Labour-saving technologies and occupational exposure

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Extended abstract

The increasing diffusion of artificial intelligence (hereafter, AI) and robotic technology in the last decade has became a renewed object of analysis in both economics and technology studies. Robots, and intelligent robots more so, represent, among the wider spectrum of the recent Industry 4.0 wave, the technological artefacts 'naturally' apt in substituting human labour. However, the actual implementation of these artefacts may well be labour-friendly, as in the case of collaborative robots. At the current stage, the economic literature tends to rely on experts judgement (so-called Delphi method) when constructing automation probability measures of occupations (see Arntz et al., 2016; Frey and Osborne, 2017; Nedelkoska and Quintini, 2018). However, a direct measure of human substitutability and occupational exposure, ideally based on the *effective* functions and operations which labour-saving technology aims at executing, is still missing.

In this paper we intend to fill the existing vacuum in the literature and to propose a direct measure of the actual penetration of labour-saving technologies within the occupational structure. To accomplish this objective, we develop a multistep strategy. First, leveraging on the identification of labour-saving technologies by means of natural language processing on robotic patents (Montobbio et al., 2020), we perform a task-based textual match between the descriptions of elicited CPC codes attributed to labour-saving patents and the O*NET

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dictionary of occupations. The match is constructed by means of a cosine-similarity matrix that informs us about the "closeness" of the two dictionaries of words.

After recovering a CPC-task matching, we weight each entry of the matrix by the frequency of the respective CPC in LS patents. In this respect we attribute a LS trait to each pair.

We then aggregate tasks into occupations by assigning the cosine-similarity measure to each task weighted according to being *core* or *supplementary* as defined by the "Task Statements" of O*NET. In this way we recover a measure of exposure of each task and related occupations to LS technologies. According to our results, most affected occupations are "Material Moving Worker", "Vehicle and Mobile Equipment Mechanics, Installers, and Repairers" (Logistic), "Food Processing Workers".

In order to externally validate our measure, we match with Occupational Employment Statistics (OES) from US Bureau of Labor Statistics and with median wage data for 6-digit SOC occupations (1999-2019). Lowess estimates present a monotonically negative relationship between occupational exposure and (i) wage levels, and (ii) employment growth. Remarkably, no expected U-shaped pattern is recovered. Cutting edge-innovative efforts look to be directed towards the weakest and cheapest segment of the labour market.

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