The in-demand skills portfolios of regions and their impact on productivity

Recent waves of digital technologies are reshaping the occupational and industrial composition of regions and the skills demanded by firms in an effort to develop and/or use such technologies (Ciarli et al., 2021). Changes in skills sets required by labour markets are closely tied to the evolution of technological trajectories: firms adapt their skill requirements in such a way as to fully exploit the existing technological opportunities, improving their market position. The demand of skills is a therefore a useful predictor of the type of technologies that firms are developing/adopting (Brynjolfsson et al., 2024; Cammeraat & Squicciarini 2021; Acemoglu et al. 2022), or more in general they are exposed to. Understanding the relationship between technological change and related changes in in-demand skills is crucial against the background of stagnant productivity in the UK and the EU, as differences in the availability and diversity of skills significantly impact productivity gaps between the top and the median firms (Criscuolo et al., 2021). Identifying emerging in-demand skills and understanding the combinations most conducive to productivity gains are therefore of critical importance.

This focus is particularly relevant in the context of yet unexplained productivity slowdowns, which may be influenced by the challenges and opportunities associated with digital technology adoption (Goldin et al., 2024). Yet, a comprehensive analysis of skill patterns and their link to regional productivity over extended time horizons remains underexplored. To address this gap, we extract information of skills from online job advertisement data for ten EU countries and the UK, and measure how changes in the skill sets demanded by regional labour markets impact the productivity of regions in the UK and the EU. Our empirical approach relies on a three-step strategy, grounded in economic complexity methods.

First, we identify the emergence of new skills across UK and European regions, for each region-industry occurrence. To identify skills, we exploit data on more than 200 million Lightcast Online Job Advertisements (OJA) across 11 countries (Austria, Belgium, Denmark, France, Germany, Luxemburg, Netherlands, Norway, Sweden, Switzerland, UK) between 2014 and 2020. Occupations and skills are mapped to the ESCO framework (European Skills, Competences, and Occupations, v.1.2). We analyse annually the skill demand trajectories within region-industry, at granular level (NUTS3 and 4-digit ISIC levels, respectively). Considering a timeframe of seven years allows to identify longer time-trends of emerging skill specialisations. Our data also allows to pinpoint the skills dynamics in service sector industries, which increasingly changed during the considered period, due to increased digital technology development and adoption (Ciarli et al., 2021).

In this context we discuss the feasibility of skill-mappings. While for instance Giambona et al. (2024) decide to analyse regional temporal skill evolution over time on single skills, we opt for a skill mapping on the most granular and – for our sample of EU countries – most representative framework: the European Skills and Competences (ESCO) framework. A main motivation is to reduce the hereafter following complex calculations to a meaningful unit of analysis, corresponding to ESCO skill hierarchies. This requires to map Lightcast skills to the ESCO framework. We compute dense vector representations (Reimers & Gurevych, 2019) to obtain Lightcast skill embeddings in the ESCO skill list and similarity of the respective embeddings, using cosine similarity. A manual review of the mapping ensures that each Lightcast skill matches at least one ESCO skill.

Second, we use different combinations of in-demand skills, such as IT-skills, to identify similar regions in terms of their changing skills demand trajectory. This is achieved by building a bipartite network connecting industries in each EU region to skills. We follow Bruno et al. (2023) in constructing a Bipartite Weighted Configuration Model (BiWCM) to statistically validate the network links. The resulting network infers similarity between skills (based on co-occurrence in regions) and between regions (based on shared skills specialisation). It clearly captures the variety of skill demand varying across regions and industries.

From the validated network we obtain indices that quantify the internal coherence and diversity of the skills demanded by each region-industry. More precisely, we measure the connectedness of skills portfolios at the regional level, using information on the strength of the connection between skills obtained from the skills space. Moreover, drawing upon the economic complexity toolbox (Hidalgo & Hausmann, 2009; Tacchella et al., 2012) we construct a measure of skill-level sophistication. Finally, we link skills portfolios – characterised by their coherence and complexity – to the performance of industries across regions in terms of labour productivity from the Annual Regional Database of the European Commission's Directorate General for Regional and Urban Policy (ARDECO). Controlling for regional occupational and industrial structures as well as relevant socio-economic factors, we estimate the relation between in-demand skills composition and regional productivity.

To address endogeneity between the skill profile of regions and their economic performance, we exploit aggregate changes that are exogenous to individual regions and common across the sample, relying on a shift-share / leave-one-out instrument design. We rely on technological shocks, such as the exposure to ground-breaking emerging digital technologies.

Our findings provide an explanation of region-industry productivity through temporal dynamics of complex skill compositions. Our findings are expected to confirm the relevance of the inflow of high skills (Criscuolo et al., 2021) and IT skills (Brynjolfsson et al., 2024) for labour productivity. Moreover, we expect new complex skills such as “machine learning” to appear in region-industry settings that require a high variety of related skills. With this new approach, we not only identify but also provide a new perspective on regional productivity, in the time of unprecedented, quick, and wide adoption of digital technologies.

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