ROBOTS AND SOCIETY

Answering the great automation question

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Modeling an automation risk index for job profiles provides insights into worker reallocation and informs retraining policy.

In 2021, more than 3 million industrial robots were operating in production activities worldwide (Fig. 1) (*1*). The diffusion of artificial intelligence (AI) in human activities is even wider and more complex to assess. It does not come as a surprise that, at least since 2006, concerns about the potential effects of technology on employment and salaries have been steadily growing. As an example, already in 2017, more than 85% of U.S. citizens were in favor of a law limiting machines to particularly dangerous and unhealthy jobs (*2*). However, these fears are nothing new in economics. They go back to the myth of N. Ludd's destruction of a loom in 1779 or later to D. Ricardo's words in the 19th century: "the opinion entertained by the laboring class, that the employment of machinery is frequently detrimental to their interests, is not founded on prejudice and error, but is conformable to the correct principles of political economy" (*3*). Estimating the effect of improvements in production technique on occupation is unfortunately such a complex task that in 1965, R. Solow, a Nobel Prize winning economist, argued that answering the question "Does automation create or destroy more jobs?" was de facto impossible (*4*). Writing in *Science Robotics*, Paolillo *et al.* (*5*) report a notable step toward answering the great automation question by proposing an automation risk index (ARI) for 967 job profiles.

Among the different approaches developed in the economic literature to answer the great automation question, the work of Paolillo and colleagues (*5*) is doubtlessly one of the most promising. By matching information on job profiles from Occupation Information Network (O*NET) and robotic abilities from European H2020 Robotic Multi-Annual Roadmap (MAR) and using Technological Readiness Level (TRL) to take into consideration the extent a human may be replaced by a robot ability, the authors obtain two key results. First, they go one step further than similar methodologies proposed in the literature (*6*, *7*) by including the role of AI advances in robotization. This innovative contribution captures a larger number of activities in which robotization may substitute workers. Second—and this is potentially the most exciting contribution of Paolillo and colleagues (*5*)—they were able to exploit information in O*NET job profiles to produce a resilience index (RI) that could be helpful in designing ad hoc retraining programs and facilitating transition to jobs with a lower exposition to automation risk.

More research is still required, however, before being able to answer Solow's "unanswerable" question. The first obstacle is that, despite the large amount of information provided by O*NET data, job descriptions cannot be comprehensive. This is a major drawback of approaches like the one by Paolillo and coworkers (*5*). Data quality therefore needs to be improved to make this tool useful for a more accurate computation of the ARI. Second, while Paolillo and coworkers (*5*) determine the ARI as the result of the mean between scenarios where robots operate below the level of a human (low automation) and where robots operate at the same level as a human (high automation), the likelihood of the two is not the same and may vary over time, regionally, across countries and among occupations. This means that all interested parties—including individuals trying to escape from high-automation risk occupations and firms and policy makers who need to take decisions at aggregate level—need a more sophisticated tool to forecast occupational profiles.

The relation between robotization and employment goes beyond the pure technical substitution effect. The long debate between mainstream positivist view and doomsayer

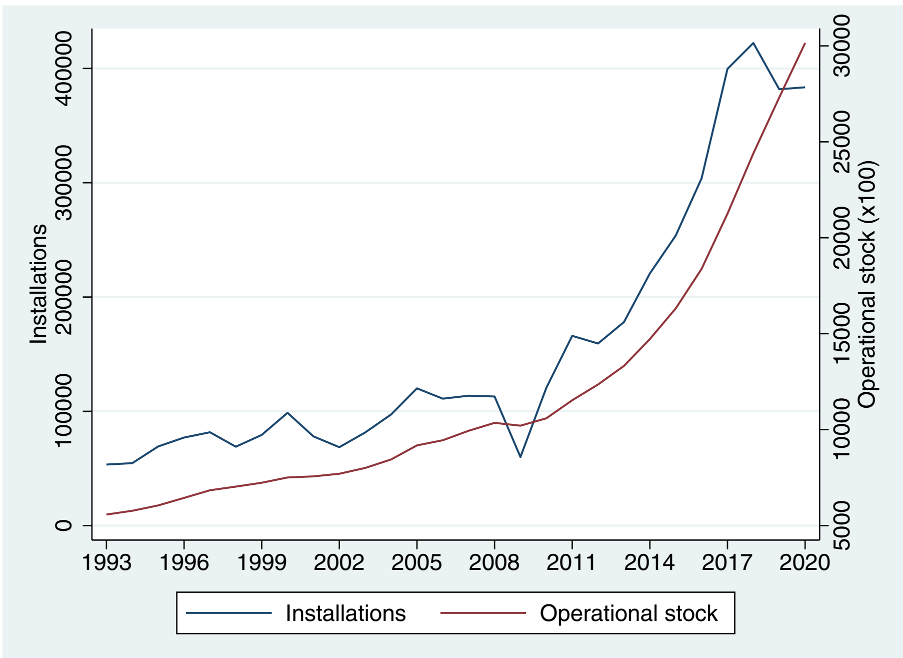

Fig. 1. Robot installation and operational stock over time. Author computation of robot installations (left) and operational stock in hundred (right) by year 1993–2020, from International Federation of Robotics (*1*) 2022 data.

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heterodox analysis is far from being exhaustive. This is mainly due to the role of aggregate demand. On the one hand, simplifying drastically the actual debate, if technology and aggregate demand grow at similar rates, we may argue that improvements in production technology increase jobs and therefore salaries, so there is nothing to worry about. On the other hand, if markets are saturated, improvements in production technology may displace workers (*8*), putting pressure not only on single occupations but also on all workers of a sector/territory and on the whole economy (*9*), potentially causing an economic crash as in 1929 and, more recently and less markedly, in 2007. This condition implies the need for retraining programs and adequate subsidies to income policies. This is where Paolillo and coworkers' contribution may produce the most important results. Joining the technical analysis with the distribution of occupations among economic sectors may allow us to estimate not only the individual exposure to robotization but also the aggregate sectoral/territorial/national exposure to robotization and, therefore, to design targeted policies.

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