertisements may represent aspirations for job candidates rather than strictly binding qualifications. If employers were even partly successful in upskilling their jobs—in the sense of hiring a higher share of college graduates into a given occupation, we would expect the average education level of new hires to increase relative to that of continuing employees. Since persistent upskilling was more prevalent within the high-skill sector, we would

expect any increase in the relative education level of new hires to be most pronounced within that sector.

As a robustness check to test whether rising education requirements were in fact binding, we use the longitudinal component of the CPS to plot the ratio of the average education level of new hires to that of continuing employees by skill sector for the period 2005 to 2017. Among high-skill occupations, where much of the persistent upskilling occurred, we find that the relative average education level among new hires experienced a modestly increasing trend over the time period, notwithstanding some fluctuations (see Figure A.7 in the appendix). In contrast, among middle-skill occupations, where much of the temporary upskilling occurred, this ratio increased exhibited a cyclical pattern—suggesting that employers were able to temporarily hire more-educated workers during the Great Recession and even well into the recovery. In the low-skill sector, where most occupations experienced no significant upskilling, there was little movement over the business cycle. The patterns suggest that the increased education requirements reflected more than mere aspirations, and that employers were at least partly successful in meeting their demand for more highly educated employees.

## *2. Changes in Required Skill Clusters Within Occupations, by Skill Sector*

While these trends are suggestive, increases in education requirements among persistent upskillers may not reflect structural changes in the actual skills required by the job, but instead may have occurred in response to a permanent increase in the supply of workers with bachelor's degrees over the time period (as opposed to a temporary decline in the reservation wage of such workers during the recession). To test for actual changes in skill (rather than just education) requirements, Table 2 performs a difference-in-difference analysis of changes in the education and skill requirements for permanent versus temporary upskilling occupations over time—both

during the recession versus the recovery. The top row shows that the share of postings requiring a bachelor's degree increased significantly between 2007 and 2010 within both the permanent- and temporary-upskilling groups (although by a larger margin in the former group). However, between 2010 and 2017 the permanent upskilling group exhibited a further increase in the share requiring a bachelor's degree—by nearly 4 percentage points--compared to a drop of 12.6 percentage points in the temporary-upskilling group. This exercise confirms that the differential changes in education requirements by skill sector since 2010 were in fact statistically significant as found in Modestino et. al. (2019).

What's even more striking is that a similar pattern holds in an analogous difference-in-difference analysis using BGT categories of measurable skill requirements from the individual job postings, rather than educational credentials. These categories include baseline skills (e.g., communication), specialized skills (e.g., accounting), and software skills (e.g., Oracle). The remaining rows of Table 3 show that all three types of skills became more prevalent among postings during the recession period (2007-2010) for both persistent- and temporary-upskilling occupations with no statistically significant differences for any specific skill group. During the recovery period (2010-2017), both persistent and temporary upskillers continued to increase the share of postings requiring baseline and specialized skills, although the increase is only statistically significant among the persistent upskillers. In contrast, the share of postings requiring software skills was flat among temporary upskillers but continued to increase among persistent upskillers. As a result, software skills were the only type of skill for which there is a significant difference in trends over time between persistent and temporary upskilling occupations. These results suggest that the persistent increases in education requirements may have been complementary to increased demand for software skills.



How did the demand for different skills within each skill sector evolve over the business cycle? Panel B of Figure 2 shows the trends in skill requirements across the low-, middle-, and high-skill sectors in the aggregate. All three sectors experienced a sharp increase in the share of postings requiring baseline and specialized skills during the recession (2007-2010), followed by some amount of reversion as the labor market tightened (2010-2014), and then a second uptick later in the recovery period (2014-2017). Yet the pattern for software skills evolved somewhat differently across the three sectors. During the recession there was an increase in the demand for software skills across all three sectors, but it was larger in magnitude for the mid- and high-skill occupations. More importantly, during the recovery, the share of postings requiring software skills was relatively flat for low-skill occupations but rising for mid- and high-skill occupations.

To further explore the nature of the skills required by postings for different skill sectors of the labor market, we delved more deeply into the BGT data and examined the change during the recovery in specific skill clusters within the baseline, specialized, and software categories. Figure 3 shows the initial share of postings requiring a particular baseline skill cluster in 2010 versus the change in the share of postings requiring that skill cluster between 2010 and 2017.

While there is some overlap across low-, middle-, and high-skill occupations in baseline skill clusters such as communication and computer literacy, the increase in the share of postings requesting these skills is highest for the high-skilled occupations and lowest for the low-skill occupations. These differences in baseline skill demands line up with our expectations across the skill sectors, indicating that the data are meaningful. For example, high-skill occupations are more likely to require research, planning, writing, and problem solving compared to middle-skill occupations, and middle-skill occupations are more likely to require organizational skills compared with low-skill occupations, which in turn are more likely to require physical abilities.

A similar pattern emerges for specialized skill clusters, as shown in Figure 4. High-skill occupations tend to require a different mix of skills and at a greater initial frequency with a more rapid increase during the recovery. For example, high-skill occupations are more likely to require teaching, budget management, and business strategy. In contrast, middle-skill occupations are more likely to require scheduling and retail industry knowledge and low-skill occupations are more likely to require food and beverage service, equipment repair and maintenance, and material handling. We observe similar differentiation even within a particular industry such as healthcare.<sup>16</sup>

Consistent with our earlier findings, greater differentiation across low-, middle-, and high-skill sectors is observed among software skill clusters.<sup>17</sup> As shown in Figure 5, software skills are much less likely to be required for low- and middle-skill jobs, with no particular software skill cluster being requested for even 1 percent of postings. The software skills that are required for low- and middle-skill jobs are very generic (e.g., Microsoft windows). In contrast, high-skill jobs require software skill clusters more frequently, with a wider variety being demanded, such as SQL programming, statistical software, C and C++, Java, and architectural design programs. These findings are consistent with our earlier evidence that technology may be driving persistent upskilling among high-skill occupations, particularly those that use specialized software packages (e.g., architectural design) or for which new software can diffuse rapidly, changing the nature of the worker's tasks (e.g., EPIC medical record technology software).

## **B. Trends in Labor Market Mismatch**

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<sup>16</sup> For example, among high-skill occupations, behavioral health and ER and intensive care are most frequently required compared to middle-skill occupations that are more likely to require basic patient care and low-skill occupations that are more likely to require basic living activities support.

<sup>17</sup> Note that due to the greater heterogeneity in software skills that are requested, the prevalence of any particular software skill is much lower than that of a particular baseline or specialized skill.

### 1. Mismatch Across Occupations by Skill Sector

Based on the evidence presented in the previous sections, we hypothesize that persistent and possibly structural increases in skill requirements that were concentrated within high-skill occupations may have led to greater persistence in labor market mismatch during the recovery compared to middle- and low-skill occupations. Specifically, the upskilling trend suggests that changes in the distribution of job vacancies within the high-skill sector favored occupations requiring more education and advanced skills. For a given distribution of unemployed workers by occupational experience, the shifting vacancy composition could have resulted in increased occupational mismatch. The temporary upskilling in the low-skill and middle-sectors might have resulted in different mismatch patterns across the business cycle compared with the high-skill sector. Of course, we acknowledge that upskilling was not the only factor that might have influenced occupational mismatch following the Great Recession, but it does have the potential to explain the persistent weakness in the labor market.

To test these hypotheses, we extend the methodology of Şahin et al. (2014) to construct separate mismatch indices (across major occupations) within each of the low-, middle-, and high-skill sectors. Panel A of Figure 6 plots the mismatch index for each sector, for 2007 and 2010 through 2017 (the period for which the normalized BGT data are available).<sup>18</sup> The figure reveals several interesting patterns. First, the *level* of mismatch is increasing in the education level of the sector: the mismatch index is highest for the high-skill occupations (0.2-0.25) and lowest for low-skill occupations (0.04 to 0.075). , suggesting that while more education makes workers more adaptive, it also makes them more specialized less substitutable across occupational

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<sup>18</sup> As a robustness check, we also replicate and extend the aggregate mismatch index from Şahin et al. (2014) across all occupations and industries using the BGT data and get very similar results to their study using the Help-Wanted-On-Line vacancy data (see figures A.10 and A.11 in the appendix).

categories, and this second effect seems to dominate—even at the two-digit level.<sup>19</sup> For example, an individual with a bachelor’s degree or higher working in the Architectural and Engineering occupational group is not likely to be able to switch costlessly to a job in another two-digit occupational group—even one that is somewhat related, such as the Computer and Mathematical group.

Second, *changes over time* in our measure of mismatch also vary by skill sector. In the high-skill sector, mismatch fluctuated moderately over the time period, increasing in 2007 and then receding between 2010 and 2012, only to increase again through 2014 and then moderate somewhat through 2017. On balance the index was little changed between 2007 and 2016-2017, but the increase during portions of the recovery (2012-2014) indicates that cyclical demand fluctuations were not driving these changes. In contrast, mismatch among middle-skill occupations fell (subject to slight fluctuations) during the recovery from 0.10 in 2010 to 0.07 in late 2017, as skill requirements receded during the recovery after the temporary run-up during the recession. Low-skill mismatch exhibited a strongly countercyclical pattern, increasing sharply in 2007 and then falling steadily during the recovery and reverting to roughly its initial value by the end of our period. These findings are consistent with other evidence from the literature. For example, job polarization has been characterized by the disappearance of routine and manual job opportunities in middle-skill occupations (Acemoglu and Autor 2011) particularly during recessions (Jaimovich and Siu 2014).

Panel B of Figure 6 shows that the degree to which mismatch contributed to the unemployment rate over the time period by skill sector. Among high-skill occupations,

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<sup>19</sup> Şahin et al. (2014) performed a similar, but not identical, exercise that appears in their online appendix. They also found that occupational mismatch was increasing in the average education level of the incumbent workers in the set of occupations under consideration.

mismatch contributed upwards of 1.6 percentage points to the unemployment rate at the peak, and, despite subsequently receding, its contribution to unemployment remains elevated as of 2017. In contrast, mismatch among middle-skill occupations, contributed only 1.0 percentage point to the peak unemployment rate in 2010 and its contribution remains only slightly elevated from its pre-recession value as of 2017. Similarly, mismatch among low-skill occupations contributed roughly 1.0 percentage point to unemployment in 2010, but as of 2017 contributes roughly the same amount (0.5 percentage point) as it did in 2007 (0.4 percentage point).

How much of the persistent weakness in the labor market during the recovery can be explained by mismatch? Table 3 calculates the share of the actual unemployment rate in each sector that can be explained by mismatch for the period 2010-15, the end of which coincided with the unemployment rate returning to its pre-recession level. Between 2010 and 2015, the share of unemployment due to mismatch increased significantly from 31 percent to 47 percent among high-skill occupations. In contrast, the share of unemployment due to mismatch has declined since 2010 in the other two skill sectors.

## *2. Mismatch Within Occupations by Upskilling Prevalence*

Based on our findings above that a significant share of high-skill occupations engaged in persistent upskilling between 2007 and 2017, we consider whether such upskilling led to occupational mismatch *within* major occupational groupings. The idea is that upskilling could have led to a shift in vacancies (within a major occupation) to more specialized minor occupations with relatively few experienced workers to draw on. To explore this concept, we calculate mismatch indices separately for 2-digit SOC major occupations based on the 3-digit SOC minor occupations within it. Because we are slicing the BGT data more finely, we limit our analysis to 2-digit occupations that have at least 1 million postings in 2010 and we focus on the

recovery period 2010-17.

We focus on comparing qualitative patterns of within-occupation mismatch across different major occupations, according to their upskilling behavior. First, we examine mismatch patterns within each of three major (2-digit) high-skill occupations characterized as “pure upskillers”—defined as a major occupation in which all of its minor (3-digit) occupations engaged in persistent upskilling between 2007 and 2017. Figure 7 shows that for two out of three of these cases (e.g., Management; Computer and Mathematical)—we observe that mismatch was either roughly flat over the recovery period or experienced a net increase since 2010—as we would expect if persistent upskilling affected matching efficiency. The exception was Business and Financial occupations, which experienced a countercyclical mismatch pattern. In contrast, Figure 8 shows that mismatch within each of the three major middle-skill occupations—those that experienced either temporary or no upskilling—was flat or declining, as would be expected when the labor market is recovering. Finally, Figure 9 shows that mismatch within each of the nine low-skill occupations that experienced little or no upskilling also exhibited patterns that were flat or declining during the recovery period. Overall, 14 out of the 15 cases studied are consistent with the theory that that persistent upskilling contributed to either stable or rising mismatch during the recovery period, which contrasts from the more common pattern of a countercyclical increase followed by abatement in the recovery. Clearly, however, there are other factors at play that can affect matching efficiency, as demonstrated by our one exception.

The evidence that we have presented thus far suggests some connection between the persistence in rising employer skill requirements and stable or rising mismatch, potentially contributing to reduced matching efficiency in the aggregate and therefore to the shift in the

Beveridge Curve.<sup>20</sup> However, the sluggish wage growth observed during most of the recovery period seems inconsistent with the mismatch hypothesis (Rothstein 2012, Abraham 2015). To explore this further, we take a cursory look at wage growth by 2-digit SOC across occupations based on their upskilling behavior. We find that six out of the 10 persistent upskillers—and three out of four of the “true 100%” upskillers—experienced wage growth between 2010 and 2015 that was faster than in the aggregate (see Table A.3 in the appendix). Among the non-upskilling group, only two out of nine occupations had above-average wage growth. Moreover, most of the five 100% upskillers also experienced employment growth that was greater than in the aggregate during this period, yet this was not the case for the non-upskillers. Prior research suggests that if mismatch is present, then employment growth will be positively correlated with wage growth, an indication that the employment and wage growth trends reported here are consistent with the presence of mismatch in occupations that exhibited persistent upskilling in the high-skill sector. (Abraham 2015).<sup>21</sup>

## V. Conclusion and Policy Implications

Using a novel database of roughly 159 million online job postings aggregated by Burning Glass Technologies, we find that movements in the demand for and supply of skills vary across low-, middle-, and high-skill sectors. On the demand-side, education requirements increased

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<sup>20</sup> We estimate the Beveridge Curve by skill sector and find that the slope of the Beveridge Curve is correlated with education such that high-skill occupations exhibit the steepest relationship and low-skill occupations have the flattest. In addition, most of the improvement in the Beveridge Curve has come from movements in the curve for low- and middle-skill occupations which show large reductions in unemployment as the number of vacancies increased. In contrast, the reduction in unemployment among high-skill occupations has been much smaller relative to the number of vacancies created. While this is suggestive evidence of the persistent “wedge” that economists have observed in the aggregate Beveridge Curve during this period, other factors affecting vacancy yields and matching efficiency may also be shifting the Beveridge Curve during this period. See Figures A.12 through A.14 in the appendix.

<sup>21</sup> One reason for this could be that mismatch arises when some occupations have very high V/U ratios and others have very low ones. The occupations with high V/U ratios will need to raise wages a lot to get more employees, because their markets are very tight, whereas the occupations with low V/U ratios will have low employment growth (low demand) since they can fill their vacancies with smaller wage increases.

across all occupations during the recession but stayed elevated only among high-skill occupations during the recovery. In contrast, middle-skill occupations exhibited more temporary upskilling versus low-skill occupations that experienced little to no upskilling during the recession and recovery periods. Comparing trends in requirements for actual categories of skill revealed that the demand for software skills continued to increase during the recovery for occupations that exhibited persistent upskilling, which largely occurred in the high-skill sector. On the supply-side, the education levels of new hires in the high-skill exceeded that of continuing employees while those of unemployed workers fell below, suggesting that job searchers may no longer be qualified for jobs within that sector. In contrast, this appeared to be a temporary phenomenon within the middle- and low-skill sectors.

We also find evidence from a variety of sources that upskilling contributed to reduced matching efficiency in portions of the labor market, either temporarily or in a persistent fashion. For example, patterns in occupational mismatch since 2010 differed across the three skill sectors in a way that lines up with the patterns in upskilling by sector: high-skill occupations consistently displayed higher mismatch rates than did either middle-skill or low-skill occupations, and mismatch in the high-skill sector increased mid-recovery without fully reverting. In contrast, mismatch in either the middle-skill or low-skill sector moved in a strongly countercyclical fashion, recovering to very low levels by 2017. Considering mismatch unemployment by skill sector, the contribution of mismatch to unemployment in the high-skill sector remained substantial as of 2015 when the unemployment rate returned to its pre-recession level. Moreover, since 2010 this contribution actually increased as a share of the actual unemployment rate in the sector. In addition, mismatch trends measured within major occupations differ according to the extent of upskilling among minor occupations in the group,



offering some corroboration of the hypothesis that persistent upskilling contributed to mismatch between the composition of vacancies and the skills of the unemployed. Together these exercises suggest that lower matching efficiency in the high-skill portion of the labor market may reflect a shift in the composition of demand towards more specialized jobs, leading to imbalances between the demand for and the supply of certain skills.

We also offer some caveats to our findings. The mismatch index and our mismatch unemployment estimates are based on the numbers of *unemployed* job-seekers in various occupations. These measures ignore how other types of job-seekers—such as employed people conducting on-the-job search and some non-labor force participants—might influence the potential hiring rate and therefore the assessment of matching efficiency. Şahin et al. (2014) showed that their estimates of occupational mismatch were robust to including on-the-job searchers. On the other hand, Hall and Schulhofer-Wohl (2015) find that estimates of matching efficiency depend significantly on whether job-to-job seekers and NILF job-seekers are included.

Labor supply side factors might explain why we don't always observe persistently elevated mismatch within occupations that saw persistent upskilling, nor do we always observe dramatic increases in wages where we would expect. Just as there is evidence that temporary upskilling was an opportunistic phenomenon taking advantage of slack labor demand during the recession, long-run increases in the supply of highly educated workers may also have enabled persistent upskilling to occur.

Our findings have important implications for both the economics literature as well as labor market policy. Regarding the literature, our results identify an additional, plausibly structural, factor contributing to reduced matching efficiency in the aggregate that has not previously been investigated in detail. Furthermore, we demonstrate that equilibrium models

where unemployed workers accumulate specific human capital and make explicit mobility decisions across distinct labor markets, can be chasing a moving target—at least among high-skilled occupations (Kambourov and Manovskii 2009; Alvarez and Shimer 2011; and Carrillo-Tudela and Visscher 2013). Going forward, these frameworks can be modified to investigate the dynamics causing job seekers to search for work in the wrong sectors.

In terms of policy-making, the characteristics of occupations experiencing more persistent shifts in skill and education requirements can point to the potential structural forces underlying these observed trends. To that end, our findings can inform debates focused on workforce development strategies and related educational policies, where decision making could benefit from the use of real-time labor market information on employer demands to provide guidance for both job placement and program development.

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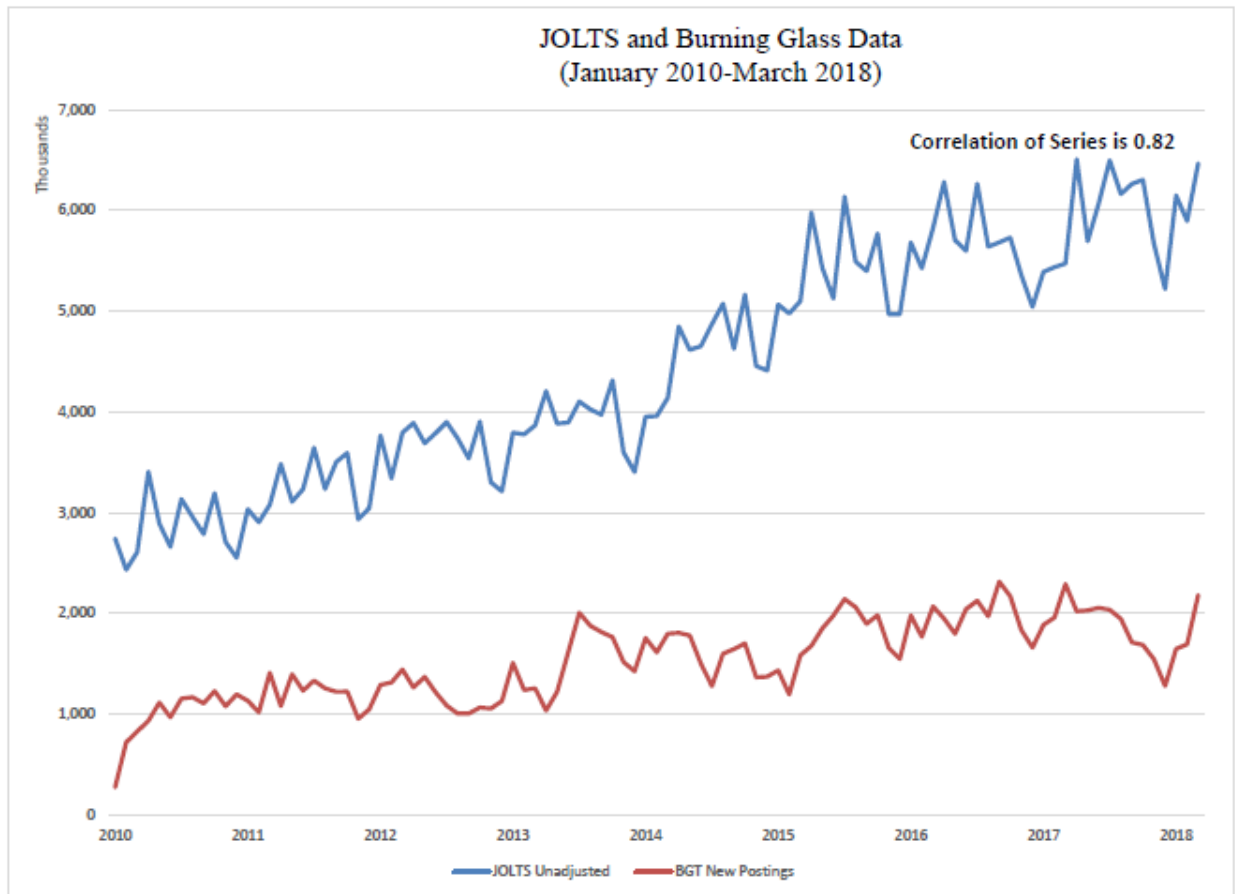
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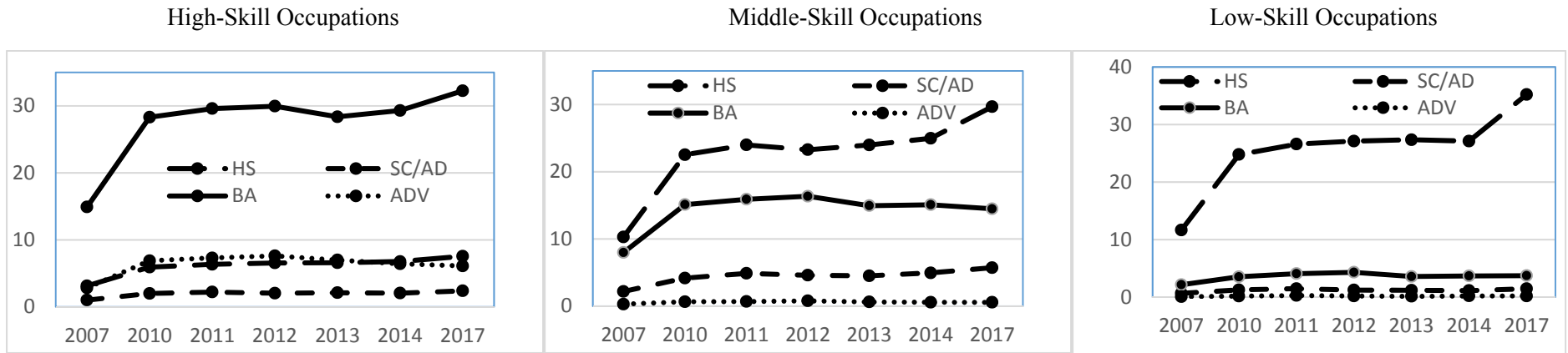
**Figure 1. Comparison of JOLTS and BGT Data**



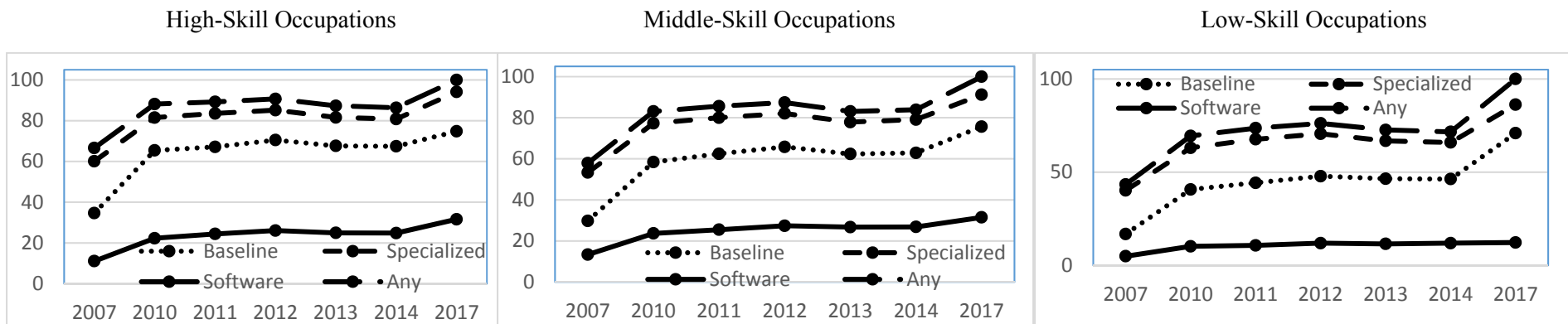
Source: Authors' calculations using data on online job vacancies from Burning Glass Technologies and job vacancies from the Bureau of Labor Statistics Job Openings and Labor Turnover Survey (JOLTS) for 2010-2018.

**Figure 2. Trends in Employer Requirements by Skill Sector, 2007-2017**

**A. Share of Postings Requiring Various Levels of Education**



**B. Share of Postings Requiring Various Types of Skills**



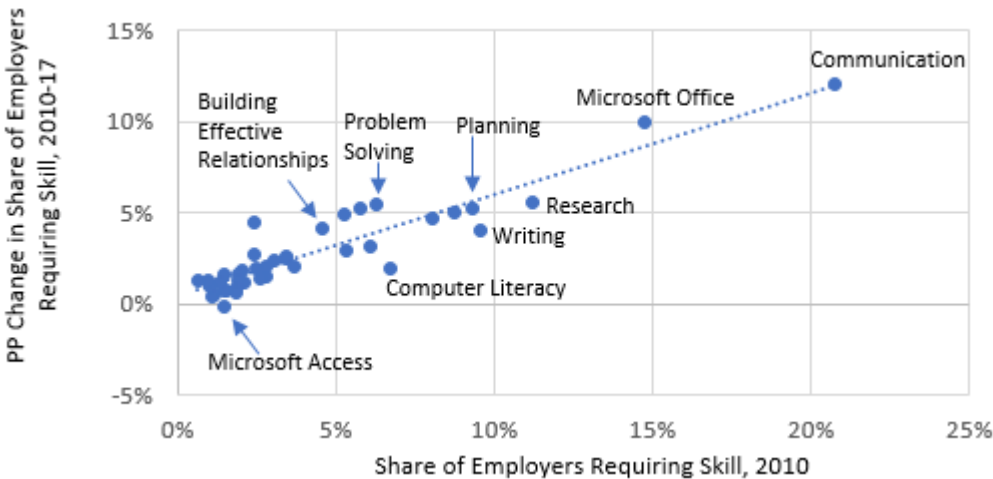
Source: Data on online job vacancies provided by Burning Glass Technologies for 2007 and 2010-2017.

Note: High-skill occupations are defined as those employing at least 40 percent of workers with a Bachelor’s degree or greater according to the 2005-07 combined American Community Survey. Low-skill occupations are defined as those employing at least 40 percent of workers with a high school education or less according to the 2005-07 combined American Community Survey. Middle-skill occupations are all other occupations that have no clear plurality of low- or high-skill workers.

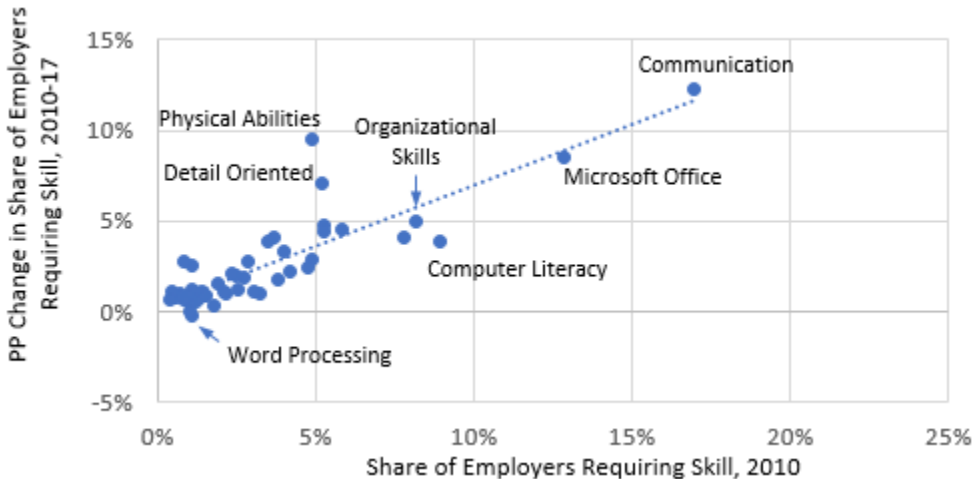


**Figure 3. Initial Level versus Change in Share of Postings Requiring Baseline Skills, 2010-17**

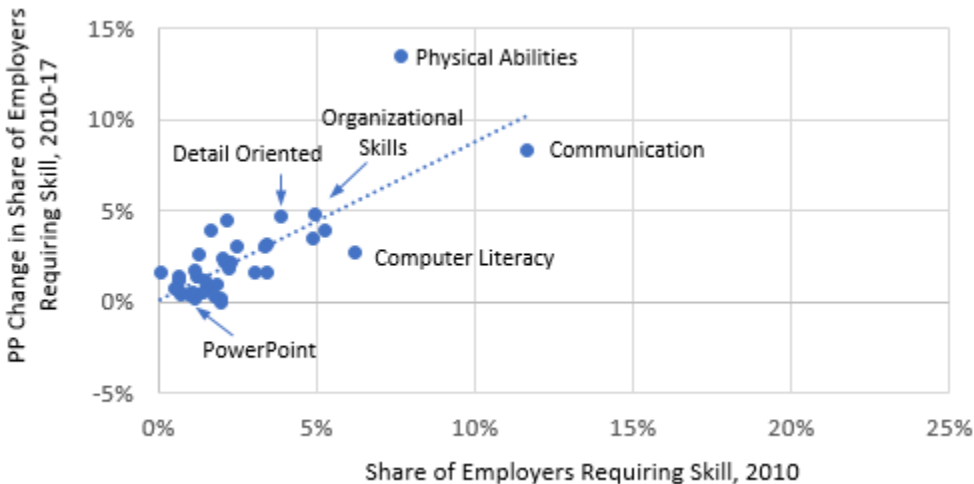
**A. High-Skill Occupations**



**B. Middle-Skill Occupations**

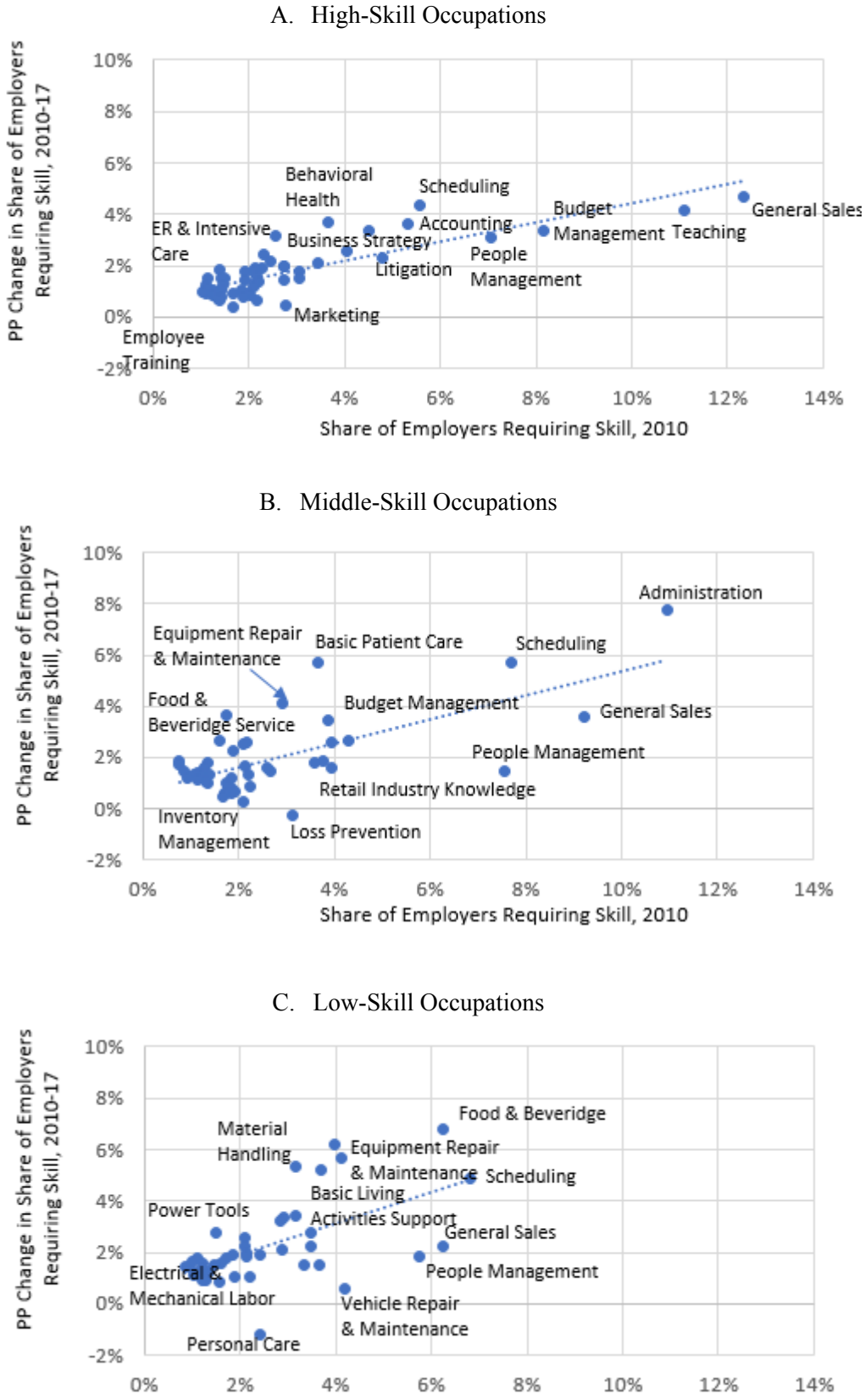


**C. Low-Skill Occupations**



Source: Data on online job vacancies provided by Burning Glass Technologies for 2010 and 2017.

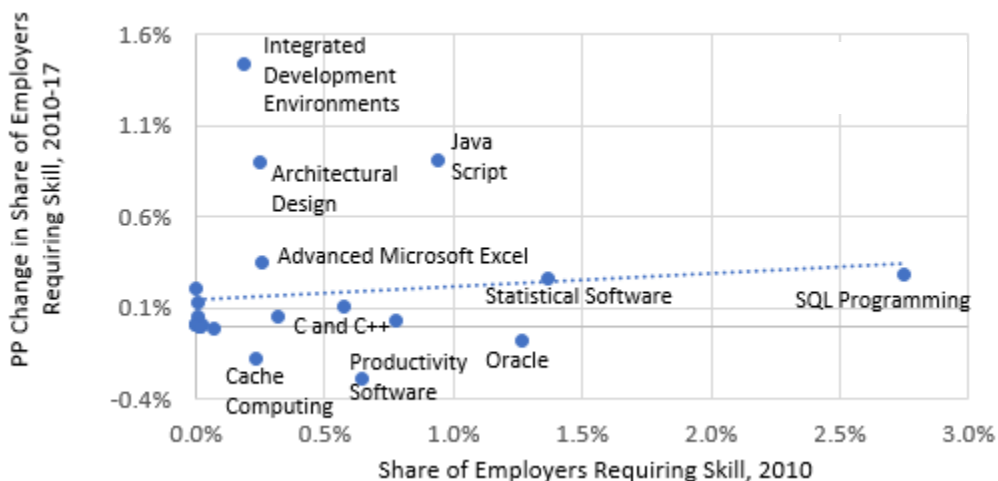
**Figure 4. Initial versus Change in Share of Postings Requiring Specialized Skills, 2010-17**



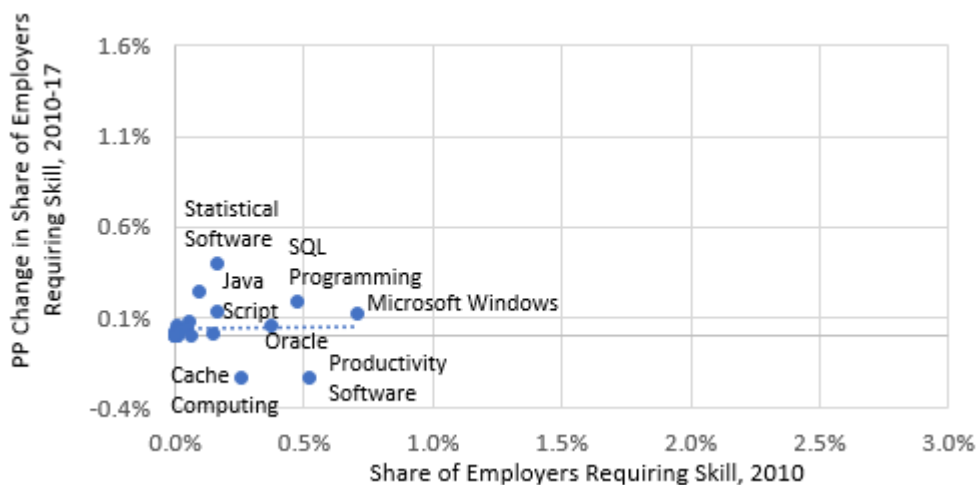
Source: Authors' calculations using data on online job vacancies from Burning Glass Technologies for 2010 and 2017.

**Figure 5. Initial versus Change in Share of Postings Requiring Software Skills, 2010-17**

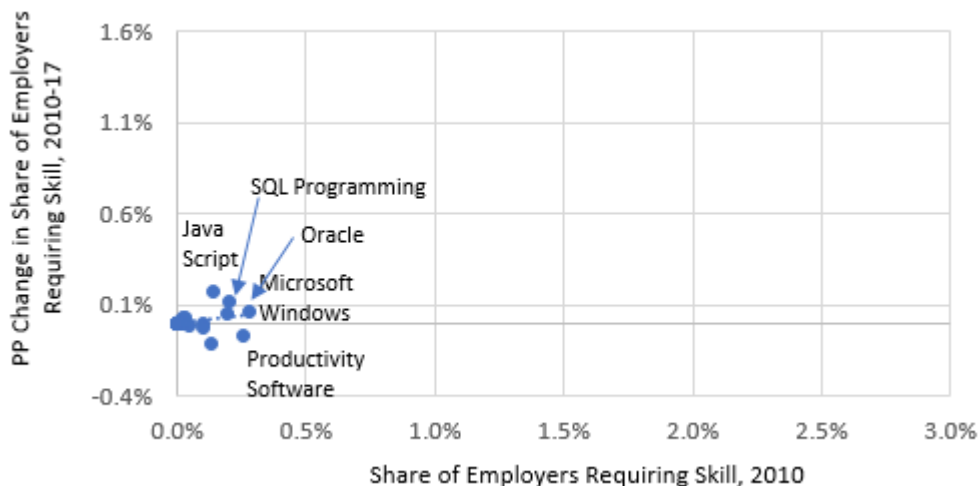
A. High-Skill Occupations



B. Middle-Skill Occupations



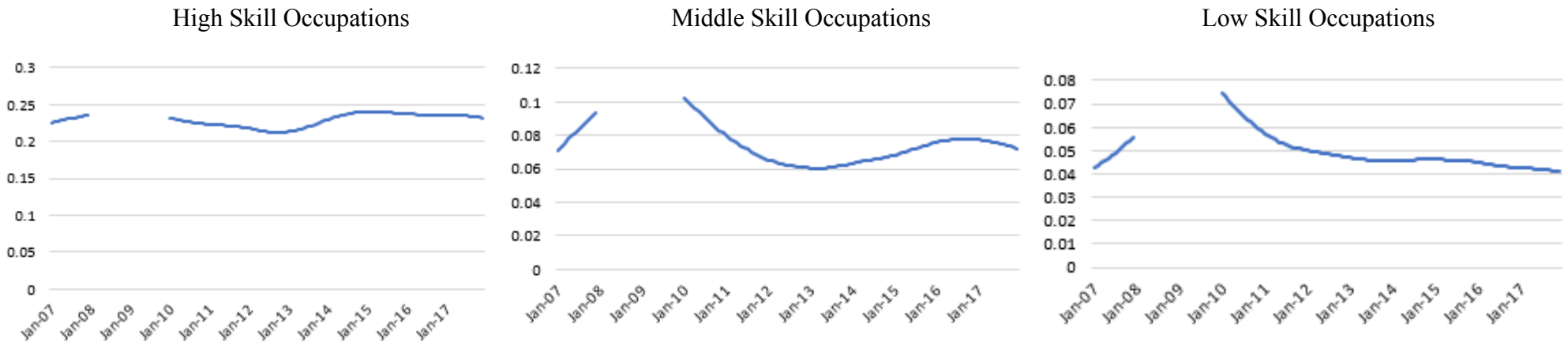
C. Low-Skill Occupations



Source: Authors' calculations using data on online job vacancies from Burning Glass Technologies for 2010 and 2017.

**Figure 6. Occupational Mismatch and Unemployment by Skill Groups (2 Digit SOC Level)**

**A. Mismatch Index Across 2-Digit Occupations**



**B. Mismatch Unemployment Across 2-Digit Occupations**



Source: Online job posting data provided by BGT and unemployment and labor force estimates from the CPS for 2007, and 2010 through 2017.

Note: The mismatch index and mismatch unemployment rate is calculated following the methodology of Şahin et. al. (2014). See the appendix for details.

**Figure 7. Mismatch Within 2-Digit High-Skill Occupations that Exhibited Persistent Upskilling**

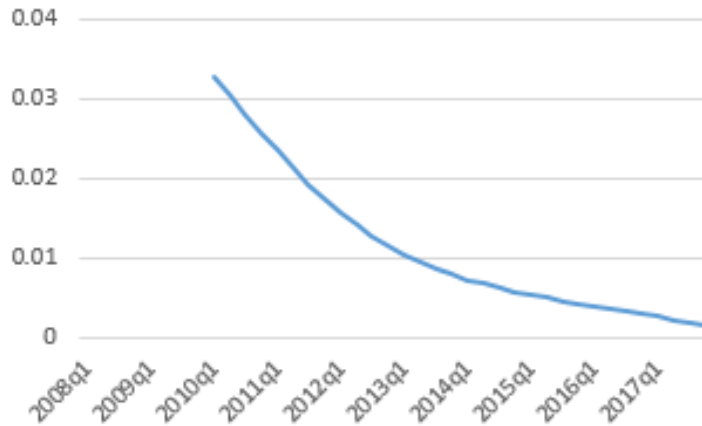
**A. SOC 11 – Management**



**B. SOC 15 – Computer and Mathematical**



**C. SOC 13 – Business and Financial**



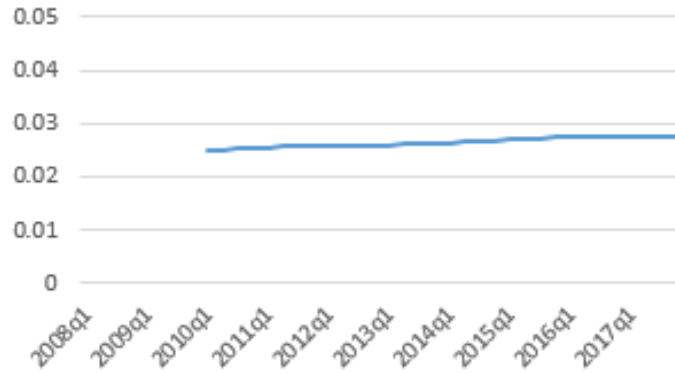
Source: Online job posting data provided by BGT and unemployment and labor force estimates from the CPS for 2010 through 2017. Note: The analysis was limited to 2-digit SOC with at least 1 million job postings in 2010. The mismatch index rate is calculated following the methodology of Şahin et. al. (2014). See the appendix for details.

**Figure 8. Mismatch Within 2-Digit Middle-Skill Occupations that Exhibited Temporary/No Upskilling**

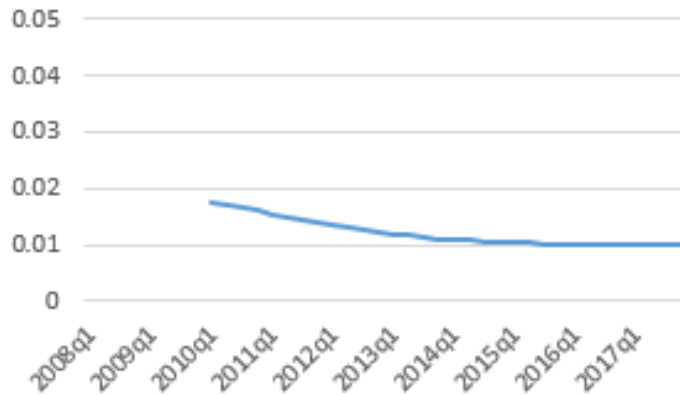
**A. SOC 31 – Healthcare Support**



**B. SOC 41 – Sales**

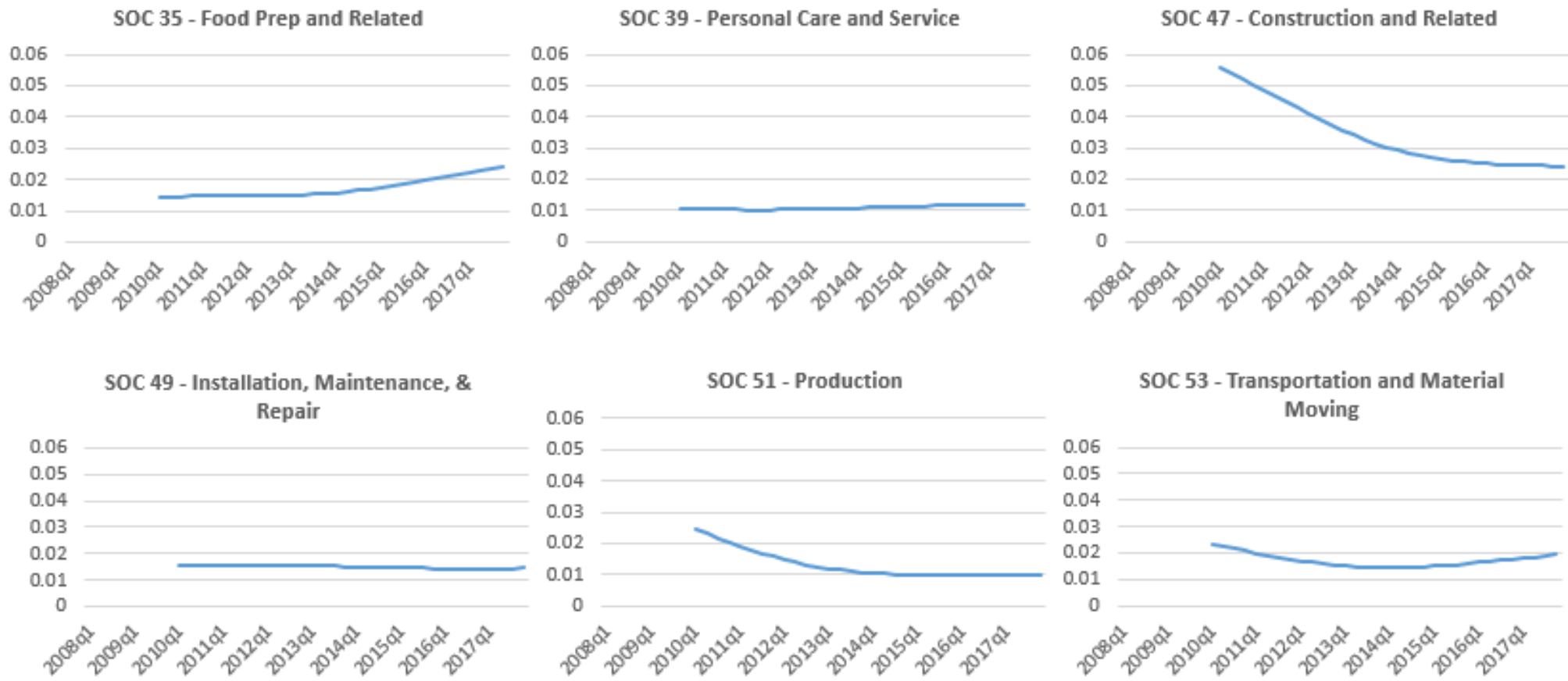


**C. SOC 43 – Office and Administrative**



Source: Online job posting data provided by BGT and unemployment and labor force estimates from the CPS for 2010 through 2017. Note: The analysis was limited to 2-digit SOC with at least 1 million job postings in 2010. The mismatch index rate is calculated following the methodology of Şahin et. al. (2014). See the appendix for details.

**Figure 9. Mismatch Within 2-Digit Low-Skill Occupations that Exhibited Temporary/No Upskilling**



Source: Online job posting data provided by BGT and unemployment and labor force estimates from the CPS for 2010 through 2017.

Note: The analysis was limited to 2-digit SOC with at least 1 million job postings in 2010. The mismatch index rate is calculated following the methodology of Şahin et. al. (2014). See the appendix for details.

**Table 1****Heterogeneity in Upskilling Across 3-Digit Occupations by Skill Group, 2007-2017****Panel A. Share of Each Skill Group by Upskilling Type**

|                          | Percent of Occupations that Engaged in: |                      |               |
|--------------------------|---|----------------------|---------------|
|                          | Persistent Upskilling                   | Temporary Upskilling | No Upskilling |
| All Occupations          | 39.6%                                   | 18.7%                | 41.8%         |
| Low-Skill Occupations    | 11.6%                                   | 18.6%                | 69.8%         |
| Middle-Skill Occupations | 40.0%                                   | 25.0%                | 35.0%         |
| High-Skill Occupations   | 82.1%                                   | 14.3%                | 3.6%          |

**Panel B. Distribution of Types of Upskilling by Skill Group**

|                       | Percent of Occupations that are: |           |            |
|-----------------------|----------------------------------|-----------|------------|
|                       | Low-Skill                        | Mid-Skill | High-Skill |
| All Occupations       | 47.3%                            | 22.0%     | 30.8%      |
| Persistent Upskilling | 13.9%                            | 22.2%     | 63.9%      |
| Temporary Upskilling  | 47.1%                            | 29.4%     | 23.5%      |
| No Upskilling         | 79.0%                            | 18.4%     | 2.6%       |

Source: Data on online job vacancies for 2007, 2010, and 2017 are from Burning Glass Technologies.

Note: An occupation is classified as “low-skill” if at least 40 percent of its workers had completed only high school or less and “high-skill” if at least a plurality (40 percent) of employed workers in that occupation had completed a bachelor’s degree or higher. Occupations in which neither of those criteria is met are classified as “middle-skill.” An occupation is defined as having upskilled during the Greater Recession if there was at least a 5 percentage point increase in the share of postings requiring a Bachelor’s degree or higher during the Great Recession (between 2007 and 2010). Occupations with less than a 5-percentage point increase in bachelor’s degree requirements during the recession are classified as having “no upskilling”. We further define an occupation as a “persistent upskiller” if the share of postings requiring a Bachelor’s degree then declined by less than half (2.5 percentage points) during the recovery period (between 2010 and 2017). In contrast, an occupation is defined as a “temporary upskiller” if the share of postings requiring a Bachelor’s degree were reversed by a more than half (2.5 percentage-points) during the recovery period. Shares are weighted by the occupation's share of total employment as of 2006.



**Table 2. Difference-in-Difference Analysis of Skill Requirements: Permanent versus Temporary Upskilling Occupations, 2007-2010-2017**

|                                    | Change in Skill Requirements |       |           |                       |        |            |
|------------------------------------|------------------------------|-------|-----------|-----------------------|--------|------------|
|                                    | Recession: 2007 to 2010      |       |           | Recovery 2010 to 2017 |        |            |
|                                    | 2007                         | 2010  | Diff      | 2010                  | 2017   | Diff       |
| Share Requiring a BA               |                              |       |           |                       |        |            |
| Persistent Upskillers              | 19.49                        | 37.29 | 17.80 *** | 37.29                 | 41.11  | 3.82       |
| Temporary Upskillers               | 13.87                        | 27.43 | 13.56 *** | 27.43                 | 14.88  | -12.55 *** |
| Diff                               | -5.61                        | -9.86 |           | -9.86                 | -26.23 |            |
| Diff-in-Diff                       |                              |       | -4.24     |                       |        | -16.37 *** |
| Share Requiring Baseline Skills    |                              |       |           |                       |        |            |
| Persistent Upskillers              | 38.56                        | 68.61 | 30.05 *** | 68.61                 | 79.98  | 11.38 ***  |
| Temporary Upskillers               | 33.74                        | 65.12 | 31.38 *** | 65.12                 | 76.03  | 10.91      |
| Diff                               | -4.82                        | -3.49 |           | -3.49                 | -3.96  |            |
| Diff-in-Diff                       |                              |       | 1.33      |                       |        | -0.47      |
| Share Requiring Specialized Skills |                              |       |           |                       |        |            |
| Persistent Upskillers              | 58.07                        | 81.09 | 23.03 *** | 81.09                 | 93.39  | 12.29 ***  |
| Temporary Upskillers               | 47.46                        | 73.56 | 26.11 *** | 73.56                 | 89.30  | 15.73      |
| Diff                               | -10.61                       | -7.53 |           | -7.53                 | -4.09  |            |
| Diff-in-Diff                       |                              |       | 3.08      |                       |        | 3.44       |
| Share Requiring Software Skills    |                              |       |           |                       |        |            |
| Persistent Upskillers              | 13.48                        | 24.97 | 11.49 *** | 24.97                 | 33.85  | 8.88 **    |
| Temporary Upskillers               | 9.29                         | 20.23 | 10.93 *** | 20.23                 | 20.75  | 0.52       |
| Diff                               | -4.19                        | -4.74 |           | -4.74                 | -13.11 |            |
| Diff-in-Diff                       |                              |       | -0.56     |                       |        | -8.37 ***  |
| Share Requiring Any Skills         |                              |       |           |                       |        |            |
| Persistent Upskillers              | 65.62                        | 88.11 | 22.49 *** | 88.11                 | 100.00 | 11.89 **   |
| Temporary Upskillers               | 51.92                        | 80.83 | 28.92 *** | 80.83                 | 100.00 | 19.17 **   |
| Diff                               | -13.71                       | -7.28 |           | -7.28                 | 0.00   |            |
| Diff-in-Diff                       |                              |       | 6.43 *    |                       |        | 7.28 **    |

Source: Data on online job vacancies provided by Burning Glass Technologies for 2007, 2010, and 2017.

Notes: An occupation is defined as having upskilled during the Greater Recession if there was at least a 5 percentage point increase in the share of postings requiring a Bachelor’s degree or higher during the Great Recession (between 2007 and 2010). We further define an occupation as a “persistent upskiller” if the share of postings requiring a Bachelor’s degree then declined by less than half (2.5 percentage points) during the recovery period (between 2010 and 2017). In contrast, an occupation is defined as a “temporary upskiller” if the share of postings requiring a Bachelor’s degree were reversed by a more than half (2.5 percentage-points) during the recovery period.

**Table 3. Change in Mismatch Unemployment by Skill Sector, 2010-15**

|                          | $u_{10} - u_{10}^*$ | $u_{10} - u_{10}^*/u_{10}$<br>(percent) | $u_{15} - u_{15}^*$ | $u_{15} - u_{15}^*/u_{15}$<br>(percent) | $\Delta(u - u^*)$ | $\Delta u$ | $\Delta(u - u^*)/\Delta u$<br>(percent) |
|--------------------------|---------------------|---|---------------------|---|-------------------|------------|---|
| Low Skill Occupations    | 0.87                | 7                                       | 0.46                | 6                                       | -.46 ppts         | -5.38 ppts | 7                                       |
| Middle Skill Occupations | 0.94                | 14                                      | 0.41                | 12                                      | -.52 ppts         | -3.33 ppts | 16                                      |
| High Skill Occupations   | 1.48                | 31                                      | 0.82                | 47                                      | -.66 ppts         | -3.16 ppts | 21                                      |

Source: Online job vacancy data provided by Burning Glass Technologies, unemployment and labor force estimates from the CPS.

Note:  $\Delta u$  varies by skill level. See the appendix for details.