Extended Abstract

Decoding skill-relatedness: noise and signals in labour mobility

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Introduction

Labour mobility has become a central focus of economics in recent times. This is partly due to the recognition that labour mobility is no longer seen as merely a random feature of social stratification but increasingly as a complex system. Essentially, labour mobility is a transition matrix illustrating how workers move between different occupations, industries, or geographical units. However, the network derived from this matrix can be seen as a good approximation of the capability space of the given spatial level (Otto, A., & Weyh, A. 2014). These networks can be used to explain economic phenomena such as the diversification of countries, regions, and firms (Neffke, F., Henning, M. 2013; Fitjar, R. D., & Timmermans, B. 2017), to explore growth and economic complexity (Davies, B., & Maré, D. C. 2021; Hidalgo, C. A. 2021; Hane-Weijman, E., et al. 2022), and to capture agglomeration effects (van Oort, F. 2015).

Labour mobility has also given rise to the concept of skill-relatedness (Neffke, F., et al. 2017), providing a good approximation of the distribution and relation of skills and capabilities found in regions (Neffke, F., et al. 2011). Yet little is known about the formation and evolution of these networks and the economic, social, and geographical phenomena driving the development of different capability structures. Each region has a unique structure according to specific resources and capabilities, making its network a fingerprint of the local economic structure. These structures respond to the region's coordination problems in allocating scarce resources. However, these responses do not always lead to an optimal allocation. Some regions may find themselves on growth paths that lead to structural lock-in or development traps (Diemer, A., et al. 2022).

However, these structures are slow to change, but unlike fingerprints, they can be manipulated and adjusted (Neffke, F., et al. 2018) or shaped by turbulences (Hane-Weijman, E., et al. 2022; Eriksson, R. H., & Hane-Weijman, E. 2017). Some regions have been able to change their economic portfolio and break out of the development trap. To find out where the focal points are that need to be altered in the structure, however, we first need to understand how these networks are constructed. We need to understand the micro-level incentives that influence the movements of workers and the allocation of knowledge because the complex architecture of these individual decisions constitutes the skeleton of the macro-structure.

Research Questions

Skill-relatedness derived from labour mobility has been used in a wide range of academic research and provides an increasingly valuable basis for many policy recommendations. However, it is still unclear what the individual specific and structuring factors are that determine mobility. When someone changes jobs, we have so far assumed that they will choose a new occupation that requires similar skills to the one they had before. So, if we observe extensive labour flow between two occupations, we have implicitly assumed that similar skills are needed to perform the two activities. However, no one has been able to show what percentage of the variance in mobility is explicitly explained by skill similarity and what other factors drive or hinder occupational mobility.

Research Question 1: What are the underlying determinants of labour mobility?

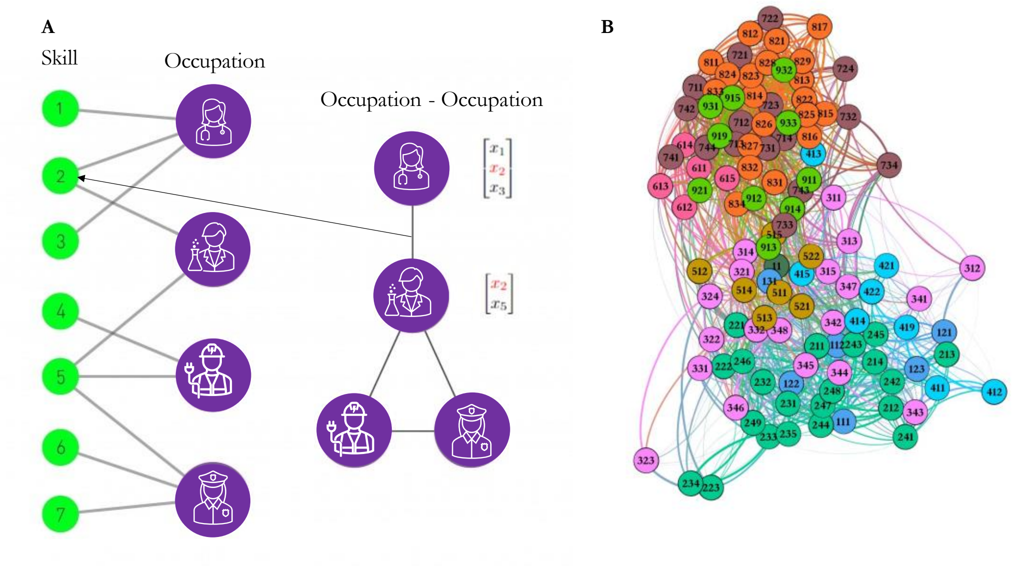
In contemporary evidence based policymaking, one of the most popular and effective tools is the creation of a relatedness network, which maps the capability space of a given country or region. Relatedness is measured through labour market flows, operating under the explicit assumption that labour movement is not random; rather, it predominantly flows among occupations and industries requiring similar skill sets. However, if we were able to perfectly measure the similarity of skills between two occupations, we would not obtain perfect correlation with the variable computed based on labour flow. The unexplained portion by skill-relatedness in labour market mobility has conventionally been regarded as necessary noise, yet the precise magnitude of this noise remains elusive. Nonetheless, leveraging the JobTech database allows for a precise measurement of the skills required for specific occupations. In this paper, employing machine learning techniques, we endeavour to distinguish noise from signal, aiming to precisely quantify the proportion of labour market mobility explained by the similarity of skills between occupations.

Research Question 2: What is the role of skill-relatedness in explaining labor mobility, and how much of the variance in occupational transitions remains unexplored, characterized as 'noise'?

Preliminary Results

We linked job advertisements in the JobTech database to the Swedish administrative database. With the JobTech data, we can determine exactly what skills are needed for each occupation. Then, for each pair of occupations, we utilized a Natural Language Processing method to calculate similarity, indicating to what extent the same skills are required to perform the jobs. This provides an unbiased variable not influenced by endogenous factors, allowing us to measure the overlap of occupation skills in a quasi-noise-free manner (see Figure 1A). Meanwhile, the administrative database enables us to track the movement of people in the labour market, creating a Swedish occupation space (Figure 1B) that informs us about occupations with more people flowing between them than expected by chance alone.

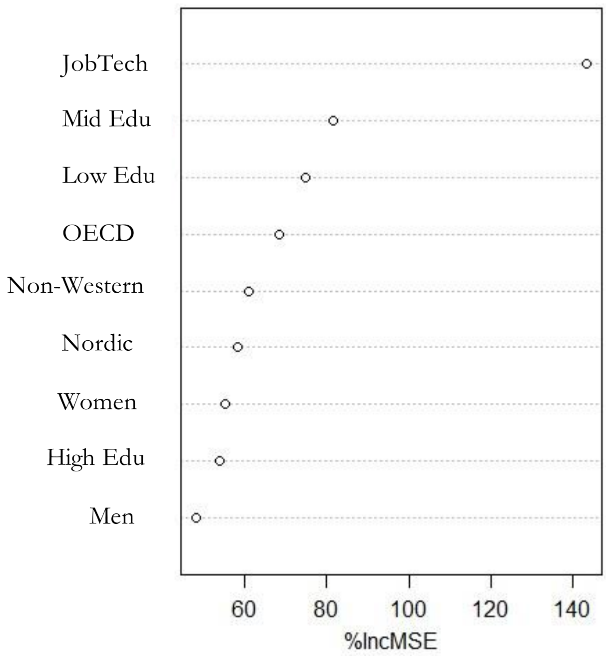
Figure 1. Job advertisement-based skill-relatedness and occupation space of Sweden.



By combining these two sets of data, we can measure the role of skill overlap in explaining the variance behind labour market mobility. First, using Random Forest techniques, we create five hundred decision trees that run through all possible pairs of occupations to determine the importance of skills in labour mobility (see Figure 2.). In addition to skills, we have included similarities between occupations in several other dimensions, such as homogeneity between genders (men-women), region of origin (native Nordic - immigrants), educational requirements for the occupations (higher education - low education), as well as the hierarchy of the geographical distribution of occupations (urban-rural divide). These dimensions are collectively referred to as homophily dimensions in our estimations, as they represent a kind of path dependency in the switching between occupations.

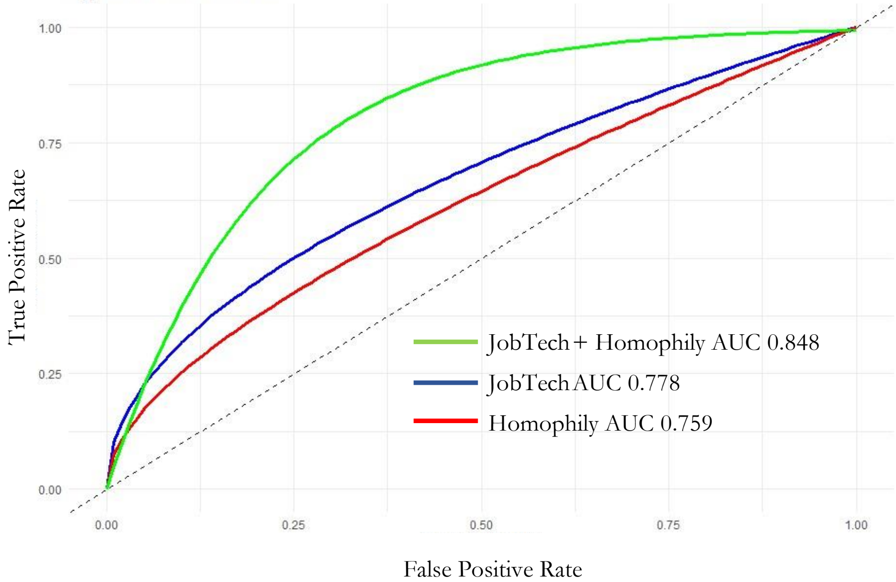
The importance of each variable is measured by the percentage change in the mean squared error (MSE). We assume that the explanatory power of a random variable is zero. Therefore, if we reshuffle the variable around its mean but at random, the error of the model will increase. If the MSE increases after randomizing a variable, then that variable contributes strongly to the accuracy of the original model. This method allows us to compare the explanatory power of different variables without being bound by the assumptions of traditional regressions. On Figure 2, we observe that the skill similarity calculated based on JobTech stands out among the other variables. Although the social homophily variables contribute to the explanatory power of the model, with educational expectations between the two occupations being the primary factor, the similarity in skills outweighs them.

Figure 2. Importance of given variable to explain labour mobility between occupations.



Finally, a classification model was constructed to predict how accurately we can distinguish between pairs of occupations that are linked in the mobility network, using only skill similarity or homophily variables. Specifically, the model examines the proportion of true positive links it identifies and compares this to the proportion of pairs that the model classifies as false positives. Using only the social homophily variables, the model correctly discriminated 75% of the occupation pairs where we observe frequent labor market mobility. Using only the JobTech-based skill similarity variable, the model accurately discriminated 78% of the pairs. However, by combining these variables, we achieved a predictive accuracy of almost 85%. These results indicate that skill overlap does indeed explain labor market mobility well. Nevertheless, there remains a noise of about 23% behind inter-occupational mobility. Furthermore, putting the two dimensions side by side reveals a 15% unexplained noise remains behind labor market movements.

Figure 3. ROC curve and predictive accuracy of inter-occupational labour movements.



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