Technology Change and Worker Transitions: Understanding Mobility through Occupational Skill Space

December 2024

The interplay of skills, technological change, and worker mobility is central to understanding evolving labor markets. This paper enhances our understanding of worker mobility by introducing a novel, data-driven approach to mapping occupational skills, constructing occupation-specific skill embeddings from job posting-derived prompts. This improved ability to account for worker mobility, compared to traditional measures, allows us to analyze the distinct impacts of technological change: both technology enhancing tasks by requiring new skills, and technology eliminating tasks. Combining this enhanced skill measure with technology exposure metrics and worker transition histories (2002-2018), our analysis reveals contrasting mobility patterns. Specifically, when technology enhances tasks but requires new, difficult-to-acquire skills within their initial occupations, moves to skill-distant occupations involve transitioning to lower-paying occupations, suggesting involuntary mobility and skill redundancy due to the difficulty in acquiring these new skills. Conversely, when technology eliminates tasks, skill-distant moves are associated with transitioning to relatively higher-paying occupations, indicating a strategic reorientation away from declining skill clusters towards opportunities where their existing skills remain valued. These findings highlight the relevance of understanding the skills landscape for effective workforce development policies aimed at smoothing worker transitions in the face of technological change.

1. Introduction

Technological change and its effects on labor market prospects remain an enduring concern for workers. Over the last decade, the occupational landscape was fundamentally reshaped by the widespread adoption of digital technologies – encompassing web-based commerce, digital instrumentation, and data analytics across sectors. While technological change can enhance productivity, it poses a dual challenge to workers: either requiring the acquisition of new skills within their occupational domain or fundamentally reducing opportunities through task automation. Understanding these divergent pressures is crucial for designing effective workforce development policies – when technology requires new skills, workers may need support adapting within their skill domain, but when technology fundamentally reduces opportunities through task automation, they may need help with more dramatic skill reorientation. These challenges have taken on new urgency as adoption of digital technologies, from automation to artificial intelligence, transform work across industries (Eloundou et al. 2024).

Traditional approaches to analyzing these changes, often relying on broad occupational categories or expert-coded skill measures, may mask important patterns in how workers navigate these distinct forms of disruption. Understanding these patterns requires approaches capable of capturing the subtle relationships between occupational skills, beyond broad categories, and connecting them to observed worker mobility and labor market outcomes. Recent work by Kogan et al. (2023) highlights the heterogeneous impact of labor-saving and labor-augmenting technologies on worker earnings, with labor-saving technologies negatively affecting directly exposed workers. Our analysis complements these findings by examining how these distinct technological trajectories actively reshape worker mobility patterns through their influence on occupational skill requirements.

Our approach provides a more nuanced understanding of occupational skill relationships by strategically leveraging the capabilities of pre-trained embedding models. By using the information within millions of job postings to create targeted prompts, we then process these prompts through OpenAI's embedding model to construct occupation-specific skill representations. This methodology allows us to capture not only explicit skill requirements but also the implicit relationships between diverse competencies. When validated against comprehensive U.S. occupational mobility data, our measure explains worker transitions substantially better than traditional approaches based on expert-coded skill categories – achieving nearly five times higher predictive power. This enhanced precision in measuring skill relationships is central to the skill-focused analysis presented in this paper and leads us to our central research question: How does the spatial correlation of technology exposure within our data-driven skill space influence worker mobility patterns and wage outcomes, particularly in light of the distinct pressures of skill acquisition versus task elimination?

Our improved measurement precision allows us to uncover a crucial pattern: technology exposure exhibits strong correlation among occupations with similar skill requirements. This correlation creates distinct adaptation challenges that align with and extend the findings of Kogan et al. (2023). When technology augments labor and requires new skills, similar occupations offer limited refuge as they face common pressure to adapt. When technology is labor-saving and diminishes existing skills, moves within affected skill clusters may compound disadvantages, necessitating transitions to more distant parts of the skill space.

We find compelling evidence of these adaptation patterns in worker transitions between 2002-2018. When technology exposure coincides with increased wages and workforce growth, moves away from skill-similar occupations involve substantially larger wage penalties, suggesting some workers struggle to acquire new skills within their domain. In contrast, when technology exposure coincides with declining wages and workforce, moves to skill-distant occupations show smaller wage penalties than moves between similar occupations, consistent with strategic reorientation away from declining skill clusters.

Our analysis builds on fundamental insights from task-based models of technological change (Autor, Levy, and Murnane 2003; Acemoglu and Autor 2011). These models view occupations as bundles of tasks, with technological change affecting different tasks differently – automating some while complementing others. We extend this framework by examining how occupations are connected through shared tasks, creating natural relationships in skill space. These connections mean that when technology affects specific tasks – either by requiring new skills or diminishing their value – it creates correlated pressures across similar occupations.

Our empirical strategy leverages these validated measures to examine exit patterns from occupations experiencing different manifestations of technological change. We focus particularly on occupations with high technology exposure, comparing those where labor-augmenting technology drives increased wages and workforce growth to those where labor-saving technology leads to declining wages and workforce. This comparison reveals how different types of technological pressure create distinct patterns in worker mobility through their effects on clusters of related occupations.

These insights take on particular urgency as artificial intelligence and automation reshape work at an accelerating pace. Understanding how workers successfully navigate technological disruption requires connecting detailed skill requirements to broader labor market outcomes. Our findings suggest that the effectiveness of different adaptation strategies depends critically on whether technology is primarily labor-augmenting or labor-saving within specific skill clusters. When technology requires new skills, programs should focus on helping workers adapt within their broader skill domain. However, when

technology fundamentally reduces opportunities through task automation, programs may need to facilitate more dramatic skill reorientation away from affected skill clusters.

The remainder of the paper proceeds as follows. Section 2 develops our approach to mapping occupation-level skill relationships and validates it using mobility data. Section 3 presents our methodology for measuring technological change and examining its manifestation in wage and workforce changes. Section 4 documents our main empirical findings about mobility patterns. Section 5 discusses implications for understanding technological change and worker adaptation. Section 6 concludes.

1.1. Literature Review

Our analysis connects to three primary strands of economic research: the measurement and impact of technological change, theoretical frameworks of occupational mobility, and empirical studies of worker adaptation. The measurement literature has evolved from early work establishing skill-biased technical change (Katz and Murphy 1992) to recent innovations in capturing technology exposure through patent-task text analysis (Kelly et al. 2021). Contemporary work by Kogan et al. (2023) provides a crucial distinction between labor-saving and labor-augmenting technologies, while studies like Acemoglu et al. (2022) demonstrate how text analysis of job postings can reveal evolving skill demands. Our contribution to this strand lies in revealing how technology exposure exhibits systematic patterns across skill-similar occupations, a dimension less explored in previous research.

The theoretical foundations for our analysis draw from models that conceptualize occupations as multidimensional skill bundles (Lise and Postel-Vinay 2020) and frameworks quantifying mobility costs between occupations (Cortes and Gallipoli 2018). These abstractions help explain why certain transitions may be more costly than others, particularly when skills are occupation-specific. Recent work has enriched these foundations by examining "skill remoteness" (Macaluso 2024) and developing gravity models of occupational transitions (Dupuy, Raux, and Signorelli 2024). While these approaches provide valuable insights into mobility constraints, our embedding-based measurement of skill relationships offers a more granular view of how workers navigate occupation transitions.

Modern analyses increasingly focus on the nuances of digital skills and their role in spread of technology adoption and shaping worker outcomes. The uneven diffusion of new technologies and the digital skills they necessitate, as evidenced by geographic concentration and gradual skill dispersion (Kalyani et al. 2024), underscores the need for a nuanced understanding of how technology's impacts unfold across the labor market. The dynamics of worker adaptation to technological change form a critical area of inquiry, from studies that link the pace of technology change to specificity of new skills (Adão, Beraja, and Pandalai-Nayar 2024) to analyses of displacement effects (Braxton and Taska 2023; Edin et al. 2023). Neffke, Nedelkoska, and Wiederhold (2024) demonstrates how skill mismatch

exacerbates post-displacement earnings losses Research on market polarization (Cortes 2016) highlights how technology can fundamentally reshape opportunity structures.

Our methodological approach advances beyond existing techniques for analyzing occupational transitions and technology exposure. While studies like Deming and Kahn (2018) and Acemoglu et al. (2022) have demonstrated the value of text analysis for understanding evolving skill demands, our use of embedding models represents a significant advancement. Machine learning techniques, as employed by Vafa et al. (2022) and leveraging methods like work2vec (Bana 2022), offer powerful tools for analyzing worker mobility patterns and skill relationships within large datasets. Unlike traditional text analysis methods that rely on keyword counts or topic modeling, embedding models capture nuanced semantic relationships between skills and occupations, allowing us to identify subtle patterns in how technological change reshapes opportunity structures.

The spatial correlation of technology exposure – a key focus of our analysis – provides new insights into the mechanisms through which technological change affects labor markets. Previous work has focused primarily on direct effects at the occupation level (Kogan et al. 2023) or broad patterns of polarization (Cortes 2016). Our analysis reveals how these effects propagate through networks of skill-related occupations, creating distinct adaptation challenges depending on whether technology augments or diminishes existing skills. This spatial perspective helps explain why traditional assumptions about the advantages of skill-similar transitions may not hold under certain types of technological change.

By connecting detailed analysis of skill requirements to broader labor market outcomes, our work bridges micro-level studies of skill demands with macro-level patterns of technological change. This integration provides a foundation for understanding how workers can successfully navigate technological disruption, while highlighting the importance of considering skill space relationships in designing effective workforce development policies. As technological change continues to accelerate, these insights become increasingly crucial for helping workers adapt to evolving labor market opportunities.

2. Mapping the Occupation Skill Space

Studying mobility in skill space requires an informative mapping of occupation skill relationships. We develop a procedural, data-driven approach to capturing occupation skill requirements, departing from traditional expert-curated characterizations. Job postings combined with modern language models offer richer, more dynamic measurement possibilities. Our approach systematically processes job market data to construct focused inputs for language models, similar to how retrieval-augmented generation strategies combine external knowledge with model capabilities. In this section, we first develop this occupation skill similarity measure and then validate it by examining its ability to account for observed patterns of inter-occupation mobility and other labor market relationships.

TABLE 1. Descriptive Summary of Job Vacancy Data

Lightcast Data	Summary
Period	weeks 1-2, Jan. '23
Number of postings	781544
Number of Firms	118669
Average Number of Skills per Job	12.46
Occupations with > 49 Vacancy Postings	539
Unique skills	21872

The table summarizes key features of our job posting data from Lightcast.

2.1. Constructing the Skill Similarity Measure

We develop our measure through a systematic process that combines extensive skill information from job postings with the semantic capabilities of language models. Figure 1 illustrates our approach, which transforms raw job posting data into occupation-specific skill embeddings through a series of carefully designed steps. The process leverages natural language processing techniques to identify and weight skills, ultimately capturing them in a continuous vector space that we expect will enable meaningful comparisons.

Step 1: Transform job posting corpus into occupation-level skill information:
Group postings by occupation and create frequency tables capturing how often each skill appears: $F_o = \{f_{o,s_1}, f_{o,s_2}, \ldots, f_{o,s_m}\}$

Step 2: Identify distinctive skills for each occupation:
Apply class-based TF-IDF weighting to determine skill importance: $W_o(s) = \text{TF-IDF}(s, o)$

Step 3: Create structured occupation skill descriptions:
Generate natural language prompts using highest weighted skills: $Q_o = \text{ConstructPrompt}(\{s \in S_o | W_o(s) \text{ is among the top } k \text{ in } o\})$

Step 4: Obtain occupation skill representations:
Map prompts to embedding space using pre-trained language model: $E_o = \text{LLM-Embed}(Q_o)$

The Lightcast dataset has become an increasingly valuable resource for labor market research, offering comprehensive insights into job vacancies and skill requirements across various industries. This proprietary dataset aggregates vacancy postings from a vast network of websites, providing an extensive representation of online job vacancies within the United States. In our sample from the initial two weeks of January 2023, we analyze 781,544 job postings from 118,669 firms, identifying 539 occupations with more

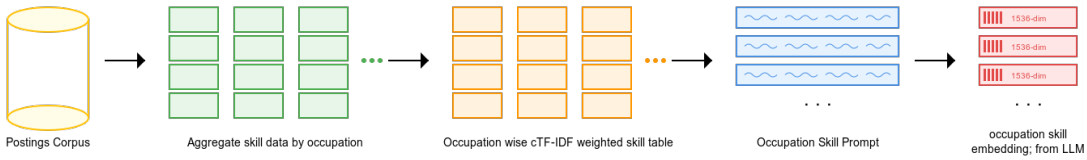


FIGURE 1. Process flow for constructing occupation skill embeddings. Starting from job postings corpus, we aggregate skill information by occupation, compute TF-IDF weights, construct skill prompts, and obtain embeddings using a pre-trained language model.

than 49 vacancy postings each. The dataset captures 21,872 unique skills, with an average of 12.46 skills listed per job. Employing sophisticated algorithms, Lightcast identifies newly posted advertisements, eliminates duplicates, and maps each posting to a six-digit Standard Occupational Classification (SOC) code while extracting specific skills, technologies, certifications, and other qualification-related terms. The dataset's utility in academic research is evident from its consistent recording of approximately 1.4 million job vacancies per month over the 2021-2022 period, making it an ideal tool for analyzing labor market trends, skill demands, and occupational shifts.[1]

The process of converting posting-level data into occupation skill embeddings begins with aggregating skills across all postings within each occupation. We adopt a modified class-based TF-IDF approach following Grootendorst (2020), which treats each occupation as a distinct class and combines all its job postings into a single document. This approach enables us to identify skills that characterize each occupation while accounting for their general prevalence in the labor market. For each occupation o, we first extract and L1 normalize the frequency of each skill within the occupation's combined document, ensuring proper weighting of skills regardless of posting volume. We then compute importance weights using:

$$W_{s,o} = \frac{\text{tf}_{s,o}}{T_o} \times \log\left(\frac{M}{\sum_j^N f_{s,j}}\right)$$

Here, $\text{tf}_{s,o}$ represents the normalized frequency of skill s in occupation o's combined document, T_o is the total number of skills mentioned in occupation o, M is the total number of postings across all occupations, and $\sum_j^N f_{s,j}$ captures the skill's presence across all occupations. This formulation balances each skill's importance within an occupation against its general prevalence, helping identify distinctively important skills for each occupation. The class-based approach appears particularly suited to our context as it preserves occupation-specific skill patterns while accounting for the varying prevalence of skills across the labor market.

[1]Several notable studies have utilized the Lightcast dataset for labor market research, including Deming and Kahn (2018), Braxton and Taska (2023), and Acemoglu et al. (2022).

Using these weights, we construct occupation-specific skill prompts that emphasize the most characteristic skills. For each occupation, we select the top 15 skills by weight, structuring them into a natural language prompt that distinguishes between the highest-weighted skills and supporting skills. This structured approach to prompt construction aims to focus the language model's attention on the most relevant aspects of each occupation's skill requirements, as illustrated in the example below:

Example Skill Text Sequence - Advertising and Promotion Managers

Key skills required for the occupation Advertising and Promotion Managers are – *digital marketing, marketing, search engine optimization, communications, social media, google analytics, detail oriented, email marketing, analytics, adobe creative suite*; other valuable skills for the occupation are: *sales, management, digital advertising, hubspot crm, writing.*

This prompt structure serves multiple purposes, integrating core principles from both prompt engineering and empirical skill measurement. By presenting skills in their empirical order of importance, we maintain focus on competencies that emerge directly from labor market data. The hierarchical organization into primary and supporting skills helps structure the embedding, potentially allowing the model to better capture both essential and complementary skill relationships. This approach adapts retrieval-augmented generation principles - while RAG typically retrieves relevant documents to augment model knowledge, we systematically process job market data to construct focused skill descriptions. The structured format provides consistent, interpretable inputs while leveraging the language model's semantic understanding of skill relationships.

These prompts serve as input to OpenAI's text-embedding-ada-002 model, which generates occupation skill embeddings E_O. Following Autor and Thompson (2024), we leverage pre-trained language models' ability to encode rich semantic relationships between skills learned from vast text corpora. The model's pre-trained understanding of language helps capture functional relationships between skills that might not be explicitly stated in job postings - for instance, understanding how analytical and programming skills often complement each other in data-focused roles. By using a general-purpose embedding model with our structured prompts, we combine broad semantic knowledge with focused occupation-specific information, potentially capturing both explicit skill requirements and their implicit relationships. This provides an efficient way to represent occupational skill sets without requiring extensive custom training or manual skill relationship coding.

Having established our embedding methodology, it's important to address its static nature. While technological change continually reshapes skill demands, our static mapping of occupational skill relationships serves a distinct analytical purpose. The embedding-

based approach captures the fundamental structure of skill relationships between occupations - how different competencies complement each other and combine to create occupational value. These higher-level relationships, such as how analytical skills complement programming expertise or how interpersonal skills enhance management capabilities, remain relatively stable even as specific technical requirements evolve. By focusing on these enduring structural relationships rather than tracking temporal changes in individual skill demands, our approach provides a stable framework for analyzing how workers navigate the skill space in response to technological disruption.

The final step computes skill similarity between occupations using the cosine similarity of their embeddings:

$$S_{o,p} = \frac{E_o \cdot E_p}{|E_o||E_p|}$$

For the 539 occupations we have similarity scores for 144,991 occupational pairs; note that the cosine similarity is a symmetric measure. The similarity values range from 0.724 to 0.976, with the middle 80% falling between 0.771 and 0.834 and the top 1% above 0.884. This relatively tight distribution suggests our measure captures meaningful variations in skill relationships while maintaining reasonable bounds on similarity scores.

Figure 2 presents example similarity networks for four occupations, showing how our measure identifies occupations requiring similar skills. For instance, Industrial Machinery Mechanics shows high similarity with Maintenance Workers and Engineering Technologists, while Healthcare Social Workers are closely linked to other social service occupations. These groupings reflect both technical skill overlap and broader occupational competencies. While these patterns appear intuitive, systematic validation is needed to verify our measure's ability to capture meaningful skill relationships.

Having developed our occupation skill mapping through this data-driven similarity measure, we next examine its validity by testing whether it aligns with observed patterns of inter-occupation mobility and other ecological relationships between skills, wages, and labor market transitions. This validation will help establish whether our approach captures economically meaningful skill similarities that influence worker mobility and labor market outcomes.

2.2. Validating the Skill Space

To validate our occupation skill mapping, we integrate two additional datasets that capture key labor market relationships: occupation-to-occupation transition data from resume records covering 2010-2018, and occupation-level wage data from the Bureau of Labor Statistics' Occupational Employment Statistics (OES). The transition data contains over 12 million job transitions across our 539 occupations, providing comprehensive coverage of

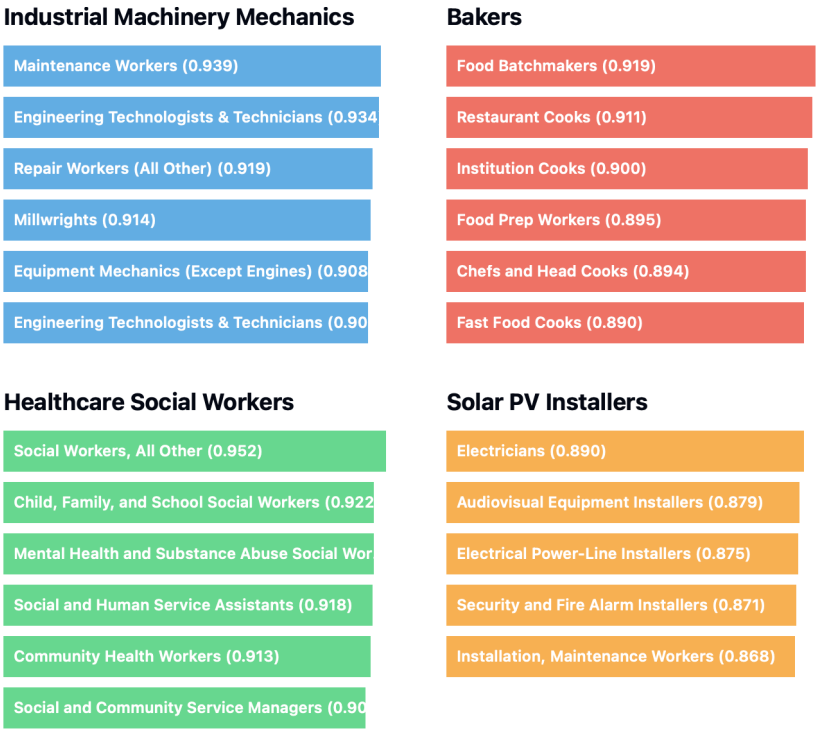


FIGURE 2. The figure displays the similarity network for four occupations. For the four chosen occupations, we retrieve occupations that have highest similarity values.

inter-occupational mobility patterns. The OES data provides annual mean wages for each occupation, averaged over 2018-2022 to reduce temporal volatility.

Our validation approach examines whether fundamental labor market patterns align with the skill relationships captured by our measure. A key test is whether the cost of switching between occupations is inversely related to their skill similarity - workers should find it easier to transition between occupations requiring similar skills. We verify this relationship and show that our measure better accounts for observed inter-occupation movement compared to traditional skill similarity measures based on expert-coded characteristics. Through these analyses, we establish that our measure captures economically meaningful skill relationships that influence worker mobility and labor market outcomes.

2.2.1. Occupational Mobility Dataset

To examine how skill similarities shape occupational transitions, we leverage a novel and comprehensive dataset of occupation-to-occupation transitions compiled as a companion to Schubert, Stansbury, and Taska (2022). The dataset measures transition shares $T_{o,p}$, representing the probability of moving from occupation o to occupation p conditional on leaving occupation o, along with the total number of workers exiting each occupation. As

TABLE 2. Occupational Mobility Dataset

Starting Occupation	Destination Occupation	Transition Share	Outflow
Accountants & Auditors	Financial Managers	0.1783	69,691
Actuaries	Financial Managers	0.0245	145
Bookkeeping Clerks	”	…	…
Financial Managers	Accountants & Auditors	…	…

Note: The table presents sample transitions from the occupation mobility dataset. Transition share represents the probability of moving to the destination occupation conditional on leaving the starting occupation. Outflow indicates the total number of workers observed leaving the starting occupation.

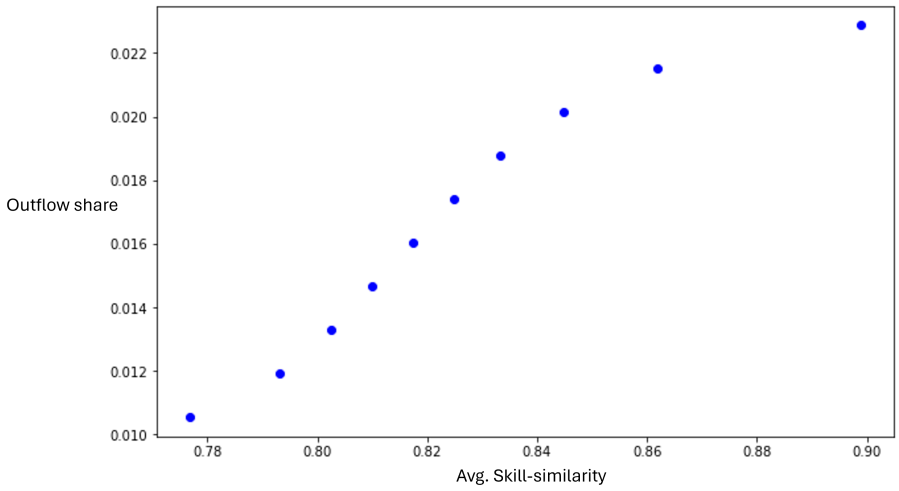
shown in Table 2, for each origin occupation, we observe both the volume of exits and how these exits are distributed across destination occupations. For instance, among the 69,691 accountants and auditors who changed occupations, 17.83% transitioned to financial manager positions.

Our analysis focuses on 445 occupations that maintained consistent classification between the 2010 and 2018 SOC systems and for which we computed skill embeddings, covering 16,453 directed occupation pairs and approximately 27.5 million transitions. The data reveals highly concentrated mobility patterns - just 620 occupation pairs (0.3% of possible paths) account for 50% of all recorded transitions. For the median occupation, transitions to approximately 22 distinct occupations capture half of all outflows, highlighting the structured nature of occupational mobility that our skill measure aims to explain.

This dataset offers three crucial advantages for studying skill-based mobility patterns. First, it provides an order of magnitude more transitions than survey-based alternatives like the Current Population Survey (CPS), enabling robust analysis of detailed occupational movements. Second, the self-reported nature of job histories reduces occupational coding errors common in survey responses where jobs must be coded from verbal descriptions. Third, the dataset provides particularly strong coverage of educated workers aged 25-40, a demographic whose mobility patterns are especially relevant for understanding how technological change affects skill-based transitions.

While comprehensive, we acknowledge several limitations of the data that are discussed extensively in Schubert, Stansbury, and Taska (2022). The resume-based nature of the dataset may overrepresent workers who change jobs more frequently and those who primarily use online job platforms. Additionally, as the data relies on self-reported employment histories, it may reflect selective reporting of career trajectories. However, the dataset's unprecedented scale and granularity in tracking occupational transitions make it uniquely suited for validating our skill similarity measure and examining how technological change shapes mobility through the occupation skill space.

FIGURE 3. Skill Similarity and Occupational Transitions



This is a binned scatterplot of outflow share (the proportion of people leaving an occupation o to move to occupation p) against skill similarity between the occupations. To create the plot, we regress the dependent variable on indicators for deciles of the independent variable and source occupation fixed effects. The y-axis values in the plot are the coefficients on the decile indicators, recentered by adding a scalar so that their mean value is equal to the average value of the dependent variable in the sample. The x-axis values in the plot are the average values of the independent variable within the corresponding decile.

2.2.2. Skill Similarity as a Predictor of Occupational Transitions

A fundamental test of our skill similarity measure is its ability to predict patterns of occupational mobility. The underlying economic logic is straightforward - workers should find it less costly to transition between occupations that require similar skills, leading to higher observed transition rates between occupations that are closer in the skill space. This relationship provides a natural validation of our measure while also allowing us to assess its informativeness compared to traditional approaches.

To quantify this relationship and compare it with traditional approaches, we estimate:

$$T_{o,p} = \alpha + \beta_1 S_{o,p} + \epsilon_{o,p} \tag{1}$$

where $T_{o,p}$ is the share of workers transitioning from occupation o to occupation p, and $S_{o,p}$ measures skill similarity. We compare our measure to a standard O*NET-based skill distance measure from Macaluso (2024) that captures dissimilarity between occupations o and p as:

$$d_{op} = \frac{1}{A} \sum_{a=1}^{A} |\ell_{oa} - \ell_{pa}|$$

where ℓ_{oa} and ℓ_{pa} are the required levels for skill a in each occupation, averaged across

TABLE 3. Skill Similarity and Occupational Transitions

	Dependent Variable: Transition Share	
	Embedding	O*NET Dissimilarity
Constant	-0.085***	0.020***
	(0.003)	(0.000)
Similarity	0.122***	-0.005***
	(0.004)	(0.000)
R^2	0.063	0.013
N	13,820	

Note: The table reports estimates from regressing transition shares on skill similarity measures. Standard errors in parentheses are robust to heteroskedasticity.
***p < 0.01, **p < 0.05, *p < 0.1

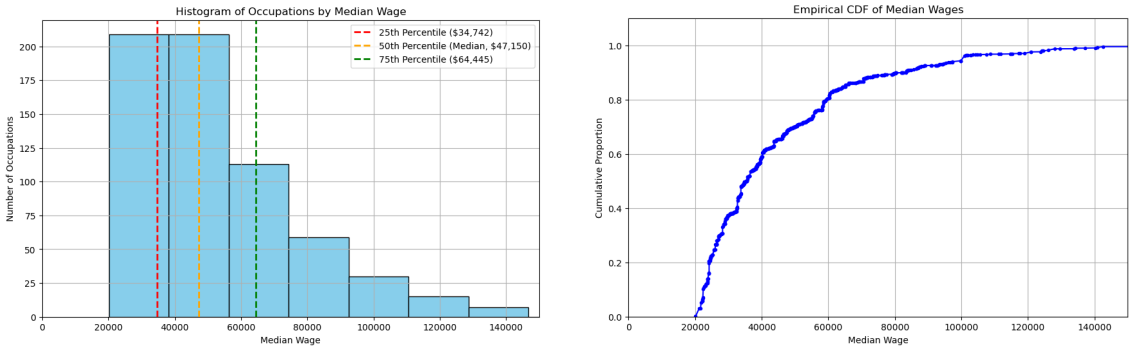
O*NET's 35 standardized skills.

Table 3 presents estimation results comparing our embedding-based measure to the O*NET dissimilarity index. The nearly five-fold higher R^2 (0.063 versus 0.013) demonstrates that our measure substantially improves our ability to explain observed mobility patterns. This dramatic improvement in predictive power validates our data-driven approach to mapping the occupation skill space. By systematically processing millions of job postings to identify occupation-specific skill requirements and leveraging a pre-trained language model's semantic understanding, we capture richer and more nuanced skill relationships than traditional expert-coded measures. The measure's superior performance in explaining worker transitions in the most comprehensive dataset of U.S. occupational mobility suggests we have constructed a more accurate representation of the skill space in which workers navigate career transitions. This enhanced measurement precision provides a stronger foundation for analyzing how technological change reshapes mobility opportunities through its effects on occupational skill requirements.

2.2.3. Skills, Wages and Mobility Patterns

Using occupation-level wage data from the Occupational Employment and Wage Statistics (OEWS) 2018, we observe a median occupation wage of $47,150. The employment-weighted distribution, shown in Figure 4, reveals that 67.5% of the workforce is employed in occupations below this median wage, and 88.9% work in occupations paying less than $75,000.

Higher-wage occupations typically require specialized skills acquired through substantial investments in education and experience. These specialized skills, while valuable, are often less transferable to occupations requiring different skill sets. Lower-wage occupations, in contrast, tend to emphasize more adaptable skills that can be deployed across different types of work.



A. Occupation Wage Distribution B. Employment-Weighted Distribution

FIGURE 4. Distribution of Occupational Wages

Panel A presents the distribution of median wages across occupations, with vertical lines marking the 25th ($34,742), 50th ($47,150), and 75th ($64,445) percentiles. Panel B shows the empirical cumulative distribution function of median wages weighted by employment, revealing that 67.5% of the workforce is employed in occupations below the median occupation wage and 88.9% in occupations below $75,000.

This basic structure suggests a testable relationship between skills and upward mobility patterns. For workers in high-wage occupations, deviating from their specialized skillset is likely to be costly, making transitions to different-skilled occupations more likely to involve wage penalties. In contrast, workers in lower-wage occupations may find opportunities for upward mobility across a broader range of occupations, as their more adaptable skills facilitate transitions even to roles requiring somewhat different skill sets.

To test this relationship, we examine how the association between skill similarity and transitioning to a higher wage level varies across the wage distribution. We estimate the following linear regression:

$$I(\bar{w}_p > \bar{w}_o) = \alpha + \beta_1 S_{o,p} + \beta_2 \bar{w}_o + \beta_3 (S_{o,p} \times \bar{w}_o) + \varepsilon_{o,p} \tag{2}$$

where $I(\bar{w}_p > \bar{w}_o)$ is an indicator equal to one for transitions to higher-wage occupations, $S_{o,p}$ is the standardized skill similarity score, and $\bar{w}_o$ is the standardized wage level of the origin occupation. The regression is weighted by the observed frequency of each transition path.

The estimates in Figure 5 Panel A show that while skill similarity alone has no significant effect on upward mobility, its association with upward transitions varies systematically with wage levels. The positive interaction term ($\beta_3 = 0.033$, SE = 0.010) indicates that skill similarity becomes increasingly important for upward transitions at higher wage levels. Panel B quantifies these effects through predicted probabilities of upward transitions. At high wage levels, workers moving to dissimilar occupations face significantly lower probabilities of upward mobility, consistent with our hypothesis that deviating from

specialized skills often necessitates moving down the wage distribution. In contrast, at lower wage levels, workers maintain similar probabilities of upward moves regardless of skill similarity, reflecting the greater adaptability of their skillsets.

Together, these analyses validate our approach to measuring occupation skill similarity. The measure, constructed by systematically processing job posting data through modern language models, captures economically meaningful relationships between occupations. It not only predicts patterns of worker transitions but also reveals how the constraints of specialized skills shape mobility opportunities differently across the wage distribution. These results demonstrate the value of our data-driven approach to mapping occupation skill relationships, providing a foundation for analyzing how technological change affects mobility through its impact on skill requirements.

3. Measuring Technological Change

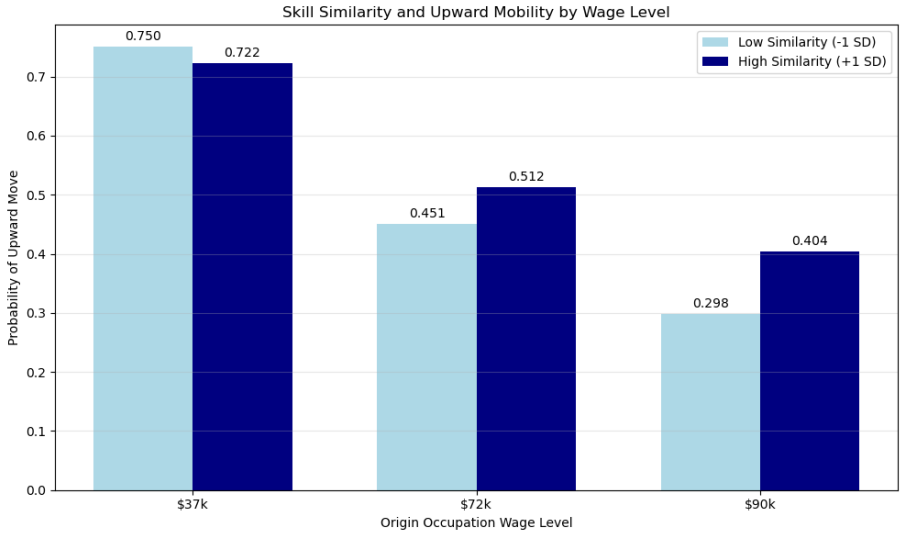
Having established a new mapping of the occupation skill space that notably improves our ability to account for worker movement, we turn to technological change. In this section we identify occupations that underwent significant technological change contemporaneous with our observed period of inter-occupation mobility (2002-2018), through a data-driven measure of technology exposure developed elsewhere. We discuss the measure and then develop a selection strategy to distinguish between two distinct types of technology change — that enhances task efficiency but requires workers to acquire new skills, and technology change that eliminates or fundamentally reformulates tasks, reducing original occupational prospects; a distinction not conveyed by the original measure. This differentiation forms the foundation for our analysis of heterogeneous mobility responses in subsequent sections.

3.1. Technology Exposure

Occupations are characterized by the tasks workers perform - for instance, registered nurses perform tasks like "report symptoms or changes in patients' conditions." The Bureau of Labor Statistics maintains detailed task descriptions for occupations, cataloging over 20,000 distinct tasks across the workforce. The key insight, building on the task-based framework of technological change in Acemoglu and Restrepo (2018), is that an occupation's output is achieved through the execution of these component tasks. Webb (2020) pioneered a novel approach to measuring technology exposure by analyzing how patents relate to these occupation tasks using natural language processing, creating relative measures of exposure to new technology. This text-based approach to measuring innovation or technological change has origins outside questions of its labor market impacts (see Kelly et al. (2021)) and has been adopted and extended to measure and investigate various

	Dependent Variable: $I(\bar{w}_p > \bar{w}_o)$
Skill Similarity ($S_{o,p}$)	0.0043
	(0.013)
Origin Wage ($\bar{w}_o$)	-0.1860***
	(0.009)
Similarity × Wage	0.0326***
	(0.010)
Constant	0.6307***
	(0.011)
Observations	12,109
R^2	0.185

A. Regression Results



B. Predicted Probabilities

FIGURE 5. Skill Similarity and Upward Mobility Patterns

Panel A reports regression estimates of the relationship between skill similarity and upward wage transitions. Panel B shows how skill similarity affects the probability of moving to a higher-wage occupation at different initial wage levels. Each pair of bars compares the predicted probability of an upward transition for high similarity (+1 SD) versus low similarity (-1 SD) transitions. The increasing gap between high and low similarity probabilities at higher wage levels demonstrates that skill similarity becomes more crucial for upward mobility as wages rise.

dimensions of technological change - from labor-saving to labor-augmenting innovations (Kogan et al. 2023), AI adoption in firms (Acemoglu et al. 2022), and in studying the creation of new work (Autor et al. 2024). The occupation exposure score provides a comparative assessment of technological change at the occupation level, which is the foundation for our analysis of technological change and labor mobility.

In examining how digital technologies reshape worker opportunities, we use the occupation exposure measure to digital technologies from Meindl, Frank, and Mendonça (2021). The measure captures innovations in software, connectivity, and data analysis that have transformed work across sectors. The measure is constructed by comparing granted patent texts from PATSTAT with occupation task descriptions from O*NET[2], which details 20-40 tasks for each occupation.[3] The approach processes both patent text and task descriptions through different stages, converting them to embeddings before computing similarity. The underlying patents show significant concentration between 2000-2013, aligning well with our study of worker transitions during 2002-2018, allowing time for these technological changes to manifest in the labor market. Table 4 presents the most and least exposed occupations in our sample based on the exposure scores imported from Meindl, Frank, and Mendonça (2021).

This technology exposure measure provides critical insight into where technological change has reshaped the occupational skill space. While our skill space characterization captures fundamental relationships between occupations through their task and skill requirements, the exposure measure identifies regions of this space that experienced significant technological disruption. This allows us to map technological change onto the skill space and examine how it affects worker mobility patterns. In highly exposed regions, we expect to see distinct mobility patterns as workers navigate whether to adapt within their existing skill domain or transition to occupations requiring different skill sets. By combining the skill space representation with this dynamic measure of technological change, we can analyze how innovation reshapes worker opportunities and transition patterns across our study period.

3.2. Spatial Correlation in Technology Exposure

Tasks are fundamental building blocks of work across occupations, and many tasks are common across occupations - from monitoring system performance in IT roles to reviewing and updating records in healthcare. These common tasks typically require similar skills across occupations performing them. The technology change exposure measure

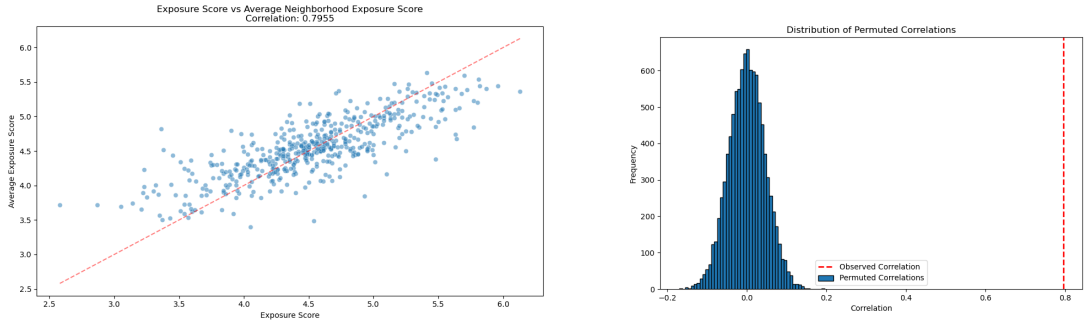
[2]The Occupational Information Network (O*NET) is the primary source of occupational information in the United States, developed under the sponsorship of the U.S. Department of Labor/Employment and Training Administration.

[3]PATSTAT is the worldwide patent statistical database maintained by the European Patent Office, containing bibliographical and legal status patent data from leading industrialized and developing countries.

TABLE 4. Most and Least Exposed Occupations

	Most Exposed	Least Exposed
1	Software Developers	Childcare Workers
2	Database Administrators	Manicurists
3	Information Security Analysts	Personal Care Aides
4	Computer Programmers	Animal Caretakers
5	Operations Research Analysts	Hair Stylists
6	Computer Network Architects	Barbers
7	Computer Systems Analysts	Bartenders
8	Industrial Engineers	Massage Therapists
9	Electrical Engineers	Fitness Trainers
10	Network Administrators	Restaurant Servers

The table presents occupations with highest and lowest exposure to digital technologies based on patent-task similarity. Data from Meindl, Frank, and Mendonça (2021).



A. Relationship between occupation exposure and skill neighbors

B. Distribution of permuted correlations

FIGURE 6. Spatial correlation of technology exposure in skill space

Panel A shows the correlation (0.795) between an occupation's technology exposure and the average exposure of its five nearest skill neighbors. Panel B shows the distribution of correlations from 10,000 permutations where neighbor occupations are randomly sampled, with the vertical line marking the observed correlation.

operates at the task level, examining how digital innovations relate to occupation tasks. When tasks are common across occupations, innovations relevant to these tasks naturally connect these occupations through the skill space, as similar skills underpin common tasks. This expected correlation between technology exposure and skill similarity provides an opportunity to check our measurements - finding such correlation would suggest the skill space mapping captures meaningful relationships between occupations, and that measuring technology change through tasks identifies relevant innovations. The correlation also has economic significance - while skill-neighboring occupations typically offer paths for easier adjustment, correlated technology exposure among neighbors suggests workers face higher costs as natural adjustment paths are similarly affected.

3.3. Differentiating Technology Change

While the technology exposure measure captures the overall ranking of technological change, our analysis requires distinguishing between two theoretically distinct types of change. The first type primarily requires workers to acquire new skills for task execution, while the second type eliminates or fundamentally reformulates tasks. Our goal is to devise a data-driven strategy to formulate two groups of high exposed occupations - one where technology change brought with it a demand for new skills and a second where technology change eliminated core tasks and thereby reduced opportunities in the occupations.

We first identify high exposure occupations using Jenks natural breaks algorithm[4]. The algorithm splits occupations into three groups by finding natural breakpoints in their exposure scores, with 22.3% classified as low exposure, 52.5% as medium exposure, and 24.3% as high exposure. This data-driven classification effectively separates occupations experiencing significant technological change from others.

To identify occupations experiencing wage growth, we examine changes in their position in the wage distribution between 2002 and 2018, using data from the Occupational Employment and Wage Statistics (OEWS). For each occupation, we measure how its median wage compared to the economy-wide average wage in each year, and then calculate the change in this relative position. Specifically, if an occupation's median wage was 1.2 times the average wage in 2002 and moved to 1.5 times the average wage by 2018, its relative wage change would be 25%. Formally:

$$\Delta w_o = \frac{(w_o/\bar{w})_{2018} - (w_o/\bar{w})_{2002}}{(w_o/\bar{w})_{2002}} \tag{3}$$

where w_o is the occupation's median wage and $\bar{w}$ is the employment-weighted average wage across all occupations. A positive change indicates the occupation's median worker improved their relative position in the economy-wide wage distribution.

We similarly track changes in workforce size using OEWS employment estimates. Table 5 presents the largest occupations (by 2018 employment) in each category, with Panel A showing high exposure occupations and Panel B showing low exposure occupations. Among high exposure occupations with increased relative wages and growing workforce, we see several managerial and analytical roles. In contrast, high exposure occupations facing both wage and workforce decline include many clerical and administrative roles where technology has automated core tasks.

Our analysis requires identifying groups of occupations where technological change

[4]The Jenks natural breaks algorithm minimizes the variance within groups while maximizing variance between groups. Formally, it minimizes the sum of squared deviations from class means while maximizing the sum of squared deviations from means of other classes: $\min \sum_{i=1}^{n} \sum_{j=1}^{k} (x_{ij} - \mu_j)^2$ where x_{ij} is the ith observation in class j, and μ_j is the mean of class j.

TABLE 5. Occupations by Wage and Workforce Changes

Panel A: High Exposure Occupations

Wage Gain		Wage Loss	
Growing	Declining	Growing	Declining
Cashiers	Bookkeeping Clerks	Retail Salespersons	Sales Representatives
Office Clerks	Executive Secretaries	Customer Service Reps	First-Line Supervisors
Operations Managers	Billing Clerks	Medical Secretaries	Info. Clerks
Admin Assistants	Tellers	Securities Sales	Delivery Drivers
Accountants	Data Entry	Driver/Sales	Mail Carriers
Financial Managers	Payroll Clerks	Insurance Agents	Sales Representatives
Rental Clerks	Ticket Agents	Planning Clerks	Bill Collectors
Service Assistants	File Clerks	Social Workers	Sales Supervisors
Financial Analysts	Messengers	Loan Officers	Legal Secretaries
PR Specialists	Travel Agents	Claims Processors	Telemarketers
Panel B: Low Exposure Occupations			
Waiters/Waitresses	Food Prep Workers	Laborers/Movers	Elementary Teachers
Support Supervisors	Packers/Packagers	Janitors/Cleaners	Carpenters
Security Guards	Fast Food Cooks	Truck Drivers	Shipping Clerks
Construction Labor	Institution Cooks	Restaurant Cooks	Auto Technicians
Maids/Housekeepers	Production Helpers	Secondary Teachers	Production Supervisors
Landscaping Workers	Food Service Mgrs	Food Prep Supervisors	Plumbers
Practical Nurses	Chief Executives	Management Analysts	Construction Painters
Police Officers	Engineering Mgrs	Medical Assistants	Laundry Workers
Bartenders	Short Order Cooks	Electricians	Press Operators
HR Specialists	Electronics Tech	Lawyers	Housekeeping Sup.

The table lists the ten largest occupations (by 2018 workforce) in each category. Panel A shows high exposure occupations and Panel B shows low exposure occupations. Occupations are categorized by changes in relative wages and workforce size between 2002-2018. Data from OEWS.

creates distinct pressures on workers. In one scenario, technology enhances task efficiency but requires workers to acquire new skills to maintain their position and prospects. In the other scenario, technology eliminates or fundamentally reformulates tasks, reducing opportunities and the value of occupation-specific skills, creating pressure for workers to transition to other occupations. Using wage and workforce changes, we develop a selection strategy to identify occupations where either of these forces is primarily at play.

Our selection strategy leverages what wage and workforce changes reveal about technological change in occupations. A rise in wages indicates the occupation's new skill requirements or modified competencies cannot be easily acquired - if they were, increased labor supply would dampen any (relative) growth in wages. Growth in workforce suggests continued demand for the occupation's services, indicating core tasks have not been eliminated or automated away. Among high-exposure occupations shown in Panel A of Table 5, those experiencing both wage and workforce growth are most likely experiencing technology change that enhances productivity while requiring new skills. The

combination of rising wages despite workforce growth suggests these new skill requirements present real barriers - if the skills were easily acquired, increased entry would moderate wage growth. Alternative explanations, such as technology eliminating lower-skill tasks and driving up average wages through composition effects, are less plausible when workforce is expanding rather than contracting.

For identifying occupations where technology primarily eliminates tasks, we focus on workforce decline as the key signal - reduction in labor demand is a direct consequence of task elimination. However, workforce decline alone is insufficient as it could also reflect increasing skill requirements creating entry barriers. The wage response helps distinguish between these scenarios. When technology eliminates core tasks, the remaining skill bundle becomes less valuable in the labor market, leading to wage decline. In contrast, if workforce decline stemmed from higher skill requirements, we would expect wages to rise. Therefore, among high-exposure occupations, those experiencing both wage and workforce decline most clearly identify where technological change manifests as task elimination. This combination suggests not just reduced opportunities but also diminished value of the occupation's traditional skill set, creating pressure on workers to transition to other occupations with better prospects. In the following section, we analyze how workers exit from these two groups of occupations, examining whether mobility patterns in the skill space align with these distinct technological pressures.

4. Technological Change and Exit Patterns in the Skill Space

Having established how technology exposure clusters across skill-similar occupations, we now examine how different types of technological change shape worker exit patterns in the occupation skill space. Our analysis distinguishes between two key scenarios: occupations where technology demands new expertise and skills versus those where it diminishes opportunities to core task elimination. This distinction allows us to identify how the nature of technological change affects workers' transition choices and their wage outcomes.

4.1. Empirical Strategy

Our analysis of exit patterns focuses on two key measurements - the wage levels at receiving occupations and whether the destinations are proximate in the skill space to the originating occupation. Critical to our empirical strategy is the spatial correlation in technology exposure documented earlier - occupations sharing similar skills face similar technological pressures as they share tasks being transformed. This correlation provides the foundation for interpreting how technology shapes mobility patterns in the skill space.

A feature of the labor market that we examined previosuly is that, exits to skill-distant

occupations predicts different outcomes depending on the wage level of the occupation which is informative about the expertise required in the occupation. At higher wage occupations that require expertise, the skills are costly to acquire either through experience or education and moving away from one's skill set involves substantial wage penalties. In contrast, at lower wage occupations where skills are relatively easier to acquire and not of an expert nature, exits to skill-distant occupations can even be associated with wage gains.

For occupations where technology demands new skills, spatial correlation ensures that skill neighbors face similar adaptation pressures. Workers exiting to skill-neighboring occupations are likely to encounter similar skill upgrading requirements, as these occupations share tasks being transformed by technology. In contrast, exits to occupations farther in the skill space might allow workers to avoid immediate skill upgrading demands, albeit at the cost of larger wage penalties, similar to patterns from high-wage occupations. However, for occupations facing task elimination, the pattern could reverse - exits to skill neighbors might mean moving to occupations facing similar displacement of tasks, while transitions to more distant occupations might offer better opportunities, mirroring mobility patterns from lower-wage occupations.

These predictions are sharpened by comparing against exit patterns from control occupations - those with low technology exposure but similar wage and workforce changes. While shrinking workforce and diminished wages generally create exit incentives, and wage and workforce growth correlate with staying incentives, the technology-driven cases are distinct. In high exposure occupations, spatial correlation of technology change means these incentives extend across the skill neighborhood, creating stronger pressure for distant exits in task elimination cases and additional barriers in skill acquisition cases. Such spatially correlated forces are absent in control occupations, where changes are driven by factors other than technology and the distinction between exits to skill neighbors versus non-neighbors should be less pronounced. This comparison helps isolate mobility patterns specifically linked to technological change, while the parallels with wage-level patterns strengthen our interpretation of technology-driven mobility.

4.2. New Skills and Worker Adaptation

We begin by examining mobility patterns from occupations where technology has enhanced productivity while requiring new skills for task execution. Our empirical strategy focuses on a key pattern - the relationship between wage drops and moves away from skill-neighbor occupations. A larger wage penalty for moving away from skill neighbors suggests that occupation-specific skills are central to maintaining wage levels. Such a pattern naturally exists in high-wage occupations where specialized skills accumulated through education and experience are fundamental to the occupation's value.

Our treatment group consists of middle-wage occupations that experienced both workforce growth and relative wage gains, and were highly exposed to digital technologies during our sample period. The spatial correlation in technology exposure means that skill-neighboring occupations, which share similar tasks, experience comparable changes in how these tasks are executed. When technology modifies task execution, workers who cannot acquire new skills face substantial wage penalties when moving away from skill neighbors, as their existing skills become less valuable or redundant. This creates a pattern similar to exits from high-wage occupations, where moves away from skill neighbors typically involve significant skill redundancy and wage losses.

The control group comprises middle-wage occupations that also experienced workforce and wage growth, but with low exposure to digital technologies. Consider medical assistants, whose growth might stem from expanded healthcare coverage increasing demand for routine patient care. While the occupation sees workforce and wage growth, skill-neighboring occupations that share tasks like patient documentation or basic health monitoring may not experience similar growth dynamics. Their changes may be driven by different factors - regulatory requirements, institutional policies, or demographic shifts - that affect occupations independently rather than through shared tasks. Consequently, when workers exit these control occupations, the wage drops they experience moving to skill-neighbors versus non-neighbors show less systematic differences, as growth is not tied to changes in task-specific skills.

At higher wage levels, where specialized skills dominate occupation value, we expect both treatment and control groups to show similar penalties for moving away from skill neighbors. The relationship between skills and wages is already firmly established through professional training and experience. However, in middle-wage occupations, only the treatment group should show such stark differences - where technology effectively creates high-wage-like skill barriers through changes in task execution. These barriers are absent in the control group where growth stems from factors unrelated to task modification. Finding larger wage penalties for exits away from skill neighbors in middle-wage treatment occupations would give us strong evidence that technology change makes skills central to mobility patterns in ways typically seen only in high-wage occupations.

Using our mobility dataset described earlier, we observe for each origin occupation o both the total number of workers who exit the occupation during 2002-2018 and their distribution across different receiving occupations. This allows us to compute for each origin occupation, the share of exiting workers moving to every occupation p in the set of receiving occupations. The combination of transition shares and total exit counts provides a comprehensive picture of mobility patterns across the occupation space during a period of significant technological change.

To examine how technology exposure affects the relationship between skill distance

and wage drops, we aggregate exits from each origin occupation into two categories - moves to skill neighbors and moves to non-neighbors. This pooling strategy offers several advantages. First, it directly addresses our core question about whether technology change makes departures from the skill set more costly. Second, it provides sufficient sample sizes for statistical inference, particularly important as many specific occupation-to-occupation transitions may be rare. Third, by reducing each origin occupation to two observations - one for skill neighbor transitions and one for non-neighbors - we maintain a balanced panel that clearly captures our key comparison.

$$\Delta_{o,p} = \beta_0 + \beta_1 I(p \in N_o) + \beta_2 I(e_o > 4.8) + \beta_3 [I(p \in N_o) \times I(e_o > 4.8)] + \bar{W_o} + \epsilon_{o,p} \quad (4)$$

Here, $\Delta_{o,p}$ represents the percentage drop in average wage from origin occupation o to destination p, $I(p \in N_o)$ indicates moves to skill neighbors, and $I(e_o > 4.8)$ indicates high technology exposure. Our main interest lies in β_3, which captures whether the neighbor advantage is larger in high-exposure occupations. The specification notably cannot include origin occupation fixed effects as our key treatment variable (technology exposure) does not vary within origin occupations. However, controlling for origin occupation median wage $\bar{W_o}$ helps account for systematic differences in mobility patterns across wage levels.

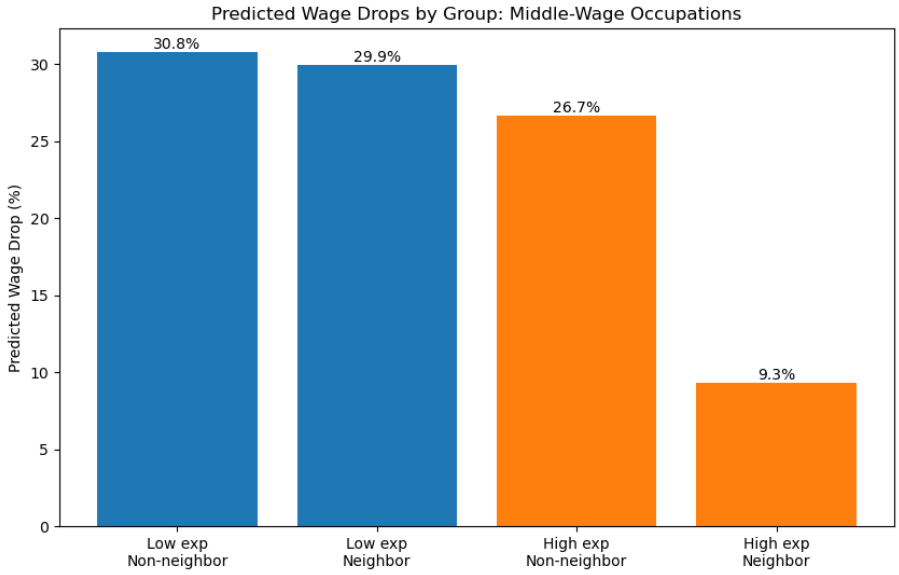
We conduct this analysis separately for middle-wage occupations (25th to 75th percentile of median wages) and high-wage occupations (above 75th percentile). We focus on these segments as they best illuminate our mechanism - technology making skills central to mobility patterns. Low-wage occupations are excluded as skills in these occupations are generally easier to acquire, making the distinction between neighbor and non-neighbor transitions less informative about skill-based mobility constraints. Moreover, as we explore in the next section, technology changes in low-wage occupations often manifest through task elimination rather than skill upgrading, creating distinctly different mobility patterns.

The results strongly support our predictions about how technology change affects mobility patterns. In middle-wage occupations, the interaction between technology exposure and neighbor status is large and negative (-16.51), indicating substantially smaller wage penalties for moves to skill neighbors in high-exposure occupations. The bar charts illustrate this stark pattern - in high-exposure occupations, moves to neighbors involve a 9.3% wage drop compared to 26.7% for non-neighbors, while this difference is minimal in low-exposure occupations. In contrast, at higher wage levels, we find no such technology effect. Both treatment and control groups show similar large penalties for moving away from skill neighbors, consistent with specialized skills driving mobility patterns regardless of technology exposure. These patterns provide compelling evidence that technology change makes skills central to mobility patterns in ways typically seen only in high-wage

Middle-Wage Sample [P25-P75]	
Constant	17.72***
	(3.59)
High Exposure	-4.11***
	(1.48)
Neighbor	-0.83
	(1.73)
High Exp × Neighbor	-16.51***
	(3.09)
Origin Wage	0.00***
	(0.00)

***p < 0.01, **p < 0.05, *p < 0.1

A. Regression Results



B. Predicted Wage Penalties

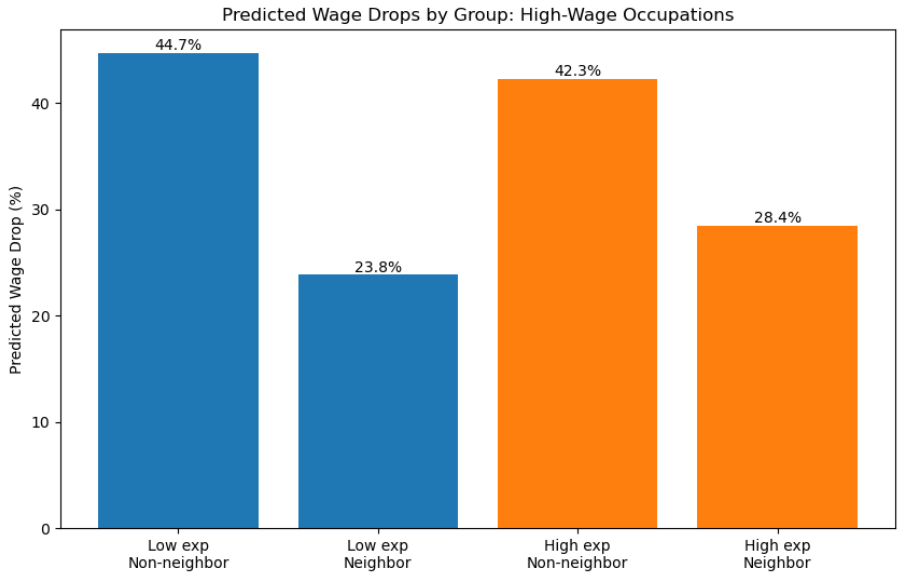
FIGURE 7. Wage Penalties in Middle-Wage Occupations

Panel A reports regression estimates of wage penalties when transitioning to different occupations. The key interaction coefficient (-16.51***) indicates that in high-exposure occupations, moves to skill neighbors involve substantially smaller wage penalties, suggesting technology change makes skill similarity crucial for maintaining wages. This effect is unique to high-exposure occupations, as shown by the insignificant neighbor coefficient (-0.83) in low-exposure cases. Panel B shows the predicted wage penalties for different transition types, illustrating how the skill-neighbor advantage emerges specifically in occupations facing technological change.

High-Wage Sample [P75+]	
Constant	34.82***
	(3.98)
High Exposure	-2.42
	(1.61)
Neighbor	-20.86***
	(1.93)
High Exp × Neighbor	7.04**
	(3.09)
Origin Wage	0.00***
	(0.00)

***p < 0.01, **p < 0.05, *p < 0.1

A. Regression Results



B. Predicted Wage Penalties

FIGURE 8. Wage Penalties in High-Wage Occupations

Panel A reports regression estimates of wage penalties when transitioning to different occupations in high-wage occupations. The large negative neighbor coefficient (-20.86***) shows strong advantages for skill-similar transitions, while the positive interaction term (7.04**) indicates this advantage moderates slightly but remains substantial under high technology exposure. Panel B shows the predicted wage penalties for different transition types, illustrating how skill similarity consistently protects against large wage penalties in high-wage occupations, regardless of technology exposure level. This pattern contrasts with middle-wage occupations where the neighbor advantage emerges primarily under high technology exposure.

occupations.

4.3. Task Elimination and Worker Transitions

We examine how different types of technological change shape worker exit patterns in the occupation skill space. Our analysis distinguishes between two key scenarios: occupations where technology demands new expertise and skills versus those where it eliminates existing tasks. This distinction allows us to identify how the nature of technological change affects workers' transition choices and their wage outcomes.

When technology eliminates core tasks, occupations sharing similar skill requirements often face common disruption pressures. This spatial clustering of technological impact means that moving to neighboring occupations may offer little refuge - these destinations are likely undergoing similar task elimination. Instead, transitions to more distant regions of the skill space may benefit workers by allowing them to access opportunities less affected by automation. This contrasts sharply with cases where technology enhances task efficiency, where staying within the skill neighborhood helps workers leverage their existing capabilities.

We test this prediction using the same empirical framework as before:

$$\Delta_{o,p} = \beta_0 + \beta_1 I(p \in N_o) + \beta_2 I(e_o > 4.8) + \beta_3 [I(p \in N_o) \times I(e_o > 4.8)] + \bar{W}_o + \epsilon_{o,p} \tag{5}$$

focusing now on exits to lower-wage occupations from our task elimination group. The key test is whether moves to non-neighbors show smaller wage penalties compared to moves to skill neighbors in high-exposure occupations, a pattern that would distinguish technology-driven exits from other causes of occupational decline.

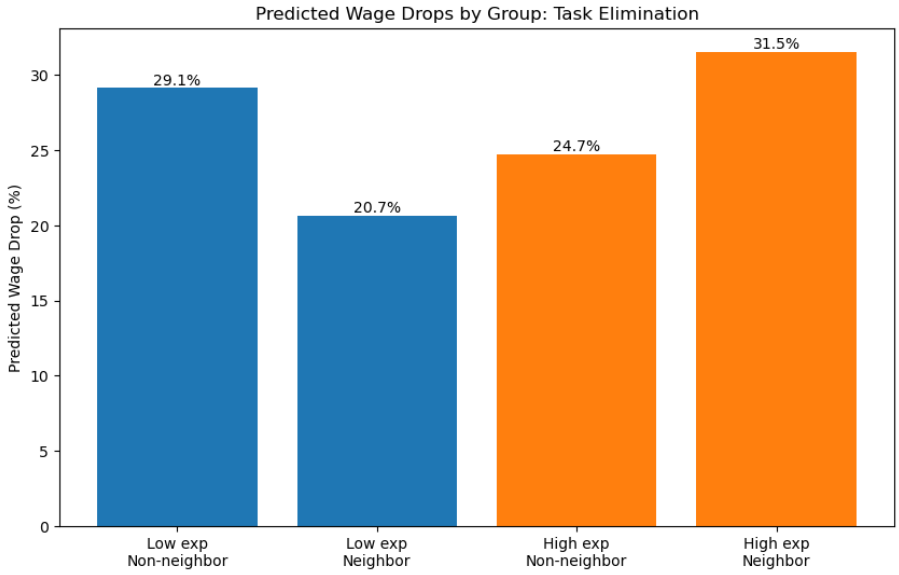
The results strongly support our predictions about how technology reshapes mobility incentives. The stark contrast revealed in Panel B - a 17.4 percentage point neighbor advantage in high-exposure occupations versus minimal differences in low-exposure cases - demonstrates how technology transforms middle-wage mobility patterns to resemble those of high-wage occupations. This emergence of strong skill barriers specifically in technology-exposed occupations suggests that technological change fundamentally alters the role of occupation-specific skills in worker transitions.

These contrasting patterns across our two analyses illuminate how different types of technological change create distinct pressures on worker mobility. In occupations where technology enhances task efficiency, exits to distant occupations at lower wages likely reflect workers struggling to acquire new skills. However, in occupations facing task elimination, workers who successfully transition to more distant opportunities demonstrate capacity for strategic skill reorientation. These patterns underscore how technological

Task Elimination Sample	
Constant	15.57***
	(2.92)
High Exposure	-4.41**
	(1.90)
Neighbor	-8.46**
	(3.42)
High Exp × Neighbor	15.26***
	(3.75)
Origin Wage	0.00***
	(0.00)

***p < 0.01, **p < 0.05, *p < 0.1

A. Regression Results



B. Predicted Wage Penalties

FIGURE 9. Wage Penalties in Task Elimination Context

Panel A reports regression estimates of wage penalties in declining occupations. The key result is the large positive interaction coefficient (15.26***) which more than offsets the baseline neighbor advantage (-8.46**), indicating that high-exposure occupations facing task elimination see larger wage penalties for moves to skill neighbors. Panel B shows the predicted wage penalties, illustrating how technology-driven task elimination reverses the typical advantage of skill-similar transitions - workers face smaller penalties when moving to skill-distant occupations, likely reflecting the benefits of escaping clusters of declining occupations sharing similar automated tasks.

change shapes not just the necessity but also the nature of occupational transitions.

5. Discussion

This paper brings new evidence on how technological change shapes worker mobility by examining transition patterns through a novel lens of occupational skill relationships. By integrating rich information from job postings with sophisticated embedding models, we create a data-driven mapping of skill similarities between occupations that surpasses previous measures built on expert-coded data (O*NET). This approach uncovers systematic patterns in how workers navigate technological change, patterns previously not illustrated in the empirical literature on technological change and worker mobility.

Our analysis demonstrates how technology change creates distinct mobility patterns through the skill space. In occupations where technology change necessitates new skills that are not easy to acquire, we observe that farther exits are correlated with transitions to lower wage level occupations. This is in contrast to occupations where technological change has reduced demand for workers, where greater skill distance to exiting occupations is correlated with transitions to higher wage levels. This pattern directly reflects the clustering of technological disruption in skill space - reduced opportunities in one occupation indicate declines in related occupations

The patterns are consistent with distinct worker responses to technological change. In the first case, workers exit to more distant and lower-wage occupations because they cannot acquire the new skills demanded by technology, reflecting the costs of skill-distance transitions when technology enhances but complicates existing work. In the second case, workers exit to more distant but higher-wage occupations as they move away from their devalued skillset, reflecting strategic adaptation when technology reduces the value of their current skills. This provides the first evidence from a skills perspective that demonstrates these distinct adaptation patterns, showing how the nature of technological change shapes mobility decisions differently through its impact on skill requirements and valuations.

Our empirical patterns strongly support recent evidence highlighting the heterogeneous impacts of technological change (Kogan et al. 2023), the challenges of adjusting when new skills diverge from existing ones (Adão, Beraja, and Pandalai-Nayar 2024), and the significant role of skill requirements in earnings losses (Braxton and Taska 2023; Neffke, Nedelkoska, and Wiederhold 2024). Our findings about how skill distance shapes mobility and wage outcomes provide a skills-based perspective on these documented patterns of heterogeneous effects and adjustment differences between younger and older workers (Kogan et al. 2023). A systematic mapping of skill relationships, possible via rich job posting data and embedding models, offers a promising new lens for studying how technological change transforms opportunities across occupations. Future research lever-

aging employer-employee linked data could directly examine how workers of different ages and experience levels navigate these transformations through skill acquisition and mobility choices, deepening our understanding of the mechanisms this paper uncovers. This skills focused approach and analyses is also an input to workfroce development programs, with an objective to smooth these transitions via worker training.

Declaration

AI (LLMs) were used in the preparation of the manuscript. All research conceptualization, methodology, data analysis, interpretation of results, and conclusions were conducted entirely by the authors. All scientific claims and findings represent the authors' original work and intellectual contribution. The authors take full responsibility for the integrity of the manuscript.

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