Job relatedness, local skill coherence and economic performance. A job postings approach

Martin Henning, Rikard Eriksson, Petrus Garefelt, Hanna Martin & Zoltán Elekes

Papers in Evolutionary Economic Geography

23.24

Utrecht University Human Geography and Planning

Job relatedness, local skill coherence and economic performance. A job postings approach

Martin Henning[1], Rikard Eriksson[2,3], Petrus Garefelt[2], Hanna Martin[1], Zoltán Elekes[4,3]

[1] Department of Business Administration, University of Gothenburg, Gothenburg, Sweden
[2] Department of Geography, Umeå University, Umeå, Sweden.
[3] Centre for Regional Science at Umeå University (CERUM), Umeå University, Umeå, Sweden.
[4] Agglomeration and Social Networks Research Lab (ANET Lab), HUN-REN Centre for Economic and Regional Studies, Budapest, Hungary.
[*] Corresponding author: martin.henning@handels.gu.se

Abstract: The local presence and composition of skills is commonly thought to have enormous implications for economic development. Yet, skills and the relations between them are notoriously difficult to pinpoint and measure. We develop a method that uses information available in Swedish job postings to measure the skill-relatedness of jobs and the skill-coherence of local economies. Our skill-relatedness measure can be assumed to be exogenous to local economic outcomes such as wages, productivity and labour mobility. We corroborate some previous research findings and show that workers tend to switch between related jobs and that local economies are on average skill-coherent. However, less coherent local economies are associated with higher average wages and productivity. Local economies where workers switch between related jobs though enjoy higher average wages. In all, this points to the benefit of local labour market clusters *within* more diverse regions. We conclude that job postings provide a wealth of information on the skill-foundations of local development. A job-level skill-relatedness matrix accompanies the paper.

Keywords: job postings; skill-relatedness; local skill coherence; regional agglomeration; labour flows.

Acknowledgements: The authors would like to thank the participants of the Geo-text Workshop organized by the Department of Geography at the University of Groningen for their constructive comments, as well as and the staff at Arbetsförmedlingen *JobTech* team for their assistance. This research was supported by the Swedish Research Council for Health, Working Life and Welfare under the *Swedish Labour Mobility Lab* [Grant 2021-01573]. Petrus Garefelt also acknowledges support from the Artic Graduate School at Umeå University.

1. Introduction

Skills are mysterious entities in economic geography and regional science – notoriously difficult to define, identify and measure. Yet, almost everyone agrees on their decisive value for regional economic development and welfare (Mellander & Florida, 2021). Traditionally, much research into the local value of skills relied on quantification of education levels, the general skill level of present occupations (Koo, 2005; Glaeser et al., 2014), or the relatedness of skills captured via inter-industry flows (Neffke & Henning, 2013). While on the one hand offering novel ways of capturing the evolving demand for education and proxying diversification potentials, these approaches on the other hand cannot detail the skills in occupations and industries used in the production of goods and service. Recently, improved access to large-scale datasets and increasingly user-friendly big-data methods provides promising opportunities to detail skills and their variations in the economy. A prominent example of such data is job postings (Deming & Kahn, 2018; Deming & Noray, 2020; Hensvik et al., 2021; Acemoglu et al., 2022; Goldfarb et al., 2023).

However, the potential for regional analyses based on job postings is largely unexplored. This paper therefore has two aims. The first is to present a method for matching the skill information from Swedish job postings to create a new measure of skills and how jobs are skill-related to each other (Neffke & Henning, 2013; Neffke et al., 2017). The second aim is to investigate what this information can tell us about the skill structures of regions and how they are associated with local economic outcomes. Although we are not quite the first to use information from job postings to analyse labour market structures (c.f., Dawson et al., 2021), we believe that the wealth of data that job postings offer to *local* economic analysis has yet to be discovered on a large scale.

We compute a job-postings-based skill-relatedness matrix (made available online[1]) and show both that local labour markets are on average skill-coherent. However, the overall skill-coherence of local labour markets is negatively associated with local average wage levels and local GDP per capita. Given this, an average of more related job-switches is however associated with better local economic outcomes. Also, lower degrees of local skill-coherence are not primarily carried by the size of local economies, but rather by the concentration of workers with

[1] https://osf.io/29ucg/?view_only=715bc20f455e41abaff6e2997e1f00de

a higher education. This paper contributes with insights about relations between skills in localities and how job postings open new research avenues in the regional sciences concerning the spatial distribution of skills and regional growth. However, there are also plenty of pitfalls using job postings for local analyses. Therefore, we argue that job postings should rather be seen as a complement to other more traditional data sources, than a complete game-changer to our science.

2. Research context: skills in regions

Since at least the "skills revolution" across the regional sciences in the 1990s, the specific skills embedded in the local workforce are widely thought to have enormous implications for economic development (Florida & Mellander, 2018; Mellander & Florida, 2021). Inspired by endogenous growth theory (e.g., Romer 1986; Lucas 1988) and the empirical change towards a knowledge-based economy, the growing regionally minded skills literature has shifted focus away from traditional approaches to regional development towards emphasizing the importance of embodied human resources. Much subsequent research in geography found inspiration in Florida's (2002) work on the creative class in U.S. cities (Florida et al., 2008; Marrocu & Paci, 2012), and Glaeser and colleagues' work linking city growth to the presence of specific knowledge and skills structures (Glaeser et al., 1992; Glaeser, 1999; Berry & Glaeser 2005; Glaeser, 2005; Glaeser & Resseger, 2010; Glaeser et al., 2014; Bacolod et al., 2009).

The definition of skills is frequently intertwined with definitions of "human capital knowledge" (Florida et al., 2012, p. 355). Skill as a term is often equalled with ability and normally used in connection with job performance (Florida et al., 2012). That is, skills are typically assumed to reflect an individual's ability to perform well in relation to a specific job (Stephany & Teutloff, 2024). Overall, however, the conceptual treatment of skills in the regional literature is unsatisfactory. In much regional research on the topic, skills themselves are not defined at all, or simply defined as having a university diploma ("high-skilled").

Our subsequent analysis relies on the definition of skills used by ESCO (European Skills, Competences, Qualifications and Occupations) from the European Qualifications Framework stating that "*skill means the ability to apply knowledge and use know-how to complete tasks* *and solve problems*"[2]. From an ontological point of view, this definition specifies a close connection between knowledge, abilities, skills and tasks. They imply each other and remain nested (Stephany & Teutloff 2024). We chose to focus on skills because, in an applied setting of jobs, these are the smallest common denominator for many related concepts (knowledge, abilities) and match well with the data framework that we use.

Because of their inherently qualitative nature, skills are notoriously difficult to capture empirically. Traditionally, most contributions aiming to grasp human capital have focused on educational attainment and education-based skills (e.g., Ullmann, 1958; Simon & Nardelli, 1996; Simon, 1998; Glaeser & Saiz, 2003; Glaeser et al., 2014). In essence such approaches focus on higher education without considering the content of the educations. More recently, occupation-related skills have increasingly gravitated to the centre of attention, emphasizing that certain bundles of skills and knowledge are required to perform the tasks of different occupations. Works by Thompson (1986), Thompson & Thompson (1987) and Markusen (2004) are well known for having brought occupational analysis to a regional setting (Koo, 2005). Occupations tend to be a better proxy for technological change than education since they directly proxy the skills needed in the production of goods and services (Håkansson et al. 2021). An occupation-centred view also facilitates grasping what workers in regional economies do rather than what types of goods and services they produce (Koo, 2005; Florida & Mellander, 2018).

Researchers have used occupations and groups of related occupations either as a proxy for activities in regions (Feser, 2003), the evolving position of regions in the (global) value chains (Massey, 1995), regional diversification (Hane-Weijman et al., 2022), or as a proxy for the skills present there (Florida et al., 2012). There is thus a commonality between this literature and a wider debate on the changing geography of jobs (Stolarick et al., 2010; Moretti, 2012). Lately, the idea of "jobs" as a specific observable operationalization of individual skill properties has been used to measure labour market polarization in countries and regions (Fernández-Macías, 2012; Henning & Eriksson, 2021), as well as local labour market upgrading (Elekes et al., 2023; Henning & Kekezi, 2023).

[2] https://esco.ec.europa.eu/en/about-esco/escopedia/escopedia/skill-0

Yet, for a long time, the required skills themselves have remained essentially as black-boxed as before. Moving closer to grasping the actual qualities of skills beyond qualification levels and attaching occupations and industries to something more than unobservable skill sets, it has become commonplace to distinguish between different categories of skills for different purposes: Florida et al. (2012)'s analytical, social intelligence and physical skills, Murmane et al. (1995)'s focus on cognitive skills, and Bacolod et al. (2009)'s physical, motor, cognitive and social skills. Relatively recently, academic distinctions have been all but overshadowed by large-scale categorizations of different types of specific skills cross-linked to occupations, such as O*NET's basic skills, cross-functional skills, soft skills and technology skills[3], or the ESCO's eight skills categories.[4] With the exceptions of a few pioneers (Florida & Mellander, 2016; Farinha et al., 2019; Castellacci et al., 2020; Czaller et al., 2021; Moro et al., 2021; Santaloha et al., 2022), these sources have so far, to our knowledge, found relatively few geographical applications. Also, even though O*NET and ESCO represent a huge leap forward in understanding the qualitative nature of skills and naming them, they do so with the assumption that an occupation also represents a certain set of skills, and that these are invariant across space and change only slowly.

Ideas about localized skills and their vast impact on regional development have also affected the debate about regional cohesion, diversification, and path dependency within evolutionary approaches of economic geography. Neffke et al. (2018), for example, argue that the skills embedded in the local workforce is among the most important of the resources that create regional path dependency. In this vein, a wide range of studies take skill-relatedness among industries and occupations as explanatory base for investigating the diversification and economic transformation paths of local economies (Fitjar & Timmermans, 2017; Neffke et al., 2017; Hane-Weijman et al., 2022; Sánches-Moral et al., 2022). This debate connects to the classic idea in economic geography about the specialization and clustering of related activities in local economies, or their "coherence" (Neffke et al., 2011; Hidalgo et al., 2018). In their seminal contribution Frenken et al. (2007) measured the impact of (related) economic variety on regional economic outcomes. Some immediate reasons to expect local labour markets to be skill-coherent (exist of occupations and jobs that are skill-related) include the dynamics of

[3] https://www.onetonline.org/
[4] https://esco.ec.europa.eu/en/classification/skills?uri=http://data.europa.eu/esco/skill/335228d2-297d-4e0e-a6ee-bc6a8dc110d9#overlayspin

localized learning, benefits to local employers in terms of access to specific locally required skills (attracting firms), and benefits to employees in terms of the presence of many potential employers (attracting skilled labour) (Marshall, 1920; Asheim, 2000; Porter, 2003; Malmberg & Power, 2005).

When it comes to measuring the local presence of skills themselves, but even more so of jobs that are related in terms of their skill content, an influential line of thought in evolutionary economic geography either relies on (1) co-occurrence analyses assuming that some relatedness (or complementarity) is present in instances when jobs co-agglomerate (e.g., Hane-Weijman et al., 2018; Farinha et al., 2019), or (2) labour flows (job switches), arguing that such a revealed channel identifies activities that are skill-related (Neffke & Henning, 2013). While these approaches proved useful for discussing for instance the direction of regional diversification, they are also potentially endogenously linked with changes in economic structure. Hence, another approach is required.

3. Method

3.1. Skills in postings and the "job skill-relatedness" matrix

We start our investigation by (1) defining a resource-efficient way to connect skills to jobs through information in job postings, and (2) calculating a job-to-job relatedness measure that provides a close link to identifiable skills. The first empirical challenge we face relates to the measurement of skills in jobs and skill-relatedness between jobs. We chose the job level of measurement, because, on the one hand, industries themselves are often too broad to meaningfully reflect the importance of their skill content. What skills are required in an occupation, can often, on the other hand, also be assumed to vary across industries. In particular, industry-only measures are likely to underestimate the heterogeneity of skills in the public sector (Hansen & Eriksson, 2023). Whereas jobs as a cross-combination of industries and occupations have not been a frequent level of study in regional analyses, it is common in the labour market polarization literature (Fernández-Macías, 2012; Henning & Eriksson, 2021). We define jobs as cross-combinations of occupations (3-digit) and industries (2-digit) in the standard classification systems SSYK2012/ISCO-08 and SNI2007/NACE rev.2 respectively.

Some examples of such jobs are: 'IT architects and system developers in data programming and data consultancy' and 'electricians in maintenance and installation of machinery'.

We use open data on job postings and enrichment methods made available by the Swedish Public Employment Service (*Arbetsförmedlingen*) and their *JobTech*-development department[5] to identify skill requirements in jobs. The idea is to use the text in the postings where employers describe required skills in terms of skills themselves, but also in terms of processes which the holders of the job need to handle, tasks, or educational tracks that summarize a collection of necessary skills for a job. Empirically, it is difficult and perhaps not even meaningful to distinguish between these categories in the job postings. Therefore, we use an open and bottom-up approach to track the skill-relatedness between jobs. Often, we can indeed observe the demanded skills themselves in the postings. But sometimes we will have to accept that the skills are represented by the tasks that employees need to perform, or even broad indicators of knowledge (such as certificates).

Figure 1 gives a schematic description of our empirical approach to construct the list of skills associated with each job. The basis for the skill extraction is the about 6 million job postings in the *Historical Jobs* database 2006-2021. This dataset contains all job postings published on the Swedish Public Employment Service's job advertisement platform (*Platsbanken*) during these years. Apart from the job requirements and descriptions written by the employers, the postings also contain information about the employer's name and address, occupation code, place of work and publication dates. Although the postings database does not contain the full universe of job openings in Sweden, it is widely used by Swedish employers. It also contains job openings from other sources, and we can comfortably assume that the platform contains postings on most full-time openings in Sweden.

[5] https://jobtechdev.se/en

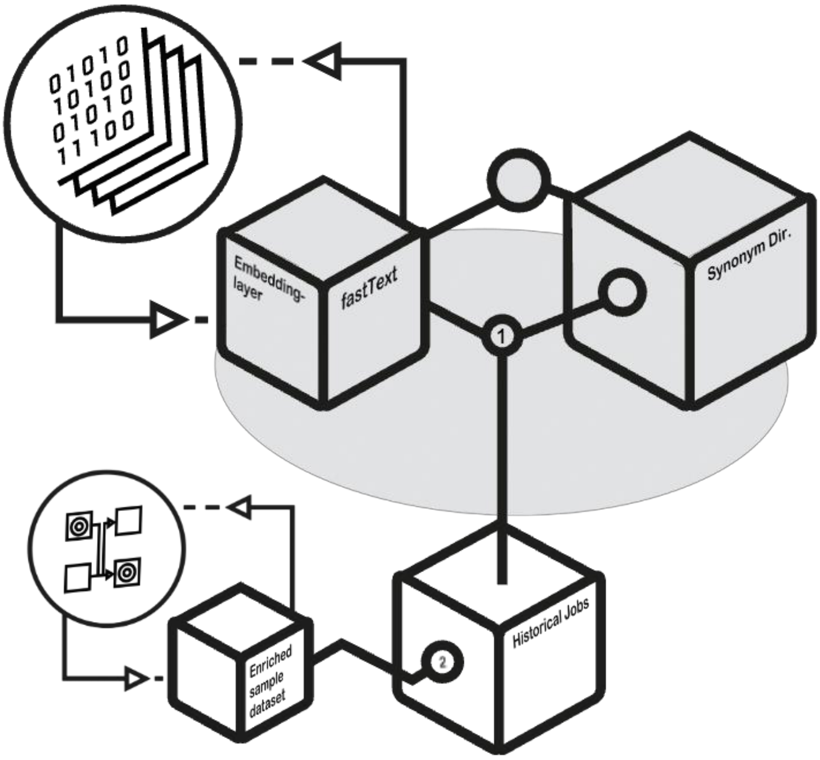


Figure 1. Overview of the job skill-relatedness workflow.

First, the dataset of postings is entered into the Job Enrichment API/toolkit designed by the *JobTech* department (shadowed area in figure 1).[6] The postings enter a *Pre-processing stage*, where raw texts are prepared for analysis. In the *FastText* stage, the toolkit uses a library of about 70,000 words and synonyms from a *Synonym Dictionary*, previously constructed by the Swedish Public Employment Service, that describe skills ("*färdigheter*") and identify different variations to these words, as well as misspelled cases, using a method defined in Bojanowski et al. (2017). This renders an *Embedding layer* which represents a method to search for and retrieve words that represent skills, given the training of the model on all 6 million job postings.

Second, using the *Historical Jobs database*, we select and merge three annual sets of job postings, detailing over 1.7 million advertised jobs 2019-2021. We chose these years to keep as up-to date as possible and somewhat limiting the extensive data processing, while at the same time keeping enough years to obtain robust results. We communicate this set to the servers of *JobTech*, where the Embedding Layer is used to extract words that are likely to be

[6] JobAd Enrichments. https://jobtechdev.se/en/components/jobad-enrichments.

representations of skill descriptions, given their linguistic context. This gives our *Enriched sample dataset*.

Although the postings are already marked with an occupation-code in the database of historical jobs, they do not come with an industry code. To achieve this posting-industry match, we attach an industry code to each posting based on the establishment (plant) to which the posting connects. We use the firm ID to search for the firm's industry codes in the *Business Retriever* repository, which is commercially available. To find out the industry code of the particular establishment, we match the text description in the posting to the firm-specific plant information given in the Business Retriever database using a Fuzzy matching strategy. It is important to avoid industry identification on firm/organization level, and rather use the establishment level.

Our procedure allows us to retrieve a list of skills attributable to each job. These lists of skills however still contain many generic terms and descriptions of tasks, such as "driving licence" or "general ability to handle a computer". Such terms represent important items for general labour market analysis or training initiatives but are too imprecise for the purposes of this investigation. To identify which skills that make jobs distinct, we calculate a "revealed specialization" of each skill in a job, analogous to the revealed comparative advantage method RCA (Alabdulkareem et al., 2018). This measures the overrepresentation of a skill in a job, compared to all other jobs. This means that we, from a long list of skills associated with each job, identify the most characteristic skills for each job.

The final step is calculating how similar jobs are in terms of required skills (skill-relatedness). We feed the lists of skills for the jobs into a feature vector representation model (Doc2Vec, see Le & Mikolov, 2014). It uses machine learning to reduce and summarize the skill set of jobs in a comparable way and quantitively represent them in feature vectors of the same length, striking a balance between preserving variation and avoiding overfitting. To assess the relatedness between jobs based on their most characteristic skills, we measure the cosine similarity between the vectors produced by the learning algorithm. The cosine of an angle θ between two feature vector representations of jobs $\boldsymbol{i}$ and $\boldsymbol{j}$ can be given by:

$$Rel_{ij} = \cos(\theta_{ij}) = \frac{\boldsymbol{i}^{\boldsymbol{T}}\boldsymbol{j}}{\parallel \boldsymbol{i} \parallel \parallel \boldsymbol{j} \parallel} = \frac{\sum_{k=1}^{n} i_k j_k}{\sqrt{\sum_{k=1}^{n} i_k^2}\sqrt{\sum_{k=1}^{n} j_k^2}} \tag{1}$$

where the smaller the angle θ_{ij}, the higher the similarity. Algebraically the numerator in *Equation 1* is the dot product of the two vectors, while the denominator is the product of the norms of the two vectors. The resulting relatedness measure is symmetric by definition ($Rel_{ij} = Rel_{ji}$).

We cannot detail the relatedness between all existing jobs in the economy. Some jobs simply have too few postings to provide reliable estimates. Also, because of its heterogeneity, we omit all job combinations containing the recruitment industry (code SNI 78). In the end, how large part of the labour market our measure covers depends on definitions. If we, for example, take out jobs in agriculture, employment agencies, the armed forces, chief executives and jobs that employ less than 250 people, we can provide reliable skill-relatedness estimates for 72% of the job switches in Sweden.

To test the empirical implications of job relatedness on regional economies, we derive and aggregate information on job affiliations for individuals from the micro-data registers of Statistics Sweden. In these registers, economic information as well as occupational affiliation is recorded for everyone on the Swedish labour market. Because the registers also connect individuals to their establishments (plants) of work, we also know in which industry and in which municipality individuals are economically active. From this database, we aggregate a set of regional indicators: the number of individuals working at the various establishments in local economies (as an average between 2019 and 2020), their average income from work (average 2019 and 2020) and the number of local workers with a post-gymnasium education (equivalent to an advanced vocational or university education, average 2019 and 2020). From the public databases of Statistics Sweden, we also collect the gross regional product of each regional economy (average 2019 and 2020) to define GDP per employee.

3.2 Regional skill-coherence of present jobs and job switches

In the geographical analysis of local job-skill coherence, *local* economies are defined as the 290 Swedish municipalities. These are not all necessarily functional economic entities. However, Statistics Sweden records that about 70 percent of employees in Sweden live and work within their municipality (in 2020). Additionally, about 70 percent of this minority of non-resident workers commute within the Stockholm metropolitan area. In the regressions, we control for whether the municipality belongs to any of the three Swedish metropolitan regions (Stockholm, Gothenburg or Malmö).

We rely on the combination of the skill-relatedness measure and information on the job affiliations of Swedish workers (2020) and how they have switched jobs (2016-2020) to derive two main variables of interest: the *skill-coherence of local economies* and the *local average switch relatedness*.

To indicate the skill-coherence of local economies, we depart from lists of workers and their jobs (occupations in industries) in each local economy. We are inspired by the closeness measure of local industries developed by Neffke et al. (2011). The skill-coherence of a local economy is defined as the average relatedness of jobs within the region. As a reference baseline for comparison and to be able to assess whether local economies are in fact coherent or not, we also calculate the average relatedness between all jobs on the national level, between all present jobs in Sweden. The local coherence indicator $Coh_r$is:

$$Coh_r = \frac{\sum_{ij=1}^{|E_r|} Rel_{ij}}{|E_r|} \tag{2}$$

where Rel_{ij} is the estimated skill relatedness between jobs i and j, while E_r is the set of skill-relatedness ties that connect jobs that are present in the local jobs portfolio of region r.

To assess the relatedness of the jobs across which people switch in local economies, we take the jobs that workers are affiliated with in 2016 and 2020 and record those individuals that switch jobs between these years. The four-year span is given by the fact that the occupation surveys need a certain timespan to catch most job switches. To measure the *average switch relatedness* $AvSw_r$, we record the skill-relatedness between the jobs that people switch between in a municipality and take the average of those:

$$AvSw_r = \frac{\sum_{ij=1}^{|E_r|} Rel_{ij} I(F_{ij,r})}{\sum_{ij=1}^{|E_r|} I(F_{ij,r})} \tag{3}$$

where Rel_{ij} is the estimated skill-relatedness between jobs i and j, $I(F_{ij,r})$ is an indicator function taking the value of 1 if there is non-zero labour flow between jobs i and j in region r ($F_{ij,r} > 0$), and 0 otherwise.

4. Results

Table 1 records the most characteristic skills for two jobs. From an intuitive point of view, our measure overall captures skills and tasks that make empirical sense for each of these jobs. Table 2 gives a couple of examples of high- and low-skill-related job pairs of different strength.

Table 1. Examples of recorded skills in jobs (1).

Job	Skills
IT architects and system developers in data programming and data consultancy	technology services, Jee, architectural design, J2ee, competence development, version handling systems, Umbraco, Xsd, software design, resource allocation, verification, Mockito, user testing, cloud technology, jbehave
Machine operators in the rubber, plastics and paper industry in manufacture of rubber- and plastic products	packaging, quality control, certificate, forklift driving, heavy lifts, good physics/shape, technical training, packaging material, packaging, cranes, product safety, manufacturing work, post-manufacturing adjustment, re-setting competence, packaging solutions

Note: Our translations and abbreviations of skills, occupation, and industry titles from Swedish.

Source: Own elaboration on data provided by the Swedish Public Employment Service.

Table 2. Examples of highly related and less related job combinations.

Job A	Job B	Skill-relatedness
Cooks in hotels	Chefs and sous chefs in hotels	0.94
Electricians in paper manufacturing	Electricians in maintenance and installation of machinery	0.93
Engineers and technicians in manufacture of electrical appliances	Production managers in machinery manufacturing (n.e.c.)	0.92
Wood processors and plant operators in paper manufacturing	Building caretakers in specialized construction	0.36
Medical and pharmaceutical technicians in technical consultancy	Sales agents in sport and leisure activities	0.18

Note: Our translations and abbreviations of skills, occupation, and industry titles from Swedish

Source: Own elaboration on data provided by the Swedish Public Employment Service and Statistics Sweden.

In figures 2 and 3, we provide a network representation of the backbone of the skill-relatedness matrix, following the approach of Hidalgo et al. (2007). First, we take the maximum spanning tree (MST) of all pairwise connections in the network to include all jobs in the visualisation. To this "skeleton" we add the strongest 5 ‰ of skill-relatedness ties. The network layout is produced using the ForceAtlas2 algorithm, as implemented in Gephi 0.10. ForceAtlas2 is a force-directed layout where nodes repulse each other, while ties attract the nodes they connect, resulting in the dynamic movement of nodes until the system converges to an equilibrium layout (Jacomy et al., 2014). In the first network, node colours correspond to broad industry categories, while in the second network, node colours represent 1-digit occupation codes. As seen already from this illustration, many jobs are clustered in families of skill-related jobs that sometimes conform to, and sometimes transcend, traditional occupation- and industry classifications.

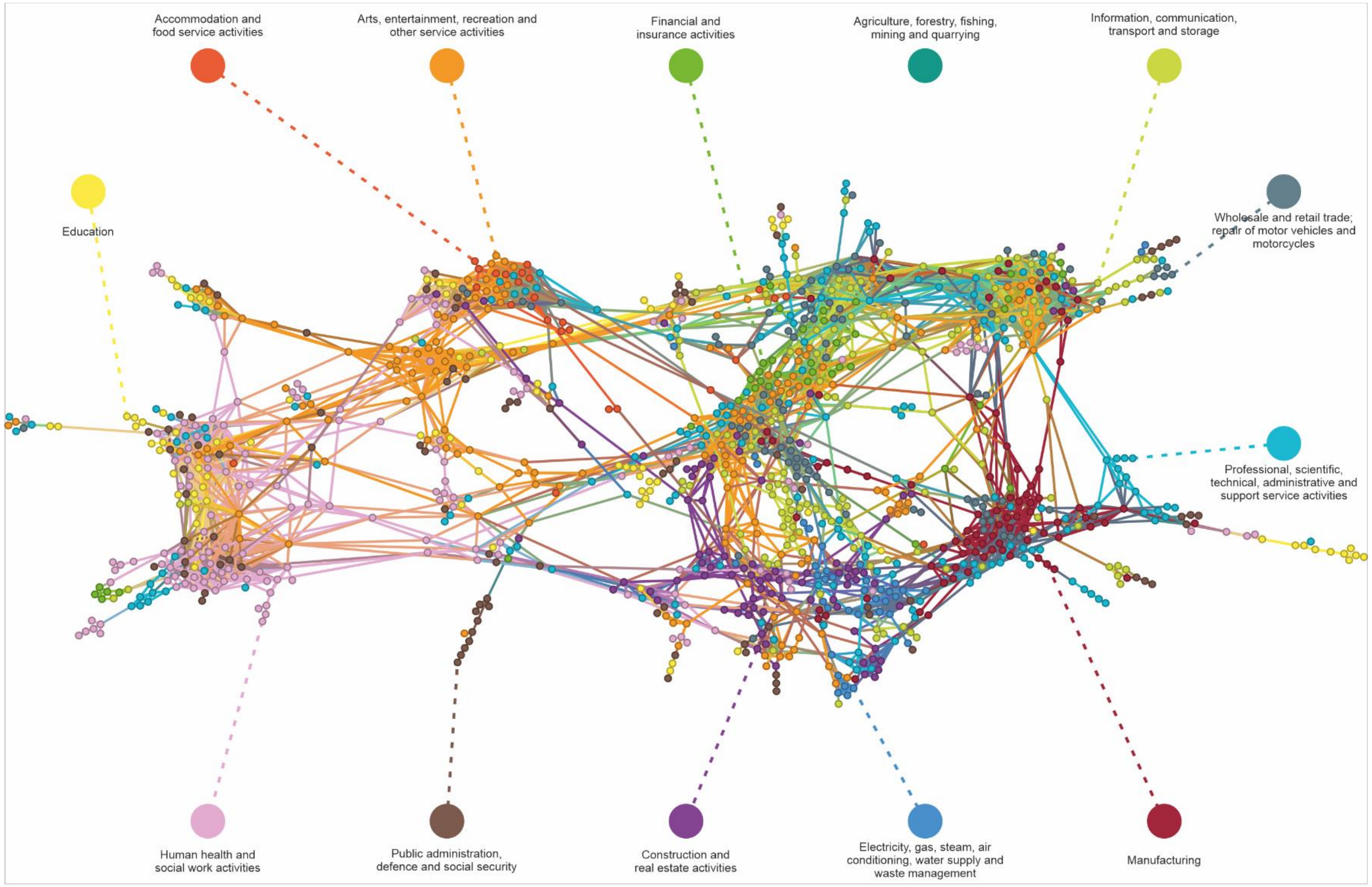


Figure 2. Network representation of the job-based skill-relatedness measure.

Note: Each node represents a job, connected by relatedness linkages. Node colours correspond to broad industry categories.

Source: Own elaboration on data provided by the Swedish Public Employment Service.

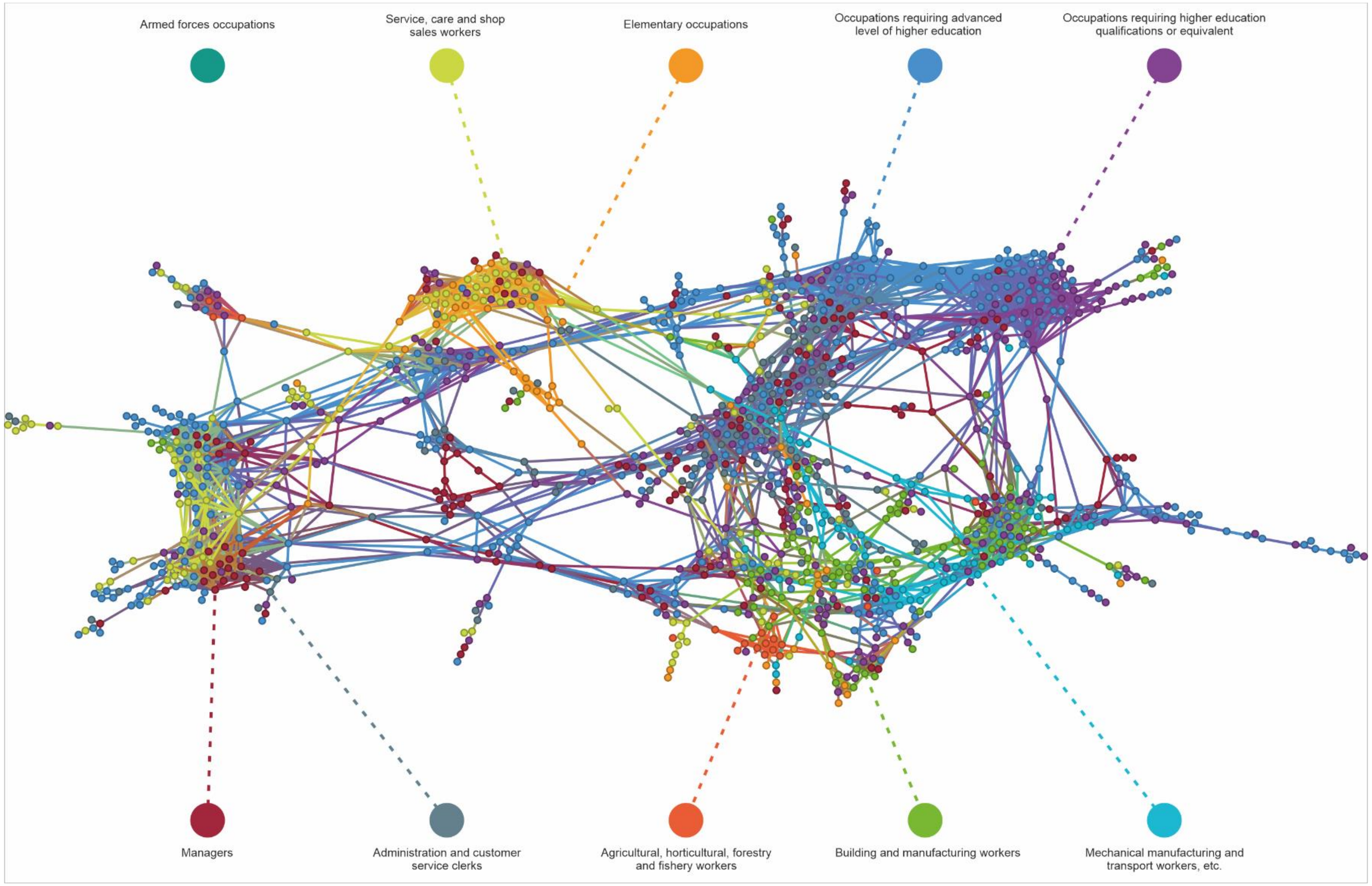


Figure 3. Network representation of the job-based skill-relatedness measure.

Note: Each node represents a job, connected by relatedness linkages. Node colours correspond to 1-digit occupation codes.

Source: Own elaboration on data provided by the Swedish Public Employment Service.

Lastly among the descriptive properties of the job skill-relatedness measure, we investigate the extent to which workers in general switch jobs between those that are skill-related (Neffke & Henning, 2013; Neffke et al., 2017). Figure 4 combines our skill-relatedness measure with information about how people switch jobs in the Swedish economy between 2016 and 2020. We sort each job-job combination in the economy in one of 10 bins according to their skill-relatedness value. These are the categories organized on the x-axis, from the job-job combinations with no relatedness (to the left) to the highest ones (to the right). Within each bin, we record the number of job-job switches. To create a switch frequency indicator that is comparable across the bins, we divide the number of job switches in each bin with the total number of job-job relatedness combinations in each bin. The resulting relative frequency on the y-axis gives an indication of the job-to-job switches, given how common the combination is in the economy. The graph supports the mobility assumptions made in the literature so far (Neffke & Henning, 2013). Workers are more likely to move between jobs that share similar skill-requirements, according to the information retrieved from job postings, than to just any other job. Workers seem to have accumulated experiences that can be transferred over the career and new career paths can be embarked on without too much effort in related jobs (c.f., Elekes et al., 2023).

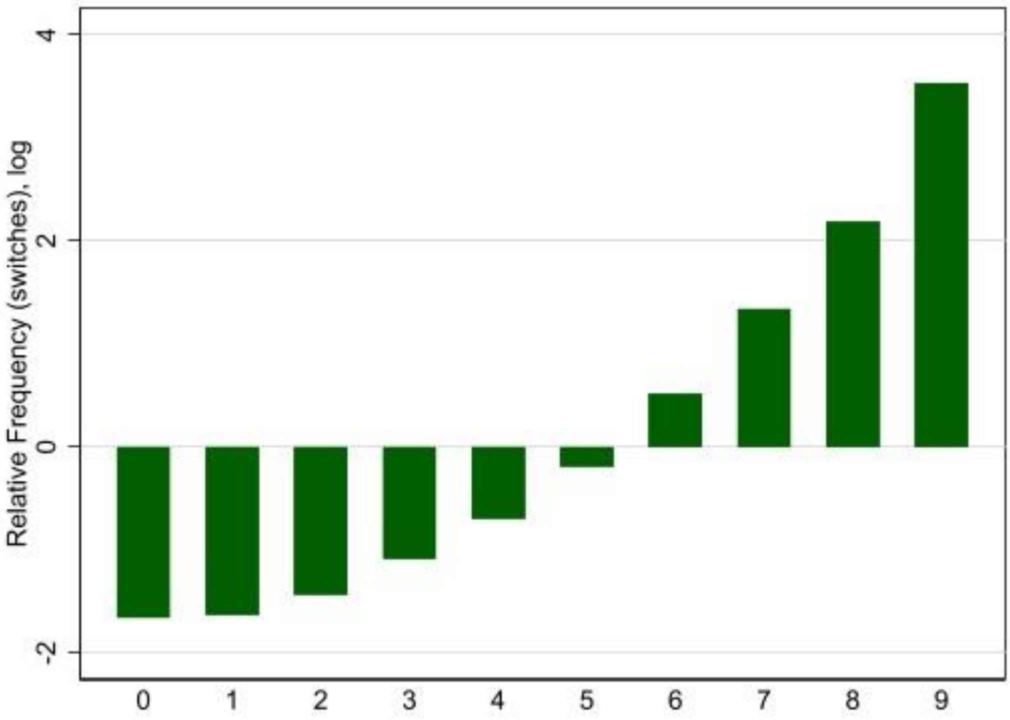


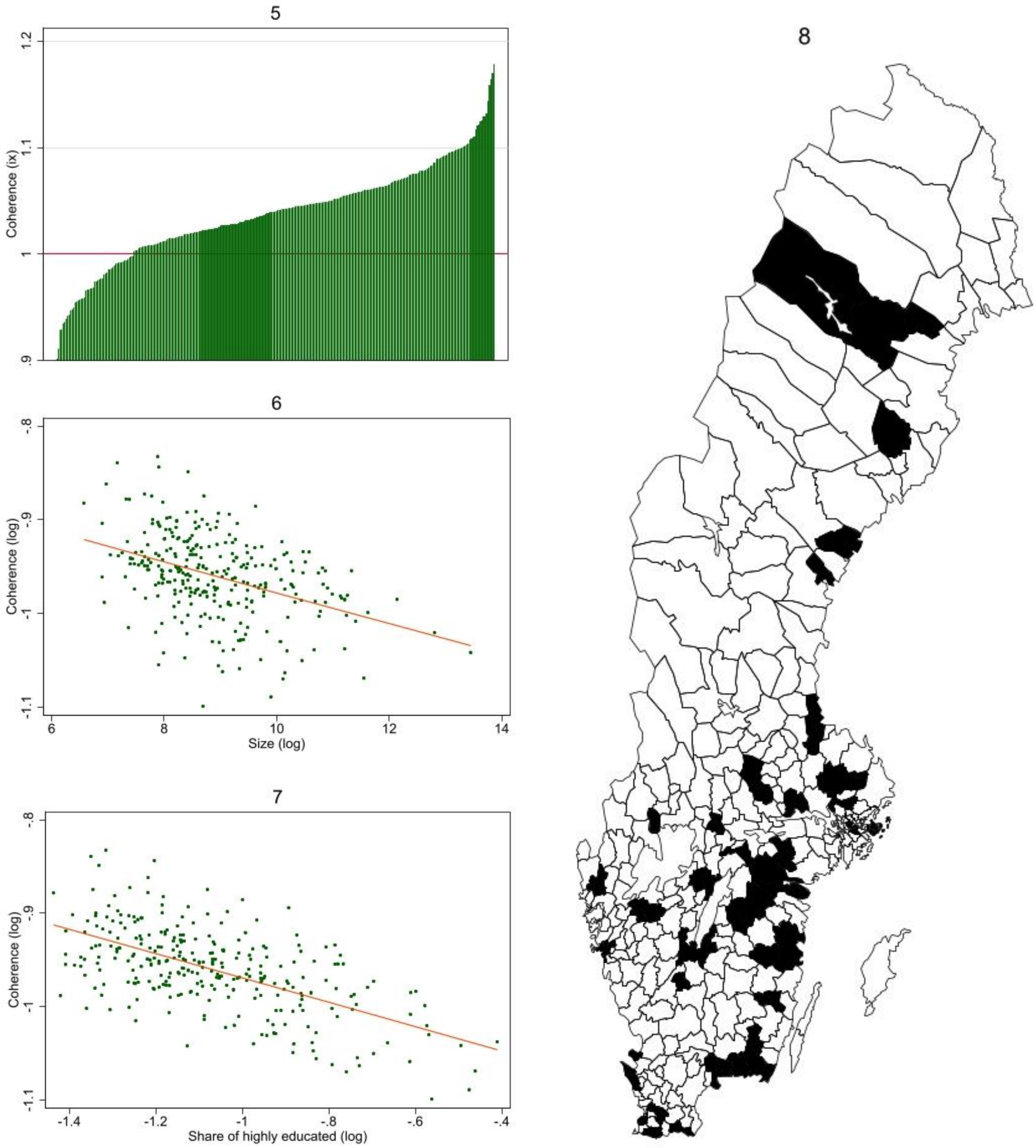
Figure 4. The relative frequency of job moves in Sweden between 2016 and 2020, per job-job relatedness strength (10 deciles).

Source: Own elaboration on data provided by the Swedish Public Employment Service and Statistics Sweden.

Moving into a regional setting, Figure 5 displays the average skill-coherence (Coh_r) for Swedish local economies. In Figure 5 these are indexed by relating them to a baseline (the horizontal line), which represents the average relatedness between all jobs in Sweden. Each bar in the graph represents the indexed skill-coherence value of every local economy. Most of the local economies (*i.e.*, 239 of the 290 municipalities) record an above-national coherence. A, by economic logics, "natural" tendency is for local economies to specialize into one or several sets of economic activities.

While this regional specialization into skill-related jobs is one of the more expected features of our measure, the most interesting issue is perhaps which regions that display a below-baseline coherence. The first determinant that comes to mind is the size of the region. The larger the region, the less coherent skillsets it should be able to sustain due to the correlation between diversity and size. Figure 6 is a scatterplot between the size of local economies (number of workers) and their coherence. While there is something of a negative relationship (the larger the local economy, the lower its coherence), there is also variation. Quite some municipalities of roughly the same size that have very different coherence levels (the bivariate correlation is -0.41). In fact, the relationship to the share of highly educated in local economies is substantially stronger (-0.6) as shown in Figure 7. Given the general tendency for local economies to be skill-coherent, a higher share of highly educated workforce enables regions to sustain a less coherent, or in other words more diverse, skill structures. A last potential caveat that we would like to investigate is that less skill-coherent local economies cluster spatially, for example to the metropolitan areas. Figure 8 dismisses such a suspicion. Below-average local economies (black on the map) are scattered all over the country and includes both densely and more sparsely populated regions.

.

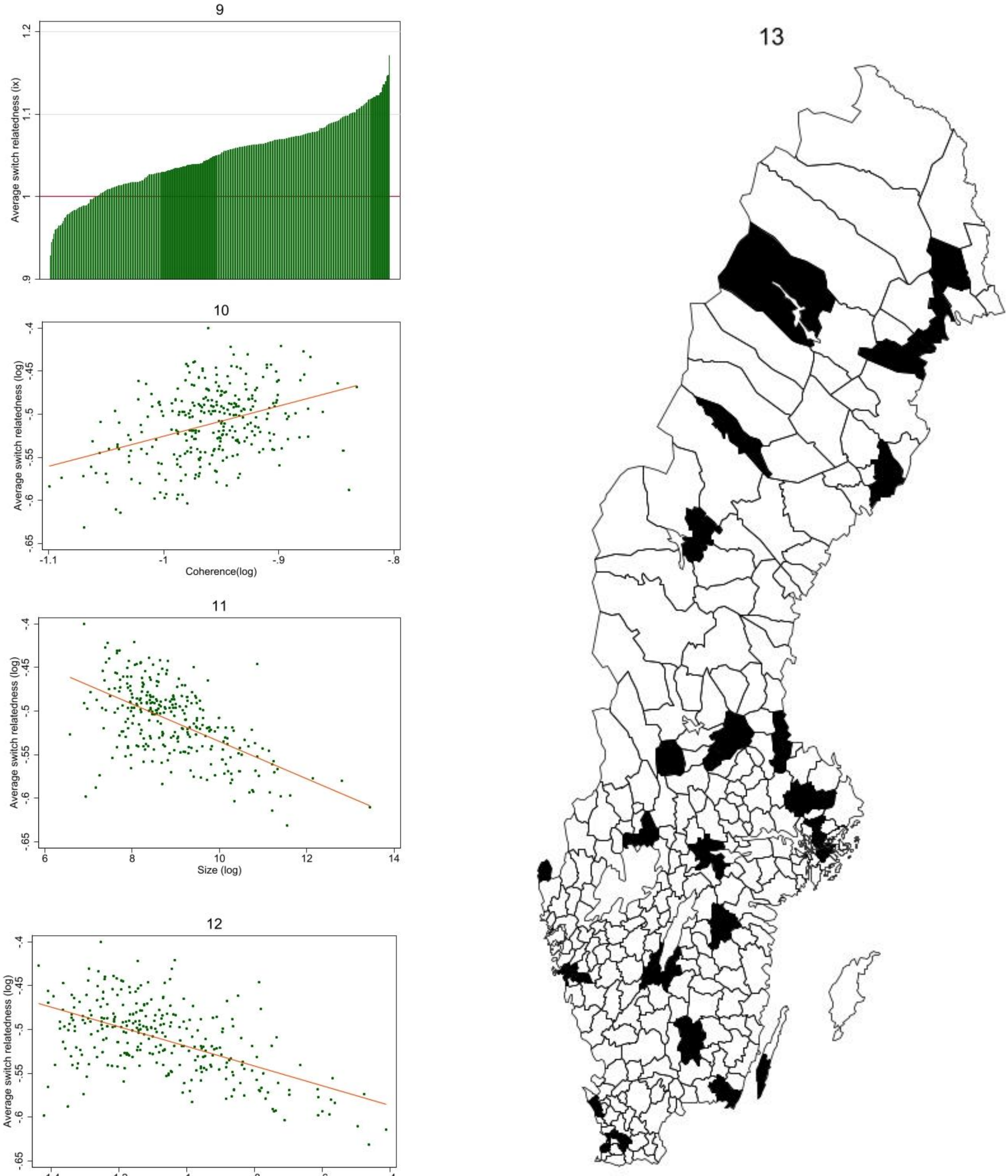


Figures 5-8 (panel). Skill coherence of Swedish municipalities.

Note: **(5)** Indexed coherence of local economies (national = 1). Bars represent local economies (municipalities). **(6)** Size (log) and coherence of local economies (log). Green dots represent local economies (municipalities). Line is linear regression prediction. **(7)** Share of highly educated of local workforce (log) and coherence of local economies (log). **(8)** Map of Swedish municipalities, below-national coherence marked by black.

Source: Own elaborations on data from the Swedish Public Employment Service and Statistics Sweden.

Besides coherence, a potentially important feature of local economies is the skill distance that job switches in the regions cover when workers change jobs. Figure 9 shows indexed average switch relatedness in the local economies (the national baseline is 1). Again, most local economies indicate high coherence, above the national baseline. One could expect a high co-variation between local coherence and the average swich relatedness since workers in less coherent local economies are likely to make moves where they on average cover larger skill-distances, for example due to the less readily access of viable local opportunities. There is indeed a positive relationship between local coherence and the average switch distance, but it comes with quite some variation (correlation 0.38, Figure 10). The association between local average switch distance and the size of the local economy (-0.58) is very similar to the relationship with shares of highly educated (-0.56) as respectively displayed in Figures 11 and 12. The larger the local economies and the higher the shares of highly educated, the lower the average job switch in the local economy in terms of relatedness. Neither in this case, we can identify any immediate signs of spatial clustering (Figure 13).

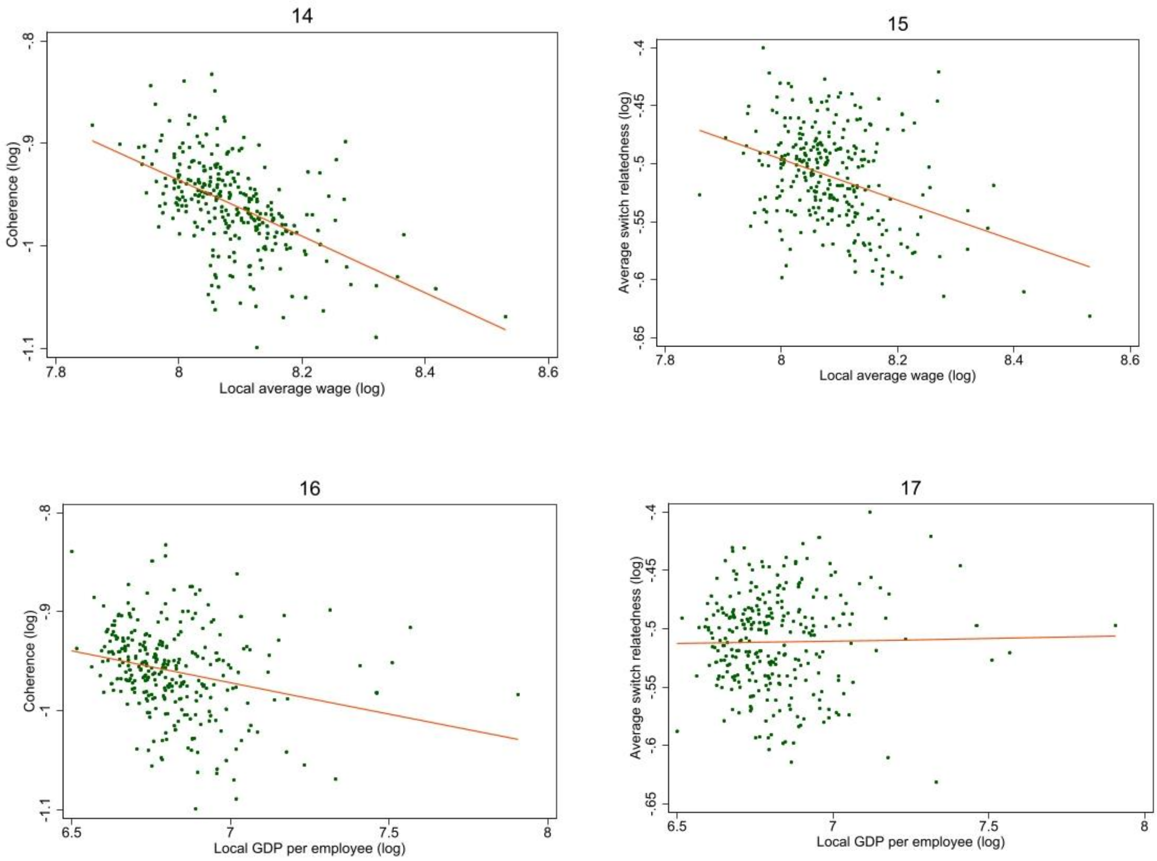


Figures 9-13 (panel). Average switch relatedness of Swedish municipalities.

Note: **(9)** Indexed average local skill-relatedness of job switch (national = 1). **(10)** Coherence of local economies (log) and average local skill-relatedness of job switch (log). Green dots represent local economies (municipalities). Line is linear regression prediction. **(11)** Size (log) and average local skill-relatedness of job switch (log). **(12)** Share of highly educated of local workforce (log) and average local skill-relatedness of job switch (log). **(13)** Map of Swedish municipalities, below-national average local skill-relatedness of job switches marked in black.

Source: Own elaborations on data from the Swedish Public Employment Service and Statistics Sweden.

We now focus on the associations between local skill coherence and average switch distance on the one hand, and two local economic indicators on the other: local average wage and GDP per employee (a proxy for local labour productivity). Figures 14-17 picture their descriptive associations. Overall relations are negative between local coherence on the one hand, and local average wages and labour productivity on the other (Figures 14 and 16), although there is room for quite some local idiosyncrasies around a linear relationship. The descriptive associations with average switch relatedness are less clear – maybe negative with average wage (Figure 15), and slightly positive with local GDP (Figure 17).



Figures 14-17 (panel). Coherence, average switch relatedness and regional welfare.

Note: **(14)** Local coherence (log) and local average wage (log). Green dots represent local economies (municipalities). Line is linear regression prediction. **(15)** Local average switch relatedness (log) and local average wage (log). **(16)** Local coherence (log) and local GDP per employee (log). **(17)** Local average switch relatedness (log) and local GDP per employee (log). Green dots represent local economies (municipalities).

Source: Own elaborations on data from the Swedish Public Employment Service and Statistics Sweden.

To clarify the relations, Table 3 records the results of OLS estimations where we regress the local average wage and labour productivity on local coherence and average local skill-relatedness of job switch. Without making claims to fully explain regional wage levels or especially labour productivity, Models 1 and 2 corroborate the negative association between coherence and average switch relatedness and the local economic outcome variables. Lower skill coherence is significantly linked to more positive local economic outcomes. Given this, however, there is a positive association with average switch distances. We believe that this combined effect is important because it signals the positive economic value of individually related switches within less coherent (more diversified) local economies. Thus, it seems like workers in diversified markets are operating within distinct knowledge pools (Bienkowska et al., 2011).

Table 3. Outcomes of OLS regression.

	(1) Average wage	**(2)** Labour productivity
Coherence	-0.684***	-1.235***
	(0.11)	(0.32)
Average switch relatedness	0.273**	0.456
	(0.10)	(0.30)
Highly educated	0.047***	-0.011
	(0.00)	(0.01)
House price	-0.034***	-0.031
	(0.01)	(0.03)
Metro	0.052***	0.114**
	(0.01)	(0.04)
Constant	7.459***	6.176***
	(0.09)	(0.25)
R^2	0.542	0.094
N	290	290

Note: Each n is a local economy (municipality). All variables in logs except Metro (binary). Standard errors in parentheses. Significance levels: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.
Source: Own elaborations on data from the Swedish Public Employment Service and Statistics Sweden.

Lastly, the number of job ads in a local economy also carries an economic meaning beyond indicating the size of the local economy. To follow our previous indication that regions with higher shares of highly educated can carry a richer diversity of skills, Figure 8 sketches the relationship between the number of job postings in the local economies (adjusted by local economy size) and the share of highly educated workers. There is a clear positive relationship. In Model 3 of Table 4 this association is established econometrically by unadjusted values, but then controlled for local size. The effect of size is also positive but statistically weaker. Again, the local job postings behaviour would point towards something fundamental for regional development due to the association with the level of education in regions. Regions with high levels of education can sustain more dynamic and qualitatively diverse labour markets. By this mechanism, they also tend to grow richer.

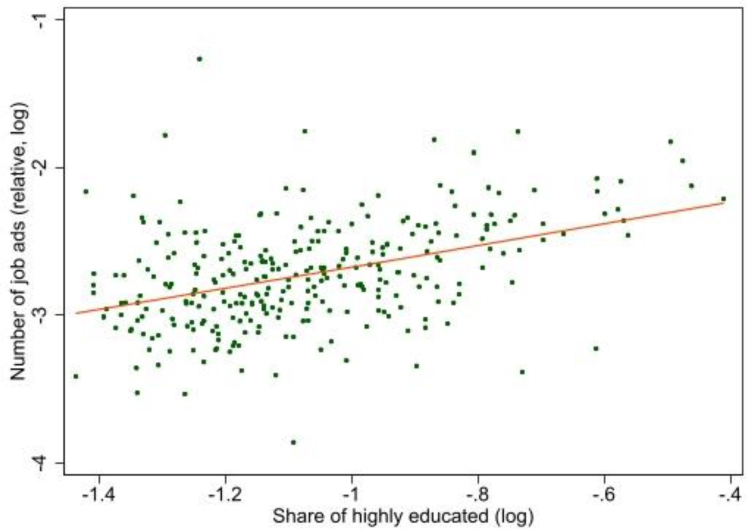


Figure 18. Number of job ads (adjusted by local economy size, log) and share of highly educated (log).
Note: Green dots represent local economies (municipalities). Line is linear regression prediction.
Source: Own elaborations on data from the Swedish Public Employment Service and Statistics Sweden.

Table 4. Outcomes of OLS regression.

	(3) Number of postings
Highly educated	0.665***
	(0.15)
Metro	-0.096
	(0.07)
Size	0.370*
	(0.16)
Constant	-2.309***
	(0.35)
R^2	0.937
N	290

Note: Each n is a local economy (municipality). All variables in logs except Metro (binary). Standard errors in parentheses. Significance levels: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Source: Own elaborations on data from the Swedish Public Employment Service and Statistics Sweden.

5. Conclusions and a future research agenda

While skills are often put at the forefront in analyses on regional development, regional skills themselves remain under-theorized and difficult to address empirically. In this paper, we have therefore made the first steps to investigate the use of job postings for the analysis of skills in regions. There is a close connection between information provided by job postings and recent developments in regional science and economic geography around the geography of skills and human capital. One of the strongest points of job postings is that they provide an exogenous (compared to *e.g.*, labour mobility patterns) and up to date source for measuring the desired skill content of jobs, occupations and industries in specific places. We find support for previous assumptions made about flows between related jobs and the fact that local labour markets are skill-wise coherent. However, more skill-coherent local markets for skills deliver lower nominal wages and productivity, even considering size. Also, there is a relationship between local skill coherence and the level of skills present in a region which goes beyond the size of the region. Local economies with higher shares of highly educated workers can sustain a lower overall coherence of skills, that in turn makes regions richer. Skill-relatedness of job moves that workers make within regions are also important. Given their coherence level, more related job moves in regions are associated with better economic outcomes. This is a typical example of how individual and local level dynamics together shape regional economic outcomes.

We have also found some pitfalls that come with doing analyses of job postings in a regional setting. Job postings are not complete lists of skills required for specific jobs. While there are recent attempts to disentangle for example skills and knowledge in postings, we have found this to be extraordinarily difficult in practice, and perhaps not even necessary for many applications to the regional context. Also, we have noted how extremely important it is to attach the posting to a specific plant (with a unique location) or even address, rather than to a firm. Moreover, while the postings could serve as an instantaneous indicator of the skill-structure of local economies, it also mainly captures the demand side of the labour market. It is difficult, if not impossible, to know whether the position is filled or the degree to which the skills of the new employee match the requirements in the post.

Job postings do, in our minds, especially open avenues for regional research in three directions. First, in the spirit of Neffke (2019) and Farinha et al. (2019), we believe that job postings can foster analyses also of complementarities between jobs and skills. Second, job postings represent an opportunity for research on the skill distribution and needs of the public sector, where traditional industry codes typically underestimate the human capital complexity. Finally, job postings reflect desires from local economic agents to reproduce themselves, grow and change. They are, from that point of view, material reflections of *change agency* (Grillitsch & Sotarauta, 2020).

As the evolutionary principles of coherence and diversification have increasingly attracted policy interest due to their compatibility with the Smart Specialization framework (Kogler & Whittle, 2018; Balland et al., 2019), there is a strong need for specific and place-sensitive measures that make concrete skills observable, or at least observable by close representation tokens. Otherwise, moving forward in terms of for example EU's regional policy recommendations for Smart Specialization will prove to be difficult as well. In all, we believe that the increasing availability of job postings, together with advancements in methods related to text data, hold the potential to complement existing and more established data sources, to revisit classical findings, and perhaps ultimately to open the black box of skills in regional analyses.

References

Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2022) Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics*, 40(1): 293-340.

Alabdulkareem, A., Frank, M. R., Sun, L., AlShebli, B., Hidalgo, C., & Rahwan, I. (2018) Unpacking the polarization of workplace skills. *Science Advances*, 4(7): eaao6030.

Asheim, B. (2000) Industrial Districts: The Contributions of Marshall and Beyond. In: Clark, G. L., Feldman, M. P., & Gertler, M. S. (Eds.). *The Oxford Handbook of Economic Geography*. Oxford. Pp. 413-431.

Bacolod, M., Blum, B. S., & Strange, W. C. (2009) Skills in the city. *Journal of Urban Economics*, 65(2): 136-153.

Balland, P. A., Boschma, R., Crespo, J., & Rigby, D. L. (2019) Smart specialization policy in the European Union: relatedness, knowledge complexity and regional diversification. *Regional Studies*, *53*(9): 1252-1268.

Berry, C. R., & Glaeser, E. L. (2005) The divergence of human capital levels across cities. *Papers in Regional Science*, 84: 407–444.

Bienkowska, D., Lundmark, M., & Malmberg, A. (2011) Brain circulation and flexible adjustment: labour mobility as a cluster advantage. *Geografiska Annaler: Series B, Human Geography*, 93(1): 21-39.

Bojanowski, P., Grave, E., Joulin, A., & Mikolov, T. (2017) Enriching word vectors with subword information. *Transactions of the Association for Computational Linguistics*, 5: 135-146.

Castellacci, F., Consoli, D., & Santoalha, A. (2020) The role of e-skills in technological diversification in European regions. *Regional Studies,* 54(8): 1123-1135.

Czaller, L., Eriksson, R. H., & Lengyel, B. (2021) Reducing automation risk through career mobility: Where and for whom?. *Papers in Regional Science*, 100(6): 1545-1569.

Dawson N, Williams M-A, & Rizoiu M-A (2021) Skill-driven recommendations for job transition pathways. *PLoS ONE*, 16(8): e0254722.

Deming, D., & Kahn, L. B. (2018) Skill requirements across firms and labor markets: Evidence from job postings for professionals. *Journal of Labor Economics*, 36(1): 337-369.

Deming, D. J., & Noray, K. (2020) Earnings dynamics, changing job skills, and STEM careers. *The Quarterly Journal of Economics*, 135(4): 1965-2005.

Elekes, Z., Baranowska-Rataj, A., & Eriksson, R. (2023) Regional diversification and labour market upgrading: local access to skill-related high-income jobs helps workers escaping low-wage employment. *Cambridge Journal of Regions, Economy and Society*, *16*(3): 417-430.

Farinha, T., Balland, P. A., Morrison, A., & Boschma, R. (2019) What drives the geography of jobs in the US? Unpacking relatedness. *Industry and Innovation*, 26(9): 988-1022.

Fernández-Macías, E. (2012) Job polarization in Europe? Changes in the employment structure and job quality, 1995–2007. *Work and Occupations*, 39(2): 157–182.

Feser, E. J. (2003): What Regions Do Rather than Make A Proposed Set of Knowledge-based Occupation Clusters. *Urban Studies*, 40(10): 1937-958.

Fitjar, R. D., & Timmermans, B. (2017) Regional skill relatedness: towards a new measure of regional related diversification. *European Planning Studies*, 25(3): 516-538.

Florida, R. (2002) *The Rise of the Creative Class*. Basic Books.

Florida, R., & Mellander, C. (2016) The geography of inequality: Difference and determinants of wage and income inequality across US metros. *Regional Studies*, 50(1): 79-92.

Florida, R., & Mellander, C. (2018) Talent, skills, and urban economies. In: Clark, G., Feldman, M. P., Gertler, M. S., & Wójcik, D (Eds.): *The New Oxford Handbook of Economic Geography*. Oxford. Pp 499-518.

Florida, R., Mellander, C., & Stolarick, K. (2008) Inside the black box of regional development – human capital, the creative class and tolerance. *Journal of Economic Geography*, 8(5): 615-649.

Florida, R., Mellander, C., Stolarick, K., & Ross, A. (2012) Cities, skills and wages. *Journal of Economic Geography* 12(2): 355-377.

Frenken, K., Van Oort, F., & Verburg, T. (2007) Related variety, unrelated variety and regional economic growth. *Regional Studies*, 41(5): 685-697.

Glaeser, E. L. (1999) Learning in cities. *Journal of Urban Economics*, 46: 254–277.

Glaeser, E. L. (2005) Reinventing Boston: 1630–2003. *Journal of Economic Geography*, 5(2): 119-153.

Glaeser, E. L., Kallal, H. D., Scheinkman, J. A., & Shleifer, A. (1992) Growth in cities. *Journal of Political Economy*, 100(6): 1126-1152.

Glaeser, E. L., Ponzetto, G. A., & Tobio, K. (2014) Cities, skills and regional change. *Regional Studies*, 48(1): 7-43.

Glaeser, E. L., & Resseger, M.G. (2010) The complementarity between cities and skills. *Journal of Regional Science*, 50(1): 221-244.

Glaeser, E. L., & Saiz, A. (2003) The rise of the skilled city. *NBER Working Paper*, 10191.

Goldfarb, A., Taska, B., & Teodoridis, F. (2023) Could machine learning be a general purpose technology? A comparison of emerging technologies using data from online job postings. *Research Policy*, 52(1): 104653.

Grillitsch, M., & Sotarauta, M. (2020) Trinity of change agency, regional development paths and opportunity spaces. *Progress in Human Geography*, 44(4): 704-723.

Håkanson, C., Lindqvist, E., & Vlachos, J. (2021) Firms and Skills The Evolution of Worker Sorting. *Journal of Human Resources*, 56(2): 512-538.

Hane-Weijman, E., Eriksson, R. H., & Henning, M. (2018) Returning to work: regional determinants of re-employment after major redundancies. *Regional Studies*, 52(6): 768-780.

Hane-Weijman, E., Eriksson, R. H., & Rigby, D. (2022) How do occupational relatedness and complexity condition employment dynamics in periods of growth and recession?. *Regional Studies*, 56(7): 1176-1189.

Hansen, H. K., & Eriksson, R. H. (2023) The public sector and regional development: Why public sector employment remains a black box in economic geography. *Progress in Human Geography,* 47(6): 833-849.

Henning, M., & Eriksson, R. H. (2021) Labour market polarisation as a localised process: evidence from Sweden. *Cambridge Journal of Regions, Economy and Society*, 14(1): 69-91.

Henning, M., & Kekezi, O. (2023) Upward job mobility in local economies. *Cambridge Journal of Regions, Economy and Society*, 16(3): 431-444.

Hensvik, L., Le Barbanchon, T., & Rathelot, R. (2021) Job search during the COVID-19 crisis. *Journal of Public Economics*, 194: 104349.

Hidalgo, C. A., Klinger, B., Barabási, A. L., & Hausmann, R. (2007) The product space conditions the development of nations. *Science*, 317(5837): 482-487.

Hidalgo, C.A., Balland, P-A., Boschma, R., Delgado, R., Feldman, M., Frenken, K., Glaeser, E., He, C., Kogler, D.F., Morrison, A., Neffke, F., Rigby, D., Stern, S., Zheng, S., & Zhu, S. (2018) The principle of relatedness. In: International conference on complex systems. Springer, Cham. Pp. 451-457.

Jacomy, M., Venturini, T., Heymann, S., & Bastian, M. (2014) ForceAtlas2, a continuous graph layout algorithm for handy network visualization designed for the Gephi software. *PLOS One*, 9(6): e98679.

Kogler, D. F., & Whittle, A. (2018) The geography of knowledge creation: Technological relatedness and regional smart specialization strategies. In: Edward Elgar Handbook on the geographies of regions and territories. Pp 153-168.

Koo, J. (2005) How to analyze the regional economy with occupation data. *Economic Development Quarterly* 19(4): 356-372.

Le, Q., & Mikolov, T. (2014) Distributed representations of sentences and documents. In International Conference on Machine Learning (pp. 1188-1196). PMLR.

Lucas, R.E. (1988) On the mechanics of economic development. *Journal of Monetary Economics*. 22: 3-42.

Malmberg, A., & Power, D. (2005) (How) do (firms in) clusters create knowledge?. *Industry and Innovation*, 12(4): 409-431.

Markusen, A. (2004) Targeting occupations in regional and community economic development. *Journal of the American Planning Association*, 70(3): 253–268.

Marrocu, E., & Paci, R. (2012) Education or creativity: what matters most for economic performance. *Economic Geography*, 88: 369–401.

Marshall. A- (1920) *Principles of Economics*. London: Macmillan.

Massey, D. (1995) *Spatial divisions of labour: social structures and the geography of production*. Bloomsbury Publishing.

Mellander, C., & Florida, R. (2021) The rise of skills: Human capital, the creative class, and regional development. *Handbook of Regional Science*, 707-719.

Moretti, E. (2012) *The new geography of jobs*. Houghton Mifflin Harcourt.

Moro, E., Frank, M. R., Pentland, A., Rutherford, A., Cebrian, M., & Rahwan, I. (2021): Universal resilience patterns in labor markets. *Nature Communications*, 12(1): 1-8.

Murnane, R. J., Willett, J. B., & Levy, F. (1995) The Growing Importance of Cognitive Skills in Wage Determination. *The Review of Economics and Statistics*, 77(2): 251-66.

Neffke, F. M. (2019) The value of complementary co-workers. Science advances, 5(12), eaax3370.

Neffke, F., & Henning, M. (2013) Skill relatedness and firm diversification. *Strategic Management Journal*, 34(3): 297-316.

Neffke, F. M., Otto, A., & Weyh, A. (2017) Inter-industry labor flows. *Journal of Economic Behavior & Organization*, 142: 275-292.

Neffke, F., Henning, M., & Boschma, R. (2011) How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. *Economic Geography*, 87(3): 237-265.

Neffke, F., Hartog, M., Boschma, R., & Henning, M. (2018) Agents of structural change: The role of firms and entrepreneurs in regional diversification. *Economic Geography*, 94(1): 23-48.

Porter, M. (2003) *The economic performance of regions*. *Regional Studies*, 37(6–7): 549–78.

Romer, P. M. (1986) Increasing returns and long-run growth. *Journal of Political Economy*, 94(5): 1002-1037.

Sánchez-Moral, S., Vale, M., & Arellano, A. (2022) Skill-Relatedness and Regional Economic Development in Spain during the International Crisis and the Post-Crisis Period. *Papers in Regional Science*, 101(3): 573-602.

Santoalha, A., Consoli, D., & Castellacci, F. (2022) Digital skills, relatedness and green diversification: A study of European regions. *Research Policy*, 50(9): 104340.

Simon, C. (1998) Human capital and metropolitan employment growth. *Journal of Urban Economics*, 43(2): 223–224.

Simon, C., & Nardinelli, C. (1996) The talk of the town: human capital, information and the growth of English cities, 1861-1961. *Explorations in Economic History*, 33(3): 384–413

Stephany, F., & Teutloff, O. (2024) What is the price of a skill? The value of complementarity. *Research Policy*, *53*(1): 104898.

Stolarick, K., Mellander, C., & Florida, R. (2010) Creative jobs, industries and places. *Industry and Innovation*, 17(1): 1-4.

Thompson, W.R. (1986) Cities in transition. *The Annals of the American Academy of Political and Social Science*, 488: 18–34.

Thompson, W. R., & Thompson, P.R (1987) National Industries and Local Occupational Strengths: The Cross-Hairs of Targeting. *Urban Studies*, 24(6): 547-60.

Ullman, E. L. (1958) Regional development and the geography of concentration. *Papers in Regional Science*, 4(1): 179–198.