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Skills demand on the labour market: Evidence from recent western European countries job postings data

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Extended Abstract

The past decades have been characterized by sequential waves of digital revolutions that deeply transforms the labour market. The current speed of digital transformations fed by the progress in artificial intelligence have also a high potential of reshaping effects on employment.

Regarding the type of jobs that are at risk, existing studies focused mainly on past digital revolutions and reveal distinguished results on the overall employment depending on four main periods. First, in the pre-computer decade of the 1960s with the introduction on the market of some technologies (e.g. Fortran, UNIVAC computer) there were insignificant effect of computerization on the labour market. Second, during the 1.0/2.0 digital revolutions that run from 1970 to the end of the 1990s, with technologies that function mechanically or electrically (like computer-aided design), the skill-biased technological change (SBTC) literature highlights that technological changes are biased toward skilled labour (e.g. Autor et al., 2003). Third, the period after concerns the 3.0 digital revolution that run since 2000 to an expected end around 2025 (Arntz et al., 2019), with technologies that are supported by computers and software algorithms (e.g. warehouse management systems, supply chain management systems). This wave is characterized by a polarization of the labour market, that implies an increase of

low skilled and high skilled jobs and a decrease of the middle skilled jobs. Moreover, since this specific wave, a huge debate takes place about forecasting the volume of jobs that are expected to disappear in the next decades. Depending on the level of analysis, some at done at the occupation level show pessimistic and huge negative effects (e.g. Frey & Osborne, 2017) whereas, others done at the job/task level highlight optimistic and much lower figures of negative effects (e.g. Arntz et al. 2016; Nedelkoska & Quintini, 2018). In OECD countries, the figures go from 9% to 47% of jobs in high risk of being replaced by automation in 2030.

Fourth, the currently running 4.0 digital revolution, that overlaps the 3.0 wave, is characterized by the use of technologies that are IT-integrated i.e. with a direct and automated communication between different parts of the value chain thanks to the progress in artificial intelligence. There is a thin but growing literature regarding the potential future impact on employment but with no consensus. According to Brynjolfsson et al. (2019), there is a risk for high-skilled workers with the expected progress in automation capacities that may automate cognitive tasks. Nevertheless, a first study done in Germany show that the current 4.0 digital revolution seems to mimic the skill-biased technological change effects observed in the past that favors higher skilled workers at the expense of lower skilled workers (Arntz et al., 2019).

Beyond these overall effects on employment, some papers underline the existence of some compensation effects between sectors. For example, Dauth et al. (2017) show that in Germany, between 1994-2017, each industrial robot adopted in the manufacturing sector, induces a loss of 2 manufacturing jobs but also a positive and significant spillover effect on the non-manufacturing sectors (gain of 2 additional jobs). However, as underlined by Cortes (2016) only a minority of displaced routine workers is able to upgrade skill to move to non-routine jobs.

To ease the transition of workers between sectors, policy-makers need to know as precisely as possible the set of skills that overlap each other to implement their policies (such as lifelong learning policies). A recent strand of research, based on O*NET data, provide some evidence of transition opportunities between activities measured through the overlap of a set of skills between activities (e.g. Alabdulkareem et al., 2018; Frank et al., 2019). For example, Frank et al. (2019), show some existence regarding skill similarity that may favour skill mobility. For example, positions in the legal sector and positions in human resource management are both at risk to lose automatable tasks (clerical, basic digital skills, and administrative activities). Positions in the legal sector are also at risk to lose more job specific skills (legal knowledge, information processing) and through the share of social skills with the other position (organizing staff, conflict resolution, influencing others) can move to this position after a retraining program.

This strand of research provide some results on the transferability of skills on the labour market to ease the mobility of workers but mainly on US. It will be useful to policy makers to have more results to identify retraining needs in order to help worker to move from one position to another in order to tackle current and future technological unemployment.

This paper contributes to this growing literature in several ways. First, we shed new lights on this question by using real time data from jobs platforms from western European countries. As underlined by Frank et al. (2019) this is one way to tackle the current barriers to provide accurate identification of skill demand and skill mobility opportunities on the labour market. Our analysis is, indeed, based on online web-scraped job postings data from 261 job portals from Luxembourg, Belgium, France and Germany between September 2018 and August 2019. This online job market is characterized on monthly average by 1.2 million job vacancies in Germany, 0.5 million in France, 0.16 million in Belgium and 7.000 in Luxembourg.

Second, whereas most of the literature that focuses on broad measure of tasks thanks to our rich data we will provide a skill taxonomy that is more granular. Existing research generally distinguish between routine (manual, cognitive) and non-routine (manual, analytical, interactive) tasks (Autor et al., 2003; Lewandowski et al. 2019). To go further, we distinguish 35 sub-components of three main skill families: (i) soft skills (e.g. planning, team work); (ii) job specific skills (e.g. customer services, foreign languages) (e.g. Cedefop, 2017); (iii) digital skills (with a distinction by usage, e.g. basic digital skills, management oriented use, analyzing data, managing data, software and application development, computer programming) (e.g. Burning Glass Technologies, 2018).

Third, we rely on a promising methodology and use unsupervised clustering techniques in order to identify the proximity of the skill between sectors. After the build of adjacency matrix and contingency matrix, community detection techniques widely used in a variety of fields such as neuroscience, social science, transportation research, business research, finance, climatology or cybersecurity or recently in labour economics (Alabdulkareem et al., 2018) are used.

Our first preliminary results show that:

- The skills related to adaptability/agility (e.g. “adapt to changing situations”) are the once that are the most transferable across sectors.

- Depending on the type of digital skills there are more or less stuck in one sector.

- Digital skills spread across a large number of sectors.

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