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DISCUSSION PAPER SERIES

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ABSTRACT

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

Although labor market "mismatch" often refers to an imbalances in supply and demand across occupations, mismatch within occupations can arise if skill requirements are changing over time, potentially reducing aggregate matching efficiency within the labor market. To test this, we examine changes in employer education and skill requirements using a database of 200 million U.S. online job postings between 2007 and 2019. We find that the degree of persistence in educational upskilling lasted longer than was previously known and was not uniform but rather varied considerably across occupations and was often coupled with an increased demand for software skills. We also find evidence that upskilling contributed to reduced matching efficiency in certain segments of the US labor market as well as in the aggregate. In particular, matching efficiency was lower in higher-skilled occupations, potentially because they are becoming more specialized, and possibly explaining growing wage polarization and inequality.

JEL Classification: D22, E24, J23, J24, J63

Keywords: labor demand, skills, vacancies, unemployment, firm behavior

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Although the term "mismatch" often refers to imbalances in the supply of and the demand for labor *across* occupations, mismatch *within* occupations can also arise if the skill requirements for a job are changing over time. Prior research has established that US employers rapidly increased education and experience requirements within occupations when hiring for open positions during the Great Recession, a trend that became known as "upskilling" (Modestino, Shoag, and Ballance, 2020). Although roughly one-third of the upskilling that occurred during the last recession was shown to have been cyclical or temporary, as much as two-thirds of the increase appeared to have persisted at least through 2015 (Modestino, Shoag, and Ballance 2016), possibly driven by structural forces such as skill-biased technological change (Hershbein and Kahn 2018).

What are the potential implications of these large shifts in education requirements during recessions for workers as well as for the labor market? If education requirements within jobs increase only gradually over time, labor supply can presumably adjust with minimal lags. However, during recessions, employers may increase skill requirements more rapidly—perhaps opportunistically but also in response to adopting new technologies—having adverse impacts on certain groups of workers and leading to larger imbalances between labor supply and demand that take longer to resolve—the proverbial "race between education and technology" (Goldin and Katz, 2008). Indeed, Figure 1 shows that the economy-wide share of vacancies requiring at least a bachelor's degree jumped by 12 percentage points—or nearly 75 percent—from 2007 to 2010, an increase that was only partially reversed over the next three years and remained relatively persistent through 2019. This large and persistent increase in educational requirements suggests that some unemployed workers would no longer have qualified for the positions they once held, lacking the newly demanded skills and/or credentials. For unemployed workers, persistent educational upskilling may have led to an extended spell of unemployment due to the need to retrain, a switch to another (possibly lower paying) occupation, or to an exit from the labor force entirely. If the supply of workers with the required credentials lagged demand for an extended period of time, this could have impaired matching efficiency in the affected occupations and possibly in the aggregate, potentially explaining the slower labor market recovery during the Great Recession (Cavounidis et al. 2021).

Using the near-universe of roughly 200 million online job postings in the United States collected by Lightcast (formerly Burning Glass Technologies), we compare changes in employer skill and education requirements between 2007 and 2019. We further explore the implications of persistent educational upskilling for the labor market as well as for certain groups of workers, namely those without a bachelor's degree. Extending an index of occupational mismatch developed by Sahin et al. (2014), we test whether persistent educational upskilling within occupations led to increased labor market mismatch during the Great Recession and subsequent recovery period. Our innovation comes from recognizing that persistent upskilling within occupations shifts the composition of vacancies in affected occupations towards workers with a bachelor's degree, possibly creating misalignment with the distribution of unemployed workers by education within those occupations.

We document a novel set of stylized facts about educational upskilling dynamics during the Great Recession, including the extent to which upskilling persisted throughout the recovery, the types of occupations that showed persistent increases in demand for bachelor's degrees, which underlying skills might be driving this persistence, and the implications for individual labor market outcomes and aggregate matching efficiency. Together, these new empirical facts provide important contributions to the literature. In particular, ours is the first paper to show that the degree of persistence in educational upskilling lasted longer than was previously known and was not uniform but rather varied considerably across occupations. Second, we demonstrate that this pattern of persistence in educational upskilling was often coupled with an increased demand for software skills, offering further evidence that structural upskilling was driven by the adoption of new technologies. Third, ours is the first paper that demonstrates the implications of persistent educational upskilling on aggregate matching efficiency, potentially reconciling the view among many economists that occupational mismatch was not a key factor in the slower employment recovery after the Great Recession with that of employers who claimed having difficulty finding skilled workers (Abraham 2015 and Davis, Faberman, and Haltiwanger 2012). Our analysis of an adjusted mismatch index suggests that these divergent views could arise because standard measures of mismatch fail to capture labor market imbalances caused by shifts in education or skill demands occurring *within* major occupations over time. Search-and-matching models of the labor market may need to account for workers chasing this moving target—at least within certain occupations.

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 (2020) show that the share of job postings requiring a four-year college degree increased by 10 percentage points during the Great Recession. They estimate that about one-third of the upskilling they observe was an opportunistic response to the greater availability of workers during that period. In a separate paper, they 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 Ballance 2016).

On the structural side, a complementary set of papers show that up to two-thirds of the upskilling that occurred during the Great Recession was persistent, possibly reflecting a permanent change in job requirements (Hershbein and Kahn 2018; Zago 2018; Blair and Deming 2020). This structural upskilling may have reflected longer-term trends such as skill-biased technological change (Katz and Murphy 1992; Autor, Katz, and Krueger 1998; Autor, Levy, and Murnane 2003) and labor market polarization (Autor, Katz, and Kearney 2008; Autor and Dorn 2008; Acemoglu and Autor 2010). In addition, cyclical forces stemming from the Great Recession may have reinforced these structural trends, as recessions have been shown to induce or accelerate long-term changes in the labor market (Hershbein and Kahn 2018; Charles, Hurst, and Notowidigdo 2012; Jaimovich and Siu 2020; Tuzeman and Willis 2013; Beaudry, Green, and Sand 2016).

One remaining explanation repeatedly put forth by employers, but receiving relatively little support from the empirical literature, was labor market mismatch. One notable exception is Şahin et al. (2014), who show that mismatch between job vacancies and unemployed workers across industries and occupations increased significantly during the Great Recession, contributing to lower matching efficiency (and therefore higher unemployment) in the aggregate, consistent with the outward shift in the Beveridge curve that occurred at the time.[1] In a related vein, Restrepo (2015) posits a model in which structural changes can lead to skill mismatch that restrains job growth for an extended period, such as when new technologies create jobs requiring skills that few workers possess and take time to acquire. In particular, the paper provides

[1]In disaggregated measures of occupational mismatch by education, Sahin et al. found that the contribution of mismatch to the increase in unemployment during the Great Recession—in relative terms, not absolute terms--was greatest for the college-educated group. However, mismatch by education sector as they measure it could not have been caused by educational upskilling within detailed occupations, as their methods hold education demands fixed by occupation over time.

evidence that the structural decline in routine-cognitive jobs resulted in skill mismatch that contributed to the large and long-lasting increases in unemployment during the Great Recession.

Although measures of labor market mismatch across occupations fell during the recovery period (Burke 2015), aggregate matching efficiency remained below pre-recession levels even after 2015 (Hobijn and Perkowski 2016; Hall and Schulhofer-Wohl 2018). However, the sluggish wage growth observed during most of the recovery period seems inconsistent with this mismatch hypothesis (Rothstein 2012; Abraham 2015). Several papers argue that weak aggregate demand offers a more convincing explanation for the outward shift of the Beveridge curve during the Great Recession than either 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; Weaver and Osterman 2017).

Yet, few studies examine skills mismatch *within* occupations or even changes in skill requirements and workers by occupation. Using the US Department of Labor's O*NET database, Vaisey (2006) compares the education requirements for various jobs to the educational attainment of incumbent workers and finds that the average worker was overqualified for their job as of 2002. Liu and Grusky (2013) also use O*NET and find evidence that certain skill requirements—including computer skills, analytical skills, and quantitative skills—had increased within job categories since 1979, but that the increases were 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 and Murphy 1992; Autor, Katz, and Krueger 1998; Autor, Levy, and Murnane 2003), some earlier papers disagreed as to whether the adoption of new technologies raised skill requirements *within* jobs (for example, see Acemoglu 2002; Zicklin 1987; and Keefe 1990).

More recent papers, however, find stronger evidence linking technological advances to upskilling within occupations. Hershbein and Kahn (2018) show that upskilling during the Great Recession coincided with routine-biased technological change that was occasioned by the recession itself. In addition, three recent papers find evidence that technological change raises skill requirements in some occupations, with negative consequences for some incumbent workers. For example, Braxton and Taska (2023) find that technological change results in large earnings losses among displaced workers, who resort to lower-paying jobs after skill demands in their former occupations increase. Similarly, Bessen, Denk, and Meng (2022) link technological adoption to increases in skill demands across a wide variety of occupations and argue that such changes have contributed to growing wage inequality within occupations. Similarly, Kogan et al. (2022) find evidence that technological change not only displaces low-skilled labor through automation but also depresses earnings growth among some (e.g., older) high-skilled workers, whose skills become obsolete because of technological adoption. Restrepo (2015) also emphasizes labor-market disruptions caused by skill mismatch brought on by technological change where new skill demands are embodied in wholly novel job descriptions, rather than the skills being newly demanded in existing jobs.

Some researchers question whether the requirements listed on job openings are binding, or instead are indicative of problems related to overqualification, rather than underqualification, within occupations (Cappelli 2014). However, jobs that require relatively high computer usage experienced large increases in wages at the upper end of the wage distribution relative to occupations involving less computer usage (Bessen 2014). Similarly, states that experienced greater job polarization during the recession—defined as a loss of routine middle-skill jobs compared to low-skill and high-skill jobs—also experienced a greater mismatch in educational qualifications during the recession and through the end of 2013 (Zago 2018).

We build on these different strands in the labor market literature by describing detailed patterns in educational upskilling that occurred over the full business cycle of the Great Recession from 2007 through 2019, drawing out the extent and contours of within-occupation changes in education and skill demands more fully than has been done previously. While such descriptions are interesting on their own, we contribute further by examining the implications of upskilling for both affected workers in those occupations as well as matching efficiency during the recovery from the Great Recession.

Data and Methods

Our primary objective is to reveal new facts about educational upskilling *within* occupations during and after the Great Recession and to examine their broader labor market implications for workers as well as for aggregate matching efficiency. Occupational mismatch is particularly important since workers can potentially qualify for similar jobs in other industries when aggregate demand falls but are less able to qualify for jobs in other occupations. We focus on educational upskilling, specifically the requirement for workers to have a bachelor's degree, because obtaining a bachelor's degree takes significant time and financial resources. In addition, completion is easily verifiable, making it a meaningful hurdle for employment. In this paper, we aim to answer the following research questions:

- Did the educational upskilling that occurred during the Great Recession (2007-2010) persist throughout the subsequent labor market recovery (2010-2019)? Was this persistence in the demand for a bachelor's degree uniform throughout the labor market? To what degree did this persistence reflect a compositional shift in job vacancies as opposed to increased demands for bachelor's degrees within detailed occupations?

- What was driving the persistence in educational upskilling during this period? What types of occupations engaged in persistent upskilling as opposed to engaging in only temporary (or little to no) upskilling during this period? Was the degree of persistence correlated with pre-recession occupational characteristics (e.g., employment, wage, or education levels)? For occupations that exhibited persistent educational upskilling, were there any specific skillsets that also showed persistent increases in demand?
- Did persistent educational upskilling within occupations harm matching efficiency, either within certain sectors of the labor market or in the aggregate? How can the usual indicators, such as the mismatch index, be adapted to detect the effects of changing educational requirements on matching efficiency?
- What are the implications of educational upskilling for workers? Did patterns of job finding rates and wage increases differ across BA versus non-BA workers within occupations depending on their upskilling patterns during and after the Great Recession?

To answer these questions, our analysis primarily consists of three parts. First, we use the near-universe of online job vacancy data provided by Lightcast to examine the demand-side changes in education and skill requirements within occupations over the business cycle, including the degree of persistence. Second, we combine the demand side data with information on unemployed workers and job flows from the Current Population Survey to generate new estimates of occupational mismatch that explore the link between persistent educational upskilling and aggregate matching efficiency. Third, we document the impact of persistent education upskilling on workers in terms of both job finding and wages.

Data Sources

Demand Side: Lightcast Online Job Posting Data

On the labor demand side, we use online job posting data collected by Lightcast (formerly Burning Glass Technologies) for 2007 and 2010–2019.[2] One of the leading vendors of online job posting data, Lightcast collects detailed information on more than 7 million current online job openings in the United States posted daily from over 40,000 sources that include job boards, newspapers, government agencies, and employer websites. Lightcast'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. Lightcast also mines over 70 job characteristics from the text of each job posting, including job title, employer name, location, years of experience, and level of education required.[3] Unlike other vendors of online job posting data, Lightcast also parses out other skills listed in the job ad that allows for measurement of skillsets beyond educational credentials.

Unlike prior research, we make use of two distinct versions of the Lightcast data. The first is the main dataset that is used by most researchers and is provided at the job-posting level on a monthly basis. It contains detailed data on the job title, occupation, industry, and location, as well as information on the requirements for education, experience, and skills. We pool the data by year which yields a time trend in the number of vacancies that closely tracks that of national surveys such as the JOLTS and also exhibits industry and occupation distributions that are very similar to those of state vacancy surveys.[4] We use this version of the Lightcast data for the upskilling analysis that describes the changes over time in employer demand for education and detailed types of skills at various levels of occupational detail.

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[2] Lightcast data are unavailable for 2008 and 2009 due to operational changes when the company was founded. This is the main reason for using three-year differences (e.g., 2007–2010),

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

[4] See Figure 1 in the appendix for more details. The Lightcast data tend to slightly over-represent industries such as finance, and slightly under-represent other industries, such as food services. Similarly, occupations such as management are slightly over-represented, while occupations such as food preparation are slightly under-represented.

Although the main Lightcast data closely track national and state surveys in terms of the *trend* in vacancies over time, the *number* of vacancies at a point in time is consistently lower in the Lightcast data than in the JOLTS. In part, this is because the JOLTS data include both online and offline job listings, such as those job openings that are circulated in print media, posted in shop windows, or posted internally within firms. In addition, the JOLTS specifically asks employers about the *number* of job openings, whereas a single online job posting in the Lightcast data may actually represent multiple job openings. In order to construct our mismatch indices (described in further detail below) we need an accurate number of vacancies by occupation and education requirement over time. Fortunately, Lightcast created a normalized (reweighted) dataset that exactly matches the monthly number of vacancies by industry as measured by the JOLTS, data that are then disaggregated by occupation using the distribution from the main Lightcast dataset.[5] We use this normalized version of the Lightcast data when calculating the number of vacancies by occupation and education to construct our mismatch indices.

Supply Side: Current Population Survey Microdata

On the labor supply side, we make extensive use of the Bureau of Labor Statistics's Current Population Survey (CPS) microdata (Flood et al. 2018) from 2007 through 2019. To construct our mismatch indexes, we use the CPS data to measure the number of unemployed workers by combination of 3-digit occupation and education level (having either completed a bachelor's degree or not). We then make use of the longitudinal dimension of the CPS to track job-finding rates within occupation groups characterized by upskilling behavior and worker education levels. The details of how we construct these various measures from the CPS data are provided below and in the appendix.

[5] This normalized Lightcast dataset is available for 2007 and 2010-2017.

Other Labor Market Data

We also make use of other labor market data to measure pre-recession occupational characteristics as well as changes over time in employment and wages at the three-digit SOC level. First, we use the American Community Survey (ACS) to calculate annual employment and the share with a bachelor's degree to disaggregate movements in the supply of labor within versus between occupations. Second, we use the Occupational Employment Statistics (OES) to measure median wages and wage inequality (e.g., ratio of wages at the 75th versus the 25th percentiles) to study the impact of educational upskilling on different groups of workers.

Methods

Measuring Demand-Side Educational Upskilling within Occupations

Using the Lightcast data, we first examine whether demand-side changes in education and skill requirements were merely temporary or instead persisted during the Great Recession and its subsequent recovery. As shown in Table 1, the share of postings requiring a bachelor's degree or higher increased by 10.7 percentage points on average across occupations (weighted by employment) during the recession period (2007-2010).[6] Yet on average upwards of 17 percent of this increase was reversed initially during the short-term recovery period (2010-2013) and as much as 10 percent over the longer-term (2010-2019).

Rather than simply measuring persistence in the aggregate as has been investigated in prior research, we measure persistence within occupations to better capture the implications for both affected workers as well as for aggregate matching efficiency. We believe this is an important distinction because one would expect that temporary educational upskilling might have increased labor market mismatch in the short-term for some occupations during the Great

[6] Note that we exclude military occupations as the requirement for having a bachelor's degree is often associated with having a rank of officer and is likely to not be as responsive to market demands.

Recession (2007-2010), potentially lengthening unemployment spells for workers without a bachelor's degree but would have resolved relatively quickly as the labor market initially recovered (2010-2013). In contrast, persistent educational upskilling could have affected matching efficiency within a subset of occupations for a longer period of time, resolving more slowly as workers either obtained the necessary credentials or switched to other occupations, with the potential for affecting aggregate matching efficiency if sufficiently widespread.

To operationalize this approach, we define an occupation as having experienced significant educational "upskilling" during the Great Recession if the percentage point change in the share of postings requiring a bachelor's degree or higher between 2007-2010 was *greater* than the economy-wide average increase of 10.7 percentage points that was observed across occupations.[7] Those upskilling occupations that subsequently experienced *less* than a 10 percent reversion of their initial increase, during both the initial recovery (2010-2013) and in the longer-term (2010-2019), are designated as "persistent educational upskillers." This threshold is based on the economy-wide average reversion 10 percent that was observed across occupations in the share of postings requesting a bachelor's degree. [8] Those upskilling occupations that experienced more than a 10 percent reversion in their demand for a bachelor's degree during both the short- and longer-term recovery periods are designated as "temporary educational upskillers." Occupations that initially had below-average increases in the share of postings requiring a bachelor's degree during the recession (2007-2010) are designate as having experienced no significant educational upskilling. Using these definitions, we classify each 2-digit and 3-digit

[7] Note that we use the percentage point change to avoid designating occupations with large percent changes in the share of postings requiring a bachelor's degree off of a small initial base as having a significant increase in educational upskilling.

[8] More conservative definitions of persistent upskilling, such as requiring no reversion at all, as well as a more liberal definition allowing up to a 20 percent reversion in BA demand produces results that are qualitatively similar.

SOC code in terms of its education upskilling behavior and examine the degree to which these changes reflected a compositional shift in job vacancies across, as opposed to increased demands for bachelor's degrees within, the associated (six-digit) detailed occupations.

We then examine what could be driving the persistence in educational upskilling during this period using a variety of methods. First, we calculate the correlation between educational upskilling and the pre-recession characteristics of occupations in terms of employment, worker education levels, and wages using the variables constructed in Table 1. This allows us to examine whether educational upskilling was more prevalent among occupations of a certain size, those with a higher share of educated workers, or those with greater productivity (as measured by wages).

Second, we examine changes in the demand for specific skillsets in relation to educational upskilling behavior by occupation as listed in Table 1. Lightcast groups these skills into broad categories of common skills (e.g., leadership), specialized skills (e.g., accounting), or software skills (e.g., Oracle). We use a difference-in-difference-in-difference analysis to test whether occupations that engaged in persistent educational upskilling also had persistent increases in the share of postings requiring skills of a given type, relative to occupations that exhibited no significant upskilling. We then delve further into the skills data, describing changes in the most frequently requested skill clusters within each of the broader categories to determine whether employers were simply seeking more of the same skillsets for a given occupation or requiring an entirely new set of skills. This allows us to examine whether educational upskilling was related to structural changes in the nature of the job, compared to changes in broad education requirements that could simply reflect signaling.

Labor Market Mismatch under Persistent Educational Upskilling

Sahin et al. (2014) develop an index of labor market mismatch quantifying the fraction of potential hiring that is lost due to a misallocation of unemployed workers relative to the distribution of vacancies.[9] By construction, the values of the index range from zero (in the case that all potential hires occur) to one (the other extreme in which none of the potential hires occur). We improve on their mismatch index in two important ways: one conceptual and the other empirical.

Our conceptual innovation consists of incorporating the effects of persistent educational upskilling into the index. This approach represents a natural, structural extension of the mismatch framework that is designed to capture the potential misalignment of vacancies and workers along the dimension of education.[10] The approach posits simply that employees with different levels of education within an occupation can be treated as searching in separate labor markets for jobs with different education requirements.

In the case of an economy with just two labor markets, a BA market and a non-BA market, hiring will be perfectly efficient (with zero mismatch) if and only if the share of vacancies requiring a BA is identical to the share of jobseekers with a BA, where this condition is readily adapted to allow for different matching efficiencies and productivity levels by education sector. As an illustration, assume that the economy starts at an efficient allocation—for example let 25 percent of vacancies require a BA and 25 percent of jobseekers have a BA. If the

[9]In the mismatch framework, the labor market is frictional in the sense that a given worker is assumed to search for jobs only within a circumscribed set of ocupations (e.g., a 3-digit SOC code) and a firm only hires workers who are searching within the 3-digit occupation. These assumptions seem more plausible for 3-digit SOC categories than for more narrowly defined occupations, although estimates of occupational mobility vary widely. For example, Molloy, Smith, and Wozniak (2017) observed that during the 2000s, there was a 4 percent transition rate across 3-digit SOC codes, while Kambourov and Manovskii (2009) reported finding a 21 percent transition rate across 3-digit SOC codes during the 1990s.

[10]Sahin et al. (2014) measured mismatch along the dimensions of occupation, industry, and geography, and also measured occupational mismatch within different education "sectors." However, their mismatch index does not capture reductions in aggregate matching efficiency over both occupation and education simultaneously.

share of vacancies requiring a BA increases abruptly, then holding the composition of jobseekers fixed, total hiring would fall below its optimal level until more jobseekers could attain a BA and eventually restore the equality between vacancy shares and jobseeker shares by education. Such a shift in education demands might be occasioned by technological advances that augment the productivity of highly-educated workers relative to less-educated workers.

To operationalize this idea, we treat vacancies for the same 3-digit occupation (among persistent educational upskilling occupations) as pertaining to different labor markets according to whether the vacancy requires a bachelor's degree or not, and similarly treat unemployed workers in a given 3-digit occupation as searching in different markets according to their degree status. We limit the educational segregation to the persistent upskillers in order to isolate the contribution of persistent upskilling to mismatch over the time period.[11]

Mathematically, the mismatch index developed by Sahin et al (2014) is based on a Cobb-Douglas matching function.[12] Building on their prior research, our adjusted mismatch index can be written as follows:

$$M_{tA} = 1 - \sum_{i=1}^{I} \sum_{j=0}^{1} \frac{\sigma_i}{\overline{\overline{\phi}}_t} \left(\frac{v_{ijt}}{v_t}\right)^{\delta} \left(\frac{u_{ijt}}{u_t}\right)^{1-\delta} - \sum_{k=1}^{K} \frac{\sigma_k}{\overline{\overline{\phi}}_t} \left(\frac{v_{kt}}{v_t}\right)^{\delta} \left(\frac{u_{kt}}{u_t}\right)^{1-\delta}$$

In the above equation, M_{tA} denotes the value of the adjusted mismatch index in month *t*. Persistent educational upskilling occupations are indexed by *i* and all other occupations (those exhibiting temporary or no education upskilling) are indexed by *k*. Education is indexed by *j*, which takes a value of 1 if the vacancy requires a bachelor's degree or higher (or, on the supply

[11] This also produces more conservative estimates of mismatch given that increases in education requirements for temporary upskilling occupations were reversed and those for non-upskilling occupations were relatively small.
[12] See the appendix for further details on the mismatch index developed by Sahin et al (2014).

side, if the worker has a bachelor's degree or higher) and equals zero otherwise . The term v_{ijt} refers to the number of vacancies in month t in the 3-digit occupation i (a persistent upskiller) with the given education requirement (either 1 or 0, for BA-requiring or not), v_{kt} is the number of vacancies in the 3-digit occupation k (which was not a persistent upskiller) in month t, regardless of education requirement, and v_t is the total number of vacancies in the economy at time t.

On the labor supply side, u_{ijt} represents the number of unemployed workers in occupation i with education level j (either BA or better, or not) as of month t, u_{kt} refers to the number of unemployed workers in occupation k in month t, and u_t denotes the total number of unemployed workers in the economy in month t. Unemployed workers are assigned to occupations and education levels based on the one they report in the CPS. The term σ_i is a parameter capturing matching efficiency specific to occupation i, which is not specific to the education requirement of the vacancy, and σ_k represents matching efficiency for occupation k.[13] The term $\overline{\phi_t}$ refers to a CES aggregator of the market-specific matching efficiencies weighted by their respective vacancy shares.

For comparison, we also calculate the standard occupational mismatch index for the same time period, treating all vacancies (or unemployed workers) in the same 3-digit occupation as belonging to the same labor market, regardless of their education requirement or level. In the equation above, these latter calculations simply drop the j subscript from all relevant terms. We also calculate mismatch indexes separately within the BA-requiring sector of the labor market and the non-BA requiring sector—segregating all occupations by education before doing so, to

[13]These parameters vary across individual 3-digit occupations—there is no component that is common to the persistent upskillers versus the other occupations. Their respective values are taken from those in Sahin et al. (2014).

further explore how aggregate matching efficiency evolved differently across the two sectors.[14]

Our empirical innovation is to use the richness of the Lightcast data to incorporate the observed educational requirements of job vacancies as they evolve over time. Using the normalized Lightcast series to obtain the actual number of vacancies per 3-digit occupation and month, we then assign a distribution of education demands according to share of postings requiring a bachelor's degree for a particular occupation based on the monthly raw data.[15] In contrast, Sahin et al. (2014) held education demands by occupation fixed at imputed values throughout their analysis, and thus were unable to detect any reductions in hiring caused by a mismatch between the changing education demands of employers and the educational attainment of workers.[16]

The Impact of Educational Upskilling on Workers

We examine two potential impacts of educational upskilling on workers. The first impact is the likelihood of non-BA workers finding a job relative to that of workers who have a BA in occupations that experienced persistent educational upskilling versus those that did not. We calculate job-finding rates from unemployment using the CPS Microdata from IPUMS. Individuals are linked across different survey months using the "cpsidp" variable, and linkages

[14]Sahin et al. (2014) estimated occupational mismatch separately for different sectors of the labor market defined by education levels. These measures capture imbalances in the *occupational* composition of vacancies versus workers in a given education sector (e.g., college graduates) rather than capturing imbalances in the *educational* composition of vacancies versus workers across the aggregate labor market, as in our adjusted index described above.
[15]Because a single posting in the raw data may refer to multiple vacancies, we use the normalized Lightcast series to obtain the actual number of vacancies per 3-digit occupation and month. We then use the BA shares from the raw Lightcast data to parse out postings by education in the normalized series by 3-digit occupation. That is, if in the raw data 60 percent of listings for a given 3-digit occupation and month demand a bachelor's degree, we assume that 60 percent of the normalized number of vacancies in that 3-digit occupation and month demanded a bachelor's degree.
[16] Specifically, the education information used in the demand side of their analysis was imputed by The Conference Board from the Bureau of Labor Statistics as measured by the 2006-2008 American Community Survey (ACS) microdata and were held fixed over time. These imputed (and static) education demands of the vacancies and the observed education levels of workers were used to construct their mismatch index, rather than the educational requirements listed on the job postings themselves.

are further verified for consistency of sex, age and race within individuals.[17] An unemployed individual as of a given month is assigned to their most recent occupation as reported in the CPS, which is assigned a 3-digit SOC code using a crosswalk.[18] Each individual is then placed into one of six categories (for the month), defined by the combination of their 3-digit occupation's upskilling category—persistent, temporary, or non-upskiller—and their bachelor's degree status—having earned a bachelor's degree or not. For each of the six categories, the job finding rate for month *t* is calculated as the share of unemployed people as of month *t-3* who were employed in month *t*, conditional on being observed in both months.[19]

The second impact we examine is on the wage rates of workers at the top versus the bottom of the distribution in occupations with persistent educational upskilling. The rapid increase in the demand for educational requirements relative to the supply to educated workers would suggest that employers may have needed to raise wages to attract workers with a bachelor's degree to those positions, possibly increasing wage inequality between workers with and without a BA within occupations. We test this hypothesis by examining changes over time in median wages and the ratio of wages at the 75th versus the 25th percentile for occupations with persistent educational upskilling relative to those that exhibit temporary or no upskilling during the business cycle.

RESULTS

Heterogeneity in Persistent Educational Upskilling Within Occupations

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[17] We thank Serdar Birinci of the Federal Reserve Bank of St. Louis and, separately, Pinghui Wu of the Federal Reserve Bank of Boston, for furnishing us with Stata code used in the calculation of the job-finding rates.

[18] Approximately 8 percent of unemployed worker observations in the relevant CPS data cannot be assigned an upskilling classification, either because of missing occupation information or because of gaps in the crosswalk.

[19] We generate quarterly estimates by calculating the 3-month mean of the seasonally adjusted monthly estimates and then generating the HP filtered trend of those values with smoothing parameter 1,600. See the appendix for more information. Results are qualitatively similar when calculating job-finding rates across an interval of either one or two months rather than 3 months.

We first use the detailed information in the Lightcast data to examine the degree to which the rapid educational upskilling during the Great Recession persisted beyond the recession, whether it was uniform across the labor market, and if this persistence reflected a compositional shift in job vacancies as opposed to increased demands for bachelor's degrees within detailed occupations. Figure 2 plots the share of postings requiring a bachelor's degree by occupation at the 2-digit SOC level over time revealing stark differences in how the educational upskilling pattern unfolded over the business cycle. Relative to the economy-wide average, occupations with persistent educational upskilling (e.g., Management, Business and Financial, and others represented by the solid lines) experienced steeper increases in educational requirements during the recession (2007-2010) that endured throughout the recovery with little sign of reversion between 2010 and 2019. Temporary upskilling occupations (e.g., Architecture and Engineering, Community and Social Service, and others represented by dotted lines) showed large increases in the share of posting requesting a bachelor's degree during the recession, yet those gains reversed by more than 10 percent during the recovery. Still other occupations (e.g., Transportation and Material Moving, Production, and others represented by the dashed lines) experienced little or no upskilling during this period. Thus, the degree of persistence with regards to educational requirements was not widespread, as has been suggested by prior research, but instead varied considerably across the labor market, with potentially adverse consequences for certain groups of workers and matching efficiency within the affected occupations.

How much of the educational upskilling associated with a given broad occupation group is due to changes in education requirements within versus between the underlying sub-occupations? If most of the changes in bachelor's degree requirements were occurring between 3-digit sub-occupations, then it might be possible to detect labor market imbalances due to educational upskilling using the canonical mismatch index. To test this, we decompose the change in the share of postings requiring a bachelor's degree for a given 2-digit SOC occupation into separate components due to changes within the underlying 3-digit occupations versus changes between the underlying 3-digit occupations caused by a shift in the composition of postings towards 3-digit occupations that had higher initial demand for a bachelor's degree.[20]

Figure 3a shows that during the recession period (2007-2010), the increase in the share of postings requiring a bachelor's degree for a given 2-digit broad occupation was largely due to educational upskilling *within* the underlying 3-digit sub-occupations, not the changing composition of job postings across those sub-occupations.[21] In addition, Figure 3b shows that half or more of the reversion during the initial recovery period (2010-2013) among the 2-digit occupations that experienced temporary upskilling was due to changing composition across the underlying sub-occupations rather than reversion within those occupations. Indeed, Figure 4 confirms that the sub-occupations within these broad occupation groups do not behave uniformly with some experiencing persistent versus temporary educational upskilling. For example, the Legal broad occupation group is composed of Lawyers, Judges, and Related workers (which experienced persistent upskilling) as well as Legal Support Workers (which experienced temporary upskilling). The bottom line is that the canonical mismatch index will not be able to capture these labor market imbalances due to educational upskilling if unemployed workers are no longer qualified for their prior jobs.

[20]The outcome to be decomposed is the net increase in the share of vacancies requiring a BA for a given 2-digit occupation over the 2007-2010 period. We calculate counterfactual changes in the vacancy share requiring a BA, respectively, holding one of the following dimensions at a time fixed: (1) the composition of 3-digit vacancies under the given 2-digit umbrella, or (2) the vector of BA demands (as a share of vacancies) for the 3-digit occupations under the 2-digit umbrella. The fraction of the actual increase occurring under each counterfactual is shown in the figure. Any difference between the sum of the counterfactual changes and the actual change in BA share demands represents the residual, or interaction, component.

[21] Results are qualitatively similar if we probe at an even more detailed level, decomposing changes within 3-digit occupations based on underlying behavior of vacancies at the 6-digit level. See Figure A8 in the appendix.

Figure 5 performs the same decomposition for the share of employed workers with a bachelor's degree. The educational level of employed workers did not keep pace with the rapid shift in demand. Decomposing the change in the share of employed workers with a bachelor's degree among the broad 2-digit occupations reveals that any increase came from changes in worker education within the underlying 3-digit occupations rather than from a compositional shift in hiring across 3-digit occupations. Overall, movements in labor supply were small during both the recession and recovery periods, likely because only a fraction of the sudden double-digit surge in demand for college education workers could be filled from the pool of unemployed workers with a bachelor's degree and obtaining a bachelor's degree would take several years for workers who no longer qualify for those positions.

Characteristics of Occupations with Persistent Educational Upskilling

Contrary to public perception, persistent educational upskilling during the Great Recession was not pervasive across all sectors of the US labor market. Table 2 shows that according to our definition, only 16 percent of occupations at the 3-digit level exhibited persistent educational upskilling during the Great Recession and initial recovery with another 19 percent showing evidence of temporary upskilling, leaving the majority (65 percent) experiencing no significant upskilling. Prior to the recession, occupations with persistent educational upskilling already had a higher number of job postings and a greater share of postings requiring a bachelor's degree as well as other skills such as specialized and software skills compared to occupations that showed temporary or no significant upskilling. Persistent upskillers also had higher employment levels, a greater share of employed workers with a bachelor's degree and paid higher wages. Given their starting point, this suggests that the recession likely accelerated the demand for workers with a bachelor's degree among the persistent upskilling occupations.

Looking at the pattern of changes over time in Table 2 also provides some clues as to the distinguishing features of occupations for which the increase in education requirements during the Great Recession was “sticky.” For example, although all occupations raised requirements for various skillsets during the recession period (2007-2010), persistent upskilling occupations were the only ones to continue to raise requirements for software skills during the initial recovery (2010-2013). Moreover, the share of employed workers with a bachelor’s degree, along with the median wage and wage inequality, increased more rapidly among persistent versus temporary upskillers during the recession period. These trends confirm that employers who raised educational requirements within the persistent upskilling occupations were able to fill those jobs with workers who had a bachelor’s degree, although they had to pay a premium to do so.

To test this more formally, Table 3 calculates the correlation between educational upskilling and these various factors. Across all occupations, although the share of postings requiring a bachelor’s degree is very highly correlated with both the share of employed workers with a bachelor’s degree and wages in any given year, the change over time—either annually or using three-year stacked differences—is less so. Also, the size of the occupation in terms of employment is not correlated with educational upskilling to any large degree, confirming that the increased demand for education is not driven by one or more large occupations. Among the skill clusters measured by Lightcast, the increase in asking for a bachelor’s degree during the recession period was most highly correlated with asking for software skills (corr=0.584), followed by specialized skills (corr=0.484) and much less so for common skills (corr=0.171).

Relationship between Educational Upskilling and the Demand for Skills

To what degree does the persistent educational upskilling reflect structural changes in the underlying skills required for the job? Table 4 reports the results of our difference-in-difference-in-difference analysis of changes in skill requirements for occupations with persistent versus temporary educational upskilling over time, relative to occupations with no significant changes in the share of postings requiring a bachelor's degree. Each column is a separate regression where the dependent variable is the share of postings requesting a particular skill. The independent variables of interest are an indicator for whether the occupation is a persistent or temporary educational upskiller. The coefficients are measured relative to the omitted category of occupations with no significant educational upskilling to control for other changes in the labor market (e.g., immigration) that might affect the demand for particular skills. We then perform an F-test to determined whether the trends between persistent and temporary upskillers are significantly different.

We find that software skills are a distinguishing feature of persistent educational upskilling. During the recession, both persistent and temporary upskilling occupations increased the share of postings requesting software and common skills (e.g., communication), relative to occupations with no significant increase in the share of postings requiring a bachelor's degree. During the recovery period, the relative increase in the demand for common skills showed significant reversion among both persistent and temporary upskilling occupations. In contrast, the relative increase in the demand for software skills occupations was persistent among occupations that had experienced persistent educational upskilling but showed significant reversion among temporary upskilling occupations. Overall, the sharp increase during the recession and subsequent persistence in the demand for software skills followed a pattern that was strikingly similar to the demand for bachelor's degrees, suggesting that employers were not simply using the BA requirement as a screening tool but perhaps as an indicator that workers had acquired or could learn the emerging software skills associated with the job.

As we saw with the basic correlations, Figure 6 confirms that occupations exhibiting persistent educational upskilling were also those that showed persistent upskilling in terms of software skills, even during the longer-term recovery period (2010-2019). This was true for occupations even beyond the obvious technology-driven sectors such as engineering, mathematical, and computer science occupations. Indeed, many business and financial occupations such as business operations specialists, financial specialists and advertising, marketing, promotions, public relations, and sales managers experience large increases in the share of postings requesting software skills. Even persistent educational upskilling occupations that have not had a large digital footprint in the past—such as librarians, curators, and archivists or health diagnosing and treating practitioners—experienced strong increases in the demand for software skills during the recession that persisted throughout the recovery.

Moreover, occupations that experienced persistent educational upskilling also requested a greater variety of software skills and at a higher frequency compared to temporary educational upskillers. Figure 7 plots the initial level in 2010 versus the change (2010-2019) in the share of postings requesting the top ten individual software skills within 3-digit occupations during the business cycle for persistent versus temporary upskillers. Occupations experiencing persistent educational upskilling sharply increased demand for a variety of software skills such as engineering software, business intelligence software, application programming interface (API), databases, statistical software, accounting and finance software, human resources software, and customer relationship management tools. In contrast, occupations experiencing temporary education upskilling showed little to no increase in software requirements during the longer-term recovery and often asked for many of the same skills across occupations such as graphic and visual design software, geospatial information and technology, and scripting languages.[22]

To what extent might the sudden increase in the demand for software skills within occupations that experience persistent educational upskilling present a barrier to workers who are displaced from their jobs during the recession? The first half of Table 5 reports the number of unique software skills requested for each of the occupations that experienced persistent educational upskilling. Employers requested over 200 different software skills on average in 2010 and continued to increase the number of unique software skills requested during the recovery period. In particular, occupations with initially lower levels of software skills in sectors such as healthcare and education experience the greatest percent increases in the demand for software skills during the recovery. Clearly it would be impossible for an unemployed worker to acquire all of these different software skills and thus be qualified for every job opening within their prior occupation. Thus, employers might be using a bachelor's degree as a proxy for an individual worker's ability to learn new software skills which could explain why these educational requirements persisted throughout the recovery if firms increased the adoption of new technology.

Moreover, the demand for some of these individual software skills increased sharply within some occupations, and not just in the obvious computer and mathematical occupations. The second half of Table 5 lists the top software skill that had the largest percentage point change in the share of postings within each of the persistent upskilling occupations. For example, the demand for customer relationship management (CRM) software skills increased by nearly 8 percentage points for advertising, marketing, promotions, public relations, and sales managers.

[22] This was also true of "common" skills such as communication and "specialized" skills such as budget management where the increase in the share of postings reflected an increased prevalence for existing skills rather than asking for new skills or a greater variety of skills.

This suggests that there is potentially increasing specialization within occupations for certain types of software skills that replace routine tasks and are perhaps more complementary with cognitive tasks requiring a bachelor's degree (Braxton and Taska, 2023).

Overall, these findings are consistent with the hypothesis that advances in technology are driving the persistent upskilling we observed within occupations, particularly those that use specialized software packages (e.g., engineering software) or for which new software rapidly diffuses, thus changing the nature of the worker's core tasks. In the next section we explore whether persistent upskilling led to greater labor market mismatch in the BA sector and ultimately affected aggregate matching efficiency during the recovery period.

Implications of Upskilling for Labor Market Mismatch

Did persistent educational upskilling within occupations harm matching efficiency, either within certain sectors of the labor market or in the aggregate? Unemployed workers in occupations with persistent educational upskilling may no longer qualify for the positions they once held if they lack the necessary skills and/or credentials to meet these new hiring requirements, possibly increasing occupational mismatch. To test this hypothesis, we initially construct separate mismatch indexes across 3-digit occupations within the BA versus non-BA educational sectors. On the demand side, we do this by parsing out the monthly normalized vacancies in each occupation by education based on the share of postings requiring a bachelor's degree as observed in the raw Lightcast data. On the supply side, we do this by parsing out the monthly number of unemployed workers in each occupation based on their observed education levels in the CPS.

Comparing the *level* of mismatch across sectors in Figure 8 reveals that the mismatch index is higher in the BA versus the non-BA sector.[23] This finding suggests that while having more education makes workers more adaptive, it also makes them more specialized and hence less substitutable across occupational categories and this second effect seems to dominate, even at the 3-digit SOC level. For example, a worker with a bachelor's degree in engineering is not likely to be able to switch costlessly to a job as a healthcare practitioner—or even to a job that is somewhat related, such as in mathematics or computing. In contrast a worker with a high school degree may have a more general set of skills that can be applied to a wider range of occupations.

Moreover, *changes over time* in the mismatch index also vary by educational sector and are consistent with the upskilling trends that we document in the first part of the paper. As employers raised education requirements during the recession, vacancies flowed out of the non-BA sector and into the BA sector, largely among the persistent and temporary upskilling occupations. In addition, the rate at which the share of postings for a BA increased was more rapid than the rate at which the supply of workers with a BA increased. This is consistent with the sharp increase in the mismatch index in the BA sector between 2007-2010 relative to little or no increase in mismatch in the non-BA sector. As the labor market tightened during the recovery and employers reduced education requirements, some of the BA jobs in the temporary upskilling occupations flowed back to the non-BA sector, consistent with the observed decrease in the mismatch index initially between 2010-2013. However, the remainder of those education requirements were sticky. Moreover, the persistent upskilling occupations continued to increase the share of postings requiring a bachelor's degree during the longer-term 2013-2017, consistent with the subsequent increase in mismatch later in the recovery.[24]

[23] All mismatch indexes presented in the paper are HP filtered to eliminate high frequency movements and better visualize the variation in the indexes. To facilitate the comparison across different educational sectors, we plot all the mismatch indexes using the same vertical distance on the *y*-axis, between 0 and 0.4 percentage points.
[24] Recall that the normalized vacancy series provided by Lightcast is only available 2007 and 2010-2017.

In contrast, there is less cyclical movement in the mismatch index for the non-BA sector since many non-BA occupations exhibited little or no significant upskilling. During the recession, the mismatch index was little changed as some jobs among the temporary upskilling occupations flowed from the non-BA sector into the BA sector between 2007-2010. During the initial recovery, the mismatch index decreased slightly between 2010-2013 as some of the temporary upskilling jobs flowed back to the non-BA sector and were filled by unemployed workers who had been left behind. During the longer-term recovery (2013-2017), the mismatch index was relatively stable as most non-BA occupations experienced little to no upskilling. Thus, the persistent increase in education demands within 3-digit occupations appears to have shifted the composition of vacancies out of line with the composition of unemployed workers, possibly resulting in reduced matching efficiency.

How can the usual indicators, such as the mismatch index, be adapted to detect the effects of changing educational requirements on matching efficiency? We extend the standard mismatch index to captures labor market imbalances due to increased demand for a bachelor's degree among the 3-digit occupations that engaged in persistent upskilling. Under this approach, we first partitioned each of the 15 persistent upskilling occupations into a BA and a non-BA part using the shares of vacancies and unemployed workers with a bachelor's degree. This effectively segments each of the persistent upskilling occupations into two distinct sub-occupations: one that is open to workers with a bachelor's degree and the other that is open to workers without a bachelor's degree. We then combined this set of 30 sub-occupations alongside the pre-existing temporary and non-upskilling occupations. AS a control exercise we also calculated the standard mismatch index at just the 3-digit SOC level, without any segregation of occupations by education demand and supply.

Figure 9 compares the standard mismatch index to our extended version that accounts for persistent educational upskilling. As before, we note that the *level* of the extended mismatch index is higher than the standard index, but this is likely to be purely mechanical given that we had disaggregated the 15 persistent occupations into 30 sub-occupations.[25] What is more relevant to our research question is comparing the *change* over the business cycle across the two indices. Both indices indicate an increase in labor market mismatch during the recession (2007-2010), although the trend is somewhat steeper for the extended versus the standard mismatch index. More striking is the pattern during the initial recovery period. Between 2010 and 2013, the standard mismatch index falls from 0.121 to 0.065—nearly a 50 percent drop. In contrast, the extended mismatch index shows a much more modest decline from 0.203 to 0.179—decreasing by a little more than 10 percent. During the longer-term recovery, the standard index is relatively flat while the extended index shows some upward trends before leveling off. Overall, the extended mismatch index exhibits a less cyclical pattern than the standard index and is more aligned with the observations of employers that some unemployed workers were no longer qualified for their jobs.

The Impact of Educational Upskilling on Workers without a Bachelor's Degree

What are the implications of educational upskilling for workers? The mismatch index could give misleading results concerning constraints on labor market matching, for example if workers move across occupations more freely than the index assumes. To shed light on this, we examine two potential impacts of educational upskilling on workers. The first impact is the likelihood of non-BA workers finding a job relative to that of workers who have a BA in

[25] As Sahin et. al (2014) note, one of the features of how the mismatch index is constructed is that it is increasing in the level of disaggregation. This property suggests that every statement about the role of mismatch should be qualified with respect to the degree of sectoral disaggregation used.

occupations that experienced persistent educational upskilling versus those that did not. To test this, we construct job-finding rates which offer a more direct measure of labor-market matching activity. Exploiting the longitudinal component of the CPS, we assign workers to the occupation in which they were last employed. We then calculate 3-month job-finding rates from unemployment for workers with and without a BA across occupation groups by upskilling type (persistent, temporary, none) over the period 2005-2019.[26]

As seen in Figure 10, job-finding rates fell sharply during the Great Recession for all workers, and did not start to recover until early 2011, well after the recession was officially over.[27] Within each upskilling category, the job-finding rates of non-BA workers exhibited steeper declines from 2005-2011 compared with the job-finding rates of workers with a college degree, consistent with a relative decline in demand for non-BAs compared with BAs. That gap, however, is most pronounced within the set of persistent-upskilling occupations, consistent with the fact that employers in such occupations on average increased their demand for workers with a bachelor's degree more sharply during the recession, and held them higher for longer, than did those in other occupation groups.

After 2011, job-finding rates improved for all workers. However, for both the non-upskilling and temporary upskilling occupation groups, the job-finding rates of non-BAs increased faster than those of BAs, with the former eventually overtaking the latter in late 2015 or early 2016, after which the BA job-finding rates stalled (for non-upskillers) or turned downward again (for temporary upskillers). The recent lag in BA job-finding rates for the non-

[26] We thank Serdar Birinci of the St. Louis Fed for providing us with Stata code and other technical assistance in calculating the job-finding rates. See Birinci et al. (2023) for a discussion of long-run trends in job-finding rates and other labor-market flows in relation to increases in job applications since the late 1970s.
[27] Values are seasonally adjusted and smoothed using an HP-filter. See figure notes for details. Results are qualitatively similar for 1-month and 2-month job-finding rates. Occupation upskilling info is missing for roughly 8 percent of unemployed workers on average in any given month, based on the inadequacy of the crosswalk from CPS occupations to SOC codes.

persistent upskillers is consistent with the notion that, as the labor market tightened between 2016 and 2019, BAs became a luxury rather than a necessity. In contrast, job-finding rates among BAs held up relatively well in the persistent upskilling occupations.[28]

The second impact we examine is on the wage rates of workers at the top versus the bottom of the distribution in occupations with persistent educational upskilling. Other researchers have noted that the sluggish aggregate wage growth during most of the recovery period seems inconsistent with the mismatch hypothesis (Rothstein 2012; Abraham 2015). The rapid increase in the demand for educational requirements relative to the supply of educated workers would suggest that employers may have needed to raise wages to attract workers with a bachelor's degree to those positions, possibly increasing wage inequality between workers with and without a BA within occupations. Table 6 confirms this hypothesis. Using the same difference-in-difference-in-difference approach as before, we find that wages increased among persistent educational upskillers compared to occupations with temporary or no upskilling during both the recession as well as the recovery period. The latter distinction is important since if occupational mismatch is present, then employment growth should be positively correlated with wage growth (Abraham 2015). In addition, changes in the ratio of wages at the 75th percentile relative to the 25th percentile indicate that the wage increases in the persistent upskilling occupations were at the top rather than the bottom of the wage distribution, further suggesting that employers were seeking to hire workers with a bachelor's degree. This is consistent with

[28] Other evidence suggests that occupations experiencing persistent educational upskilling were relatively more successful in hiring workers with a bachelor's degree. Compared to occupations that exhibited temporary or no upskilling, persistent upskilling occupations initially experienced less cyclicality in the education levels of new hires relative to continuing employees. In contrast, temporary upskillers saw a sharp drop in the education levels of new hires during the initial recovery, consistent with the decline in the share of postings requiring a bachelor's degree. See Figure A10 in the appendix.

recent evidence that shows workers who are “occupation stayers” in occupations exposed to technological change experience larger earnings gains (Braxton and Taska, 2023).

Conclusions and Policy Implications

Using a novel database of roughly 200 million online job postings in the US, we find that movements in the demand for and supply of skills varied over the business cycle across occupations. Building on the prior literature, we find that in the aggregate about one-third of the increase in bachelor’s degree requirements were reversed by 2013, while two-thirds persisted through 2019 but that these trends varied considerably across occupations. In fact, many occupations (e.g., construction) experienced little or no educational upskilling while others (e.g., community and social services) experienced only temporary educational upskilling that was mostly confined to the recession period. Only a subset of occupations (e.g., computer and mathematical) exhibited a pattern of persistent educational upskilling that extended well after the Great Recession. Moreover, these movements were driven by upskilling that occurred *within* occupations rather than changes in the composition of vacancies *across* occupations over time towards those that had demanded bachelor’s degrees prior to the Great Recession.

Examining the specific skills listed on job postings reveals further that the demand for software skills was a distinguishing feature of occupations that exhibited a pattern of persistent educational upskilling. Relative to occupations that showed little or no educational upskilling, both temporary and persistent educational upskillers increased the share of job postings requiring software skills between 2007 and 2010, consistent with prior research indicating that recessions accelerate skill-biased technological change (Jaimovich and Siu 2020, Hershbein and Kahn 2018). However, between 2010 and 2013, more than half of the increase in software skills was reversed among occupations that had experienced a temporary increase in the share of postings requiring a bachelor's degree, whereas persistent educational upskillers continued to increase demand for software skills, confirming the complementarity between education and technology.

Other indicators suggest that upskilling had different consequences for workers with bachelor's degrees versus those without. On the supply side of the labor market, the education levels of employed workers increased, albeit slowly, suggesting that employers succeeded in hiring increasingly qualified workers but that perhaps supply was not keeping pace with demand in occupations that experienced persistent educational upskilling. During the Great Recession, not surprisingly, job-finding rates fell for all workers, and declined more sharply for those without a bachelor's degree. However, the gap in job-finding rates between workers with and without a bachelor's degree grew especially wide—and persisted for longer after the recession—within the group of occupations that displayed persistent educational upskilling, relative to occupations that engaged in either temporary or no upskilling. This is bolstered by evidence showing that wages increased among occupations with persistent educational upskilling, where these wage increases occurred at the top of the wage distribution, consistent with the need to attract workers with a bachelor's degree.

We also find evidence that upskilling contributed to reduced matching efficiency in certain segments of the US labor market as well as in the aggregate. In particular, mismatch was higher for the BA sector, suggesting that there is lower matching efficiency in higher-skilled occupations, potentially because they are becoming more specialized, and possibly explaining growing wage polarization and inequality. In addition, mismatch in the BA sector also displayed a more cyclical pattern than the non-BA sector, as BA jobs flowed out of the non-BA sector and into the BA sector during the recession, although only a portion of this movement persisted through the initial recovery and beyond. Finally, we extend the standard mismatch index to account for persistent educational upskilling and find that doing so produces a pattern that is less cyclical. Whereas the standard mismatch index shows a marked increase during the Great Recession and a relatively quick recovery in the years immediately after, our adjusted mismatch index that incorporates persistent upskilling within occupations stays elevated for an extended period during the labor market recovery.

Taken together, these trends suggest that lower matching efficiency in the US labor market may reflect a shift in demand towards more specialized jobs that require particular software skills, thus leading to imbalances between the demand for and the supply of certain skills. Our findings contribute to the literature by identifying upskilling related to technological change as a factor that contributed to reduced aggregate matching efficiency. Furthermore, our results suggest that search-and-matching models of the labor market may need to account for the fact that workers could be chasing a moving target (Kambourov and Manovskii 2009; Alvarez and Shimer 2011; and Carrillo-Tudela and Visscher 2023). Related research by Kogan et al. finds that older and/or more experienced, highly-skilled workers appear to suffer skill obsolescence when breakthrough innovations occur, whereby new technologies are complementary to new skills.

However, we offer some caveats to the conclusions that can be drawn from our findings. Our mismatch index 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 a search and individuals counted as non-participants in the labor force—might influence the potential hiring rate and therefore the assessment of matching efficiency at any point in time. However, recent research suggests that the impacts of upskilling on displaced workers does not lead to significant job loss but rather these unemployed workers then direct their search for a new job to an occupation with a lower level of technology used in production where their skills are still employable, but wages are lower (Braxton and Taska, 2023).

Nonetheless, our findings that demonstrate the adverse impacts of upskilling on workers without a bachelor's degree also contribute to debates about workforce development and related educational policies. For example, distinguishing between persistent versus temporary shifts in skill demands within certain occupations could help policymakers identify which human capital investments are likely to have higher returns in the long run and should be a funding priority during economic recoveries. Such information could also be used by workforce development practitioners to target sector-based or job-driven training in key occupations (Holzer 2015). Similarly, knowing that upskilling can occur rapidly within occupations, educational institutions and training providers should regularly monitor job qualifications, particularly during recessions, to adjust curriculum and advise students. Finally, recognizing that persistent upskilling is likely to affect certain groups of workers more than others can help career counselors to better advise job-seekers about the suitability of their qualifications for various jobs and retraining opportunities.

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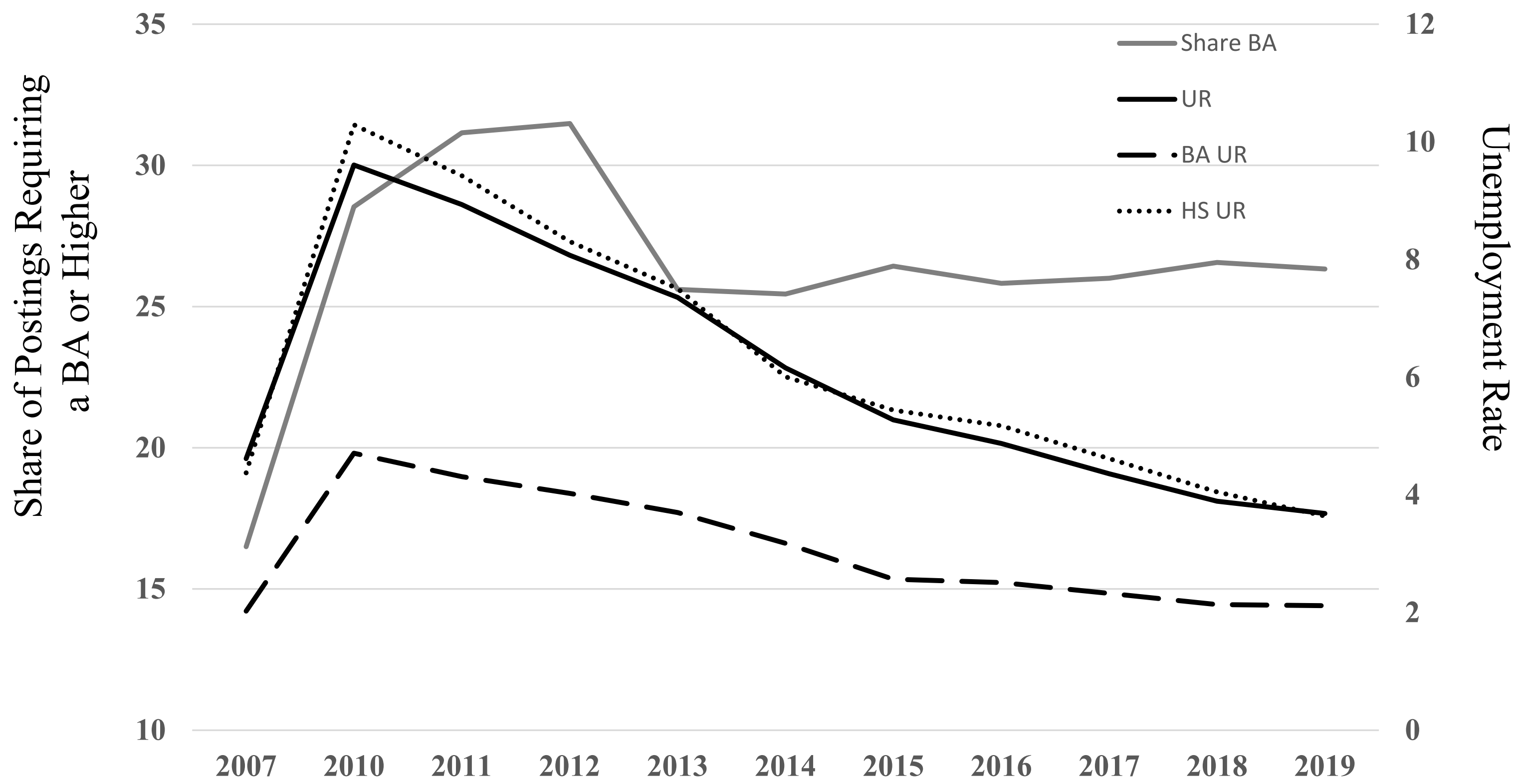
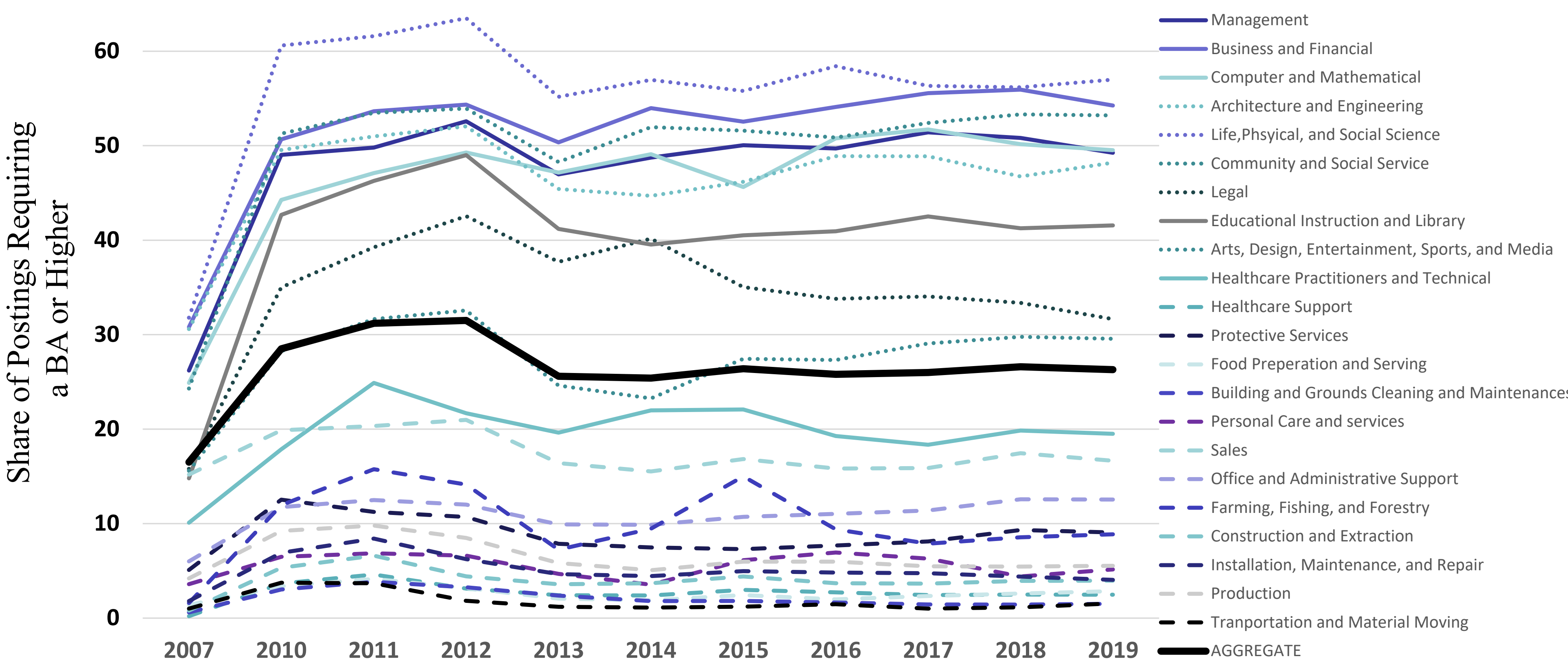
Figure 1. Trend in Requested Educational Qualifications versus Labor Market Slack



Source: Authors' calculations using job vacancy data provide by Lightcast and unemployment rate data as reported by the Bureau of Labor Statistics.

Figure 2. Requested Educational Qualifications by 2-Digit SOC, 2007-2019

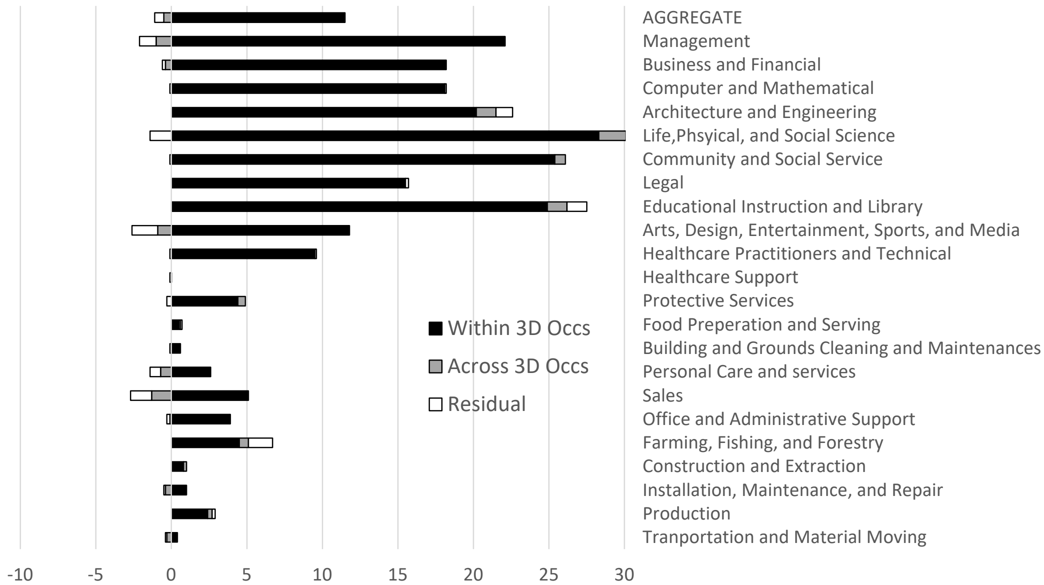


Source: Authors' calculations using job vacancy data provide by Lightcast.

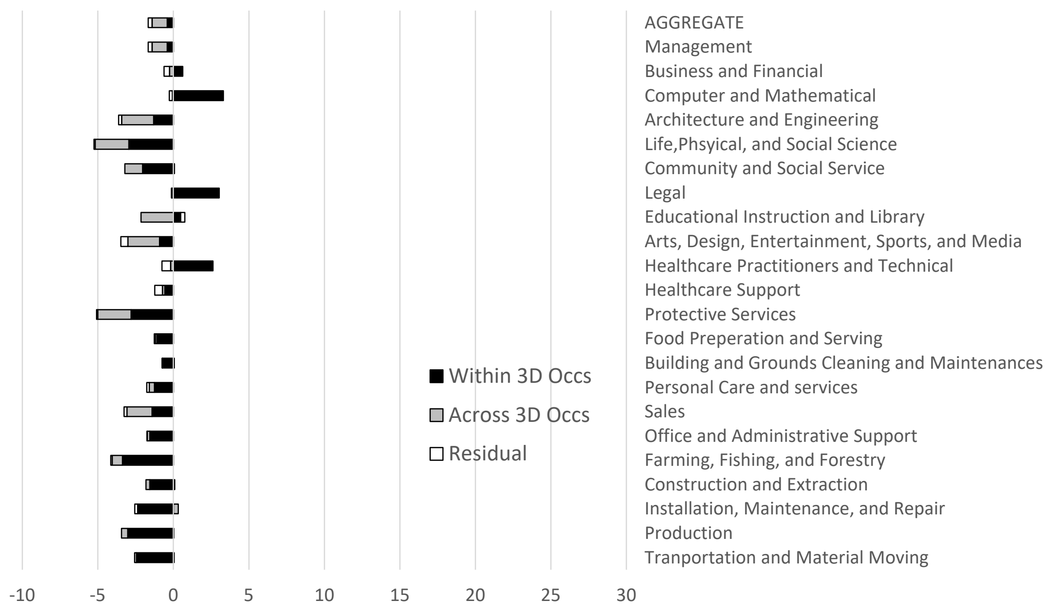
Note: Occupations with a percentage point change in the share of postings requiring a bachelor's degree during the recession (2007-2010) that is greater than the economy-wide aggregate increase are defined as having significant upskilling. Those that also experience less than a 10 percent decline during the initial short-term recovery (2010-2013) and in the longer-term (2010-2019) are defined as persistent upskillers.

Figure 3. Decomposition of Change in Requested Educational Qualifications within versus between 3-Digit SOC

A. Change in Share of Postings Requesting a Bachelors Degree 2007-2010

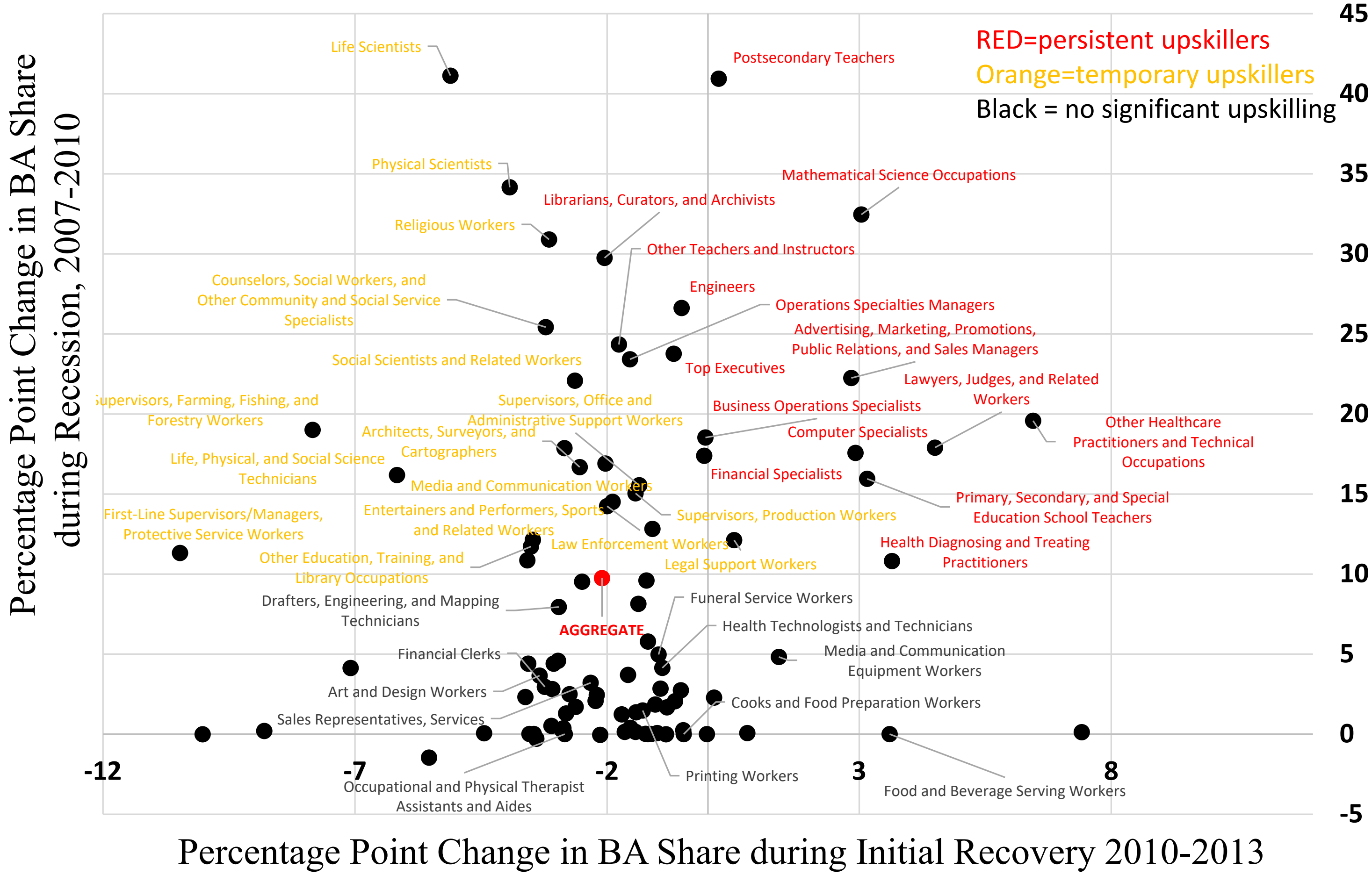


B. Change in Share of Postings Requesting a Bachelors Degree 2010-2013



Source: Authors' calculations using job vacancy data provide by Lightcast.
Note: The outcome to be decomposed is the net increase in the share of vacancies requiring a BA for a given 2-digit occupation over the 2007-2010 period. We calculate counterfactual changes in the vacancy share requiring a BA, respectively, holding one of the following dimensions at a time fixed: (1) the composition of 3-digit vacancies under the given 2-digit umbrella, or (2) the vector of BA demands (as a share of vacancies) for the 3-digit occupations under the 2-digit umbrella. The fraction of the actual increase occurring under each counterfactual is shown in the figure. Any difference between the sum of the counterfactual changes and the actual change in BA share demands represents the residual, or interaction, component.

Figure 4. Change in Requested Educational Qualifications by 3-Digit SOC over the Business Cycle

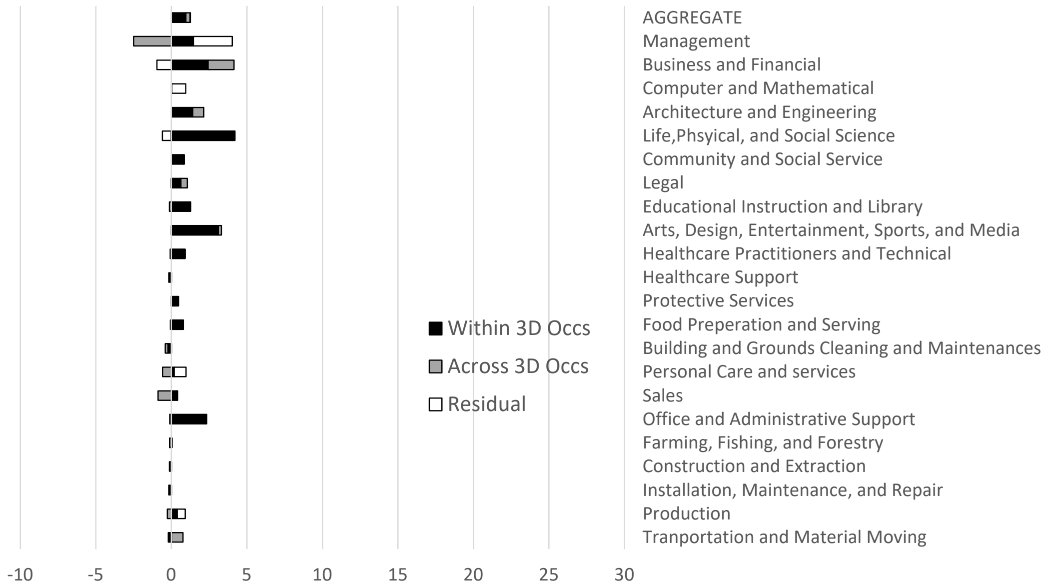


Source: Authors' calculations using job vacancy data provide by Lightcast.

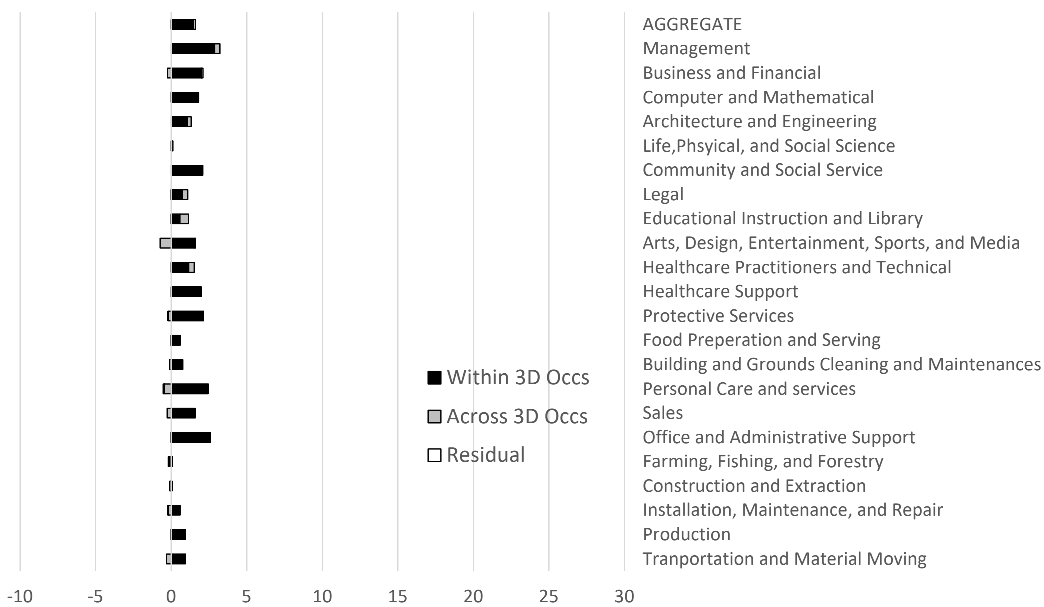
Note: Occupations with a percentage point change in the share of postings requiring a bachelor's degree during the recession (2007-2010) that is greater than the economy-wide aggregate increase are defined as having significant upskilling. Those that also experience less than a 10 percent decline during the initial short-term recovery (2010-2013) and in the longer-term (2010-2019) are defined as persistent upskillers.

Figure 5. Decomposition of Change in Employed Workers with a Bachelors Degree within versus between 3-Digit SOC

A. Change in Share of Employed Workers with a Bachelors Degree 2007-2010

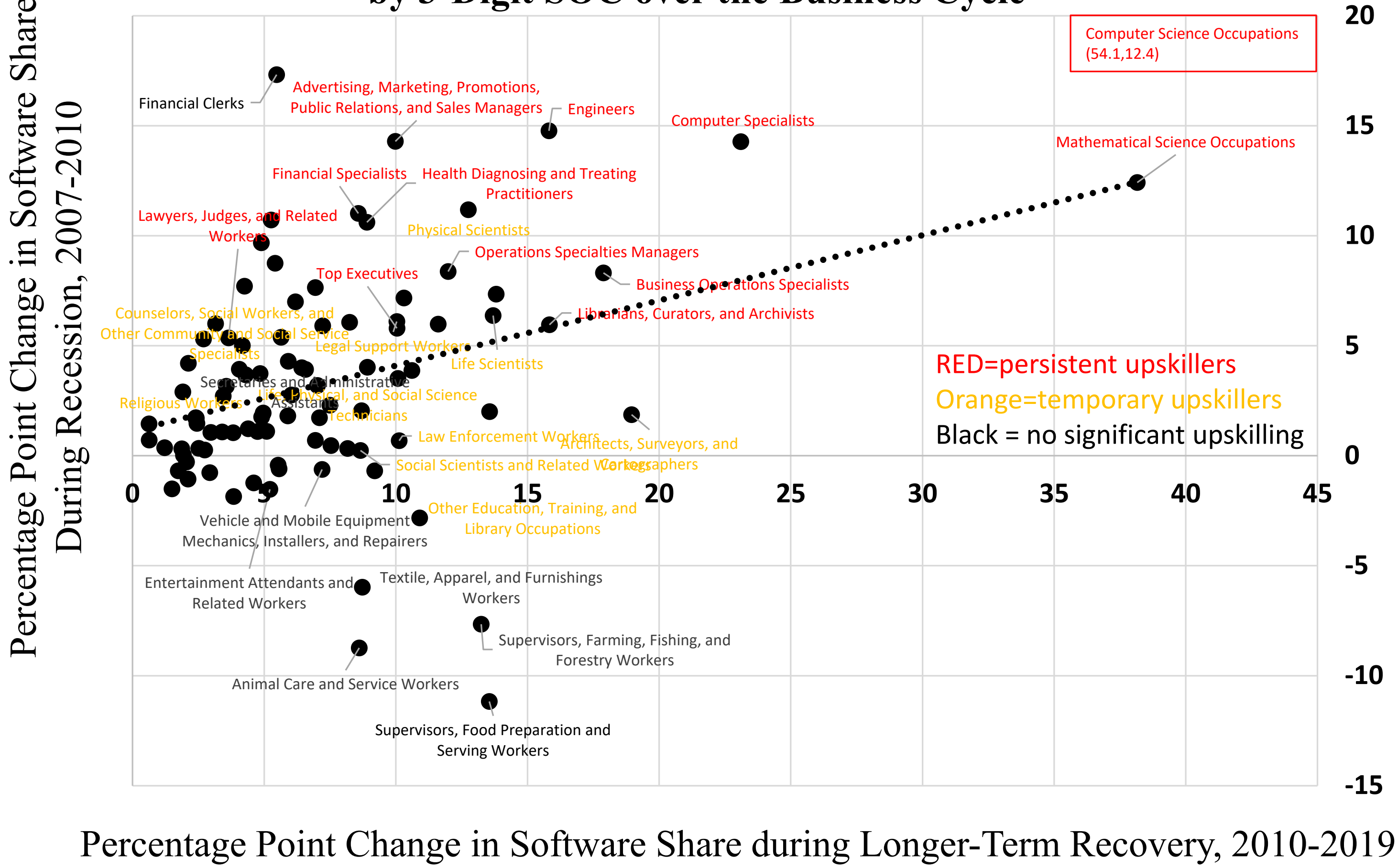


B. Change in Share of Employed Workers with a Bachelors Degree 2010-2013



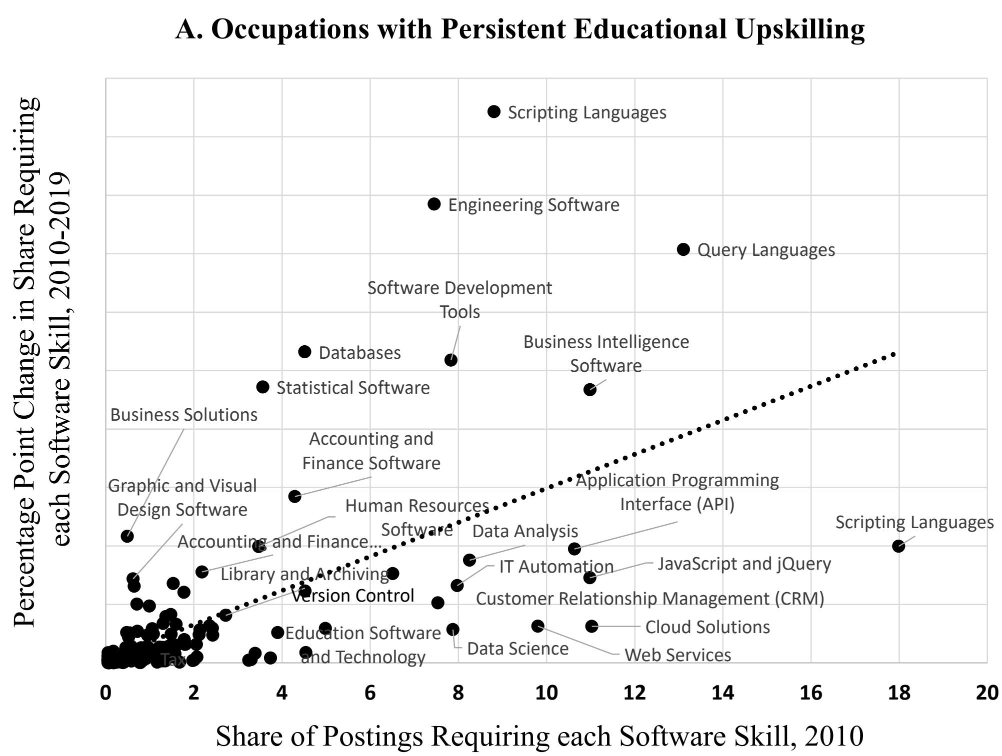
Source: Authors' calculations using job vacancy data provide by Lightcast.
Note: The outcome to be decomposed is the net increase in the share of vacancies requiring a BA for a given 2-digit occupation over the 2007-2010 period. We calculate counterfactual changes in the vacancy share requiring a BA, respectively, holding one of the following dimensions at a time fixed: (1) the composition of 3-digit vacancies under the given 2-digit umbrella, or (2) the vector of BA demands (as a share of vacancies) for the 3-digit occupations under the 2-digit umbrella. The fraction of the actual increase occurring under each counterfactual is shown in the figure. Any difference between the sum of the counterfactual changes and the actual change in BA share demands represents the residual, or interaction, component.

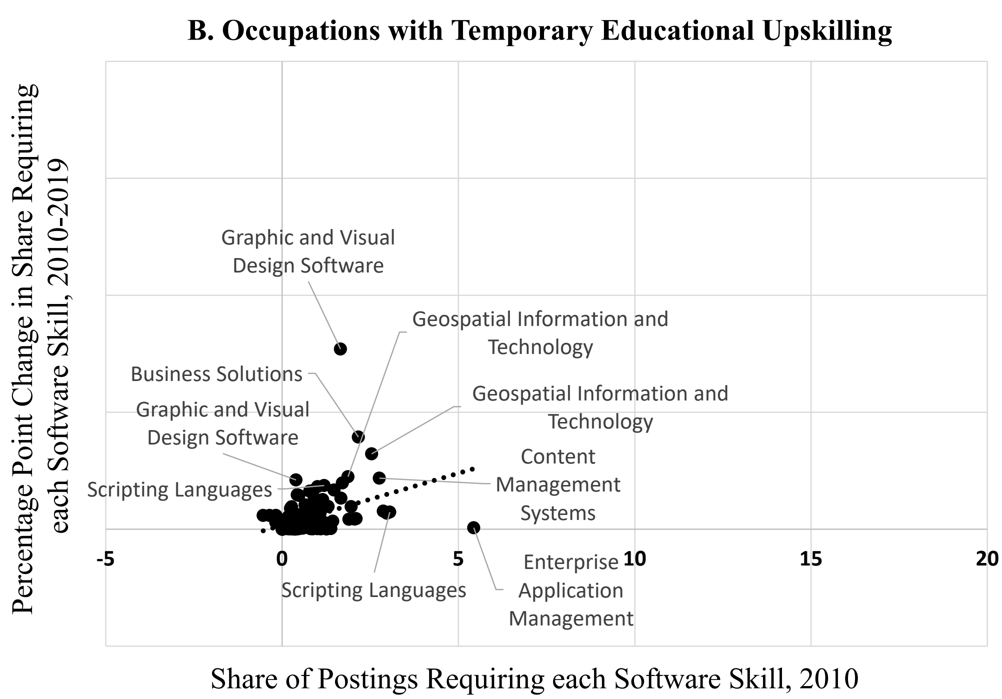
Figure 6. Change in Share of Postings Requesting Software Skills by 3-Digit SOC over the Business Cycle



Note: Occupations with a percentage point change in the share of postings requiring a bachelor's degree during the recession (2007-2010) that is greater than the economy-wide aggregate increase are defined as having significant upskilling. Those that also experience less than a 10 percent decline during the initial short-term recovery (2010-2013) and in the longer-term (2010-2019) are defined as persistent upskillers.

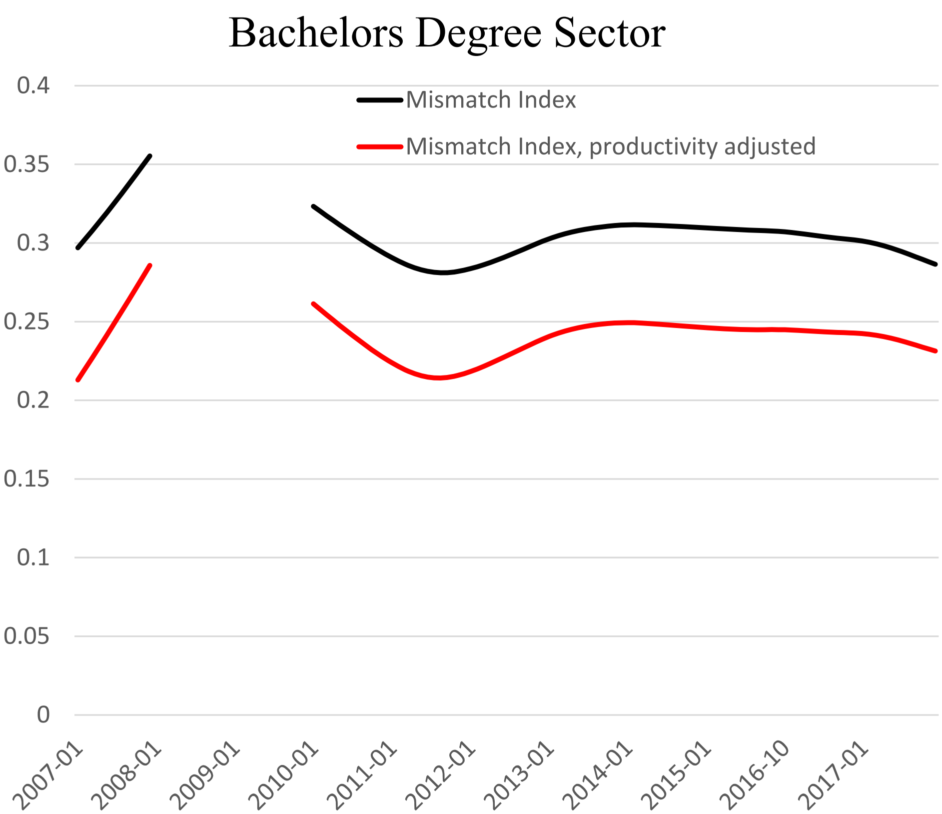
Figure 7. Initial Level versus Change in Share of Postings Requesting the Top 10 Software Skills within 3-Digit SOC during the Business Cycle

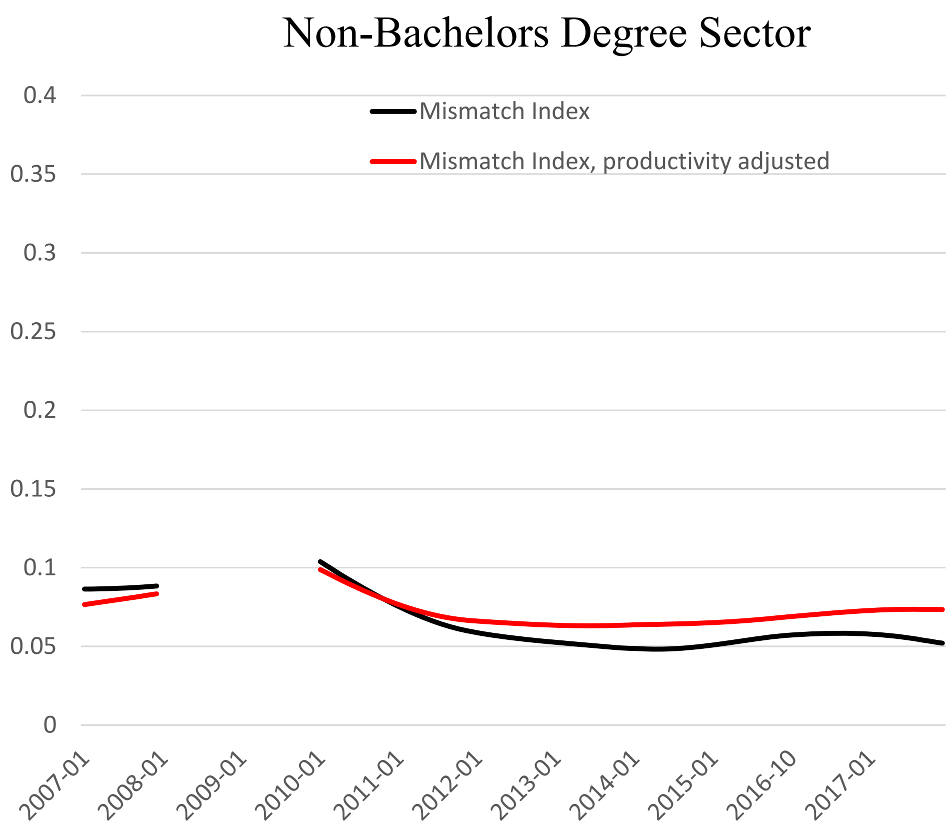




Source: Authors' calculations using job vacancy data provide by Lightcast.
Note: Occupations with a percentage point change in the share of postings requiring a bachelor's degree during the recession (2007-2010) that is greater than the economy-wide aggregate increase are defined as having significant upskilling. Those that also experience less than a 10 percent decline during the initial short-term recovery (2010-2013) and in the longer-term (2010-2019) are defined as persistent upskillers.

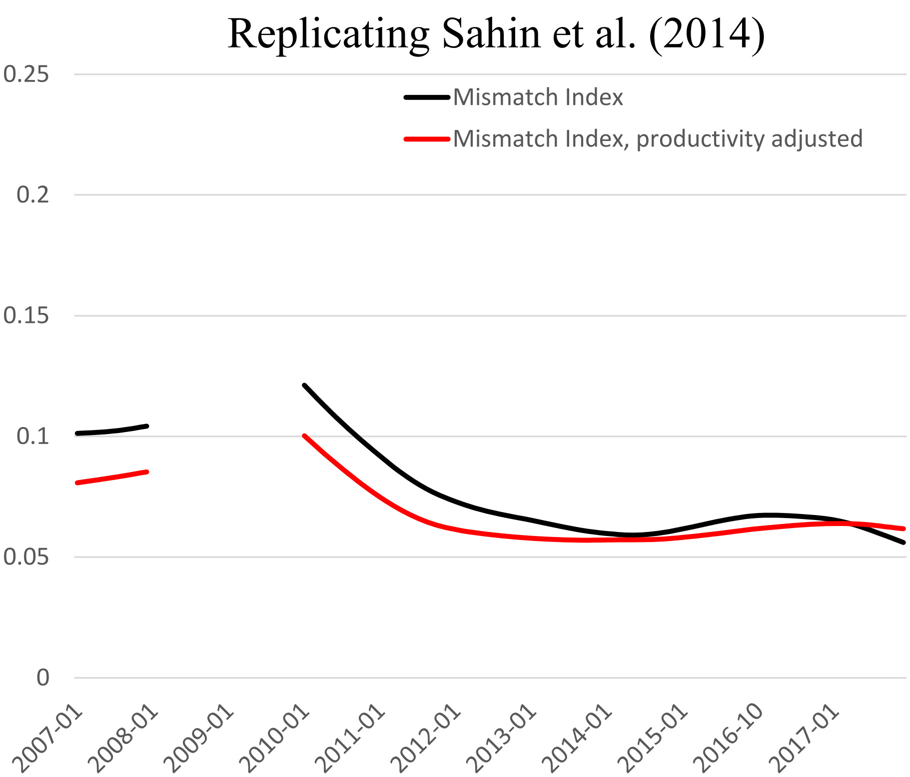
Figure 8. Mismatch Index by Educational Sector

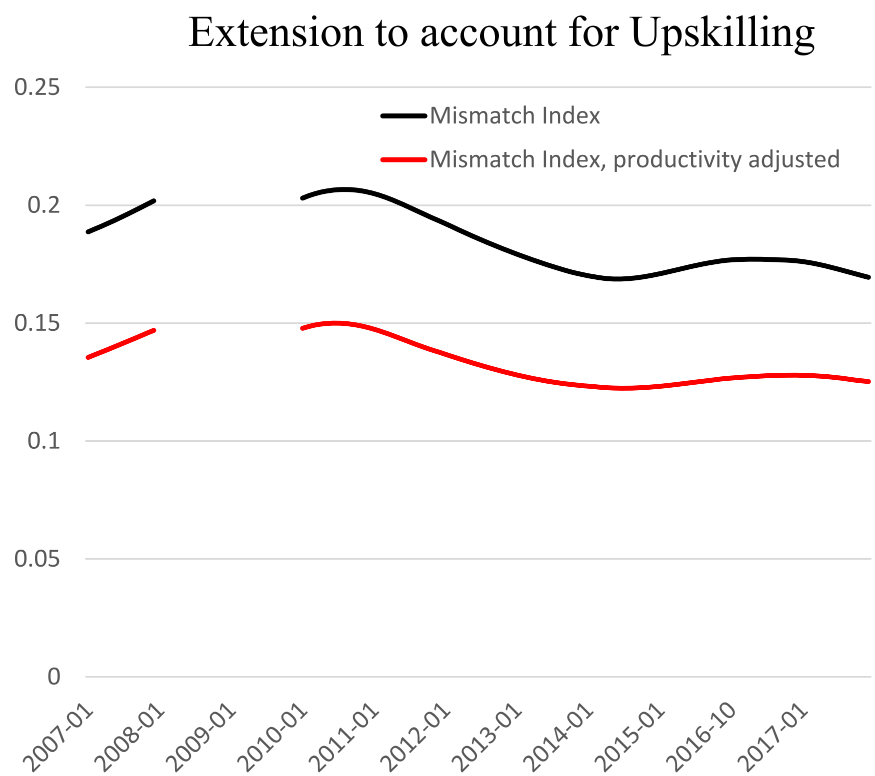




Source: Author's calculations using monthly online job posting data provided by Lightcast (2007, and 2010-2017) and unemployment and monthly labor force estimates from the Current Population Survey.
Note: All mismatch indexes presented in the paper are HP filtered to eliminate high frequency movements and better visualize the variation in the indexes. To facilitate the comparison across different educational sectors, we plot all the mismatch indexes using the same vertical distance on the y-axis, between 0 and 0.4 percentage points. See the appendix for details on the construction of the mismatch index.

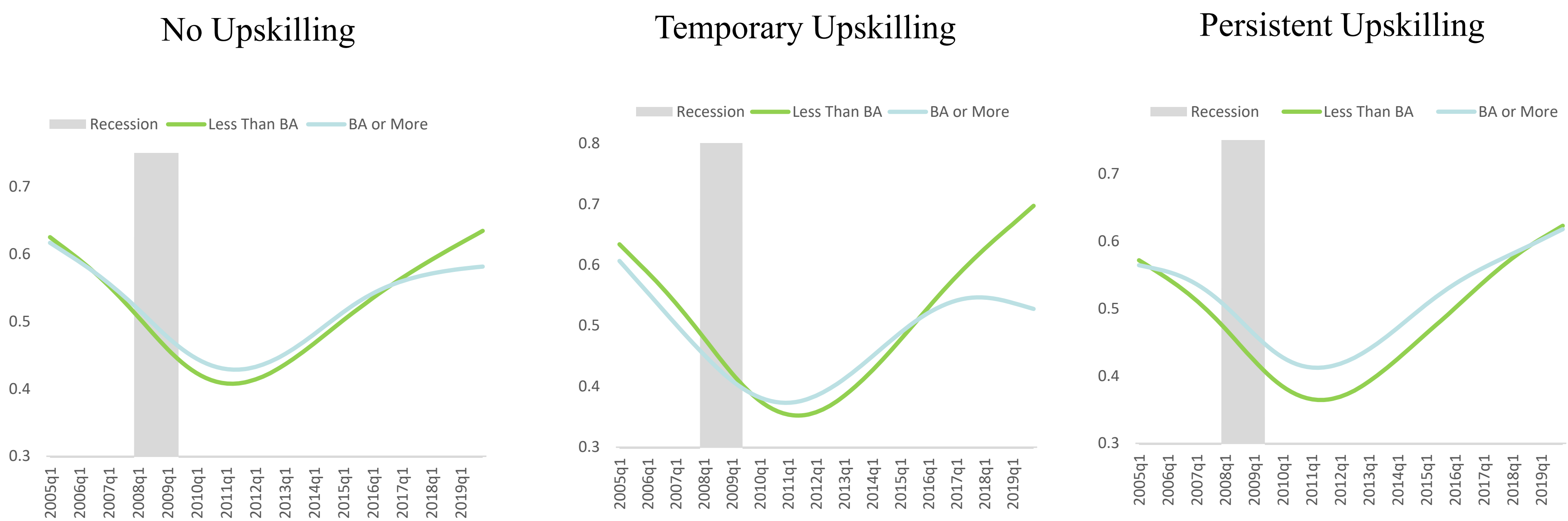
Figure 9. Extending the Aggregate Mismatch Index to accounting for Persistent Educational Upskilling





Source: Author's calculations using monthly online job posting data provided by Lightcast (2007, and 2010-2017) and unemployment and monthly labor force estimates from the Current Population Survey.
Note: All mismatch indexes presented in the paper are HP filtered to eliminate high frequency movements and better visualize the variation in the indexes. To facilitate the comparison across different indices, we plot all the mismatch indexes using the same vertical distance on the y-axis, between 0 and 0.25 percentage points. See the appendix for details on the construction of the mismatch index.

Figure 10. Job Finding Rates by Occupation Type and Worker Education



Source: Authors' calculations using code and instructions provided by Derar Birinci of the Federal Reserve Bank of St. Louis and data from the Current Population Survey.

Note: The job finding rate is calculated in month t as the share of unemployed people in month t-3 who are employed in month t, conditional on being observed in both months. The data displayed at a quarterly level, taking the 3 month mean of seasonally adjusted monthly estimates, then taking the HP filtered trend of those values with smoothing parameter 1,600.

Table 1. Summary Statistics for Employer Skill Requirements, Employment, and Wages for Occupations at the 3-Digit SOC Level

	Observation Period				Recession	ST Recovery	LT Recovery
	2007	2010	2013	2019	Δ2007-2010	Δ2010-2013	Δ2010-2019
Employer skill requirements							
Number of raw job postings							
Mean	139,603.70	127,078.90	218,317.00	356,284.30	-12,524.80	91,238.10	229,205.40
Standard deviation	(245,052.20)	(233,608.00)	(339,077.10)	(550,944.80)	(50,486.51)	(118,965.30)	(326,968.20)
Mean percent of job postings requesting:							
Bachelor's degree or higher	10.01	20.77	18.92	19.69	10.77	-1.85	-1.08
Common skills	65.80	67.55	71.93	83.33	1.76	4.38	15.78
Specialized skills	57.12	78.07	80.35	88.45	20.95	2.29	10.38
Software skills	5.97	12.99	12.71	16.18	7.02	-0.27	3.19
Employment							
Annual number of employed workers							
Mean	1,054,938.00	986,104.00	999,048.40	1,054,253.00	-68,834.00	12,944.40	68,149.00
Standard deviation	(1,164,488.00)	(1,103,781.00)	(1,129,397.00)	(1,261,859.00)	(154,437.30)	(63,197.16)	(312,436.40)
Mean percent with a bachelor's degree or higher	31.80	28.81	34.29	36.98	-3.00	5.49	8.17
Wages							
Median Real Wage							
Mean	22.52	22.93	22.69	23.35	0.41	-0.24	0.41
Standard deviation	(12.16)	(11.91)	(11.99)	(11.86)	(3.71)	(1.50)	(1.95)
Ratio: 75th/25th percentile wages							
Mean	1.63	1.66	1.72	1.71	0.03	0.05	0.04
Standard deviation	(0.31)	(0.22)	(0.25)	(0.22)	(0.28)	(0.08)	(0.09)
Number of 3-digit occupations	94	94	94	94	94	94	94

Source: Data on employer skill requirements are provided by Lightcast, weighted by annual employment from the American Community Survey, and aggregated by occupation at the 3-digit SOC level. Data on labor market conditions are calculated by 3-digit occupation using the American Community Survey from the Census Bureau. Data on wages are as reported by the Occupational Employment Statistics from the U.S. Bureau of Labor Statistics.

Table 2. Characteristics of 3-Digit SOC Occupation by Type of Educational Upskilling

	Pre-Recession: 2007			Recession: Δ 2007-2010			ST Recovery: Δ 2010-13		
	Persistent Educational Upskilling	Temporary Educational Upskilling	No Educational Upskilling	Persistent Educational Upskilling	Temporary Educational Upskilling	No Educational Upskilling	Persistent Educational Upskilling	Temporary Educational Upskilling	No Educational Upskilling
Employer skill requirements									
Number of BGT raw job postings									
Mean	377,580.20	87,493.37	96,611.18	-34,412.30	-16,140.84	-5,907.76	163,836.10	54,006.57	84,878.48
Standard deviation	(107,435.70)	(201,309.80)	(129,978.40)	(59,536.49)	(35,374.03)	(51,228.46)	(147,004.00)	(54,006.58)	(105,673.80)
Mean percent of job postings requesting:									
Bachelor's degree or higher	24.29	18.04	3.89	22.39	20.77	4.69	1.08	-4.28	-1.81
Common skills	60.66	70.28	65.66	14.35	5.84	-2.69	3.72	0.19	5.86
Specialized skills	67.61	56.66	54.64	20.39	25.30	19.37	1.17	1.10	3.64
Software skills	12.36	7.17	3.99	11.10	9.97	5.07	1.14	-3.58	-0.54
Employment									
Annual number of employed workers									
Mean	1,516,926.00	792,040.20	1,018,310.00	-64,923.00	-80,948.10	-54,574.30	42,615.00	-756.60	10,270.90
Standard deviation	(1,221,693.00)	(1,329,768.00)	(1,083,564.00)	(108,166.30)	(109,695.30)	(172,730.40)	(87,135.35)	(48,147.21)	(59,635.34)
Mean percent with a bachelor's degree or higher	71.87	53.91	15.16	2.16	1.10	0.87	1.08	1.12	1.26
Wages									
Median Real Wage									
Mean	33.12	27.78	18.29	1.67	-0.89	0.49	0.68	-0.33	-0.45
Standard deviation	(18.63)	(13.51)	(6.36)	(3.18)	(7.47)	(1.43)	(2.74)	(1.39)	(0.95)
Ratio: 75th/25th percentile wages									
Mean	1.62	1.81	1.58	0.14	-0.01	0.01	0.06	0.06	0.05
Standard deviation	(0.46)	(0.21)	(0.27)	(0.53)	(0.05)	(0.22)	(0.10)	(0.10)	(0.07)
Number of 3-digit occupations	15	18	61	15	18	61	15	18	61

Source: Data on employer skill requirements are provided by Lightcast, weighted by annual employment from the American Community Survey, and aggregated by occupation at the 3-digit SOC level. Data on labor market conditions are calculated by 3-digit occupation using the American Community Survey from the Census Bureau. Data on wages are as reported by the Occupational Employment Statistics from the U.S. Bureau of Labor Statistics.

Notes: Occupations with a percentage point change in BA share between 2007-2010 that is greater than the aggregate are defined as having significant upskilling. Those that also experience less than a 10 percent decline during the initial recovery (2010-2013) and in the longer-term (2010-2019) are defined as persistent upskillers.

Table 3. Correlation between Educational Upskilling and Other Occupational Characteristics

	BA Share Annual Level 2010-2019	BA Share Annual Change 2010-2019	BA Share 3 Year Change 2007-2010
Percent of postings requiring a BA			
Mean	20.321	-0.120	10.766
Standard Deviation	(20.296)	(2.535)	(9.702)
Correlation with pre-recession level of occupational characteristics			
BA share of employed, 2007	0.878	0.092	0.233
Real median wage, 2007	0.627	0.033	0.122
Total employment, 2007	0.018	0.045	0.038
Correlation with contemporaneous measures of other skill requirements			
Share of postings requiring software skills	0.583	0.346	0.584
Share of postings requiring specialized skills	0.489	0.283	0.484
Share of postings requiring common skills	0.402	0.304	0.171
Number of 3-digit occupations	94	94	94

Source: Data on employer skill requirements are provided by Lightcast, weighted by annual employment from the American Community Survey, and aggregated by occupation at the 3-digit SOC level. Data on labor market conditions are calculated by 3-digit occupation using the American Community Survey from the Census Bureau. Data on wages are as reported by the Occupational Employment Statistics from the U.S. Bureau of Labor Statistics.

Table 4. DDD Change in Skill Requirements within Occupations by Type of Educational Upskilling

	Percentage Point Change Relative to Occupations that Exhibited No Educational Upskilling								
	Software Skills			Specialized Skills			Common Skills		
	Recession	ST Recovery	LT Recovery	Recession	ST Recovery	LT Recovery	Recession	ST Recovery	LT Recovery
	Δ2007-10	Δ2010-13	Δ2010-19	Δ2007-10	Δ2010-13	Δ2010-19	Δ2007-10	Δ2010-13	Δ2010-19
Persistent	0.047 ***	0.010 **	0.029 **	0.013	-0.025 *	-0.065 ***	0.108 **	-0.034 *	-0.045 **
	(0.011)	(0.005)	(0.012)	(0.039)	(0.013)	(0.014)	(0.049)	(0.021)	(0.021)
Temporary	0.045 **	-0.026 **	-0.003	0.041	-0.047 ***	-0.056 ***	0.060 **	-0.058 **	-0.058 **
	(0.015)	(0.007)	(0.016)	(0.055)	(0.012)	(0.020)	(0.023)	(0.029)	(0.030)
Persistent-Temporary	0.003	0.036 **	0.031 *	-0.028	0.023	-0.008	0.048	0.024	0.014
(F-test p-value)	(0.883)	(0.041)	(0.069)	(0.228)	(0.270)	(0.708)	(0.539)	(0.477)	(0.686)
Number of 3-digit occupations	94	94	94	94	94	94	94	94	94

Source: Authors' calculations using vacancy data provided by Lightcast weighted by 2007 employment level from the Occupational Employment Statistics at the 3-digit level of the Standard Occupational Classification (SOC) system.

Note: Each column is a separate regression where the dependent variable is the share of postings requesting a particular skill and the omitted category is a dummy variable for occupations with no upskilling.Occupations with a percentage point change in BA share between 2007-2010 that is greater than the economy-wide average are defined as having significant upskilling. Those that also experience less than a 10 percent decline during the initial recovery (2010-2013) and in the longer-term (2010-2019) are defined as persistent upskillers. Statistical significance is indicated at the ***one percent, **five percent, and *ten percent levels respectively.

Table 5. Change in Individual Software Skills for Persistent Educational Upskilling Occupations, 2010-2019

SOC	Persistent Upskilling Occupation	Number of unique software skills			Software Skill with Largest Percentage Point Change in Share of Postings by SOC			
		2010	2019	Change		2010	2010	Change
152	Mathematical Science Occupations	219	242	11%	Scripting Languages	3.99	21.98	17.99
151	Computer Occupations	251	261	4%	Cloud Solutions	1.25	12.28	11.03
112	Advertising, Marketing, Promotions, Public Relations, and Sales Managers	214	238	11%	Customer Relationship Management (CRM)	2.05	9.59	7.54
172	Engineers	215	246	14%	Engineering Software	15.70	23.15	7.45
132	Financial Specialists	202	229	13%	Accounting and Finance Software	5.69	9.98	4.29
251	Postsecondary Teachers	155	200	29%	Education Software and Technology	1.03	4.94	3.90
131	Business Operations Specialists	237	256	8%	Human Resources Software	3.98	7.45	3.47
254	Librarians, Curators, and Archivists	120	148	23%	Library and Archiving	1.63	4.35	2.72
113	Operations Specialties Managers	229	248	8%	Accounting and Finance Software	3.11	5.30	2.19
299	Other Healthcare Practitioners and Technical Occupations	71	116	63%	Health Information Management and Medical Records	0.64	2.46	1.82
111	Top Executives	200	236	18%	Customer Relationship Management (CRM)	0.60	2.21	1.61
291	Healthcare Diagnosing or Treating Practitioners	159	197	24%	Health Information Management and Medical Records	0.31	1.88	1.57
252	Preschool, Elementary, Middle, Secondary, and Special Education Teachers	116	177	53%	Education Software and Technology	0.58	2.02	1.44
253	Other Teachers and Instructors	101	153	51%	Education Software and Technology	0.40	1.63	1.23
231	Lawyers, Judges, and Related Workers	133	177	33%	Tax Software	0.14	1.06	0.92

Source: Data on employer skill requirements are provided by Lightcast.

Note: Occupations with a percentage point change in BA share between 2007-2010 that is greater than the economy-wide average are defined as having significant upskilling. Those that also experience less than a 10 percent decline during the initial recovery (2010-2013) and in the longer-term (2010-2019) are defined as persistent upskillers.

Table 6. DDD Change in Real Wages within Occupations by Type of Educational Upskillir

	Change Relative to Occupations that Exhibited No Educational Upskilling					
	Real Median Wages			Ratio 75th/25th		
	Recession	ST Recovery	LT Recovery	Recession	ST Recovery	LT Recovery
	Δ2007-10	Δ2010-13	Δ2010-19	Δ2007-10	Δ2010-13	Δ2010-19
Persistent	0.084 **	0.147 *	0.124	-0.010	0.008	0.094 *
	(0.033)	(0.085)	(0.087)	(0.150)	(0.038)	(0.053)
Temporary	0.022	0.060	0.016	-0.059	-0.0177	0.016
	(0.028)	(0.073)	(0.075)	(0.128)	(0.033)	(0.046)
Persistent-Temporary	0.062 **	0.087	0.108	0.049	0.026	0.078 *
(F-test p-value)	(0.032)	(0.244)	(0.156)	(0.705)	(0.438)	(0.094)
Number of 3-digit occupations	94	94	94	94	94	94

Source: Authors' calculations using vacancy data provided by Lightcast weighted by 2007 employment level from the Occupational Employment Statistics at the 3-digit level of the Standard Occupational Classification system.

Note: Each column is a separate regression where the dependent variable is the change in wages and the omitted category is a dummy variable for occupations with no upskilling. Regressions also control for share of workers with a BA within each occupation as calculated from the 2005-07 American Community Survey. Occupations with a percentage point change in BA share between 2007-2010 that is greater than the economy-wide average are defined as having significant upskilling. Those that also experience less than a 10 percent decline during the initial recovery (2010-2013) and in the longer-term (2010-2019) are defined as persistent upskillers. Statistical significance is indicated at the ***one percent, **five percent, and *ten percent levels respectively. Statistical significance is indicated at the ***one percent, **five percent, and *ten percent levels.