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Labour-saving automation: A direct measure of occupational exposure

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Abstract

This article represents one of the first attempts at building a *direct* measure of occupational exposure to robotic labour-saving technologies. After identifying robotic and labour-saving robotic patents, the underlying 4-digit CPC (Cooperative Patent Classification) code definitions, together with O*NET (Occupational Information Network) task descriptions, are employed to detect functions and operations which are more directed to substituting the labour input and their exposure to labour-saving automation. This measure allows us to obtain fine-grained information on tasks and occupations according to their text similarity ranking. Occupational exposure by wage and employment dynamics in the United States is then studied, and complemented by investigating industry and geographical penetration rates.

KEYWORDS

labour markets, labour-saving technology, natural language processes, technological unemployment

1 | INTRODUCTION

Robots are coming! Statements such as this have become a mantra in recent years, together with the perception that "This time is really different" (Brynjolfsson & McAfee, 2012, 2014; Ford, 2015).

Much literature on the effects of the new wave of automation on human labour has been produced since then. Indeed, the pervasiveness of such new technological artefacts has been one of the most relevant aspects portending troublesome scenarios; among the most radical authors, Frey and Osborne (2017) suggest that 47% of total US employment is associated with occupations that are potentially automatable, a very much debated figure which has been revised downwards by further estimations (Arntz et al., 2016) giving a figure of 9% when looking at tasks rather than occupations. Nedelkoska and Quintini (2018), performing an analysis across 32 OECD countries, also reveal a large degree of cross-country variability, with estimated automation probabilities for the median job ranging between 39% and 62%. Recent empirical evidence tends however to agree that low- and medium-skilled workers, mainly, executing routinised tasks, are particularly at risk (Acemoglu & Restrepo, 2018, 2019, 2020a; Autor & Dorn, 2013; Frey & Osborne, 2017). At the same time, while some papers find a negative impact on employment and wages, systematic evidence of the labour market impact of robotic technologies remains elusive (Calvino & Virgillito, 2018; Mondolo, 2022).

In the literature, the unfolding of the impact of robotics on labour markets, in terms of occupations and wages, has mainly been estimated by two alternative methods. The first method is based on experts' judgement on a subset of occupations, expanded over the entire occupational structure by a classifier-system algorithm (e.g., Frey & Osborne, 2017; Nedelkoska & Quintini, 2018). The second approach has been leveraging robotic adoption at the sectoral level, relying on the International Federation of Robotics dataset and looking at the impact on local labour markets (e.g., Acemoglu & Restrepo, 2018, 2019, 2020a).

Currently, a direct measure of human substitutability and occupational exposure, ideally based on the functions and operations executed by labour-saving (LS) technologies, is still absent (see Section 2). We contribute to this literature and provide a direct link between human tasks and machine functions and, as a result, quantify occupational exposures to LS innovation in robotics. In doing so, we build a new measure of similarity between the textual description of the tasks performed in an occupation and the functions performed by observed robotic LS innovations.

First, we leverage the identification of robotic LS technologies by means of natural language processing on robotic patents (Montobbio et al., 2022) and we then perform a task-based textual match between the descriptions of technological classifications (the so-called CPC codes) attributed to robotic LS patents and the O*NET dictionary of occupations. The match exploits a cosine-similarity matrix that measures the proximity of the two dictionaries of words. The first result of our study is therefore the construction of a direct measure of similarity between a dictionary of technological LS functions and a dictionary of human-based functions. This is a methodological advancement to measure proximity between humans and machines and allows us to derive a direct measure of exposure.

In the second step, we aggregate tasks into occupations and derive a measure of exposure of each task and related occupations to robotic LS technologies. We find that the distribution of the similarity scores across tasks and occupations is very skewed, with high-similarity events being quite rare, given the underlying heterogeneity between the two text corpora. Nonetheless, restricting the analysis to the top decile of the similarity distribution, around 8.6% of the overall US employed workforce (approximately 12.6 million jobs) is at risk of substitutability. The most affected occupations are "Material Moving Workers", "Vehicle and Mobile Equipment Mechanics, Installers, and Repairers", "Other Production Occupations". Logistics and production activities are those most exposed to LS technologies, in line with the evidence that among the top owners of LS patents, Amazon and UPS stand out (Montobbio et al., 2022). However, among the top patent holders, a quite diverse range of firms is visible, e.g., Boeing, Seiko, Canon, Hyundai Motors. The logistics segment is therefore targeted not because it reflects the sector of belonging of patent owners, but rather because it is considered easier to automate by means of robots within different industries. In line with the lean production paradigm, logistics activities have to be minimised and eventually completely automated.

To validate our methodology, we perform a robustness analysis by replicating the text similarity exercise between robotic LS patents' full texts and the same O*NET task descriptions (see Appendix 3). The patent-task match, when full texts are used but LS functions are not (through CPC code descriptions, see above), correctly pinpoints those occupations developing new innovative robotic technologies and their systems of adoption (e.g., Robotics Engineers; Robotics Technicians). This result reinforces the goodness of our procedure because it shows that it distinguishes substitutability detected via more prevalent functions in LS patents from complementarity detected via the match with the entire patent text.

Then, we link the similarity measure to the actual US labour market in terms of occupations and wages. We match our data to the Occupational Employment and Wage Statistics (OEWSs) from the US Bureau of Labor Statistics for 8-digit SOC occupations (1999–2019). Regression estimates present a monotonically negative relationship between occupational exposure and both (i) wage level and growth and (ii) employment growth. Remarkably, the expected U-shaped pattern (Acemoglu & Autor, 2011) is found neither in wages nor in occupational growth. In other words, cutting-edge robotic innovative efforts look to be directed towards the weakest and cheapest, and not the middle, segment of the labour market. Finally, a geographical breakdown across US states shows that the Rust Belt area, the region surrounding the Great Lakes experiencing industrial decline, and the South-East area, with a higher prevalence of African-American communities, record the largest employment shares of occupations that are particularly exposed to robotic LS technologies.

Our results highlight the fact that the drivers of labour-saving innovations are not those theoretically expected according to a theory of labour substitution induced by higher prices of labour inputs. Indeed, labour-saving innovative efforts are more directed at substituting and automating the cheapest segment of the labour market. Nonetheless, some of the highly targeted occupations, like Transportation and Material Moving, are still growing in terms of employment share. Therefore, the overall labour market dynamics cannot be defined uniquely by the direction of labour-saving technical change but rather by the interaction between demand-driven structural change and supply-driven technical change. Again, the archetypical case is Amazon, which represents the second US employer and whose massive share of the labour force involves Transportation and Material Moving operators. The latter occupations are targeted by LS efforts but still represent the fourth occupation by employment share in 2019.

The remainder of the article is organised as follows: Section 2 discusses the literature and evidence available; Section 3 presents the datasets used and Section 4 the adopted methodology; Section 5 shows and discusses our results, presenting task and occupational exposure, labour market, industry and geographical penetration rates. Section 6 concludes the article.

2 | STATE OF THE ART

As briefly mentioned in the introduction, the effect of robotic applications on labour markets, in terms of occupations and wages, has been estimated in previous research mainly by using two alternative methods. The first method is that introduced by Frey and Osborne (2017), who