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DISCUSSION PAPER SERIES

IZA DP No. 16542

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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 demand for labor *across* occupations, mismatch *within* occupations can also arise if the skill requirements for a job are changing over time. During the Great Recession, U.S. employers rapidly increased requirements within occupations for a bachelor's degree when hiring for open positions, a trend that became known as "educational upskilling" (Modestino, Shoag, and Ballance 2020). Although roughly one-third of educational upskilling during the last recession was shown to have been cyclical or temporary, as much as two-thirds of that increase appeared to have persisted during the initial recovery (Modestino, Shoag, and Ballance 2016), possibly driven by structural forces such as skill-biased technological change (Hershbein and Kahn 2018).

What are the broader implications of educational upskilling for workers and the labor market? If educational requirements within jobs increase gradually over time, labor supply can presumably adjust with minimal lags. However, employers may increase educational requirements more rapidly during periods of labor market disruption, such as when responding to recessions or adopting new technologies. This can create larger imbalances between labor supply and demand that take longer to resolve, such as the ongoing "race between education and technology," with adverse impacts for less-educated workers (Autor, Goldin, and Katz 2020).

We study this question during the Great Recession, when the share of vacancies requiring at least a bachelor's degree jumped by more than 10 percentage points (over 70%) between 2007 and 2010. Figure 1 shows this increase was only partially reversed over the next 3 years before remaining relatively stable through 2019. This persistence in rising educational requirements suggests some unemployed workers lacking these newly demanded credentials would no longer qualify for jobs they once held, possibly extending their jobless spells—due to retraining or switching to another occupation—or causing them to exit the labor force entirely. If the supply of qualified workers lagged demand for an extended period, educational upskilling may have impaired matching efficiency both within affected occupations and in the aggregate, potentially explaining the slower labor market recovery after the Great Recession (Cavounidis et al. 2021).

Using the near-universe of roughly 200 million U.S. online job postings collected between 2007 and 2019 by Lightcast (formerly Burning Glass Technologies), we document a novel set of stylized facts about educational upskilling dynamics over the business cycle. First, we explore how the increased demand for a bachelor's degree varied considerably by occupation during the Great Recession and persisted beyond the initial recovery. Second, we examine how this persistence in bachelor's degree requirements was correlated with rising demand for software skills within occupations, providing a direct link between the adoption of new technologies and structural educational upskilling.

Finally, we are the first to document the impact of persistent educational upskilling on aggregate matching efficiency and its implications for workers. We develop an adjusted mismatch index to detect labor market imbalances caused by shifts in educational requirements *within* occupations over time. Using this adjusted mismatch index, we demonstrate how persistent educational upskilling shifts the composition of vacancies toward workers with a bachelor's degree, creating misalignment with the educational composition of unemployed workers within occupations and decreasing matching efficiency in the aggregate. We further document lower job-finding rates for noncollege workers among occupations with persistent educational upskilling. Together, these contributions to the literature reconcile prior studies finding little evidence of labor market mismatch (Davis, Faberman, and Haltiwanger 2012; Abraham 2015) with industry reports linking the dearth of skilled workers to slower hiring after the Great Recession (Weaver and Osterman 2017). Our findings suggest that search-and-matching models should account for rapidly changing educational requirements that present a moving target for unemployed workers to qualify for re-employment (Pissarides 2000).

Related Literature

Recent studies have found that changes in employer skill requirements during the Great Recession reflected both cyclical and structural forces. On the cyclical side, Modestino, Shoag, and Ballance (2020) demonstrated the share of job postings requiring 4-year college degrees increased by 10 percentage points between 2007 and 2010. They estimated one-third of this educational upskilling was an opportunistic response to the greater availability of educated workers during the recession. Separately, they showed employer demand for college degrees and certain skills fell by roughly one-third of their initial increase as the labor market recovered between 2010 and 2014 (Modestino, Shoag, and Ballance 2016).

On the structural side, a complementary set of papers confirmed the remaining two-thirds of educational upskilling that occurred during the Great Recession persisted through 2014, possibly reflecting a structural change in job requirements (Hershbein and Kahn 2018; Zago 2018; Blair and Deming 2020). Persistent educational upskilling *within* occupations may reflect longer-term trends such as skill-biased technological change (Katz and Murphy 1992; Autor, Katz, and Krueger 1998; Autor, Levy, and Murnane 2003) or labor market polarization (Autor, Katz, and Kearney 2008; Autor and Dorn 2008; Acemoglu and Autor 2010). For example, Hershbein and Kahn (2018) found that rising IT capital investments, particularly in routine-cognitive occupations, were correlated with educational upskilling. These structural trends may have been accelerated by cyclical forces stemming from the Great Recession, as downturns tend to hasten long-term changes in the labor market (Charles, Hurst, and Notowidigdo 2012; Tuzeman and Willis 2013; Beaudry, Green, and Sand 2016; Jaimovich and Siu 2020).

Some scholars argue that educational requirements listed on job openings are not binding but instead reflect existing workers being overqualified within certain occupations (Cappelli 2014). Yet several studies find employers are willing to pay a premium for rising skill requirements within occupations induced by technology adoption. Bessen, Denk, and Meng (2022) show that jobs requiring higher computer usage experience larger relative wage increases, contributing to growing wage inequality within occupations. Kogan et al. (2022) demonstrate that technological change not only displaces low-skilled labor through automation but also depresses earnings growth among older high-skilled workers whose skills become obsolete. Braxton and Taska (2023) find technological change results in large earnings losses among displaced workers who switch to lower-paying jobs when skill demands in their prior occupations increase.

Despite these impacts on earnings, whether educational upskilling could be large or persistent enough to affect matching efficiency—either within affected occupations or in the aggregate—remains unclear. The U.S. Department of Labor's O*NET database shows that computer, analytical, and quantitative skills have increased within job categories since 1979, but the increases were modest (Liu and Grusky 2013). Yet other studies show that states exhibiting greater mismatch in educational qualifications during the Great Recession also experienced greater job polarization, suggesting that shifting skill requirements can restrain job growth in the aggregate for an extended period, consistent with an outward shift in the Beveridge curve (Restrepo 2015, Zago 2018).

While standard indices constructed *across* occupations indicate labor market mismatch contributed to joblessness during the Great Recession, they fail to detect mismatch as a significant factor during the sluggish employment recovery. Şahin et al. (2014) show that labor market mismatch across occupations increased by 22% between 2007 and 2010, accounting for 29% of the rise in unemployment during the Great Recession. However, this standard mismatch index returned to pre-recession levels by 2012 (Burke 2015), despite aggregate matching efficiency remaining below pre-recession levels beyond 2015 (Hobijn and Perkowski 2016; Hall and Schulhofer-Wohl 2018). The anemic wage growth observed in the aggregate during the recovery period was also inconsistent with the labor mismatch hypothesis (Rothstein 2012; Abraham 2015). Instead, economists argued that weak aggregate demand, rather than skills mismatch or other structural factors, better explained the continued outward shift of the Beveridge curve after the Great Recession (Barlevy 2011; Lazear and Spletzer 2012; Rothwell 2012; Carnevale, Javasundera, and Cheah 2012; Diamond 2013; Diamond and Şahin 2015; Weaver and Osterman 2017). Yet these prior studies could not account for shifting educational requirements *within* occupations, possibly explaining why the economic literature contradicted employer reports claiming the high vacancy rate during the recovery reflected a lack of skilled workers (Bessen 2014).

Data Sources

We extend the literature to reveal new facts about educational upskilling *within* occupations over the full business cycle of the Great Recession, from 2007 through 2019, and demonstrate their broader implications for both workers and aggregate matching efficiency. We focus on *educational* upskilling, the increase in demand for workers with a bachelor's degree, because obtaining a 4-year college degree takes significant time and financial resources and completion is readily verifiable, making it a meaningful hurdle for employment. We focus on *occupational* mismatch since workers can potentially qualify for similar jobs in other industries but are less able to qualify for different jobs in other occupations when aggregate demand falls.

To measure labor demand, we use data from over 200 million U.S. online job postings collected by Lightcast for 2007 and 2010–2019.[1] Using a proprietary algorithm to de-duplicate ads, Lightcast scrapes over 40,000 sites from job boards, newspapers, government agencies, and employers, capturing more than 7 million unique job openings daily. Lightcast parses the text of each job posting to categorize occupation, industry, and educational requirements (e.g., bachelor's degree) as well as specific types of common (e.g., communication), specialized (e.g., accounting), and software (e.g., Python) skills.

We use two versions of the Lightcast data. The first is the "main" vacancy dataset used by researchers that provides unique job postings on a monthly basis. We pool this data by year to study changes over time in employer demand for education and specific skillsets by occupation. These time trends closely track movements in both aggregate vacancies from national surveys (e.g., Job Openings and Labor Turnover Survey [JOLTS]) and breakdowns by occupation and education distributions from state surveys (e.g., Minnesota).

Although the main Lightcast dataset closely tracks vacancy *trends* from national and state surveys over time, the *number* of vacancies at a point in time is consistently lower. This is because Lightcast cannot capture job openings that are posted behind online paywalls or advertised physically (e.g., sign in the window). Moreover, whereas surveys explicitly ask employers about the *number* of openings, one online posting can represent multiple openings. Fortunately, Lightcast constructed a "normalized" (reweighted) dataset that exactly matches the monthly number of industry vacancies as measured by JOLTS and then disaggregates this monthly count by using the occupational distribution within each industry from the main

[1] Lightcast data are unavailable for 2008 and 2009 because of operational changes when the company was founded. See the appendix for more details.

Lightcast dataset.[2] We use this normalized version of the Lightcast dataset to measure the *number* of vacancies by education level within occupations when constructing our mismatch indices.

To measure labor supply, we use microdata on unemployed workers collected by the Current Population Survey (CPS) from 2007 through 2019 (Flood et al. 2018). The cross-sectional component provides the number of unemployed workers by occupation and education level to construct our mismatch indices. We also use the longitudinal dimension to track job-finding rates by worker education level within occupations experiencing temporary versus persistent educational upskilling.

Finally, we use other labor market data to measure changes over time in employment and wages. We use the American Community Survey (ACS) to disaggregate movements in the supply of labor by educational attainment within versus between occupations at various levels of the Standard Occupational Classification (SOC) system. We use the Occupational Employment Statistics (OES) to measure changes in wage levels and inequality over time within occupations experiencing persistent versus temporary or no educational upskilling.

Methods

Measuring Educational Upskilling within Occupations

Using the main vacancy dataset, we first examine whether rising educational requirements during the Great Recession (2007–2010) were temporary or persisted throughout the subsequent recovery (2010–2019). Unlike prior studies, we measure persistence *within occupations* to reveal heterogeneity in labor imbalances masked by aggregate measures. For example, some occupations may have experienced mostly opportunistic (e.g., temporary)

[2] This normalized Lightcast dataset is only available for 2007 and 2010–2017.

educational upskilling driven by the greater availability of college-educated workers during the recession. This could increase mismatch in the short term by temporarily lengthening unemployment spells for workers without a bachelor's degree, resolving relatively quickly as the labor market initially recovered (2010–2013). Other occupations may have experienced more structural (e.g., persistent) educational upskilling driven by technology adoption, leading to larger labor market imbalances that resolved more slowly as workers either obtained the required credentials or switched occupations (2010–2019).

To operationalize this approach, we define an occupation as having experienced "significant" educational upskilling during the Great Recession if the change in the share of postings requiring a bachelor's degree or higher was *greater* than the employment-weighted average increase that was observed economy-wide. Table 1 shows this share increased on average by 10.77 percentage points within occupations during the recession (2007–2010). Occupations that had *below-average* increases in this share during the Great Recession are designated as having experienced *no* significant educational upskilling.[3]

Among the occupations that experienced *above-average* increases in the share of postings requiring a bachelor's degree during the recession, we further differentiate between whether this increase in educational requirements was "persistent" or "temporary." According to Table 1, on average 10% of the initial recessionary increase in the demand for a bachelor's degree within occupations was reversed during the longer-term recovery period (2010–2019). We designate occupations as "temporary" educational upskillers if they experienced *greater than* a 10% reversion of their initial recessionary increase during either the short-term (2010–2013) or

[3] We follow the prior literature and use the *percentage point* change in educational requirements to avoid designating occupations with large *percent* changes from a small initial base as posing a significant barrier for workers without a bachelor's degree.

longer-term (2010–2019) recovery. We designate occupations as "persistent" educational upskillers if they experienced *less than* a 10% reversion of their initial recessionary increase during both the short- and longer-term recovery periods.[4]

Using these definitions, we classify each occupation in terms of educational upskilling behavior at both the two-digit and three-digit SOC levels. We then test whether persistent changes in educational requirements primarily reflect a compositional shift in job vacancies *across*, as opposed to an increase in demand for bachelor's degrees *within*, the underlying detailed occupations.[5] We also explore whether persistence in educational upskilling was more prevalent among occupations of a certain size, those with a higher initial share of educated workers, or those with greater productivity.

Finally, we use a difference-in-difference approach to test whether occupations that engaged in persistent educational upskilling also had persistent increases in the share of postings requiring other skills (e.g., common, specialized, or software) relative to occupations that exhibited temporary or no significant educational upskilling. To further explore how persistent educational upskilling might be driven by technology adoption, we examine whether occupations with persistent increases in requiring a bachelor's degree were simply seeking more of the same software skills or requiring new software skills that might reflect structural changes in the job.

Detecting Educational Labor Market Mismatch within Occupations

We adapt the standard labor mismatch index developed by Şahin et al. (2014) to quantify potential hiring lost because of a misallocation of unemployed workers relative to the distribution of vacancies by education within occupations. The standard index is based on a

[4] Results are qualitatively similar using a more restrictive definition of persistent upskilling that does not allow for *any* reversion in the share of postings requiring a bachelor's degree.

[5] We decompose the net increase in the share of vacancies requiring a bachelor's degree for a given two-digit occupation into movements within versus between the underlying three-digit occupations for the 2007–2010 period.

Cobb–Douglas matching function, with hires increasing in the number of both unemployed workers (u_{it}) and vacancies (v_{it}) in market *i* at time *t*. Markets are typically defined by industry, occupation, or geography, but here we delineate them by occupation alone:[6]

$$M_t = 1 - \sum_{i=1}^{I} \frac{\varphi_i}{\overline{\varphi_t}} \left(\frac{v_{it}}{v_t}\right)^{\delta} \left(\frac{u_{it}}{u_t}\right)^{1-\delta} \tag{1}$$

The terms u_t and v_t refer to the total number of unemployed workers and vacancies in the economy, respectively. The parameters δ and $(1-\delta)$ capture the vacancy and unemployment elasticity of hires, respectively. The term φ_i represents matching efficiency specific to occupation *i*, and $\overline{\varphi_t}$ represents a CES aggregator of the market-specific matching efficiencies weighted by their respective vacancy shares.

By construction, the value of the index ranges from 0 (when all potential hires occur) to 1 (when no potential hires occur), depending on how closely the occupational composition of unemployed workers (u_{it}) matches that of vacancies (v_{it}), while accounting for different matching efficiencies across occupations. Zero mismatch should be considered an idealized benchmark for a social planner capable of costlessly reallocating unemployed workers across different occupational labor markets accordingly. However, since reallocation is typically *not* costless, this standard mismatch index can be interpreted as an upper bound (Şahin et al. 2014).

We extend the standard mismatch index in two important ways: one empirical and the other conceptual. Empirically, we use the richness of the Lightcast data to incorporate *observed changes* in educational requirements for job vacancies over time. Because of data limitations, Şahin et al. (2014) impute labor demand by education for occupations using the pre-recession distribution of educational attainment for incumbent workers from the BLS. Their approach

[6] Şahin et al. (2014) assume each unemployed worker searches for jobs in a particular occupation and each employer encounters only the workers searching in that occupation.

holds this educational distribution fixed over time and assumes that the "educational requirements of newly created vacancies for each occupation is equal to the educational content in the existing jobs for that same occupation."[7] By construction, their measure cannot detect labor market mismatch arising from *changes* in the educational demands of employers during the recession. In contrast, Lightcast's normalized vacancy dataset allows us to measure the *observed* number of vacancies demanded by education level within occupations each year to capture changes in mismatch arising from educational upskilling over time.

Conceptually, we develop an *adjusted* mismatch index to capture persistent educational upskilling *within* rather than across occupations. Şahin et al. (2014) measured occupational mismatch for different educational "sectors" by estimating their standard mismatch index using Equation (1) by two-digit occupation separately within an education group (e.g., college-educated). However, this approach only detects reductions in hiring caused by mismatch between the composition of job vacancies versus that of unemployed workers *across* occupations (e.g., registered nurse versus sales representative) for a given education level (e.g., bachelor's degrees).[8] By construction, it cannot detect mismatch between the educational demands of employers and the educational attainment of unemployed workers *within* occupations (e.g., the share of registered nursing vacancies requiring bachelor's degrees versus the share of job-seeking registered nurses with bachelor's degrees), which can arise when education requirements shift rapidly in response to structural changes such as technology adoption.

This misalignment of vacancies and workers due to structural, rather than temporary, changes in educational requirements could have long-term implications for the efficient level of

[7] Ibid, pp. 3549–50.

[8] In the appendix, we also replicate Şahin et al. (2014) to calculate the standard mismatch index separately by educational sector using the Lightcast data.

educational investments. To test this, we adjust the standard mismatch index to capture persistent educational upskilling over time within occupations. Specifically, we treat vacancies for a given three-digit persistent educational upskilling occupation as pertaining to different labor markets according to whether the vacancy requires a bachelor's degree. Similarly, we treat unemployed workers in that same three-digit occupation as now searching in different labor markets according to their degree status. For all other occupations—both temporary and non-upskilling—we follow the standard approach and define the market solely on the basis of the three-digit occupation. More precisely, our adjusted index can be expressed as follows:

$$M_{tA} = 1 - \sum_{i=1}^{I} \sum_{j=0}^{1} \frac{\varphi_i}{\varphi_t} \left(\frac{v_{ijt}}{v_t}\right)^{\delta} \left(\frac{u_{ijt}}{u_t}\right)^{1-\delta} - \sum_{k=1}^{K} \frac{\sigma_k}{\sigma_t} \left(\frac{v_{kt}}{v_t}\right)^{\delta} \left(\frac{u_{kt}}{u_t}\right)^{1-\delta} \quad (2)$$

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 educational upskilling) are indexed by *k*. Education level is indexed by *j,* which takes a value of 1 if the vacancy requires a bachelor's degree or higher (or if the worker has a bachelor's degree or higher) and equals 0 otherwise. On the labor demand side, v_{ijt} represents the number of vacancies in occupation *i* (exhibiting persistent upskilling) with given education requirement *j* (bachelor's degree or not) in month *t*, v_{kt} is the number of vacancies in occupation *k* (exhibiting either temporary or no upskilling) in month *t*, regardless of education requirement, and v_t is the total number of vacancies in the economy in month *t.* On the labor supply side, u_{ijt} represents the number of unemployed workers in occupation *i* with education level *j* (bachelor's degree 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.*

The remaining terms are defined similarly to Equation (1). The term φ_i still represents matching efficiency specific to occupation i, that is not specific to the education requirement of the vacancy, and σ_k represents matching efficiency for occupation k.[9] The term $\overline{\varphi_t}$ represents a CES aggregator of the market-specific matching efficiencies among the occupations indexed by i, weighted by their respective vacancy shares, and $\overline{\sigma_t}$ represents the analogous term for the occupations indexed by k.

Our approach assumes persistent educational upskilling reflects structural changes that would justify some increase in the share of job seekers with a bachelor's degree (under costless retraining), whereas temporary upskilling might not justify such investment.[10] We acknowledge that in practice, it is often not socially optimal to increase the share of job seekers with bachelor's degrees to *fully* meet increased demand—even within persistent educational upskilling occupations—because producing more college graduates is costly in terms of both time and money. And even if it were socially optimal, private decisions might need to be subsidized if some of the benefits of obtaining additional education are external to the worker. Nonetheless, subsidizing existing workers within an occupation (e.g., healthcare) to obtain additional education (e.g., bachelor's degree) could be more efficient than retraining existing college graduates in other occupations (e.g., sales), as assumed under the standard mismatch index. For future labor market entrants, college course offerings and choice of majors do respond to changes in job postings, especially for lower-cost course offerings (Conzelmann et al. 2024).

Quantifying the Impact of Educational Upskilling on Workers

We examine two potential impacts of educational upskilling on noncollege versus

[9] These parameter values are found in Şahin et al. (2014) and only vary across three-digit occupations—there is no common component across the persistent upskillers versus other occupations. The parameters δ and $(1-\delta)$ capture the vacancy and unemployment elasticity of hires as before.

[10] This produces more conservative estimates of mismatch within occupations since increases in education requirements for temporary-upskilling occupations were partially reversed and those for non-upskilling occupations were small or nonexistent.

college-educated workers in occupations that experienced persistent educational upskilling versus those that did not. First, we calculate job-finding rates from unemployment by assigning each unemployed individual to their most recent occupation using a three-digit SOC crosswalk following Birinci et al. 2023. Each individual is then placed into one of six categories based on a combination of their occupation's upskilling category—persistent, temporary, or non-upskilling—and their educational attainment—having earned a bachelor's degree or not. For each category, 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.[11]

Second, we compare changes in wage levels and inequality over time within occupations experiencing persistent versus temporary or no educational upskilling. The rapid increase in demand for educational requirements relative to the supply of educated workers within occupations might necessitate employers raising wages to attract workers with a bachelor's degree to those positions, possibly increasing wage inequality within occupations between workers with and without a college degree. We test this hypothesis by comparing changes over time in median wages and the ratio of wages at the 75th versus 25th percentiles for occupations with persistent educational upskilling relative to those without.

RESULTS

Heterogeneity in Educational Upskilling within Occupations

We first examine the persistence in educational upskilling during the Great Recession, whether it varied across the labor market, and the degree to which it reflected a compositional shift in job vacancies across, versus increased demand for bachelor's degrees within, the underlying detailed occupations. Figure 2 plots the share of postings requiring a bachelor's

[11] Approximately 8% of unemployed workers in the CPS cannot be assigned an occupation because of missing data or gaps in the crosswalk. Results are qualitatively similar for 1- and 2-month job-finding rates.

degree by occupation at the two-digit SOC level over time, revealing stark differences in how educational upskilling unfolded over the business cycle. Relative to the economy-wide average, occupations with persistent educational upskilling (e.g., management and others, represented by the solid lines) experienced steeper increases in educational requirements during the recession (2007–2010); these increases endured throughout the recovery (2010–2019), with little sign of reversion. Temporary-upskilling occupations (e.g., community and social services and others, represented by dotted lines) showed large increases in the share of postings requiring a bachelor's degree during the recession, yet those gains reversed by more than 10% during the recovery. The remaining occupations (e.g., production and others, represented by the dashed lines) experienced little or no upskilling during this period. Thus, the magnitude and degree of persistence in rising educational requirements was not widespread, as prior research has suggested, but instead varied considerably across the labor market. This heterogeneity could have adverse consequences for less educated workers within the affected occupations as well as aggregate matching efficiency.

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* the underlying sub-occupations, then it might be possible to detect labor market imbalances due to educational upskilling by calculating the standard mismatch index across those sub-occupations. To test this, we decompose the change in the share of postings requiring a bachelor's degree for a given two-digit SOC occupation into separate components due to changes *within* versus *between* the underlying three-digit occupations for both the recession (2007–2010) and initial recovery (2010–2013) periods.

Panel A of Figure 3 shows that during the recession, the increase in the share of postings requiring a bachelor's degree for a given two-digit broad occupation was largely due to educational upskilling *within* the underlying three-digit sub-occupations, not the changing composition of job postings across those sub-occupations. In contrast, Panel B shows that half or more of the reversion during the recovery period for the two-digit occupations that experienced temporary upskilling was due to changing composition across the underlying sub-occupations rather than reversion within those occupations.[12]

Disaggregating even further, Figure 4 confirms that the three-digit sub-occupations within a given two-digit broad occupation group also did not behave uniformly in terms of educational upskilling. For example, the broad legal occupation group is composed of lawyers, judges, and related workers (which experienced persistent upskilling) as well as legal support workers (which experienced temporary upskilling). In fact, 61 out of the 94 sub-occupations experienced no significant upskilling between 2007 and 2010, with the change in the share of postings requiring a bachelor's degree falling below the economy-wide average threshold of 10.77 percentage points. Although a handful of these occupations did experience large *percent* increases in the share of postings requiring a bachelor's degree during the recession, it was from a very low base (most were below 10%) and all but one experienced some reversion in those demands during the recovery period with one in seven ending up at or below their 2007 level.

Among the 33 sub-occupations that did experience significant educational upskilling during the recession, only 15 were "persistent upskillers," using our definition—meaning the reversion in the share of postings requiring a bachelor's degree during the recovery period was less than the economy-wide average of 10%. The remaining 18 occupations that experienced

[12] The results are qualitatively similar when decomposing changes within three-digit occupations based on the underlying occupations at the six-digit level. See Figure A8 in the appendix.

significant educational upskilling during the recession were classified as “temporary upskillers”—exhibiting a degree of reversion during either the initial or longer-term recovery period that was greater than 10%. Interestingly, Figure 4 reveals there is no systematic relationship between the size of the initial increase in the share of postings requiring a bachelor’s degree during the recession and whether an occupation was classified as either a “temporary” or “persistent” upskiller during the recovery.

Figure 5 reveals that movements in labor supply were relatively small compared to those of labor demand during both the recession and recovery periods. This is likely because only a fraction of the sudden double-digit surge in demand for college-educated workers could be filled from the pool of unemployed workers with a bachelor’s degree and because obtaining a bachelor’s degree would take several years for workers who no longer qualified for those positions. Decomposing the change in the share of employed workers with a bachelor’s degree among the broad two-digit occupations reveals that any increase came from changes in worker education levels rising *within* the underlying three-digit occupations rather than from a compositional shift in hiring *between* three-digit occupations. This pattern is consistent with greater occupational specialization arising from new education investments—either among incumbent workers or entering cohorts—rather than occupation switching among existing college graduates. Overall, however, the educational attainment of employed workers did not keep pace with the rapid shift in demand within occupations, suggesting that persistent educational upskilling could affect aggregate matching efficiency if unemployed workers were no longer qualified for their prior jobs.

Characteristics of Occupations with Persistent Educational Upskilling

Examining the characteristics of occupations reveals that the recession likely accelerated the demand for workers with a bachelor's degree within certain occupations. Table 2 shows that before the recession, occupations with persistent educational upskilling were growing—having a higher number of job postings and a greater share of postings as a percentage of employment compared with occupations that showed temporary or no significant upskilling. Persistent-upskilling occupations also had a higher pre-recession share of postings requiring a bachelor's degree and other skills, such as specialized and software skills, as well as a higher share of employed workers with a bachelor's degree and higher wage levels.

The pattern of changes over time in Table 2 highlights other distinguishing features of occupations for which the increase in education requirements during the Great Recession was "sticky." For example, although all types of 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 qualified workers to some degree, although they had to pay a premium to do so.

Table 3 calculates the correlation between educational upskilling and these pre-recession characteristics for three-digit occupations. Although the annual share of postings requiring a bachelor's degree is highly correlated with both the 2007 share of employed workers with a bachelor's degree and real median wages, the *change* in the share of postings requiring a bachelor's degree—either annually or using 3-year stacked differences—is much less so. Also, the size of the occupation in terms of total employment is not highly correlated with educational upskilling, confirming that the increased demand for education is not driven by a handful of large occupations. Examining skill clusters, the increase in the share of postings requiring a bachelor's degree during the recession was most highly correlated with an increase in the share requiring software skills (corr = 0.584), followed by specialized skills (corr = 0.484) but not common skills (corr = 0.171)—suggesting both technology and specialization played a role.

Relationship between Educational Upskilling and Technology Skills

To what degree does persistent educational upskilling reflect structural changes in the underlying skills required for the job? Table 4 reports the results of our 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 requiring a particular skill. The independent variables of interest are an indicator for whether the occupation experienced persistent or temporary educational upskilling. 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 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 demand for common skills showed significant reversion among both persistent and temporary-upskilling occupations relative to those experiencing no significant educational upskilling. In contrast, the demand for software skills continued to increase among occupations that had experienced persistent educational upskilling but showed significant reversion among temporary-upskilling occupations. Overall, the sharp increase during the recession and the 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 using the bachelor's requirement not simply as a screening tool but possibly as an indicator that workers had acquired or could learn emerging software skills associated with the job.

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 even for occupations beyond the usual technology-driven sectors such as engineering, mathematical, and computer science occupations. For example, occupations such as financial specialists, health diagnosing and treating practitioners, and advertising, marketing, promotions, public relations, and sales managers experienced large increases in the share of postings requesting software skills.

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 10 individual software skills within three-digit occupations during the business cycle for persistent versus temporary upskillers. Panel A shows that occupations experiencing persistent educational upskilling sharply increased their demand for software skills specific to engineering, statistics, accounting, finance, business intelligence, and human resources software as well as database, customer relationship management, and application programming interface (API) tools. In contrast, Panel B shows that occupations experiencing temporary education upskilling showed little or 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.[13]

To what extent might the sudden increase in the demand for software skills within occupations that experienced persistent educational upskilling present a barrier to workers who were displaced from their jobs during the recession? Panel A of Table 5 reports the number of unique software skills requested for each of the occupations that experienced persistent educational upskilling. Employers requested upwards of 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 experienced the largest 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 use a bachelor's degree as a proxy for a worker's ability to learn new software skills, which could explain why educational requirements persisted throughout the recovery as firms increased their adoption of new software technology.

Moreover, the demand for certain unique software skills increased sharply within occupations, even those not usually considered technical or technology driven. Panel B of Table 5 lists the top software skills that had the largest percentage point change in the share of postings within each persistent-upskilling occupation. For example, the demand for customer relationship management (CRM) software skills increased by nearly 8 percentage points for advertising,

[13] Similarly, the increase in the share of postings for "common" skills such as communication and "specialized" skills such as budget management reflected an increased prevalence for existing skills rather than requests for new skills or a greater variety of skills across occupations.

marketing, promotions, public relations, and sales managers. This increasing specialization within occupations for certain types of software skills might replace routine tasks and perhaps be complementary with cognitive tasks that require a bachelor's degree (Braxton and Taska 2023). Overall, our findings are consistent with the hypothesis that technological advances are driving the persistent educational upskilling observed within occupations, particularly those that use specialized software (e.g., engineering software) or those for which new software rapidly diffuses (e.g., managers), possibly changing the nature of job tasks.

Implications of Upskilling for Labor Market Mismatch

Did persistent educational upskilling within occupations affect matching efficiency, either in the aggregate or within certain sectors of the labor market? Unemployed workers in occupations with persistent educational upskilling may no longer qualify for the positions they once held if they lack the necessary skills or credentials to meet these new hiring requirements, possibly increasing occupational mismatch. To test this hypothesis, we estimate our adjusted mismatch index from Equation (2). We first partition each of the 15 persistent-upskilling occupations into two distinct sub-occupations by education: one that is open to workers with a bachelor's degree and the other that is open to workers without a bachelor's degree. For example, financial operations vacancies that require a bachelor's degree and unemployed financial operations workers who hold a bachelor's degree are assigned to a separate financial operations BA sub-occupation. Financial operations vacancies without that requirement and financial operations workers without that degree are assigned to a different financial operations non-BA sub-occupation. Occupations experiencing temporary or no significant upskilling are not partitioned since changes in the demand for a bachelor's degree were more transitory or much smaller, respectively.

We then calculate our adjusted mismatch index accounting for persistent educational upskilling *within* occupations using Equation (2) and compare it to the standard mismatch index from Equation (1). Figure 8 shows that the *level* of the adjusted mismatch index (Panel A) is higher than that of the standard index (Panel B), but this is somewhat mechanical since the adjusted index is calculated at a slightly more disaggregated level than the standard index.[14] More relevant to our research question is the relative comparison of the *changes* in these two indices over the business cycle. Both signaled an increase in labor market mismatch during the recession (2007–2010), although the rise was steeper for the adjusted versus the standard mismatch index. The pattern during the recovery period was even more striking. Between 2010 and 2013, the standard mismatch index fell from 0.121 to 0.065—nearly a 50% drop. In contrast, the adjusted mismatch index declined more modestly from 0.203 to 0.179—decreasing by roughly 10%. After 2013, the standard index was relatively flat, while the adjusted index rose slightly before leveling off. Overall, the adjusted mismatch index exhibited a less cyclical pattern than did the standard index, aligning with industry reports that some unemployed workers were no longer qualified for their jobs.

How does educational upskilling affect occupational mismatch *within educational sectors* as vacancies are reallocated from the non-bachelor's sector to the bachelor's degree sector over time? For comparison, Figure 9 compares the standard mismatch index *across* occupations separately for each educational sector, showing the misallocation of vacancies across the same set of occupations for unemployed workers with a bachelor's degree (Panel A) versus unemployed workers without a bachelor's degree (Panel B).[15] Note that the *level* of mismatch is consistently higher in the bachelor's versus the non-bachelor's sector. Thus, while having more

[14] By construction, the mismatch index is increasing in the level of disaggregation.
[15] In the appendix, we replicate this prior analysis from Şahin et al. (2014) using the Lightcast data.

education makes workers more adaptive, it also makes them more specialized and potentially less substitutable across occupations, with this second effect being dominant. 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. In contrast, a worker with a high school degree may have a more general set of skills (e.g., customer service) that can be applied to a wider range of occupations (e.g., waitstaff versus sales).

Figure 9 also shows that *changes over time* in the standard mismatch index also vary by educational sector and are consistent with the educational upskilling trends documented earlier. As employers raised education requirements during the recession, vacancies were reallocated from the non-BA sector to the BA sector, largely among the persistent and temporary-upskilling occupations. Yet, we showed earlier that the rate at which the share of postings for a bachelor's degree increased was more rapid than the rate at which the supply of workers with a bachelor's degree increased. This would be expected to sharply increase mismatch in the BA sector between 2007 and 2010, as shown in Panel A, relative to little or no increase in mismatch in the non-bachelor's sector, as shown in Panel B.

As the labor market tightened during the initial recovery, employers reduced education requirements in the temporary-upskilling occupations so that some jobs in the BA sector were reallocated back to the non-BA sector. This would be expected to result in an initial decrease in mismatch index for the BA sector between 2010 and 2013, as shown in Panel A. However, many of the persistent-upskilling occupations continued to increase the share of postings requiring a bachelor's degree during the longer term, consistent with the subsequent increase in mismatch in the BA sector later in the recovery (after 2013). In contrast, Panel B reveals less cyclical movement in the mismatch index for the non-BA sector since most non-BA occupations exhibited little or no significant upskilling.

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

What are the implications of educational upskilling for workers? If workers were able to transition across educational levels and occupations more easily than the mismatch index indicated, we might overestimate the degree to which educational upskilling constrained hiring during the recession and recovery period. To test this, we examine two potential impacts of educational upskilling on workers. First, we compare whether workers without a bachelor's degree had greater difficulty in finding a job relative to workers with a bachelor's degree in occupations that experienced persistent educational upskilling versus those that did not. Figure 10 confirms that 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. Yet within each of our three upskilling categories, the job-finding rates for workers without a bachelor's degree declined more steeply during the recession compared to those for workers with a bachelor's degree, consistent with the relative decline in demand for workers by education level. This gap is most pronounced for persistent-upskilling occupations, consistent with employers increasing their demand for workers with a bachelor's degree more sharply during the recession, and keeping those demands higher for longer, compared to occupations with temporary or no significant educational upskilling.

After 2011, job-finding rates improved for all workers as the economy recovered. However, the job-finding rates for workers without a bachelor's degree increased *faster* than their more educated peers among occupations with temporary or no significant upskilling and exceeded that of workers with a bachelor's degree by 2016. This pattern is consistent with the narrative that, as the labor market tightened between 2016 and 2019, workers with a bachelor's degree once again became a luxury rather than a necessity for these occupations. In contrast, job-finding rates among workers without a bachelor's degree were consistently lower than those of workers with a bachelor's degree throughout the recovery period for persistent-upskilling occupations.[16]

The second impact we examine is on the wage rates of workers at the top versus the bottom of the distribution within occupations. 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 among occupations with persistent educational upskilling would suggest employers raise wages to attract workers with a bachelor's degree to those positions, possibly increasing wage inequality between workers within occupations. Based on the same difference-in-difference approach as before, the results in Table 6 demonstrate that median wages increased among occupations with persistent educational upskilling relative to occupations with temporary or no upskilling during both the recession and recovery periods. 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 relative to the 25th percentile indicate that rising wages among persistent-upskilling occupations occurred at the top rather than the bottom of the wage distribution, suggesting that workers with a bachelor's degree were likely the recipients of higher wages. This is consistent with recent evidence that workers who are not displaced from their occupation by technological change experience larger earnings gains

[16] Comparing education levels of new hires relative to continuing employees, Figure A10 shows that occupations experiencing persistent educational upskilling were more successful in hiring new workers with a bachelor's degree during the initial recovery compared to occupations with temporary or no significant upskilling.

(Braxton and Taska 2023).

Conclusions and Policy Implications

Using a novel database of roughly 200 million U.S. online job postings, we find that movements in the demand for college educated workers varied much more across occupations over the business cycle than was previously known. 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., business and financial) exhibited a pattern of persistent educational upskilling that extended well after the Great Recession. Moreover, this persistence in requiring a bachelor's degree was driven by educational upskilling *within* occupations rather than the changing composition of vacancies *across* occupations over time toward those with a higher share of postings requiring a bachelor's degree.

Examining specific skillsets further reveals that the demand for software skills was a distinguishing feature of occupations with persistent educational upskilling. Relative to occupations that showed little or no educational upskilling, those experiencing temporary or persistent educational upskilling 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 (Hershbein and Kahn 2018; Jaimovich and Siu 2020). However, between 2010 and 2013, more than half of the increase in software skills was reversed among occupations experiencing temporary educational upskilling, whereas those experiencing persistent educational upskilling continued to increase their demand for software skills, demonstrating the complementarity between education and technology.

Other indicators suggest persistent educational upskilling had different consequences for workers with bachelor's degrees versus those without. Although the education levels of employed workers did increase, suggesting employers succeeded in hiring more qualified workers, supply did not keep pace with demand for occupations that experienced persistent educational upskilling. As a result, the gap in job-finding rates between workers with and without a bachelor's degree grew especially wide during the recession—and persisted for longer during the recovery—for occupations experiencing persistent educational upskilling, relative to those with either temporary or no upskilling. Moreover, wages increased among occupations with persistent educational upskilling, primarily at the top of the wage distribution, consistent with the need to attract workers with a bachelor's degree.

Finally, we are also the first to document that educational upskilling contributed to reducing aggregate matching efficiency during the sluggish labor market recovery after the Great Recession. We develop an adjusted mismatch index to account for persistent educational upskilling *within* occupations and find that this produces a pattern of labor market mismatch that is less cyclical and more aligned with employer observations. Whereas the standard mismatch index calculated *across* occupations shows a marked increase during the Great Recession and a relatively quick recovery in the years immediately after, our adjusted mismatch index stays elevated for an extended period during the labor market recovery. This is consistent with prior evidence showing greater movements in the standard mismatch index across occupations in the bachelor's degree sector as jobs were reallocated across educational sectors during the recession (Şahin et al. 2014).

However, we acknowledge that our mismatch estimates are based on the number of *unemployed* job seekers in various occupations, ignoring the job-seeking behavior of both employed workers and individuals not in the labor force. We also acknowledge that we may underestimate mismatch due to educational upskilling by assuming no long-term impact arising from either occupations where the share of postings requiring a bachelor's degree reversed more than average (e.g., temporary upskilling) or occupations where the initial increase in bachelor's degree requirements was large in percentage terms but from a small initial base (e.g., no significant upskilling). While there may have been disruptions for certain workers in occupations with temporary or no significant upskilling, they did not pose a persistent barrier in job-finding rates or wage growth for less-educated workers.

Taken together, our findings contribute to the literature by identifying educational upskilling related to technological change as a factor in reducing aggregate matching efficiency, in ways not previously recognized by economists. Specifically, our findings suggest that lower matching efficiency in the U.S. labor market after the Great Recession may reflect a shift in demand toward more specialized jobs that require particular software skills, thus leading to imbalances between the demand for and supply of educational credentials. This is supported by recent research showing that unemployed workers displaced by technology direct their job search toward new occupations where their skills are still employable but wages are lower (Braxton and Taska 2023). As a result, search-and-matching models of the labor market should account for periods of persistent educational upskilling, when workers are more likely to be chasing a moving target for re-employment (Kambourov and Manovskii 2009; Alvarez and Shimer 2011; and Carrillo-Tudela and Visscher 2023).

Lastly, our findings also contribute to debates about workforce development and related educational policies by documenting the adverse impacts of persistent educational upskilling on workers without a bachelor's degree. For example, recognizing that meaningful shifts in educational requirements occurs only in certain occupations, rather than economy-wide, can guide workforce development practitioners to better target sector-based training (Holzer 2015). Similarly, understanding that educational requirements can shift rapidly should incentivize educational institutions and training providers to partner more closely with employers in monitoring job qualifications, adjusting curriculum development, and advising students, particularly during recessions. Moreover, distinguishing between persistent versus temporary shifts in educational demands within occupations could help policymakers identify which human capital investments are worthwhile in the long run (e.g., vocational versus baccalaureate degrees) and encourage employers to shift from credential towards skills-based hiring in the short run, especially in occupations with well-defined skill requirements (e.g., healthcare). Finally, knowing that persistent educational upskilling is likely to affect certain groups of workers more than others can help career counselors tailor their coaching for job seekers based on the suitability of their qualifications for various jobs and retraining opportunities.

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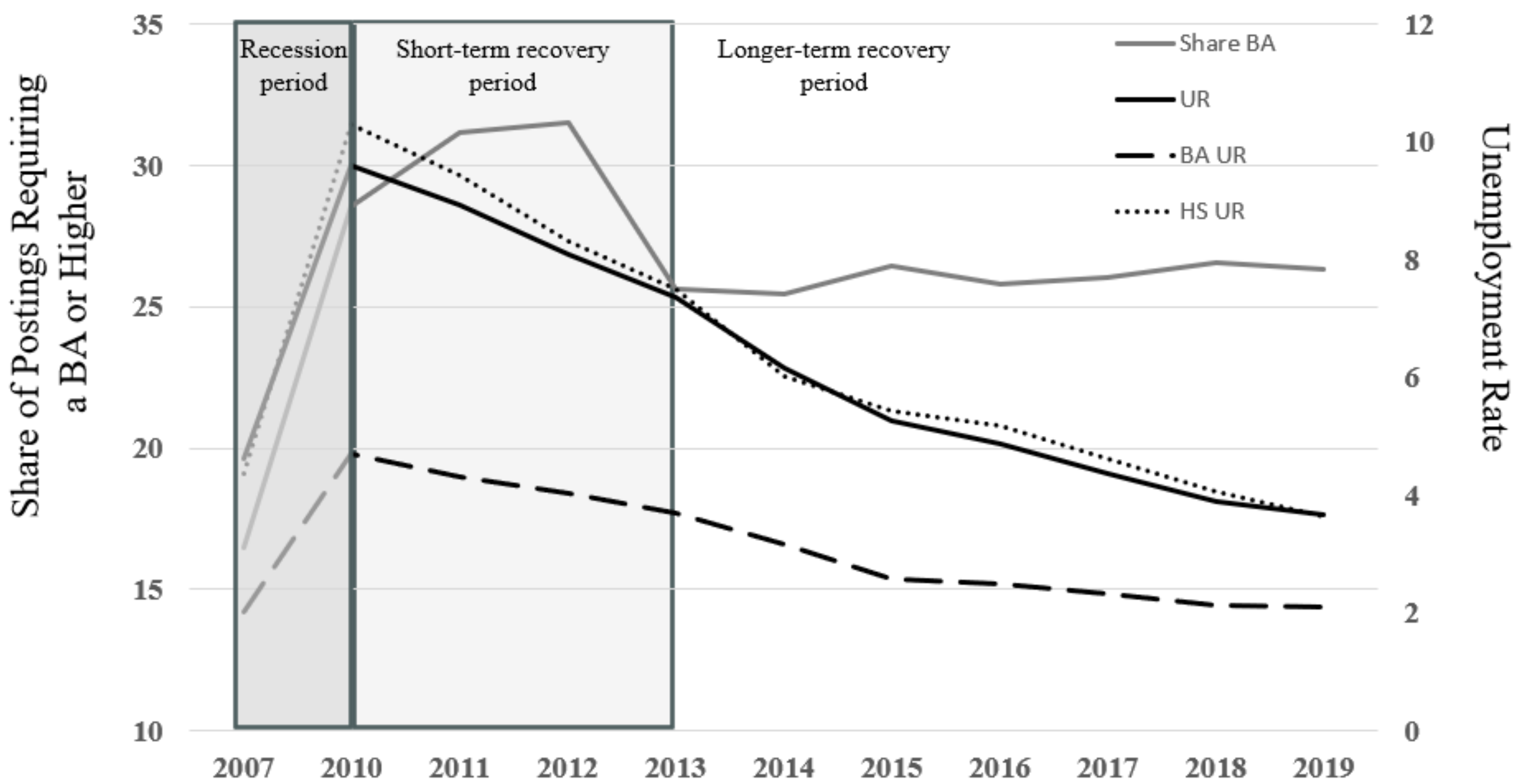
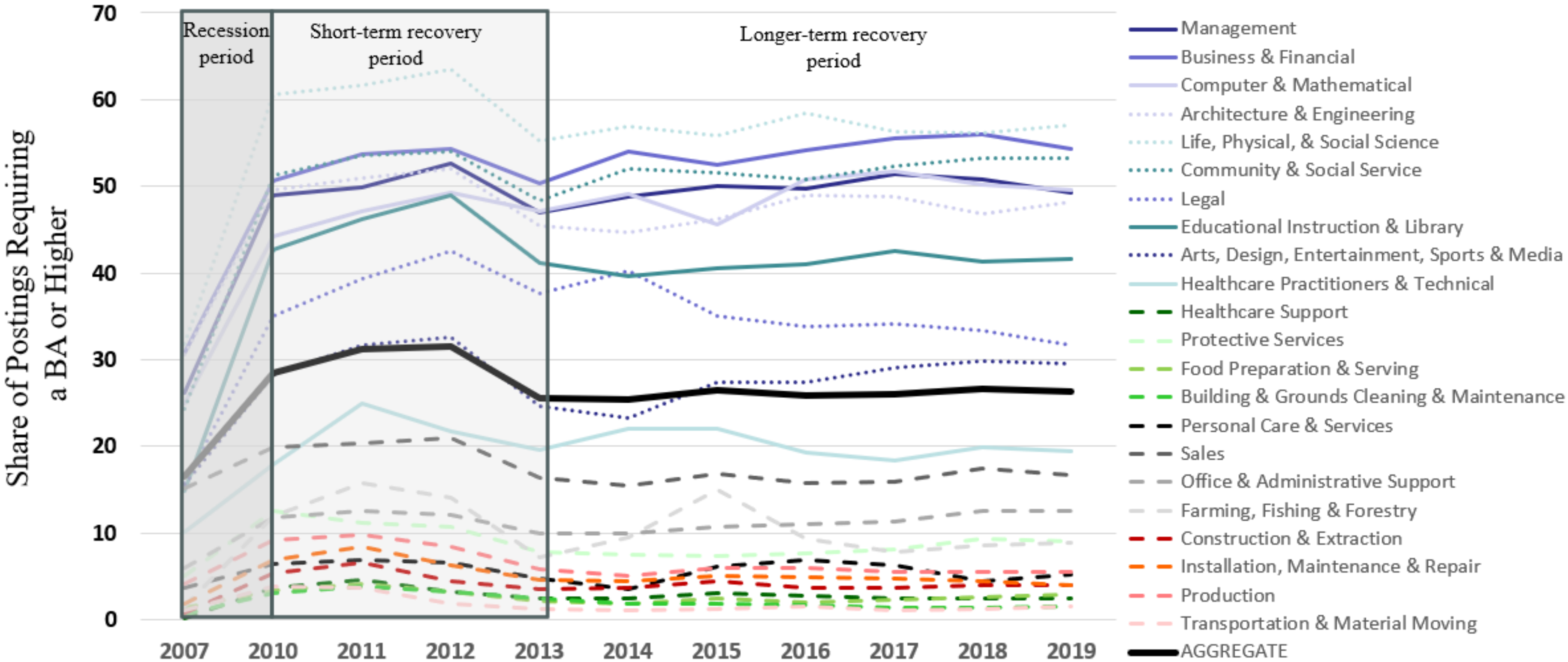
Figure 1. Requested Educational Qualifications versus Labor Market Slack



Source: Authors' calculations based on job vacancy data from Lightcast and unemployment rate data from the BLS.

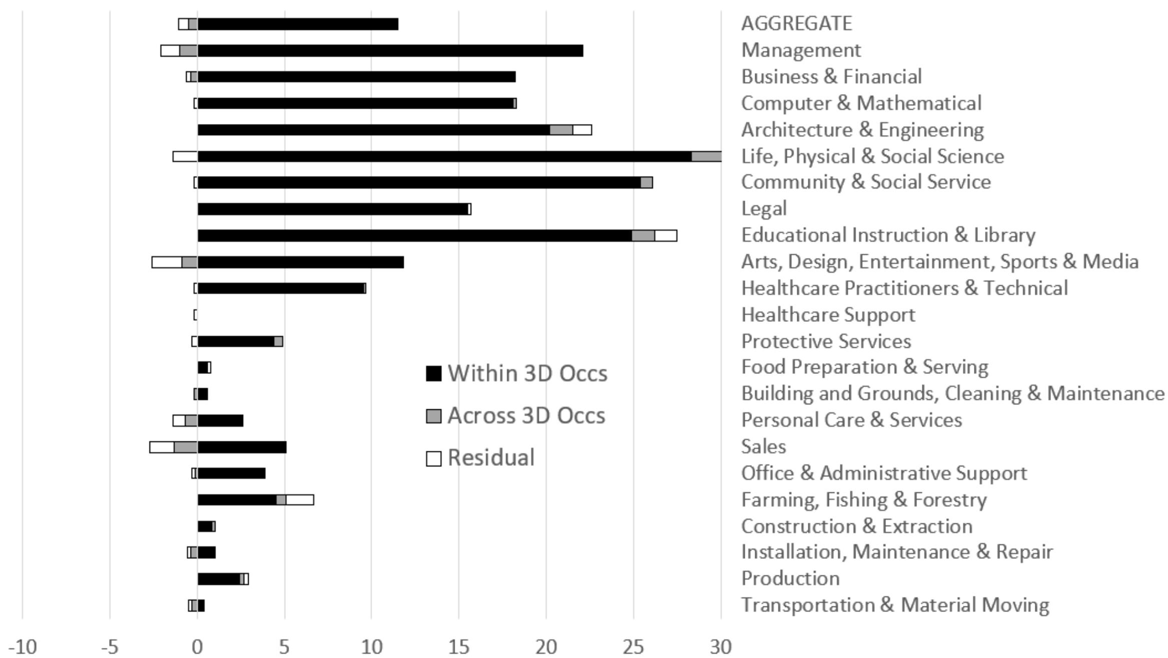
Figure 2. Requested Educational Qualifications by Two-Digit SOC, 2007–2019



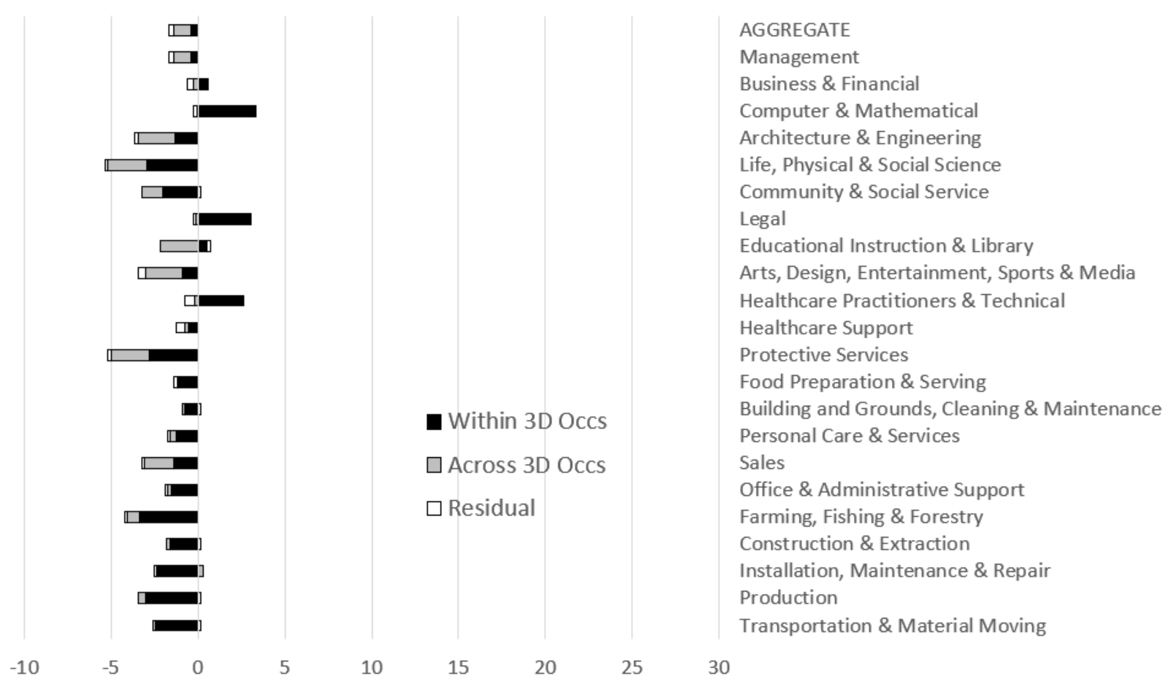
Source: Authors' calculations based on job vacancy data from Lightcast.
Note: Occupations are categorized as exhibiting persistent (solid lines), temporary (dotted lines), and no upskilling (dashed lines) according to the definitions in the "Methods" section.

Figure 3. Decomposition of Change in Share of Postings Requesting a Bachelor's Degree within versus between Three-Digit SOC

A. Recession Period (2007–2010)

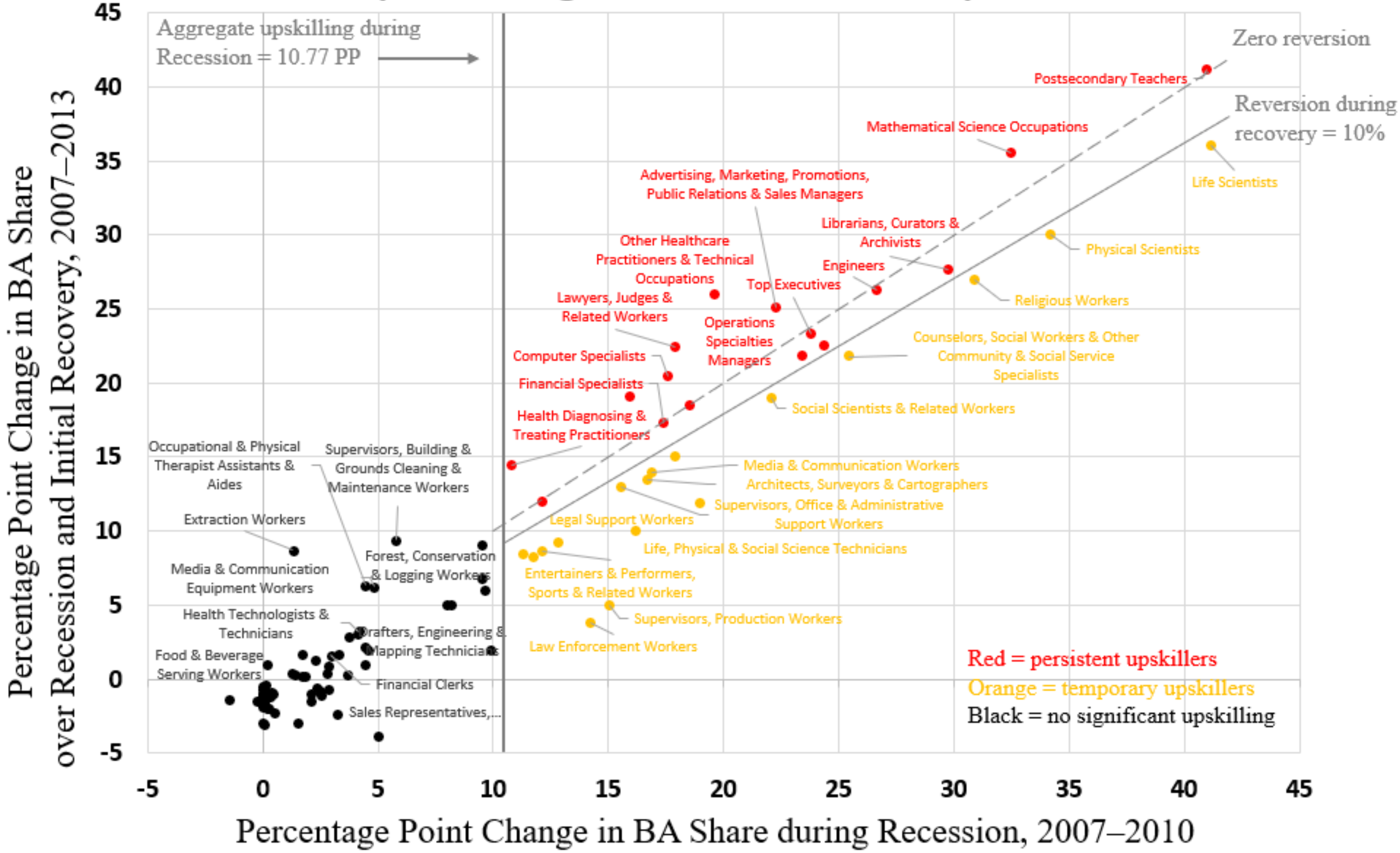


B. Recovery Period (2010–2013)



Source: Authors' calculations based on vacancy data from Lightcast.
Note: 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 the share of postings with a bachelor's degree represents the residual, or interaction, component.

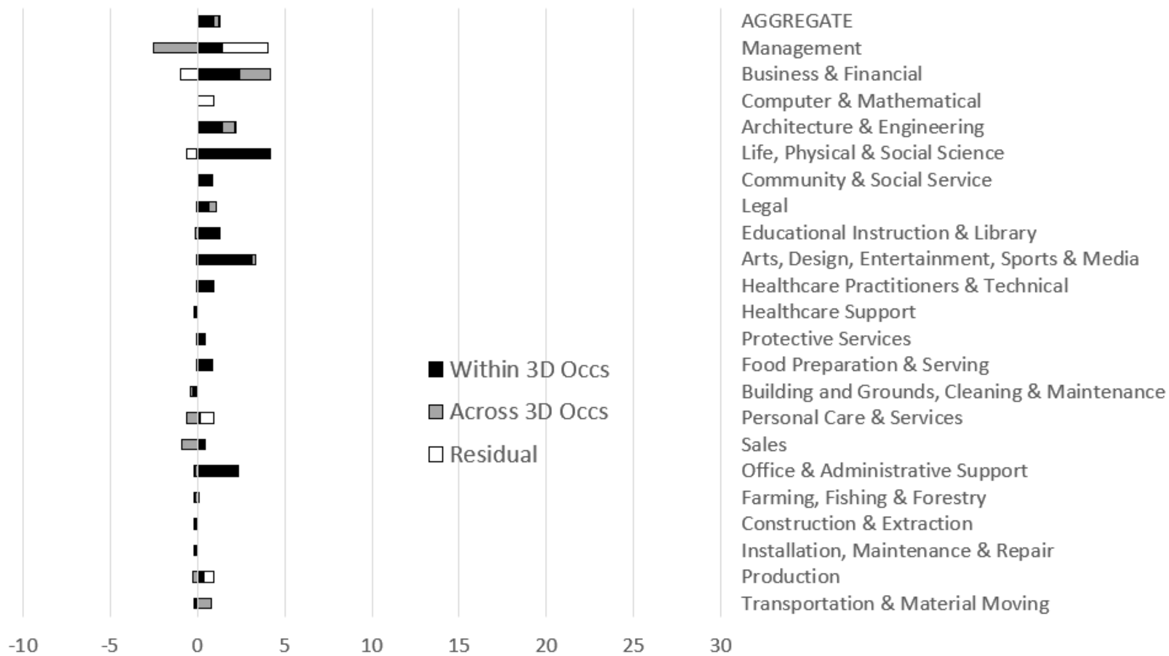
Figure 4. Change in Requested Educational Qualifications by Three-Digit SOC over Business Cycle



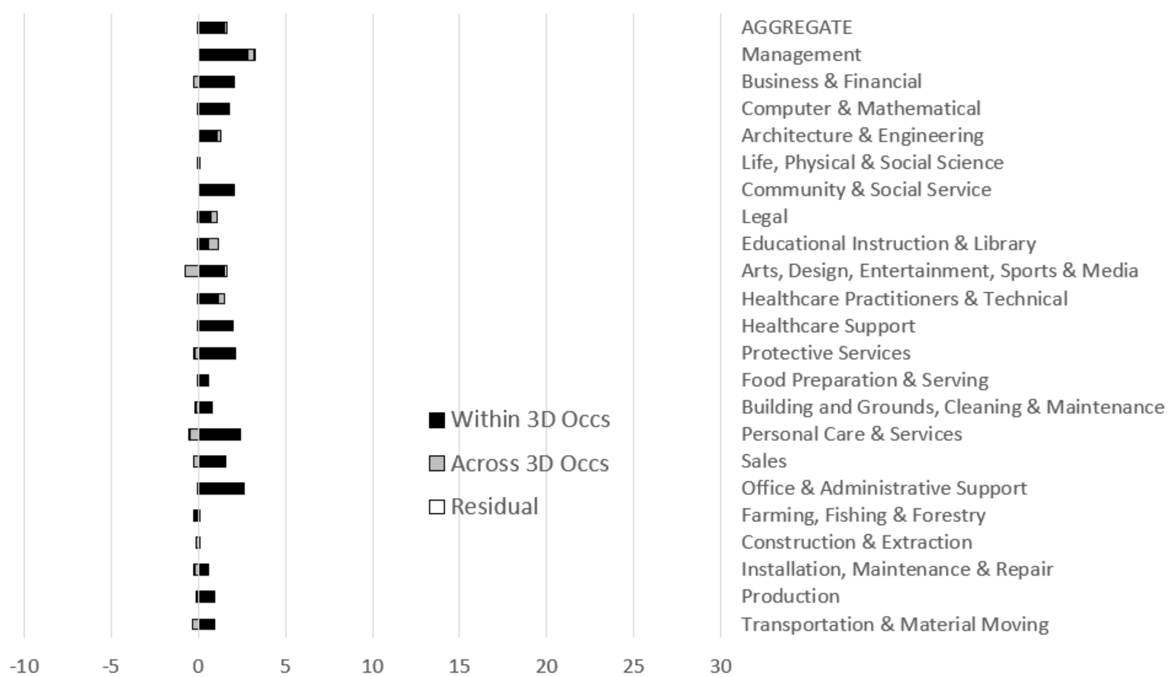
Source: Authors' calculations using job vacancy data from Lightcast.

Figure 5. Decomposition of Change in Share of Employed Workers with a Bachelor's Degree within versus between Three-Digit SOC

A. Recession Period (2007–2010)

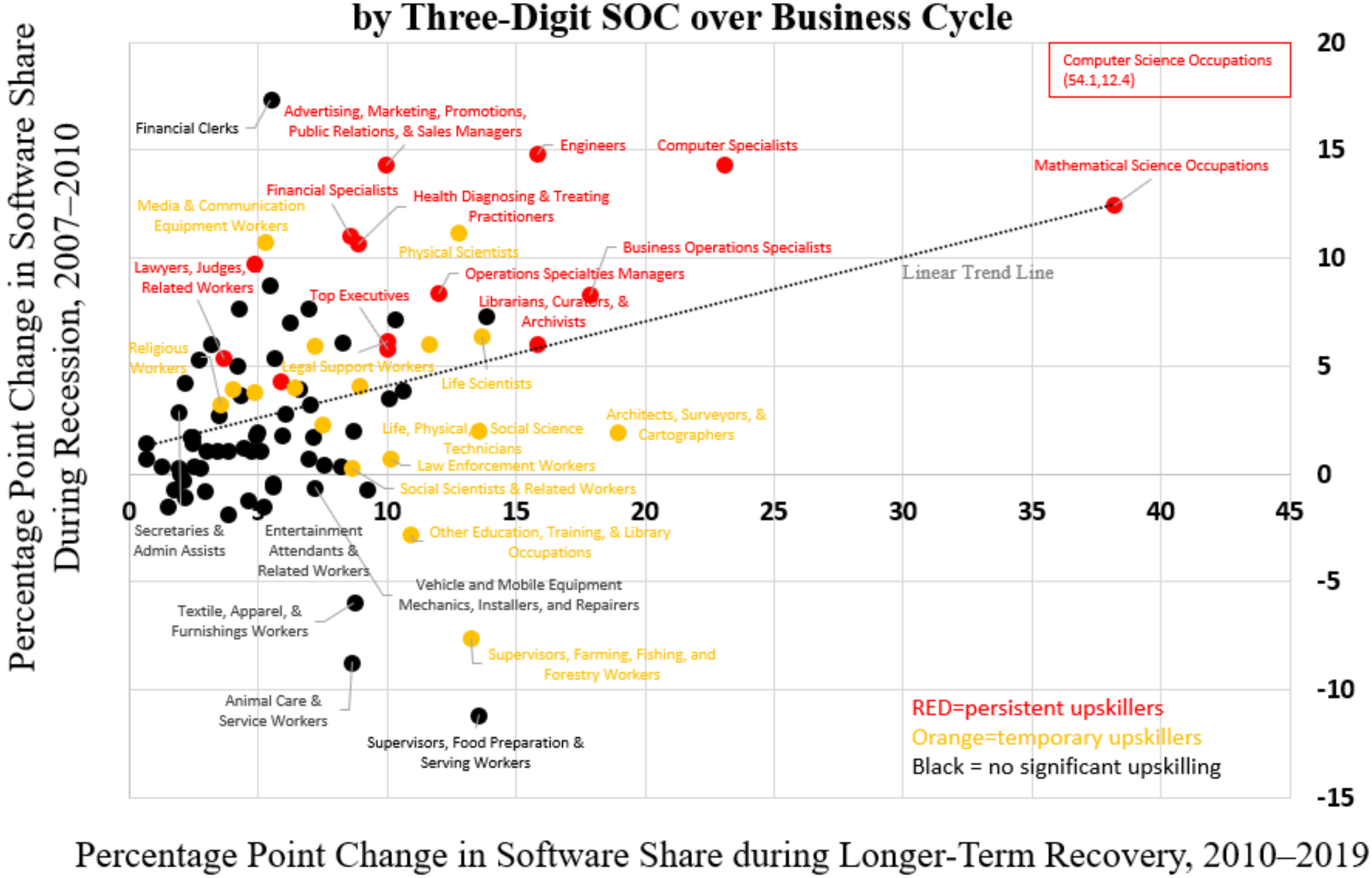


B. Recovery Period (2010–2013)



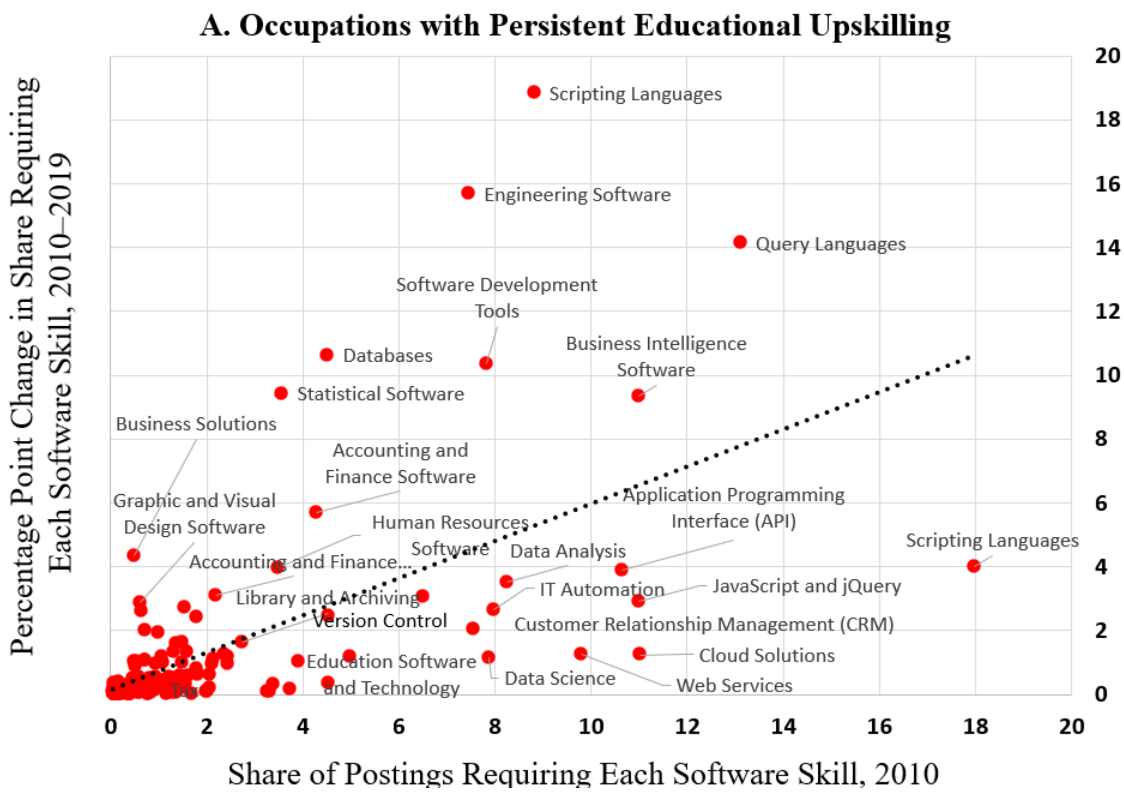
Source: Authors' calculations based on employment data from the ACS.
Note: The fraction of the actual increase occurring under each counterfactual is shown in the figure. Any difference between the sum of the counterfactual changes and the actual change in the share of workers with a Bachelor's degree represents the residual, or interaction, component.

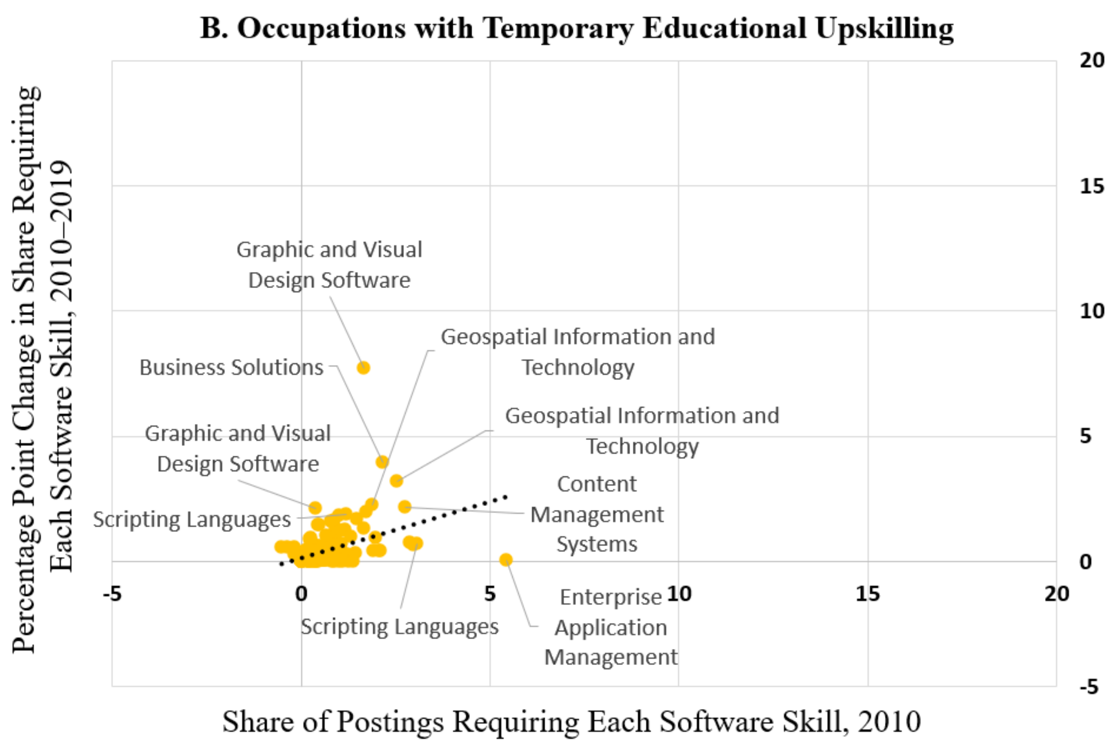
Figure 6. Change in Share of Postings Requesting Software Skills by Three-Digit SOC over Business Cycle



Source: Authors' calculations based on job vacancy data from Lightcast.

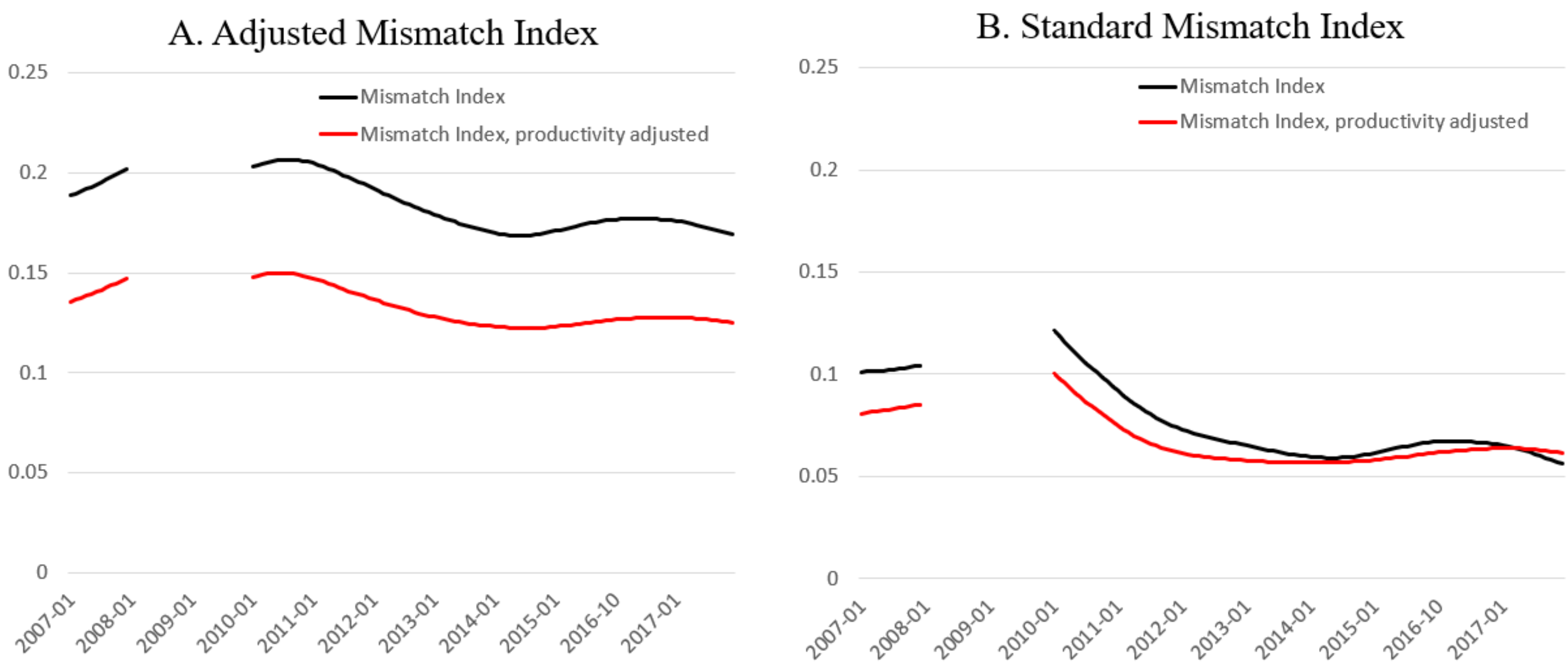
Figure 7. Initial Level versus Change in Share of Postings Requesting Top 10 Software Skills within Three-Digit SOC during Business Cycle





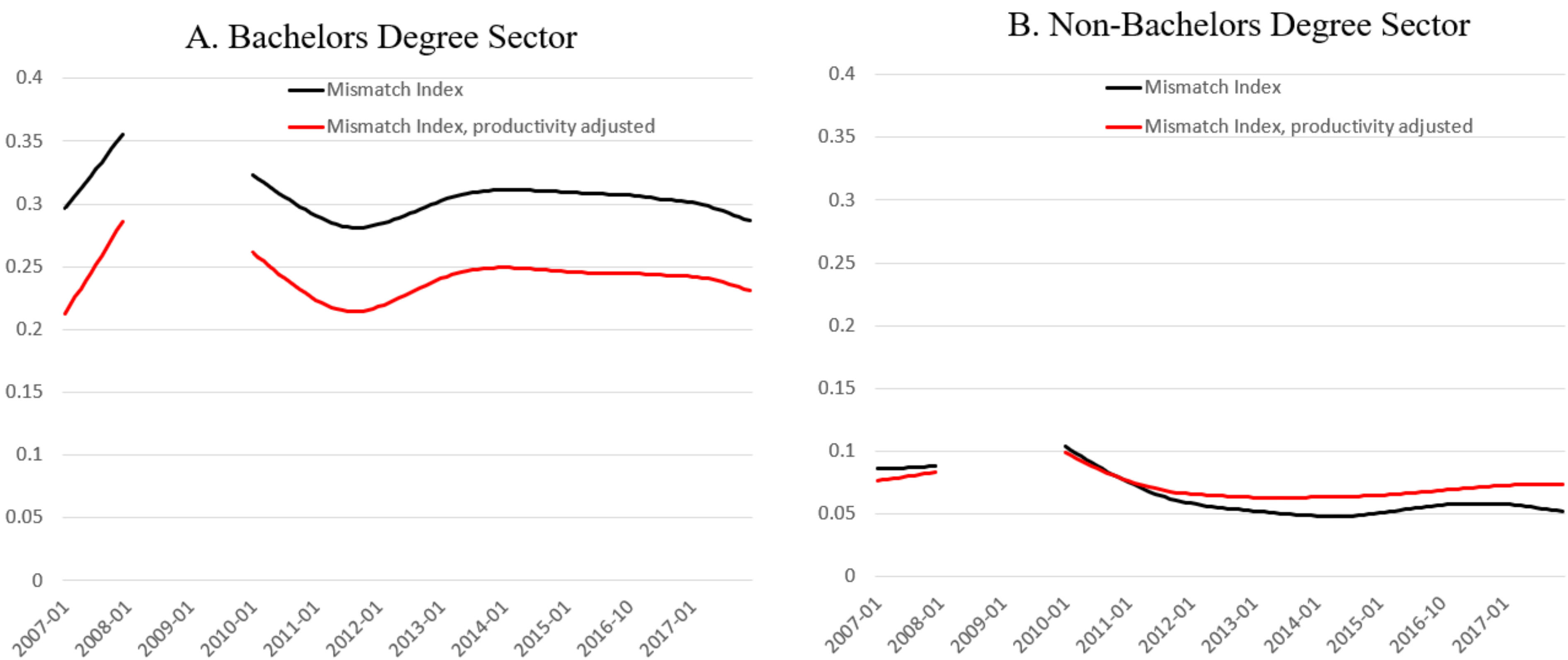
Source: Authors' calculations based on job vacancy data from Lightcast.

Figure 8. Adjusted Mismatch Index Accounting for Educational Upskilling Within Occupations



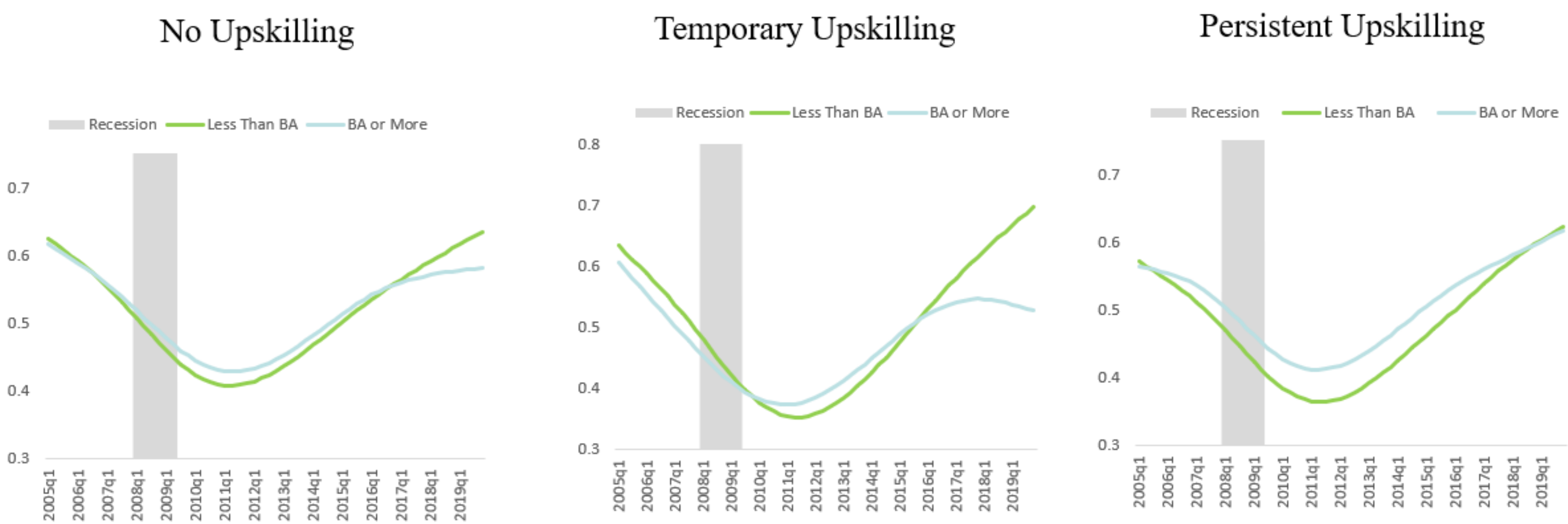
Source: Author's calculations using monthly online job posting data provided by Lightcast (2007, and 2010-2017) and unemployment and monthly labor force estimates from the Current Population Survey.
Note: Mismatch indexes are HP filtered to eliminate high frequency movements and better visualize trends over time. See the appendix for details.

Figure 9. Standard Mismatch Index Across Occupations 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: Mismatch indexes are HP filtered to eliminate high frequency movements and better visualize trends over time. See the appendix for details.

Figure 10. Impact of Educational Upskilling on Job Finding Rates by Educational Attainment



Source: Authors' calculations using data from the Current Population Survey and code provided by Birinci et al. (2023).
Note: Quarterly job finding rates are 3 month mean of seasonally adjusted monthly estimates that are HP filtered to eliminate high frequency movements. See the appendix for details.

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

	Year				Recession	Short-term recovery	Longer-term recovery
	2007	2010	2013	2019	Δ2007–2010	Δ2010–2013	Δ2010–2019
Employer skill requirements							
Number of 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 three-digit occupations	94	94	94	94	94	94	94

Source: Data on employer skill requirements are from Lightcast, weighted by annual employment from the American Community Survey (ACS). Data on wages are from the Occupational Employment Statistics (OES).

Table 2. Characteristics of Occupations by Type of Educational Upskilling

	Pre-recession: 2007			Recession: Δ2007–2010			Short-term recovery: Δ2010–2013		
	Persistent	Temporary	None	Persistent	Temporary	None	Persistent	Temporary	None
Employer skill requirements									
Number of 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 three-digit occupations	15	18	61	15	18	61	15	18	61

Source: Data on employer skill requirements are from Lightcast, weighted by annual employment from the ACS. Data on wages are from the OES.

Note: Occupations with a percentage point change in BA share between 2007 and 2010 that is greater than the aggregate are defined as having significant upskilling. Those that also experience less than a 10% 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 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)
<u>**Correlation with pre-recession level of occupational characteristics**</u>			
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
<u>**Correlation with contemporaneous measures of other skill requirements**</u>			
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 three-digit occupations	94	94	94

Source: Data on employer skill requirements are from Lightcast, weighted by annual employment from the ACS. Data on wages are from the OES.

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

	Percentage point change relative to occupations that exhibited no educational upskilling								
	Software skills			Specialized skills			Common skills		
	Recession period	Short-term recovery	Long-term recovery	Recession period	Short-term recovery	Long-term recovery	Recession period	Short-term recovery	Long-term recovery
	Δ2007–10	Δ2010–13	Δ2010–19	Δ2007–10	Δ2010–13	Δ2010–19	Δ2007–10	Δ2010–13	Δ2010–19
Diff persistent vs. no upskilling	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)
Diff temporary vs. no upskilling	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)
Diff (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 three-digit occupation	94	94	94	94	94	94	94	94	94

Source: Authors' calculations based on vacancy data provided by Lightcast, weighted by 2007 employment level from the ACS.
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. Statistical significance is indicated at the ***1%, **5%, and *10% levels, respectively.

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

SOC	Persistent-upskilling occupation	A. Number of unique software skills 2010	2019	Change	B. Software skill with largest percentage point change in share of postings for each persistent-upskilling occupation	2010	2019	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 & 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 & 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 & Special Education Teachers	116	177	53%	Education Software and Technology	0.58	2.02	1.44
253	Other Teachers & Instructors	101	153	51%	Education Software and Technology	0.40	1.63	1.23
231	Lawyers, Judges & Related Workers	133	177	33%	Tax Software	0.14	1.06	0.92

Source: Data on employer skill requirements are from Lightcast.

Table 6. Change in Real Wages within Occupations by Type of Educational Upskilling over Time

	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 three-digit occupations	94	94	94	94	94	94

Source: Authors' calculations based on vacancy data provided by Lightcast, weighted by 2007 employment level from the ACS.

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. Statistical significance is indicated at the ***1%, **5%, and *10% levels, respectively.