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Automation technologies: Long-term effects for Spanish industrial firms

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ABSTRACT

The introduction of automated technologies has raised concern about how this will transform the productivity and employment. This paper examines the link among automation technologies, productivity and employment in the long-term using a panel data analysis for 5511 Spanish industrial firms. We test four different hypothesis and we show the following results: (i) the use of automation technologies predicts some of the main firm consolidated results, such as sales, added value, exports, innovation and R&D activities; (ii) although the use of robotics and flexible production systems would boost long-term productivity, computer-aided design and manufacturing, and data-driven control would either slow down or do not explain productivity. In addition, the connection between four automation technologies in the explanation of productivity has not been confirmed; (iii) the use of industrial robots, data-driven control and flexible production systems have been consolidated as a labour-reducing factor; and (iv) despite this technological labour-reducing effect, the overall complementarity factor of four automation technologies and human capital enhance long-term trend of employment. Our results highlight the importance of the implementation of new management methods based on data-driven decision making and the generation of public policies to support automation skills.

1. Introduction

Industrial robots have been present in business activity for a long time. Their link with automation technologies (i.e. robotics and artificial intelligence, big data, Internet of Things, cloud computing or 3D printing) has, recently, generated a renewed academic interest concerning how and when automation will transform the labour market and, in particular, their effects on productivity and employment (Autor, 2015; Frey and Osborne, 2017; Pratt, 2015).

Regarding productivity, the available empirical evidence suggests a clear link amongst robotic density (robots per worker or hours worked), labour productivity and economic growth in the period prior to the last economic crisis that began in 2007 (Graetz and Michaels, 2018). However, the recent declines in aggregate productivity during the last decade in the world's leading economies has, once again, opened the debate about the effects of automation and digitization on the dynamics of productivity (Byrne et al., 2016). Brynjolfsson et al. (2017) find clear similarities with the effects of previous waves of new technologies, especially in the first digital wave. Similar to other general purpose technologies (GPTs) (Bodrozic and Adler, 2018; Bresnahan and Trajtenberg, 1995; Trajtenberg, 2018), the full effects of automation will not become widespread until new waves of related technological and management innovations materialize. In particular, the authors point out the existence of clear complementarity relations with investment and innovation in intangible assets, such as R&D activities, business process redesign, organizational changes and new labour skills. In the same vein, Schuelke-Leech (2018) points out that second-order disruptive technologies, which if interconnected can lead to Kondratieff long waves, interact with a broad set of institutional, educational, financial and public policy factors.

Regarding employment, new evidence shows that, in the long term, we are not moving towards an overall substitution of jobs, but towards job polarization (Goss et al., 2014). At the same time, the interaction between automation and employment not only generates a reallocation of tasks and a displacement of occupations (particularly low-skilled workers in routine jobs), but also augments human work (especially skilled workers or new specializations within occupations) (Bessen, 2016; Ramaswamy, 2018). In this context, the existing literature has focused on understanding the scope of these labour-augmenting and labour-share-displacing processes (Karabarbounis and Neiman, 2014).

In this context of productivity mismeasurement (Brynjolfsson et al.,

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2018; Syverson, 2017) and less-augmenting and displaced labour (Autor and Salomons, 2018), firm-level literature has developed the industry 4.0 construct (hereinafter, I4.0) to study the effects of automation technologies (Lu, 2017). I4.0 is a multidimensional and constantly evolving construct used to define the current process of digital transformation in industrial firms, which evolve towards more flexible production systems, and strategic and operational decision making based on the analysis of massive data in real time (Porter and Heppelmann, 2014; Xu et al., 2018).

The literature has pointed out that I4.0 technologies are capable of generating a broad set of benefits for the industrial firm, ranging from additive manufacturing, flexible production and customized products (Brettel et al., 2014; Weller et al., 2015); the support and constant adaptation of decision-making (Brynjolfsson and McElheran, 2016; Michaels et al., 2018; Schuh et al., 2017); resources (especially energy) management efficiencies (García de Soto et al., 2018) and sustainability (Bechtsis et al., 2018; De Sousa-Jabbour et al., 2018; Jeschke et al., 2017); or new and collaborative business models, derived from horizontal integration and collaboration networks (Wei et al., 2017). However, most of the available evidence is more related to the research on the I4.0 technologies implementation factors or how I4.0 modifies the firm value generation (Frank et al., 2019; Wang et al., 2016), than with the study of I4.0 consolidated effects on firm results. In fact, the little available evidence on firm results usually works at the level of the expected benefits by the managers of the firms (Dalenogare et al., 2018).

The aim of this paper is to provide a quantitative analysis of the effects of automation technologies on the productivity and level of employment of consolidated Spanish industrial firms. To this purpose, we provide answers to the following questions: are automation technologies able to predict firm results, such as sales, value added, gross margin, exports or innovation? What is the effect of automation technologies on productivity and employment and what is the explanation of that interaction?

Our results show that the use of automation technologies predicts some of the main firm consolidated results, such as sales, added value, exports, innovation and R&D activities. However, the effects of automation technologies on firm productivity are mixed. While the use of robotics and flexible production systems boost long-term productivity, computer-aided design and manufacturing, and data-driven control do not boost productivity. In addition, and regarding employment, the use of industrial robots, data-driven control and flexible production systems are consolidated as a labour-reducing factors.

The reminder of the paper is structured as follows: Section 2 reviews the related literature and Section 3 describes the model and hypothesis and the empirical specification and data. Section 4 presents the main results for the effects of automation on productivity and employment, and Section 5 discusses and concludes.

2. Literature review

Firm productivity drivers are multiple and complex (Syverson, 2011). Over the last few years, new literature has attempted to explain the sources of firm productivity in the recent competitive environment linked to the global knowledge economy (Venturini, 2015). Regarding knowledge flows, the link between research and development (R&D) and information and communication technologies (ICT) has been identified in the literature as a set of internal knowledge externalities to explain firm productivity (Hall et al., 2013). It has been widely confirmed that R&D is crucial to improve firms' technological absorption capacity and, through ICT-related innovation, boosting their productivity levels (Doraszelski and Jaumandreu, 2013; Luintel et al., 2014).

However, ICT does not give rise to widespread productivity improvements until firms and their workers have achieved the required educational/training levels, and strategic, organizational, labour and cultural skills. To fully exploit its growth opportunities, ICT need changes in organizational and business process, generally linked to intangible assets (Brynjolfsson et al., 2017). In this context, the effects of ICT on firm productivity are indirect, especially in SMEs. Complementary relationships are established with other dimensions, in particular with employees' training and workplace innovation. These results add new evidence of a direct link between labour costs and productivity (Faggio et al., 2010; Mahy et al., 2011). Better trained, more skilled (in particular concerning digital skills) and committed workers generate greater returns for firms with regard to productivity and they obtain higher wages. These spillovers are widely demonstrated in previous research using firm-level data (for a review of this literature see Cardona et al., 2013; Díaz-Chao et al., 2015).

Beyond the interaction among the traditional dimensions of knowledge flows, the recent literature highlights the growing importance of the use of automation technologies, especially robotics and artificial intelligence (AI), in explaining sectoral and firm productivity (Brynjolfsson et al., 2018; Graetz and Michaels, 2018). This evidence connects with the new findings in the literature on firm productivity divergences, which highlights clear increases in the dispersion of productivity. The increase in the productivity gap between global frontier and laggard firms could reflect technological divergence (Andrews et al., 2016; Berlingieri et al., 2017) and suggests a new link between the automation technologies, and firm productivity.

Regarding the effects of automation on employment, on the one hand, a starting point in the literature has been the empirical verification of the jobless recovery. Since the 1990s, gross domestic product (GDP) recoveries in the US have been accompanied by weak employment growth (Brynjolfsson and McAfee, 2012). This trend, which fits with ICT-skills polarization (Michaels et al., 2014), could be explained by the relationship among digitization, business cycles and employment skills. During the recession there was a destruction of middle-skills jobs, usually linked to routine tasks, while during the recovery phase these displaced workers had great difficulties transitioning into other jobs (Goos et al., 2014).

However, new research has ostensibly nuanced the approach of jobless recovery (Graetz and Michaels, 2017). For a large sample of developed countries, industries and recent economic cycles, a recovery in employment faster than GDP is highlighted. Neither industries nor middle-skill-intensive jobs (more exposed to the impact of robotization) have experienced slower job recoveries. This suggests that automation technologies were not the cause of jobless recoveries outside the US. Indeed, complementary evidence tends to refine the jobless recovery approach. Muro and Andes (2015) certify that, despite the general trend of employment losses in the manufacturing industry, the countries with highest investment in robotics (South Korea, Japan and Germany, among others) have lost fewer industrial jobs. Likewise, industries with more intensive robotics use (automotive, electronics, metallurgy and chemistry) differ from the less intensive industries because they employ more qualified workers (20% more engineers) and pay higher wages. These results motivate the interest in studying the predictions for the Spanish case.

On the other hand, the literature has focused on routine-task and middle-skills employment substitution. Frey and Osborne (2017) estimate the probability of computerization for 702 detailed occupations in the US. According to their estimations, around 47% of total US employment (both industrial and services employees) is at high risk of automation relatively soon (at most in two decades). Along the same lines, Acemoglu and Restrepo (2017) analyse the impact of industrial robotization on local labour markets in the US. Their conclusions also reinforce the substitution hypothesis of industrial employment. Although the effects of robotization on employment appear to be much more modest than other structural industry transformations (such as offshoring, the fall in routine employment, or investment in ICT capital), their impact is negative.

However, these results do not seem to take into account the dynamic relationship among automation technologies and labour. In this context, Acemoglu and Restrepo (2018a, 2018b) have developed a much more complete framework that, based on task analysis, takes into