Emerging Labour Flow Networks

Keywords: labour mobility, labour flow networks, labour market shocks, agent-computing model, emergence

Extended Abstract

Labour flow networks (LFNs) allow us to explore the short-term micro-level dynamics of labour mobility, including how economic behaviour drives movements on these networks. Within a LFN, each node contains a pool of jobs with some set of shared characteristics (e.g. they belong to the same occupation, industry, geographical region, etc.) Additionally, the weights of flows (edges) between nodes indicate the relative frequency with which people move from a job on one node to a job on the other, reflecting structural constraints caused by labour market frictions.

Though LFNs were originally introduced as a way of describing real-world labour flows, recent work has moved towards simulating dynamics on these networks. Modelling employment dynamics on LFNs through random walks, in the style of econophysics, allows us to make predictions about labour market trends. These models have been shown to provide more nuanced estimations of key labour indicators, such as the unemployment rate [1, 2]. One recent model departs from the econophysics approach by underpinning firm hiring rates with economic micro-foundations [3]. This model has been expanded upon to consider the connections between labour mobility and wealth inequality [4]. These two models are the only that, to our knowledge, incorporate economic foundations in their description of worker dynamics on LFNs.

The aforementioned models assume some static, exogenously determined network structure, often generated from historical data [1, 2, 3, 4, 5, 6]. This assumption is supported by evidence that labour flows between firms tend to persist through time [1]. Nevertheless, the possibility remains that there are scenarios where, while it would be useful to apply LFN models, the assumption of a static network does not hold. For example, drastic technological transformation could restructure the LFN; dramatic shifts in the skill sets required to perform certain jobs could lead to the disappearance of established labour flows, and the emergence of new flows between previously unconnected jobs. Additionally, any exploration of the impact of shocks on LFN structure performed using a model which assumes a static, exogenously determined network will require ad hoc assumptions about how and to what extent LFN structure is altered. In machine-learning parlance, long-term dynamics that undergo structural transformations are difficult to predict because there is no training data on such transformations. As such, there is significant value in developing LFN models that emerge realistic labour flow networks from fundamental economic behaviour.

We propose a novel agent-computing model that endogenously generates LFNs closely resembling those observed in historical data. We begin with an analysis of employment microdata for the United Kingdom (UK) to quantify the creation and persistence of links within the UK LFN. Then, we introduce an agent-computing model that emerges labour flows, where job switching decisions are based on individual agents attempting to improve their utility. The agent's decisions are based on more fundamental variables such as occupational skill similarities and geographical proximity between current and prospective positions, instead of using exogenous transition probabilities determined by historical LFN structure as in previous models. We demonstrate that this model, informed by UK microdata, generates LFNs which strongly resemble the observed UK LFN (Fig. 1). We validate this model by showing that the fundamental variables (e.g. skill similarities between occupations) are not able to explain the observed LFNs, and that our model creates new information to explain them. Finally, we use the model to explore how shocks impacting the underlying distributions of jobs and wages alter the topology of the LFN. This framework represents a crucial step towards the development of models that can answer questions about the future of work in an ever-changing world.

References

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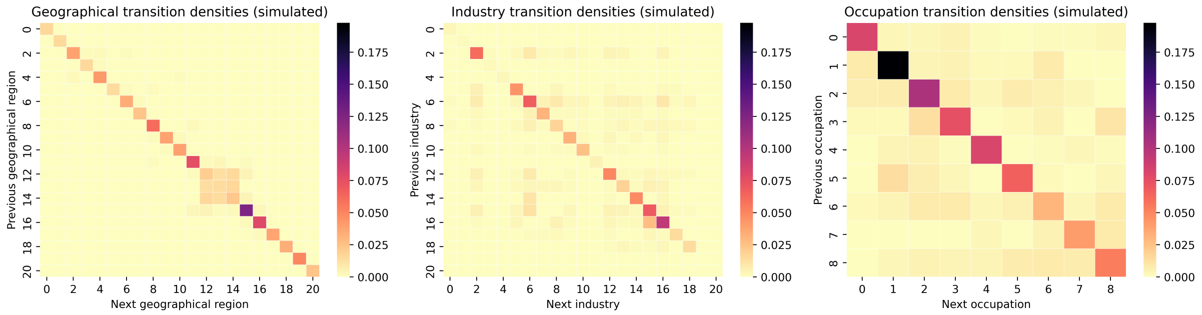

Figure 1: Simulated job-to-job transition densities within the UK labour market. These densities are calculated from the simulated flows between nodes in the LFN, with a darker colour indicating a higher flow density. The Pearson correlation coefficient (resp. Frobenius norm) values generated by comparing these simulated LFNs to the observed LFNs are 0.98 (0.05) for the geographical region LFN, 0.96 (0.06) for the industry LFN, and 0.93 (0.09) for the occupation LFN.