Low-skilled occupations face the highest re-skilling pressure*

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Abstract

Substantial scholarship has estimated the susceptibility of jobs to automation, but little has examined how job contents evolve in the information age as new technologies substitute for tasks, shifting required skills rather than eliminating entire jobs. Here we explore the patterns and consequences of changes in occupational skill contents and characterize occupations and workers subject to the greatest re-skilling pressure. Recent research suggests that high-skilled STEM and technology-intensive occupations have experienced the highest rates of skill content change. Analyzing 727 occupations across 167 million job posts covering the near-universe of the U.S. online labor market between 2010 and 2018, we find that when skill distance is accounted for, re-skilling pressure is much higher for low-skilled occupations, no matter how “low-skill” is defined, either by skill number, pay level, or education degree. We investigate the implications of uneven occupational skill change on workers and find that those from large labor markets and large employers experienced less change, while non-white males in low-skill jobs are the most demographically vulnerable. We conclude by discussing the broad potential of our skill embedding model, which learns skill proximity from skill co-presence across job posts and represents it as distance in the high-dimensional space of complex human capital that corresponds with skilling costs for workers. This model offers a fine-grained measure of the extent to which jobs evolve, and also indicates in what direction job are evolving, as illustrated by the decline in demand for human-interface skills and the rise for those at the machine-interface.

Keywords: skills, job change, the future of work, word embedding, manifold learning

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1 Introduction

With rapid advances in automation, computerization, and Artificial Intelligence (AI) technologies, substantial scholarship and public debate has focused on estimating the susceptibility of jobs to full or partial automation and the employment consequences that follow [1–8]. Yet relatively little work has examined how job contents evolve. New technologies often substitute for some skills within jobs while simultaneously creating new ones, which alter job skill demands and impose re-skilling pressure on workers [9–12]. Here we focus on the future of work not in terms of job elimination and displacement, but job transformation [11, 13].

Measuring job transformation by skill change is a relatively recent and emerging research program. The bulk of prior empirical studies focus on analyzing specific jobs, skills and industrial forces of changes [9, 11, 14–17]. This work demonstrates the importance of compositional skill change, but lacks quantification of the magnitude in overall skill or task change on the job level, without which it is hard to systematically compare jobs and understand which group of workers faces more re-skilling challenges amid various economic and social changes. The major challenge for quantifying systematic job skill change lies in obtaining accurate skill measurements [13]. Recent research has shifted from inferring skill changes indirectly from changes in relative wages and the supply of highly-educated labor [18], to direct measurement of skill change. Still, this work relies on static, coarse task taxonomies such as the Dictionary of Occupational Titles [14], the Occupational Information Network Database (O*NET) [13, 19], or occupation titles from Census coding volumes [10]. Most recently, Deming and Noray (2020) [20] developed the first direct, dynamic and precise measurement of job skill change using high-quality job advertisement data. Specifically, they calculated the sum of absolute skill proportion change over all required skills within the same occupation between two time points, including removed (obsolete) and added skills (See SI for equation).

The limitation of this quantification, however, lies in its failure to adequately account for skill distance, thereby inducing an upward bias for technology-intensive and specialized occupations that possess many more listed “skills” across the union of job ads attributed to them than occupations with less specialization. Not only is no one worker expected to possess all skills across all occupationally-coded job ads, but the old skills replaced by new ones remain close, reassuringly similar, and requiring small marginal cost, like the acquisition of a new programming language when one already knows several (see computer programmer illustrated in Fig.1B). That measurement approach to skill change also exhibits downward bias for low-skilled occupations with fewer old skills displaced, but by new skills distant and challengingly different (see food batchmaker in Fig.1A). To overcome these limitations, we propose to investigate and quantify the distance between skills as they do not distribute uniformly in the underlying space of complex human capital [21]. Instead, some skills are closer to one another, creating local, accessible transition paths. As illustrated by Fig.2A-B, the marginal effort required for a computer programmer to adapt to a shift in demand within the “Programming” skill cluster from one coding language to another is smaller than the required shift for a food batchmaker who manufactures large quantities of food for packaging and distribution to their first coding language. The shift in education-weighted skills (see Data and Methods) for the two occupations involved a decrease in required education of 0.53 years for programmers between
2010 and 2018, but an increase of 1.47 years for food batchmakers, who move from the center of the skill cluster for “Health, Medical Care” (food preparation) and towards “Programming” (database administration). Priced at in-state tuition, room and board from a public university, this additional schooling would represent approximately $40K in real student costs.\(^1\)

Given this concern, we advocate for an alternative quantification of skill change from \(^{20}\) that models skill distance. Deming and Noray (2020) suggested that high-skilled STEM and technology-intensive occupations experienced the most skill content change from 2007 to 2019 \(^{20}\). Here we use the same dataset as \(^{20}\) but present a dramatically different observation: low-skilled occupations changed much more than high-skilled occupations, and suggesting very different employment and skilling policies. Using the skill probability change measure as suggested by \(^{20}\) without considering skill distance, computer programmer changes 175% more than food batchmaker (7.453 vs 2.708) (Fig1C). However, after modeling skill distance using skill vectors learned from job ads with word embedding \(^{22}\), the assessment of who faces the higher re-skilling pressure is reversed—food batchmaker changes more than computer programmer, 130% in terms of new skills creation and 220% for old skill obliteration (Fig1D). As we show below, precise skill change measurements also allow us to understand how these are distributed across many dimensions of the U.S. economy and manifest a correspondence with the educational cost required for skill acquisition (see Fig2C-D). We note that an intermediate version of Deming and Noray’s measure, formally equivalent to \(^{20}\) but using data-driven clusters also reverses their assessment (see SI).

Data and Methods explains how we recover skill distance in quantifying skill change and demonstrates its correspondence with the educational cost of skilling (see Fig2C-D). Based on this improved measurement, we analyze skill requirements from 727 occupations across 167 million job ads, which cover the near-universe of the U.S. labor market in the past decade, and confirm that low-skilled occupations face the highest re-skilling pressure, no matter how we distinguish between low and high skill jobs, either by skill number, pay level, or education degree (Fig2). To better understand the unevenness of skill change beyond low and high skill jobs, we further distinguish between jobs across locations, employers, and demographic groups. Our evidence suggests that big labor markets and large employers buffer jobs from skill instability and obsolescence, presenting an advantage over workers from small cities and businesses \(^{23}\) (Fig3). Non-white males in low-skilled jobs are the most vulnerable to re-skilling (Fig3). We conclude by discussing the broad potential of our skill space model, with a demonstrated application to analyze the evolution of human vs. machinery skills (Fig4).

2 Data and Methods

2.1 Data

We analyzed a dataset of more than 167 million job ads from 2010 to 2018 provided by Burning Glass Technologies (BG). BG constructed multiple variables for each job ad, including job title, occupation, location of latitude and longitude values, skill requirements, education requirement,
salary, employer name, and more. We used 6-digit Standard Occupational Classification (SOC) to define occupations. BG collects information from more than 40,000 job boards and company websites to create the largest dataset of the U.S. labor market [16]. Admittedly, not all new jobs appear online, but online recruitment represents an increasing share of labor market search, even for jobs historically associated with informal recruitment, offline recruitment. A 2013 study estimated 60−70% jobs were posted online [24]. Recent research suggested 85% [25]. To verify the representativeness of BG data on the U.S. job market, we calculated occupational demand, pay level, and education requirements using BG data and found that these values are highly correlated with BLS statistics in 2010 and 2018 (See SI), justifying the overall consistency and credibility of BG data during the time period of our analysis, despite coverage limitations [16].

2.2 Training Skill Vectors

We apply the skip-gram word2vec model [22] to obtain the skill vectors representations of jobs. Word2vec learns vector representation of words within a large-scale corpus such that two words frequently occurring in the same direct or indirect linguistic contexts remain close to one another within the latent space, often measured by cosine distance of the angle separating them along the surface [22] and suggesting semantic and/or syntactic correspondence. Using the 167 million job posts describing a set of required skills as instances of training context, we obtain a 200-dimensional vector for BG’s 15,182 unique skills.

2.3 Quantifying the Magnitude of Occupational Skill Change

We calculate the vector of an occupation \( o \) at a given year \( t \) by averaging the vectors of \( m \) core skills required by \( o \) in \( t \). To derive reliable estimates, we focus on 727 active occupations with 100 or more job ads every year and analyze their 5% most frequently required skills in each year, referred to as “core skills”. In the SI, we demonstrate that our findings presented in the main text are robust to alternative definitions of skill content, including expansion of core skills to include all skills and a consideration of skill frequencies as weights. As core skills change over time, the same occupation may manifest evolving vector representations across years even though each skill has only a fixed, globally trained vector. In this way, we focus on occupational skill content change caused by the substitution of core skills [22]. Specifically, we use one minus the Cosine distance between vectors of the same occupation in 2010 and 2018 as the skill change score. We calculate job skill change for all 727 occupations between 2010 and 2018. Calculated scores vary from 0.002 to 0.340, with a median of 0.027. As occupation vectors encode skill distance, this measurement of skill change reflects more precise efforts needed for re-skilling than [20], as illustrated in Fig.1.

Note that the re-skilling cost inferred from an occupational skill change relative to that same occupation at a previous time point is a second-order measurement. This is fundamentally different from important first-order metrics that capture the absolute training cost required to qualify for an occupation from the position of no relevant skill, such as an occupation’s: educational requirement, O*NET job zone[2] or skill number. Our main empirical analysis examines how second-order re-

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[2]https://www.onetonline.org/help/online/zones
skilling costs vary among occupations with different first-order skill levels (Fig. 2).

2.4 Validating the Re-skilling Costs Reflected by Occupational Skill Change

We further validate the inference of re-skilling costs from our occupational skill change measurement by demonstrating that distance in the skill space correlates with the amount of costly re-education required for workers to move from one distribution of skills to another. In Fig 2D, we show that occupations with larger skill change require a higher increase in re-education cost. We coarsely identify the re-education cost of a given job by measuring the skill-level education requirement change, calculated as the difference between the average required education level for its newly-added core skills in 2018 and the education requirement for the focal job in 2010. Required education level of a skill in 2018 is approximated as the average required education level for occupations that demand this skill in 2018. The correlation between job skill vector change and the required coarse-grained shift in education is modest ($\rho = 0.14$) but highly significant ($p < .0002$). For example, jobs with pay in the bottom 25% of the compensation distribution experienced an increase in required schooling of 1.29 years between 2010 and 2018, and those requiring less than college education in 2010 experienced an increase in .65 years in the same period, while jobs in the top of the pay and education distributions experienced marked decreases. Priced conservatively at in-state tuition, room and board from a public university these increases represent real costs of $31,588 and $15,917, respectively. We note that this measured shift in educational level does not account for the necessary shift in educational type. For example, shifting from a computer programming to a biomedical job may not require a higher level of education (e.g., a Bachelor of Science degree), but is more likely to require a different type of degree as distance in the skill space increases.

2.5 Identifying the Direction of Occupational Skill Change

Occupation vectors predict not only the magnitude of skill change but also its direction. First, we construct a “coordinate system” of the skill space by using the discourse atom topic modeling approach, which performs $k$-SVD matrix factorization on skill vectors to accurately and efficiently label the skill space. The derived vectors or “skill atoms” represent near-orthogonal axes capturing the essential “bases” of distinct human capacity, which can be linearly combined to recover the vector representations of 15,182 actual skills. Specifically, each skill is represented as a linear combination of $k$ skill atoms. We trained models by setting the atom number $k$ from 50 to 500. The model performs best with 210 atoms based on a balance between (1) $R^2$, which measures how well the atoms predict all skill vectors; and (2) topic diversity, which measures how distinct the atoms are from one another. After we obtain the 210 skill atoms to anchor our skill-space as coordinates, we specify the direction of occupational skill change within this system. We quantify the rise and fall of skill atoms as a function of how all 727 occupations shift collectively. Rising atoms are those a majority of occupations approach, and declining atoms are those a majority of occupations depart. Specifically, we calculate the overall importance of a skill atom as the sum of its weights across all occupations in that year and compare how overall importance changed between.

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[3]https://educationdata.org/average-cost-of-college
2010 and 2018 (See SI for method details). Fig 4A presents these 210 skill atoms in a matrix of 14 rows and 15 columns. To demonstrate the relative location of all 210 atoms on a 2-D graph, we first apply the T-SNE transformation on the original skill atom vectors to reduce their dimension from 200 to 2. We then construct a grid of 15 columns and 14 rows on the area between the lowest and highest values for each of the 2 dimensions for all atoms. Finally, for each node in the grid, we assign the nearest unassigned atom to occupy it. Finally, we employed two human coders to label these 210 skill atoms “human” or “machine”-related based on the closest 25 skills to a given skill atom in the space to observe how these two kinds of skill atoms rose or declined in the past decade.

3 Findings

3.1 Low-skilled occupations face the highest re-skilling pressure

Across the analyzed 727 occupations, low-skilled occupations experience more skill change than high-skilled occupations during 2010-2018; no matter how we distinguish between low and high skill occupations, either by the average number of core skills across years (Fig 2A), the annual median pay for the occupation (Fig 2B), or the average education requirement (Fig 2C). In other words, re-skilling pressure is higher for workers in low skill complexity, low compensation, and low education occupations. The only exception is that jobs requiring master’s or doctorate degrees change more than those requiring bachelor’s degrees, but both change markedly less than jobs requiring only an associates or high school degree. In Fig 2D, we sorted twenty-two 2-digit SOC occupation categories by decreasing skill change to obtain face validity of the distinction between low and high skill occupations. Occupations related to farming, fishing, and forestry, construction and extraction, and transportation and materials moving change most; while occupations related to management, business and financial operations, and computer and mathematical change least. In SI Table S1, we present OLS regression models of occupational skill change on skill number, education level, and pay level, showing that the effect of skill number is substantial and consistent when all three variables are included. We also show that this pattern still holds when average occupation-level employer concentration is controlled, or when O*NET job zones, which reflect not only formal schooling but also informal experience and training, are used to measure job skill level.

We find that the skill vectors not only predict skill change within an occupation over time, but also predict worker mobility between occupations. We extract the number of transitions between 1,990 pairs of 6-digit SOC occupations in 2018 from nationally-representative Current Population Survey (CPS) data widely used across the literature [28], in which individuals report their current occupation and their occupation from the previous year. We calculate the skill similarity between each pair of occupations as the Cosine similarity between their occupational skill vectors in our 2018 data set. The Pearson correlation coefficient between skill similarity and corresponding worker mobility (logged) is 0.283 ($p < 0.001$). We further assess the additional explanatory power of skill vectors by regressing mobility against its baseline predicted by occupation popularity, calculated as $\log(\text{Employment}_i * \text{Employment}_j)$ between occupations $i$ and $j$ using 2018 BLS data, before and after controlling for skill similarity. We find that including skill similarity greatly improves
the baseline model; R-squared increases by 129% from 0.062 to 0.142. Taken together, these results suggest that low-skill workers not only face high re-skilling pressure over time, but may also confront mobility challenges if jobs of similar skill content are unavailable in the region when they are displaced [29].

3.2 Big labor markets and large employers buffer jobs from skill instability and obsolescence

To investigate how the size and structure of the labor market moderate occupational skill change, we separated the data into two subsets: job posts of large vs. small markets. We labeled a location a large market if the number of its annual job posts is among the top 10% across all the 27,239 locations in 2010 and 2018, and labeled it as a small market otherwise. Each location is identified by combinations of longitudes and latitudes at .1 decimal degree precision, which recognizes large cities or districts. We then calculate two different skill change scores for the same occupation using their job posts in two subsets. We did not retrain skill vectors such that differences between skill change scores reflect distinct core skill requirements between small and large markets. Large local markets buffer occupational skill change, especially for low-skilled occupations (Fig.3B). We visualize variation in occupational skill change on a U.S. map, demonstrating how re-skilling pressure is markedly lower in populous coastal states and urban areas (Fig.3A). In the map, we calculate the average re-skilling pressure for each location as the average occupational skill change across all active occupations, weighted by the number of job posts from that occupation in 2018.

We then distinguish between job posts for occupations from large and small employers. Large employers are defined as those with more than ten job posts annually in 2010 and 2018, which puts them in the top 10% and distinguishes them from the remaining 90% small employers. Fig. 4B shows a strong employer size effect: the same occupation experiences a much smaller skill change in large employers than in smaller employers and this effect is larger for low-skilled jobs.

Table S2 in the SI demonstrates that the buffering pattern of large markets and employers is substantial and consistent after controlling for occupational employer concentration using fixed-effect regressions. These findings are consistent with theories of ecological inertia [30, 31] and skill premia [32]. Bureaucratization and structural inertia increase with organization and market size, such that larger organizations may be less sensitive to market pressures for task change [30, 31]. With greater size and density of complementary skills, tasks, and occupations in the local market, ecological resilience may arise from the scale of network dependencies, such that larger labor markets are more resistant to abrupt global pressures for job task change [23, 33, 35]. This would enhance the comparative advantages of larger and more efficient skill markets where workers can not only better identify others with whom to maximize the complementary value of their skills and individually obtain better trades, but also sustain the value of their existing skills for longer [32, 34].
3.3 Low-skilled nonwhite male workers face the greatest re-skilling pressure

To understand the implication of skill change on workers, we associate occupational skill change with worker demographics, leveraging data from the Bureau of Labor Statistics (BLS). We group occupations of different skill levels by corresponding workers’ dominant gender and race/ethnicity, and calculate average levels of skill change across occupations from the same group. In determining occupations’ “dominant” demographic characteristics, we link an occupation to a social group if it is 1.5 times or more likely to be employed in the focal occupation, compared to its fraction in the U.S. labor force according to the 2018 Current Population Survey\(^4\). For example, ∼80% Registered Nurses are female, and females account for roughly 50% of the worker population, giving them a dominant score of 1.6=80%/50%. One occupation can over-represent multiple social groups; there are disproportionate male (1.5 = 75%/50%) and Hispanic (1.5 = 25%/17%) Construction workers. As illustrated by the heatmap in Fig.3C, low-skilled, nonwhite, and male workers face the greatest impact from re-skilling.

4 Discussion

A number of recent works seek to contribute to a deeper empirical science of skills and job change through modeling skill distances. The expanding literature includes \cite{29, 36, 37} who derive skill vectors to calculate skill distance and predict worker mobility. Nevertheless, these studies consider skills as independent from one another. To overcome this limitation, \cite{21, 34, 38, 39} constructed skill networks to model interdependency between skills, but networks do not yield straightforward distances between skills (nodes) or jobs (communities), as many paths connect them. Our work builds upon, and contributes to, this convention of skill representation. Using large-scale job advertisement data, coupled with widely verified manifold learning methods from machine learning and artificial intelligence \cite{40, 41}, our work advances the state of science on how skills are represented and learned. Specifically, by introducing continuous geometry to supplant network topology, our model both captures skill interdependencies and generates vectors that permit efficient calculation of distance between skills and jobs. We demonstrate that this methodological advancement overturns recent, high-profile findings regarding the burden of skill change in the U.S. economy \cite{20}. We advance the charge leveled in recent perspectives on the important role of new data and methods for identifying key micro-level processes that drive the effects of AI and automation on the future of work \cite{13, 42}.

We develop a skill embedding model – skill2vec – to represent occupational skill content and reveal hidden inequities in re-skilling biased against low-skill workers. Our model encodes skill proximity learned from massive-scale job posts and represents it as distance in a high-dimensional space representing the complex system of human capital with minimal distortion. This continuous model allows for better quantification of re-skilling pressure than discrete models \cite{20} at the occupational level and allow us to explore re-skilling consequences for workers across markets, employers, and demographic groups.

\(^4\)https://www.bls.gov/cps/cpsaat11.htm
In addition to a more fine-grained measure of the extent to which a job has transformed, our skill embedding model reveals the direction of movement for each occupation, labeled by skill atoms distilled as near-orthogonal axes representing the essential “bases” of distinct human capability. For example, Fig.4A displays these skill atoms and Fig.4B shows two exemplary occupations and their most dramatically altered atoms, 2010 to 2018. We also present human-interface skill atoms that decline in importance across all jobs and machine-interface atoms that increase in importance in this period (Fig.4C-D) to highlight global transformations of skill in the U.S. labor market (See SI for method details). Future work can build on these spaces to explore other causes and consequences of the rise and fall of skill atoms for skill change across distinct occupations.

The focus and limitations of this study suggest directions for future research. First, our model of skill change focuses on revealing the hidden distance between skills using only demand-side data, which captures the evolving landscape of work opportunity. This ignores the success or failure of labor demands for attracting desired workers, and how far worker skills must migrate to satisfy it on average. Future work should also consider direct measures of re-skilling pressure through learning costs in time, money, and psychological stress. Furthermore, we did not include worker mobility in our analysis or the transportation and moving costs required for continued employment. Job skill change may not translate into re-skilling pressure if workers can move to nearby regions supplying similar job opportunities [43]. Finally, with the increasing dominance of teamwork in the workplace, occupations should not be the only unit of analysis assessed in skill change. Our findings on the buffering effect of big labor markets and large employers point to future research that more closely examines skill complementarity within teams, companies, cities, and nations to characterize how economic change and technological advance reshapes the work and lives of individuals. Nevertheless, our findings reveal systemic inequities in deskilling and required re-skilling for sustained employment that disproportionately affect poor, less-educated, people of color in rural labor markets and small companies that should inform the structuring of regional and national education, skilling and employment policies.
Figure 1: Measuring occupational skill content change without considering skill proximity induces biases in estimating the re-skilling pressure. (A) Food Batchmakers have fewer new 2018 core skills than computer programmers, but the new skills located much further from the 2010 core skills. Each dot represents a skill: the blue dots are the focal occupation’s old core skills with top 5% occurrence in 2010; the red dots are among the top 5% in 2018. We illustrate the distinctiveness of skill ‘regions’ by identifying 6 well-formed clusters (See SI for method details on how the clusters are identified.) Each new core skill is linked to its nearest old skill. (B) Computer Programmers have many new core skills in 2018 not among their 2010 core skills, but 2018 and 2010 skills are very similar. (C) Without considering skill distance, computer programmers are assessed as experiencing substantially higher skill change than food batchmakers, 2010 to 2018. Each unit of the x axis corresponds to a skill ranked from highest to lowest in terms of skill probability change. The y axis denotes skill probability change for each skill. (See SI for details on the calculation of skill probability change.) (D) After controlling for skill distance, food batchmakers are associated with much larger skill change than programmers. Each unit of the x axis corresponds to a core skill ranked from highest to lowest in terms of job skill vector change attributed to each 2018 new core skill. The y axis denotes skill vector change attributed to each skill. The inner panel presents the same skill vector change distribution calculated from the 2010 old core skills that no longer appear as core skills in 2018. (See data and method section for details on how job skill vector change is calculated and see SI for details on how job skill vector change is attributed to each old removed and new added core skill.)
Figure 2: Low-skilled occupations face higher re-skilling pressure 2010-2018 when skill distance is accounted for. (A) Occupations with lower skill complexity have higher average skill content change. Each bar denotes the average skill vector change for a group of jobs whose core skill number fall within the range labeled on the x-axis. (B) Occupations with lower pay have higher average skill vector change. (C) Except for graduate degrees, occupations with lower education requirement change more; jobs requiring masters or doctorate degrees change more than those requiring bachelor’s degree. (D) Occupation skill change corresponds to the amount of re-education cost required for workers to move from one distribution of skills to another. The three bars represent the average skill vector change for 0 – 1/3 quantile, 1/3 – 2/3 quantile, and 2/3 – 1 quantile of occupations ordered in terms of the average education requirement change. (E) The skill vector change distribution for 2-digit SOC occupation groups. Bins are ordered from the group with the largest median change to the one with the lowest median change.
Figure 3: The variation in re-skilling pressure for different local markets, organizations, and social groups. (A) Mapping occupational skill change in U.S. regions. States and counties are grouped into three quantiles in terms of average job skill change. (B) Large local markets and organizations buffer occupational skill change, especially for low-skilled occupations. Jobs are divided into ten equal-sized groups according to their required skill number. For each occupation group, the $y$-axis denotes the difference between average occupational skill change for (1) small markets and large markets (blue bars) and (2) small companies and large companies (green bars). (C) Low-skilled nonwhite male workers face the highest re-skilling pressure compared with other social groups. Each cell presents the average occupational skill change for occupations of different skill-levels and with an over-representation of employees from specified social groups. Occupations are classified into five skill types according to their percentile in the skill number distribution for all occupations.
Figure 4: Occupations’ re-skilling direction. (A) Each dot denotes a latent skill atom learned from the skill embedding space, embodying a meaningful dimension in the skill space and embedding its relationship to the other skill atoms as well as to each compositional skills. There is a division between orange skill atoms defined predominantly by the human interface, and blue atoms defined by requiring machine-operation and/or interface. More machine-interface skill atoms rise in importance between 2010 and 2018, while more human-interface skill atoms fall during the same period. (B) Examples of the re-skilling direction for individual occupations. For Gaming Dealers employed by casinos, the skill atom that declines most in importance from 2010 to 2018 is hospitality industry knowledge, whereas the one that increases in importance most is big data processing. For Management Analysts, the web development atom declines most and the web analytics atom rises most in importance (2010-2018). (C) The declining human-interface skill atoms with negative ($\beta$) importance change in the job space: the less transparent an atom, the larger its importance decline. (D) The rising machine-interface skill atoms with positive ($\gamma$) importance increase: the less transparent an atom, the larger its importance increase.
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A  Extended Methods: Formula and Replication of Deming and Noray’s (2020) Job Skill Change Measurement

As is demonstrated in equation [1], Deming and Noray (2020) measure the skill content change of occupation $o$ as the sum of the absolute value of difference in share for each skill from 2007 to 2019, in which a given skill $s$’s share of occupation $o$ in year $t$ is defined as the proportion of $o$’s job ads that require $s$ in year $t$. To account for temporal compositional changes in job post number and skill number per job post, [20] weight the skill change rate calculated from equation [1] by multiplying the ratio of skill occurrence divided by post number in 2007 to that in 2019, for each occupation.

$$SkillChange_o = \sum_{s=1}^{S} \{Abs[(\frac{JobAds_o^s}{JobAds_o})_{t_1} - (\frac{JobAds_o^s}{JobAds_o})_{t_0}])\}$$  (1)

We replicate this measurement on the same job ads dataset compiled by Burning Glass Technologies, limiting the sample to posts with non-missing employer and MSA information. Our replication for 6-digit SOC occupation skill change rates from 2007 to 2019 highly correlates with the scores listed in [20] appendix with 0.87 Pearson correlation. The replicated measure does not obtain exactly the same values for two reasons: (1) We only have access to the first 5 month of job posts data in 2019, whereas [20] uses 10 months’ data for 2019; (2) [20] further filter the sample by only retaining posts with employers that could be matched to a specific Compustat dataset inaccessible to us.

B  Extended Methods: Pointwise Mutual Information Network Construction and Community Detection for Figure 1A and B

We construct a skill network based on 2010 BG job postings that builds on the skill co-occurrence network, a topological representation of skills linked by co-presence within job advertisements [21]. Our approach adds geometric precision to create a Pointwise Mutual Information (PMI) skill network. We first calculate the PMI of each pair of skills in our skill vector space using equation [2], with each skill a node in the network and an edge added if the PMI between the two is larger than 0, implying that these two skills are more likely to co-occur in the same or similar job posts than expected under independence [44]. The weight for each edge is the PMI score between the two skill nodes connected by an edge. The 6 skill communities are detected by the commonly-used Louvain community detection algorithm: (1) business skills, (2) engineering, technical, and physical skills, (3) programming skills, (4) clerical and administrative skills, (5) scientific knowledge, (6) health and medical care skills. The modularity of the partition is 0.51, indicating that this division is very strong, and represents substantial community structure in the network [45].

For skill $i$ and $j$, $PMI_{i,j} = \log(\frac{p_{i,j}}{p_i \times p_j})$  (2)
where \( p \) refers to probability and \( p_{i,j} = \sum_{v=1}^{V} p(i|v) \times p(j|v) \times p(v) \) denotes the probability of skill \( i \) and \( j \) co-occurring in the same or a similar job post \( v \).

C Extended Methods: Occupational Skill Change Measurements in Figure 1C and D Illustration

In Figure 1C, the area under the curve of each occupation corresponds to Deming and Noray’s (2020) job skill change measurement discussed in section A. Note that all skills appearing in the job ads of a given occupation are taken into account. Because the measurement sums up the probability change for each skill required by the job in either start or ending year, we can easily decompose the total skill change for an occupation and rank skills by the proportion of occupation change for which they account.

For figure 1D, we first calculate the occupational skill vector change for Food Batchmaker and Computer Programmer using the method described in Data and Methods. Namely, we represent the occupation skill content in 2010 and 2018 with the average vector of top 5% core skills required in those two years, respectively (see robustness to this threshold below). With these occupation vector representations, we measure occupational skill change as one minus the cosine distance between occupation vectors in 2010 and 2018.

We then locate two groups of skills that contribute to the occupation skill change and attribute occupation level change to each skill. For each new core skill that emerges in 2018, we remove it and recalculate the occupation vector representation in 2018 based on the remaining skills. We then use the cosine distance between this adjusted 2018 occupation representation and the 2010 representation to estimate the occupational skill vector change rate that would have occurred if a given new skill were not added in 2018. We approximate the change that a given skill accounts for as the absolute value of the difference between the real occupation skill vector change rate and this controlled occupation skill vector change rate. Similarly, for each removed core skill that only appears in 2010, we estimate the adjusted occupation skill vector change rate that would have arisen if this skill were absent in 2010. Using the same approach, we then estimate the change contributed by each removed skill.

D Extended Methods: Cluster Approach to Measure Occupational Skill Change

In order to construct a more conservative test of our conclusion regarding the reskilling burden for low-paid and low-educated occupations relative to that of Deming and Noray (2020), we develop a version of occupational skill formally equivalent to Deming and Noray’s approach, but using data-driven skill clusters rather than individual skills. Utilizing the 6 communities automatically detected from the PMI network, we calculated skill community change with equation 3. Fig. 5A shows that this measurement reverses the assessment of Deming and Noray. Fig. 5B suggests that this measurement highly correlates with our main skill vector change measurement.
SkillChange_o = \sum_{sc=1}^{SC} \{ \text{Abs}\left[\left( \frac{NSkill^{rc}_o}{NSkill_o} \right)_{t_1} - \left( \frac{NSkill^{sc}_o}{NSkill_o} \right)_{t_0} \right] \} \tag{3}

E Extended Data: Representativeness of Job Ads Data Collected by Burning Glass Technologies

Burning Glass Technologies (BG) data could be biased for multiple reasons. They may include duplicated job ads and oversample high skill jobs which are more likely than low skill jobs to appear in online posts. Moreover, among the analyzed job ads, only 50% specified educational requirements and 17% listed salary. To address these concerns, we have compared BG data against the 2010 and 2018 occupational employment statistics assembled by U.S. Bureau of Labor Statistics (BLS) in labor market share, education requirement, and salary for the entire sample of occupations. We confirm that these two data sources are highly consistent in all three variables. Specifically, Pearson correlation coefficient \( r \approx 0.8 \) (\( p < 0.001 \)) for labor market share (Fig. 6 A), \( r \approx 0.8 \) (\( p < 0.001 \)) for salary (Fig. 6 B), and \( r \approx 0.9 \) (\( p < 0.001 \)) for education (Fig. 6 C). We also verify the Two-step De-duplication Process that BG used [25], in which the key component is to build advanced parsing engine to extract and normalize a number of data elements from each job listing, including job title, job ID, source, posting date, employer name, location, job description text, etc., and then use these variables to screen for duplicates. In our data analysis, we did not find job posts that duplicated all of these fields.

F Extended Methods: Re-skilling Directions Identification

1. The compositionality of occupations based on skill atoms:

   (a) Map each occupation to 5% core skills filtered by skill probability

   (b) Map each skill to atoms - Denote each skill \( s \) with its weights on each atom \( j \):

   \[
   s = \sum_{j=1}^{210} weight_{sj} \tag{4}
   \]

   Note that according to the current model, there are only 5 non-zero \( weight_{sj} \) for each skill \( s \).

   (c) Map each occupation to atoms - Denote each of the 727 occupations in a given year (2010 or 2018) as a combination of atoms by adding up its core skills represented by atoms in the equation [4]. The weight of each atom for each occupation is normalized by dividing the sum of all atom weights for the given occupation. For an occupation \( O_t \) with \( S_t \) core

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[4]https://www.bls.gov/oes/tables.htm

---

20
210 \sum_{j=1}^{210} weight_{otj}

in which

\text{weight}_{otj} = \frac{\sum_{s=1}^{St} weight_{sj}}{\sum_{j=1}^{210} \sum_{s=1}^{St} weight_{sj}}.

(6)

2. The overall importance change of skill atoms on the job space:

(a) Measure the overall importance level for each skill atom on the job space at a given time point - for each atom \( j \) at each time point \( t \), summing up its normalized weight for each occupation \( o \) (\text{weight}_{otj}):

\text{importance}_{jt} = \frac{\sum_{o=1}^{275} \text{weight}_{otj}}{275}

(7)

(b) Measure atom overall importance change on the job space between 2010 and 2018 - for atom \( j \):

\text{ImportanceChange}_{j} = \text{importance}_{j2018} - \text{importance}_{j2010}

(8)

G Extended Results: Job Zone and Skill Change

We use O*NET five-level job zone classification (i.e., “little or no preparation”, “some preparation”, “medium preparation,” “considerable preparation”, “extensive preparation”) as a proxy for occupational skill level. The job zone measure reflects on-the-job training and experience in addition to formal education in capturing the first-order learning costs associated with each job—their relative difference from no education. Fig 7 demonstrates that skill change decreases as job zones increase from 1 to 5 except that jobs in zone 5 change more than those in zone 4. We compare the predictive power between job zones and education years in anticipating skill change, by calculating Pearson and Spearman correlation coefficients accordingly for the same sample of 602 occupations. We find that job zones consistently predict skill change better than education year (0.205 vs 0.185 for Pearson coefficients and 0.2989 vs 0.2985 for Spearman coefficients).

H Extended Results: Robustness Checks

H.1 Controlling for Employer Concentration

For occupations with high average local employer concentration, their skill change could be overwhelmingly determined by changes induced by a few employers. Therefore, we perform several robustness checks to ensure that the job skill change variation by job skill complexity, employer size and local market size does not merely reflect variation in occupational employer concentration within the local labor market.
Following [46], we measure employer concentration with the Herfindahl-Hirschman Index (HHI) of the share of BG vacancy postings from each employer for each SOC 6-digit occupations within a local labor market in a given year, as specified in equation 9. To align with the geographical unit used in examining job skill variation by local labor market size, here we identify the local labor market with combinations of longitudes and latitudes at .1 decimal degree precision, corresponding to large cities or districts. As a result, our employer concentration values are systematically larger than those measured on the level of Metropolitan Statistical Area or Commuting Zone [46–48].

\[
EmpConcentr_{o,k,t} = \sum_{i=1}^{N} \left( \frac{JobAds_{i,o,k,t}}{\sum_{i=1}^{N} JobAds_{i,o,k,t}} \right)^2
\]

(9)

where \( JobAds_{i,o,k,t} \) refers to the number of BG vacancy advertisements posted by employer \( i \) on occupation \( o \) in region \( k \) during year \( t \).

The regression analyses in this section and the next are all based on a dataset that concatenates job skill change values calculated from four different sub-samples: job posts of large local markets and large employers, those of large local markets and small employers, those of small local markets and large employers, and those of small local markets and small employers. Large employers or local markets refer to those in the highest 10th percentile of job posts annually. For each of the four sub-samples, we extract core skills for each occupation based on the job posts of firms and local markets of given size and construct occupation vector representations for different time points. For example, with 2010 and 2018 occupation vectors constructed from job ads posted by large employers in large local markets, we calculate a set of job skill change scores for large firms in large local markets. Concatenating four sets of occupational skill change scores, we end up with 1824 observations, each of which summarizes its occupation, employer size, and local market size information.

Assuming that job skill level is constant across regions and organizations, we use the same collection of occupational skill level measurements for observations from different sub-samples. We measure skill complexity as the log number of top 5% core skills calculated based on the full sample; education as the average required entry level education years calculated based on the full sample; and pay as the log of average annual median salary calculated based on the full sample. For employer concentration, we calculate two sets of average occupational employer concentration for large and small local markets. For each occupation and local market combination, we average the 2010 and 2018 employer concentration scores. To adjust for left skewness in the employer concentration distribution, we use squared employer concentration for regression estimation.

Table 1 presents OLS regression results explaining job skill change variation with the three different measurements for job skill level: job skill complexity, pay, and education. Consistent with figure 2 in the main body, models 1-3 show that low-skilled occupations change more. Models 4-5 demonstrate that this pattern still holds when employer concentration is controlled. The coefficients for employer concentration align with the findings in [48] — occupations with larger local employer concentration experience more re-skilling.

Table 2 presents a series of occupational fixed effect model results describing how skill content change for the same occupation varies with organization and local market size. Model 1 and 2 show
that larger organizations and larger local markets buffer occupations from skill change. As is shown in model 3, these results are still robust when employer concentration is taken into consideration, when market size is controlled for testing employer size variation, as well as when employer size is controlled for testing market size variation. Surprisingly, when employer and labor market size is controlled, larger employer concentration correlates with lower job skill change. Given that employer concentration is constructed at a relatively narrow region level, this pattern might result from the high collinearity between local market size and employer concentration.

To examine whether the buffering from organization size varies between occupations of different skill levels, model 4 includes an interaction term between employer size and job skill complexity on the basis of model 1. Here we choose skill complexity to represent the work place skill level of an occupation as we find it a more appropriate measurement than pay, which reflects a variety of factors beyond job skill level, and education, which better reflects worker human capital than job characteristics. Consistent with figure 4, we find that occupations experience less change in large organizations, especially for low-skilled jobs. Similarly, model 5 shows that occupations change less in larger local markets, especially for low-skilled jobs. Model 6 combines models 4 and 5 as well as adding the employer concentration covariate to demonstrate the robustness of these two findings.

**H.2 Different Job Content Scope with Skill Weights**

While the BG job postings data provide rich and valuable information on dynamic job skill requirements that enables analyses in this paper, the data also create the new task of identifying the relative importance of skills to jobs as compared with the O*NET data. In the main analysis, we adopt a discrete approach to account for skill importance difference in representing occupational skill content — limiting occupational skill composition to the most common 5% skills for a given occupation. This 5% threshold is arbitrary, however, and a discrete approach is not necessarily better than a continuous approach that assigns weights to each skill. Therefore, we present a series of robustness checks here with different job content scopes (all skills, top 50% core skills, and top 75% core skills) using a continuous approach to incorporate skill importance differences: we represent occupation vectors as the sum of weighted skill vectors, as shown in equation (10).

\[
Vector_{o,t} = \sum_{s=1}^{S_t} \frac{Freq_{o,s,t}}{Freq_{o,t}} \times Vector_s
\]

where the weight is the proportion of occurrences of skill s in job posts on occupation o in year t among the sum of occurrences for all skills that appear in job posts on occupation o in year t.

Table 3 consists of three sets of estimations of model 4 in the main table that explain job skill change variation with skill complexity using all skills, top 50% core skills, and top 75% core skills to define job skill content, respectively. Similarly, table 4 presents estimations of model 6 in the main table testing organization and local market size buffering patterns with different job content scopes. All findings are robust to the continuous skill weight approach and different thresholds for job skill content definition.
Figure 5: (A) After roughly controlling for skill distance through tracking skill community share change instead of individual skill probability change, food batchmakers are associated with much larger skill change than programmers. Each unit of the x axis corresponds to a skill community ranked from highest to lowest in terms of skill community share change. The y axis denotes skill community share change for each skill community. Area under the curve (AUC) of skill community share change for each occupation demonstrates the sum of skill community changes for all 6 skill communities from 2010 to 2018. (B) Occupation skill change measured by skill community share change and skill vector change highly correlate with a 0.76 pearson correlation.
Figure 6: (A) BG occupational demand is highly consistent with the state of occupational employment in the U.S. Each dot represents a 6-digit SOC occupation. Coral dots are occupations in 2018, while royal blue dots are occupations in 2010. 786 Occupations can be matched between BG job post data and U.S. Bureau of Labor Statistics (BLS) Occupational Employment Statistics (OES) data in 2018; 759 occupations can be matched between the two datasets in 2010. The X axis denotes the log of BG vacancy post number for each occupation. The Y axis denotes the log value of BLS estimated employment for each occupation. The Pearson correlation between the log of BG occupational vacancy post number and the log of BLS occupational employment is 0.8 in 2018 and 0.75 in 2010. The red line is the diagonal \( y = x \). The black line shows the red line’s vertical translation upward. The magnitude difference between BLS occupational employment data and BG occupational demand data could be attributed to the fact that not all jobs hire workers through online job ads and a single job post may seek to hire more than one worker. (B) BG occupational median pay accurately represents occupational median pay in the U.S. Each dot represents an occupation – purple dots are occupations in 2018, while pink dots are the same in 2010. 772 occupations can be matched between BG and BLS-OES datasets in 2018; 743 occupations can be matched between the two datasets in 2010. X and Y axes denote the log value of BG and BLS average annual median salary for each occupation, respectively. The Pearson correlation between the log of BG and BLS occupational annual median pay is 0.87 in 2018 and 0.83 in 2010. The red line is the diagonal \( y = x \). (C) The BG occupational entry education level information could be trusted to represent the occupational entry education requirement in the U.S. Each dot represents an occupation in 2018, summing to 682 matches between BG entry education requirement data and BLS education and training assignments by detailed occupation data in 2018. The X axis denotes the average BG entry education year requirement for each occupation in 2018. The Y axis denotes the BLS estimated typical entry education year for each occupation in 2018. Here 12 refers to High school diploma or equivalent; 14 to Associate’s degree; 16 to Bachelor’s degree; 18 to Master’s degree; 21 to Doctoral or professional degree. Note that in BG’s job posts, education year could only take a value from the set \{12, 14, 16, 18, 21\}, denoting different degrees (‘high school’, ‘associates’, ‘bachelors’, ‘masters’, ‘doctorate’). Nevertheless, because we calculated the average education year from all job posts for each occupation, the occupational average education year could take on value between those in the set. BLS, on the other hand, only provides entry degree level for each occupation: ‘No formal educational credential’; ‘High school diploma or equivalent’; ‘Some college’. ‘No degree’; ‘Postsecondary nondegree award’; ‘Associate’s degree’; ‘Bachelor’s degree’; ‘Master’s degree’; ‘Doctoral or professional degree’. In order to compare the two datasets, occupations with ‘No formal educational credential’ are left out; ‘Some college’, ‘No degree’ as well as ‘Postsecondary nondegree award’ are coded as 12 (the same as ‘High school diploma or equivalent’). The Pearson correlation between BG and BLS’ 2018 occupational entry education level is 0.92.
Figure 7: Occupations have higher average skill content change as job zone increase from 1-4. Each bar denotes the average skill vector change for a group of jobs in a specific job zone labeled on the $x$-axis.
Table 1: Explaining Job Skill Change Variation with Skill Complexity

|                          | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|--------------------------|---------|---------|---------|---------|---------|---------|
| Skill Complexity         | -0.043*** | -0.034*** |         |         |         |         |
|                          | (0.002) | (0.002) |         |         |         |         |
| Log Annual Pay           | -0.025*** | -0.023*** |         |         |         |         |
|                          | (0.004) | (0.003) |         |         |         |         |
| Education                | -0.004*** | -0.004*** |         | 0.070*** | 0.109*** | 0.111*** |
|                          | (0.001) | (0.001) |         | (0.005) | (0.006) | (0.006) |
| Sq. Emp. Concentr.       |         |         |         |         |         |         |
| Observations             | 1,824   | 1,824   | 1,824   | 1,824   | 1,824   | 1,824   |
| $R^2$                    | 0.263   | 0.023   | 0.019   | 0.324   | 0.196   | 0.197   |
| Adjusted $R^2$           | 0.262   | 0.023   | 0.018   | 0.323   | 0.195   | 0.196   |
| Residual Std. Error      | 0.054(df = 1822) | 0.062(df = 1822) | 0.062(df = 1822) | 0.052(df = 1821) | 0.056(df = 1821) | 0.056(df = 1821) |
| F Statistic              | 649.854*** | 43.328*** | 35.102*** | 435.946*** | 221.279*** | 223.380*** |
|                          | (df = 1.0; 1822.0) | (df = 1.0; 1822.0) | (df = 1.0; 1822.0) | (df = 2.0; 1821.0) | (df = 2.0; 1821.0) | (df = 2.0; 1821.0) |

Note: Sq. Emp. Concentr. refers to squared employer concentration.
| Model  | Dependent variable: Job Skill Change | Large Employer | Large Market | LE * SC | LM * SC | Sq. Emp. Concentr. | Occ. FE | Observations | R² | Adjusted R² | Residual Std. Error | F Statistic |
|--------|-------------------------------------|----------------|--------------|---------|---------|-------------------|---------|--------------|----|------------|---------------------|-------------|
| 1      |                                     | -0.018***     | -0.036***    | 0.011** | 0.016*** | -0.086***         | Yes     | 1,824        | 0.652 | 0.542      | 0.046(df = 1174)   | 3.382       |
| 2      |                                     | -0.006***     | -0.077***    | 0.004   | 0.003   | 0.006***          | Yes     | 1,824        | 0.652 | 0.542      | 0.046(df = 1174)   | 4.327       |
| 3      |                                     | -0.109***     | -0.144***    | 0.020** | 0.023** | 0.028**           | Yes     | 1,824        | 0.652 | 0.542      | 0.046(df = 1174)   | 5.081       |
| 4      |                                     | -0.117***     | -0.066***    | 0.005   | 0.004   | 0.005             | Yes     | 1,824        | 0.652 | 0.542      | 0.046(df = 1174)   | 3.411       |
| 5      |                                     | -0.024***     | -0.077***    | 0.011** | 0.016*** | 0.019             | Yes     | 1,824        | 0.652 | 0.542      | 0.046(df = 1174)   | 4.436       |
| 6      |                                     | -0.117***     | -0.066***    | 0.005   | 0.004   | 0.005             | Yes     | 1,824        | 0.652 | 0.542      | 0.046(df = 1174)   | 5.408       |

Notes: LE refers to Large Employer dummy. LM refers to Large Market dummy. SC refers to Skill Complexity of job, which is measured by the log number of top 5% core skills. Sq. Emp. Concentr. refers to squared employer concentration. Occ. FE refers to Occupation Fixed Effect.
Table 3: Explaining Job Skill Change Variation with Skill Complexity, Different Job Content Scope and Skill Weights

|                                      | All Skills | Top 50% Skills | Top 75% Skills |
|--------------------------------------|------------|----------------|----------------|
| Skill Complexity                     | -0.020***  | -0.020***      | -0.021***      |
|                                      | (0.001)    | (0.001)        | (0.001)        |
| Sq. Emp. Concentr.                  | 0.028***   | 0.028***       | 0.026***       |
|                                      | (0.004)    | (0.004)        | (0.004)        |
| Observations                         | 2,390      | 2,390          | 2,390          |
| $R^2$                                | 0.196      | 0.196          | 0.202          |
| Adjusted $R^2$                       | 0.195      | 0.195          | 0.202          |
| Residual Std. Error                  | 0.042(df = 2387) | 0.042(df = 2387) | 0.044(df = 2387) |
| F Statistic                          | 290.175*** | 291.110***     | 302.718***     |
|                                      | (df = 2.0; 2387) | (df = 2.0; 2387) | (df = 2.0; 2387) |

Note: Sq. Emp. Concentr. refers to squared employer concentration.
Table 4: Explaining Job Skill Change Variation with Organization and Local Market Size, Different Job Content Scope and Skill Weights

|                       | All Skills | Top 50% Skills | Top 75% Skills |
|-----------------------|------------|----------------|----------------|
| Large Employer        | -0.031***  | -0.031***      | -0.021**       |
|                       | (0.007)    | (0.007)        | (0.007)        |
| Large Market          | -0.045***  | -0.045***      | -0.038***      |
|                       | (0.009)    | (0.009)        | (0.009)        |
| LE * SC               | 0.006***   | 0.006***       | 0.004*         |
|                       | (0.002)    | (0.002)        | (0.002)        |
| LM * SC               | 0.008*     | 0.008*         | 0.008*         |
|                       | (0.003)    | (0.003)        | (0.003)        |
| Sq. Emp. Concentr.   | 0.013      | 0.014          | 0.021          |
|                       | (0.019)    | (0.019)        | (0.019)        |
| Occ. FE               | Yes        | Yes            | Yes            |
| Observations          | 2,390      | 2,390          | 2,390          |
| $R^2$                 | 0.670      | 0.670          | 0.678          |
| Adjusted $R^2$        | 0.523      | 0.524          | 0.535          |
| Residual Std. Error   | 0.033(df = 1655) | 0.033(df = 1655) | 0.033(df = 1655) |
| F Statistic           | 4.573***   | 4.583***       | 4.738***       |

Notes: LE refers to Large Employer dummy. LM refers to Large Market dummy. SC refers to Skill Complexity of job, which is measured by the log number of top 5% core skills. Sq. Emp. Concentr. refers to squared employer concentration. Occ. FE refers to Occupation Fixed Effect.