Network constraints on worker mobility

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Abstract

Career mobility requires desirable workplace skills and access to relevant labor markets. Division of labor suggests that workers should specialize their skills over their careers but standard skill classifications of "cognitive" or "college educated" can obfuscate career dynamics. Here, we model career transitions as a network of occupations connected by the similarity occupations' skill requirements. Using a nationally representative survey and two resume data sets each representing 100 million individual workers, we show that skill similarity predicts transition rates between occupations and that predictions improve with increasingly-granular skill data. These observations inform a new measure for skill specialization from a worker's embeddedness in their economy's occupation network. Job changes and/or relocations that decrease embeddedness correspond to increased wages and workers tend to decrease their embeddedness over their careers. While low-embeddedness workers may leverage their locally-rare skills in wage negotiations, employers might also offer higher wages as an incentive for skilled workers to relocate. We find evidence for the latter since the combined embeddedness of city pairs corresponds to increased Census migration and increased flows of enplaned passengers according to the US Bureau of Transportation Statistics. This study directly connects workplace skills to workers' career mobility and spatial mobility, thus offering new insights into skill specialization and current urbanization trends.

As automation, off-shoring, and globalization shape the future of work, how can workers advance up the career ladder and how can policy makers maximize employment opportunities in their communities? Although education determines workers' entry into the workforce, limited upward mobility [1] and access to higher education challenge educational institutions in the presence of changing skill demands. Recent studies use *skills* to explain US job polarization as a divide between high-skill and low-skill workers [2]. Yet, these broad labor categories can obfuscate job seeker dynamics [3, 4]. For example, civil engineers and medical doctors are both highly-educated, well-paid, cognitive, non-routine occupations, but the skills required by each occupation are largely non-transferable. The differences between occupations and the forces with which they compete (e.g. different technologies) are most easily understood when we consider occupations as abstract bundles of skills and abilities [5, 3, 6].

In this project, we employ data-driven techniques to compare occupation pairs based on a nationally-representative taxonomy of workplace tasks and skills. We show that occupations that share characteristic skills exhibit greater flows of workers between them according to the nationally-representative Current

Population Survey from the US Census Bureau and two large resume datasets from Burning Glass Technologies and FutureFit.AI (see Fig. 1A for an example resume from one of the authors). Next, we construct an occupation network from pairwise skill similarity scores. We use this national occupation network in combination with urban employment distributions from the US Bureau of Labor Statistics to describe urban labor markets (see Fig. 1B). Since shared skill requirements undergird career mobility, we use the resume data to explore how workers move through these urban labor networks over their careers. In both data sets, we find that workers tend to decrease their employment-weighted network embeddedness (i.e., $w_j^{(c)} = \sum_{i \in Jobs} skillsim(i,j) \cdot share(c,i)$) over their careers and individual career transitions that decrease this embeddedness correspond to increases in wages even after controlling for employment share, city size, year fixed effects, and city fixed effects (see Fig. 1C&D for example visualizations). The wage effect is even stronger when the career move corresponded with a relocation to a new city (see Fig. 1E).

Motivated by the relationship between wages, a worker's location in their occupation network, and relocation, we explore how the network properties of city pairs relates to spatial mobility through both urban migration according to the US Census and flight patterns according to the US Bureau of Transportation Statistics. We find that city pairs with greater combined occupation embeddedness (i.e., $\hat{w}_{c,c'} = \sum_{j \in Jobs^(c) \cap Jobs^{(c')}} 1/\left(w_j^{(c)} w_j^{(c')}\right)$) had greater spatial mobility between them. Including simple density measurements of the cities' occupation networks improves mobility predictions by 30% over the gravity model and highlights that combined occupation embeddedness significantly moderates the effect of city size on inter-city mobility.

Policy makers can address income inequality by fostering worker mobility and career success. However, the gap between macroscopic labor statistics and microscopic workplace requirements masks the features that shape workers' careers. A renewed focus on granular skills and their role in worker mobility offers a new perspective on labor dynamics and, in combination with data-driven techniques, offers an empirical validation for labor theory. Further, relating occupations based on skill requirements improve models for economic resilience as policy makers quantify the connections within and between urban labor markets. The methods in this study directly connect specific workplace skills to workers' career mobility and spatial mobility, and enable targeted investigations into the types of workplace skills that promote economic well-being for workers and workforces.

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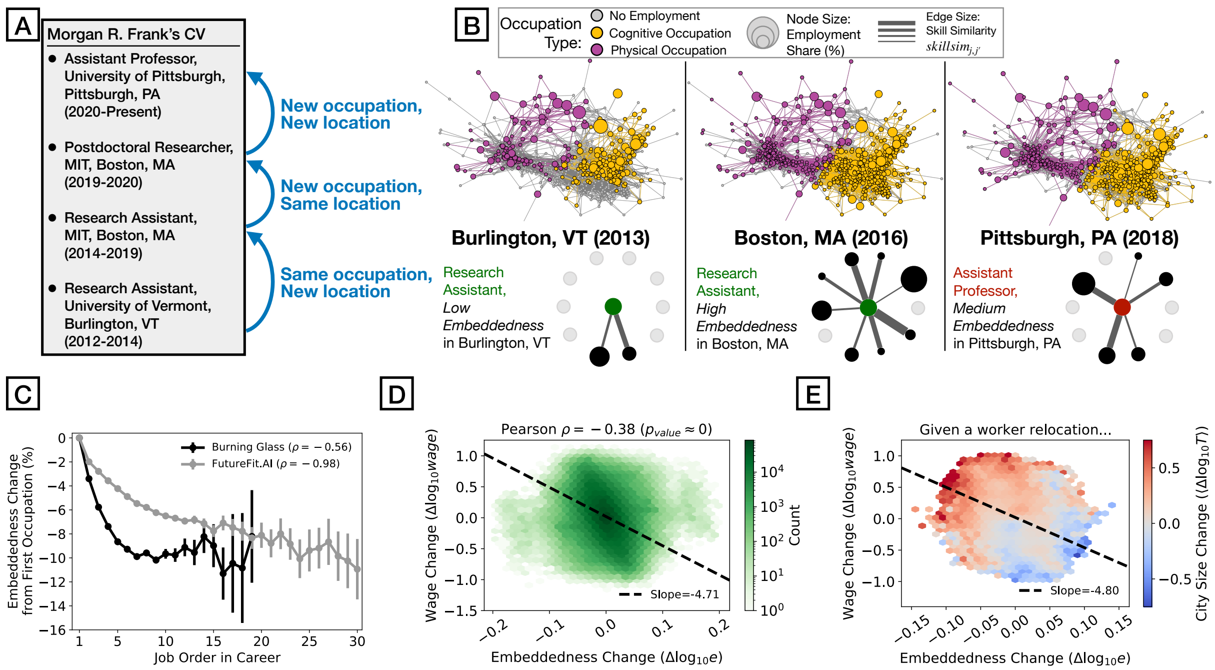

Figure 1: Workers decrease their employment-weighted embeddedness, $w_j^{(c)}$, throughout their careers and career moves that decrease $w_j^{(c)}$ correspond to higher wages according to resume data. **(A)** An example career trajectory from the resume of one of the authors. A career move is a transition to the same or a different occupation and may correspond to a relocation between cities. **(B)** A city's labor market is represented as an occupation network according to the local occupations with nonzero employment and the pairwise skill similarity among those occupations. A worker changes between networks when they relocate between cities and $w_j^{(c)}$ may change as a result. **(C)** Workers decrease $w_j^{(c)}$ throughout their careers according to Spearman correlations ($p_{value} < .02$ for both data sets). Vertical lines represent 95% confidence intervals. **(D)** Using wage estimates from the US Bureau of Labor Statistics data by occupation, city, and year, individual workers increased wages when a career move decreased $w_j^{(c)}$. **(E)** Given a relocation associated with a career transitions, changes in $w_j^{(c)}$ were a stronger predictor of wage gains than changes in city size. Color represents the average wage change in each bin for bins containing at least 20 observations. (D) and (E) use resume data from FutureFit.AI.