Firm-level impacts of automation may be labour-friendly

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Abstract

There are widespread concerns that the latest wave of new technologies, including robots and AI among the others, may negatively affect labour. In this note, we take stock of the current empirical evidence on the labour outcomes of such technologies. In particular, we focus on firm-level outcomes, in terms of employment dynamics, employment composition, and the within-firm wage distribution, around episodes of new technology adoption by firms. Overall, a labour-friendly picture of automation seems to emerge. Indeed, investment in capital goods embedding automation technologies is associated with increases in firm employment, and of wages across the entire wage distribution, while the occupational composition and within-firm wage inequality (also among genders) do not seem to be significantly affected.

It is a widely held opinion that the world is witnessing a phase of technological change that has the potential to revolutionize production processes as well as people's daily lives. Indeed, a Fourth Industrial Revolution is believed to unfold, as new digital technologies, such as the Internet of Things, additive manufacturing, and artificial intelligence (AI) are deployed by firms. This generates concern for the future of labour: are "machines" going to steal our jobs, change their nature, and cause us to earn less? Such technological anxiety has repeatedly emerged every time, since the (First) Industrial Revolution, that waves of technological progress have led to Schumpeterian "creative destruction". Yet, catastrophists have regularly been proven wrong as, time and again, job creation have overcome job destruction (Mokyr et al., 2015).

Still, many economists think that this time is different: in an influential book, Brynjolfsson and McAfee (2014) foretell a "second machine age", bringing about an unprecedented bounty of gains, but also an unprecedented concentration of these gains in few hands. In the contemporary economic scenario, one can indeed envisage new challenges. Notably, AI can impact work in a much broader way than previous waves of innovations have (Furman and Semans, 2019). In the past, manual jobs were the ones most at risk of being replaced by a machine. Currently, all jobs that are rich in routine intensive, highly codified tasks are exposed to the risk of being replaced, and this process is largely orthogonal to the traditional classification in blue- versus white-collar jobs (Autor et al., 2003; Goos et al., 2014).

It is therefore of paramount importance to understand how the adoption of the most recent technologies impacts labour, along various dimensions (notably employment stability and wage) and at different levels (country, firm, individual, etc.). Not surprisingly, several studies have undertaken this task in the past few years. Firm-level evidence is consistent in showing a positive effect on the employment of firms that adopt automation (Acemoglu et al., 2020; Aghion et al., 2020; Bessen et al., 2020; Bonfiglioli et al., 2020; Dixon et al., 2019; Domini et al., 2021a; Koch et al., 2019). But if firms adopting these technologies expand, this may be at the expense of their competitors, and the net impact on total employment is difficult to pinpoint. Indeed, aggregate-level contributions have failed to find a consensus: the effect of automation on aggregate employment is negative according to Acemoglu and Restrepo (2020) and Acemoglu et al. (2020), neutral according to Graetz and Michaels (2018) and Dauth et al. (2018), and positive according to Klenert et al. (2020).

As for wages paid out to workers, Barth et al. (2020), Dinlersoz et al. (2018), and Humlum (2020) observe an increase in the average wage in firms adopting automation technologies, while Aghion et al. (2020), Bessen et al. (2020), and Koch et al. (2019) do not report a significant effect. Besides the average wage effect, the distribution of wages may also be impacted, as technological change may be skill- or routine-biased, hence wage gains or losses could be observed within firms across different worker groups. However, the picture is not clear-cut, as Barth et al. (2020) and Humlum (2020) find an increase in wage differentials among workers, while Domini et al (2021b) do not observe significant changes in within-firm inequality measures in adopting firms.

Employment and wage effects of new technologies are difficult to generalize, also because of a lack of consensus on the definition and measurement of such technologies. While some studies look at specific ones, in particular robots, others look at broader sets of automation technologies. In addition, data on the adoption of new technologies, however defined, are typically not readily available from administrative data, such as national statistics or firm-level accounts; hence researchers resort to a multiplicity of sources to capture the phenomenon of technology adoption in different countries. One option is to run surveys, which allows to ask specific questions and identify technologies precisely but usually limits sample size. Another approach is instead to use large-scale administrative databases, with opposite benefits, i.e. large sample size but more imperfect identification of technology adoption.

For what concerns the adoption of automation and AI, a popular option is to exploit import data (Acemoglu et al. 2020; Aghion et al. 2020; Bonfiglioli et al. 2020; Dixon et al. 2019). In particular, this is the approach that we use in two studies based on French administrative data (Domini et al. 2021a, 2021b), which we are going to focus on in the rest of this note, as they jointly provide a comprehensive picture about the firm-level labour outcomes of the adoption of a broad set of automation technologies, including robots, numerically controlled machines, automated machine tools and dedicated machinery, as well as (in the latter study) AI-related capital goods.

We observe that the imports of capital goods embedding such technologies display the behaviour that typically characterises investment variables: they are spiky, which means that they are rare across firms (at a given point in time, few firms import/adopt such technologies) and within firms (a given firm that imports/adopts such technologies does so only once or few times), and that a firm's largest episode of import/adoption is much larger than others. This episode can be defined as an automation spike.

Once a firm's automation spike is identified, we can look at what happens around it, on average, to several variables of interest, in particular firm employment, its rate of growth, the rates at which new workers are hired and incumbent workers separate from the firm, the occupational composition of employment, wage levels and wage inequality. Our main findings are as follows:[1]

It should be noticed that our two studies (Domini et al. 2021a, 2021b), though based on the same datasets, differ in terms of temporal (2002-2015 vs 2002-2017) and sectoral coverage (manufacturing only vs manufacturing and services), scope of the automation measure (automation only vs automation and AI), sample construction (all importing firms vs automation and AI importers only), methodology (propensity-score reweighted estimation vs event study), in addition to the variables of interest (employment growth and

- On average, in the year of a spike, a firm's growth rate increases (by circa 3 percentage points), as the hiring rate increases and the separation rate decreases. This reverses after the spike; however, overall, the effect on firm employment is positive.
- Automation spikes do not alter the composition of the workforce, as the shares of different occupational categories, also in terms of routine-intensity, do not significantly change.
- After an automation spike, wages increase (modestly, by circa 1%) at different points of the within-firm wage distribution.
- This occurs in spite of the fact that productivity decreases immediately after a spike. A rent- sharing explanation for the increase in wages can therefore be ruled out. The increase in wages appears instead to be driven by the hiring of new workers.
- As wages rise uniformly along the wage distribution, within-firm wage inequality is not significantly altered. The gender wage gap is also unaffected.

A broad labour-friendly picture of automation technologies emerges from these results. An important caveat is that these positive firm-level labour outcomes may still be consistent with negative aggregate outcomes, as observed by Acemoglu et al. (2020). Furthermore, our quantitative results say nothing about aspects of work other than employment stability and remuneration, e.g. workers' satisfaction and mental health (Abeliansky and Beulmann 2021). All in all, the cautious recommendation that can be derived for policy-makers is to sustain firms' efforts to adopt new technologies, while comprehensively monitoring labour outcomes and intervening timely to address negative ones, e.g. by providing displaced workers with opportunities for re-training and re-insertion.

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[1] It should be noticed that our two studies (Domini et al. 2021a, 2021b), though based on the same datasets, differ in terms of temporal (2002-2015 vs 2002-2017) and sectoral coverage (manufacturing only vs manufacturing and services), scope of the automation measure (automation only vs automation and AI), sample construction (all importing firms vs automation and AI importers only), methodology (propensity-score reweighted estimation vs event study), in addition to the variables of interest (employment growth and composition vs wage distribution). Yet their findings draw a consistent picture. In the case of both studies, a broad battery of robustness checks was performed.

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