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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 account the dynamic relationship between technology and employment. According to this approach, automation initially replaces routine employment, which reduces employment demand and wages. But, through cost savings and capital accumulation, automation also generates productivity increases, which improves the demand for non-automated employment. Nevertheless, in the short term, these countervailing effects would be insufficient, so that gains in productivity would always be higher than wages, which determines a reduction in the share of labour in national income. For countervailing forces to be complete it is necessary to create new non-routine tasks that require or re-incorporate the workforce into new activities. In this sense and for an international sample of 40 countries, Dechezleprêtre et al. (2019) confirm the dynamic relationship between skill-based wages and innovations in automation: exogenous increases in low-skill wages lead to more automation innovations, and increases in high-skill wages tend to reduce automation innovations. Similarly, Dengler and Matthes (2018) use this approach in a task-differentiated analysis to correct the labour-reducing effect of automation technologies in Germany.

Autor and Salomons (2018) use data from 1970 on 28 industries in 18 OECD countries to analyse the effect of automation on employment and labour share. Their main result is that, during the last four decades, automation (measured through the increase of total factor productivity, TFP, or robotics adoption) has increased employment, but also has reduced the relative weight of labour on added value. Industries with persistent productivity growth have reduced, to the same extent, their labour share (direct labour-share-displacing effect). At the same time, the remaining industries have not been able to compensate for this direct effect through employment-augmenting indirect effects linked to input-output linkages, compositional shifts, or final demand increases. This result has accelerated from the 1980s and it is more substantial in the 2000s. Dauth et al. (2017) and Chiacchio et al. (2018) obtained similar evidence from German and EU-wide data, respectively. Dauth et al. (2017) found that robot adoption leads to worker reallocation (from industry to services) but has no net impact on employment or wages. Chiacchio et al. (2018) find that robotization reduces the European employment rate but do not point to robust and significant results on wage growth.

These findings indicate that automation would boost firm productivity, but regarding employment automation would become less labour-augmenting and more labour-displacing. However, previous research has mainly focused in robotics and AI at an aggregate or industry level, while research focusing in firm level analysis is quite scarce (Seamans and Raj, 2018). The recent literature on I4.0 examines the effects of automation technologies to cover this field.

From a technological point of view, it has been pointed out that I4.0 integrates traditional physical elements (such as machines or production devices) and digital elements (such as sensors and networked software), with the aim of generating data that lead to a more efficient way of firm management. These complementarities between physical and virtual environments surpass the technological dimensions and extend to all the elements of firm value processes (Szalavetz, 2019). In this sense, I4.0 can be seen as a new model of organization and management of the value chains during the life cycle of products or, even, as a collective concept that brings together new digital technologies and new ways of firm organization. Considering its technological, strategic, organizational and production complementarities, I4.0 can be interpreted as: "an integrated, adapted, optimized, service-oriented and interoperable manufacturing process that correlates with algorithms, big data and high technologies" (Lu, 2017, p. 3).

I4.0 is based on the use of digital technologies, such as Internet of Things (IoT), Internet of services (IoS), cloud computing, wireless sensor networks, or big data to collect data in real time and analyze it in order to generate useful information and improve the efficiency of manufacturing systems (Wang et al., 2016). This collection and analysis of massive data allows the creation of cyber-physical systems (CPS), and, consolidates the trend to integrated production systems and the servitization of the industry. The CPS are: "collaborating computational entities which are in intensive connection with the surrounding physical world and its on-going processes, providing and using, at the same time, data-accessing and data-processing services available on the Internet" (Monostori et al., 2016, p. 621). For example, sensor controllers or numerical control machines that exchange massive data through integrated computer terminals, wireless applications or cloud computing.

The implications of the introduction of CPS on work organization include important modifications in the role of human labour within production systems. Basically CPS: (1) combine data and information with products and physical factors of production; (2) monitor and create a virtual copy of the physical world; and (3) integrate the factory with the entire product life cycle and with the activities of the supply chains. The possibilities for autonomous and decentralized decision-making, communication and cooperation between automation technologies and people in real time, and the growing transition from products to services by all agents involved in the networks of value creation, demand new ways of organizing work. I4.0 also implies important modifications in the role that people play within the production systems. The tasks in the new value networks are carried out with smart work approaches (Longo et al., 2017; Phuluwa and Mpofu, 2018). In this sense, the intelligent work of the I4.0 reconfigure the integrated production systems, which also evolve and fit with the idea of advanced manufacturing or smart manufacturing: a new adaptable system where flexible lines automatically adjust production processes for multiple types of products and changing conditions, which improves quality, productivity and flexibility, while it helps achieving customized products on a large scale and in a more sustainable way (De Sousa-Jabbour et al., 2018).

The use of technologies, work and intelligent production ends up configuring a final dimension of I4.0: smart products. These complementarities can provide information on the development of new products/services, new solutions for customers or new opportunities for service providers (Porter and Heppelmann, 2015). Similarly, the intelligent integration of the entire value chain (smart supply chain), from supplies to distributors and end customers, allows the I4.0 firms the combination of resources and collaborative manufacturing. For example, share resources on industrial platforms, focus on their core competencies and develop complementary products/services with more added value (Tao et al., 2018; Zhong et al., 2017).

Regarding the effects of I.40 technologies on firm results, a pioneering research, using an international sample of 814 firms that have used big data and massive data analysis, obtains that the uses of I4.0 technologies are associated with productivity improvements located between 3% and 7% (Müller et al., 2018). Moreover, they conclude that the technological intensity and competitive capacity of the industrial subsector reinforce the ability of firms to improve their productivity. Outside the technology-intensive sectors or with low competitive pressure, the effects of big data technologies and massive data analysis on productivity are not significant. In the same line, Brynjolfsson and McElheran (2019) use a large sample of 7,100 US manufacturing establishments and obtain that data-driven decision making (DDD) is strongly associated with an increasing productivity, especially for early adopters when adoption rates in the sector were lower.

Expanding the number of 4.0 technologies and the scope of their results, Dalenogare et al. (2018) contrasted, for a large sample of 2,225 industrial firms in Brazil, the effects of automation on firm results. The authors analyze the effects of nine different I4.0 technologies: (1) computer-aided design and manufacturing (CAD/CAM); (2) integrated engineering systems; (3) digital automation, robotics, IoT and sensors; (4) flexible manufacturing lines; (5) digital production control systems type (i.e., ERP or MES); (6) big data; (7) digital products/services; (8) additive and 3D manufacturing; and (9) cloud computing services, and aggregate information on expected benefits in three types of firm results: (1) for the products: customization, quality and reduction of launch times; (2) for operations: operating costs, productivity, and visualization and control; and (3) side effects: sustainability and worker satisfaction. The results of the predictive analysis are mixed. They observe that only three of the nine analyzed technologies (computer-aided design and manufacturing, digital automation and big data) predict positive operational effects, while additive manufacturing predicts negative effects. The rest of I4.0 technologies do not predict expected operating benefits.

Following this literature, our study analyses long-term effects of automation technologies on productivity and employment for the Spanish manufacturing firms. For that purpose, we will use four automation technologies widely analyzed by the literature (Chen and Tsai, 2017; Dalenogare et al., 2018; Frank et al., 2019; Liao et al., 2017): (1) robotization (R), which refers to the use of industrial robots; (2) computer-aided design and manufacturing (CADM), which refers to the use of CAD or CAM technologies: (3) data-driven control (DDC), which refers to the use of machines, tools or algorithms for numerical control of the activity; and (4) flexible production systems (FPS), which refers to the use of non-standardized and high-frequency change production technologies. The postulated hypotheses, related to individual and complementarity effects, are empirically tested using a large sample of 5,511 firms in the period intervals of 1991–2016 and 2000–2016. The objective of the analysis is to capture the differential effects since the 2000s. For the best of our knowledge, it is the first quantitative paper that provides empirical evidence for industrial firms in Spain.

3. Methodology

3.1. Model and hypothesis

Adapting Van Reenen (1997), Kromann et al. (2011) and DeCanio (2016), our baseline model considers a perfectly competitive firm operating under constant returns to scale. We assume a constant elasticity of substitution (CES) production function with three perfect substitutable inputs (labour, capital and human capital) and four automation-based technologies of the form:

$$Q = \left[(RN)^{\frac{\sigma-1}{\sigma}} + (CADMN)^{\frac{\sigma-1}{\sigma}} + (DDCN)^{\frac{\sigma-1}{\sigma}} + (FPSN)^{\frac{\sigma-1}{\sigma}} + K^{\frac{\sigma-1}{\sigma}} + H^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{1}$$

where Q is firm output, N, K and H are firm labour, firm capital and firm human capital, respectively; R (robotization), CADM (computer-aided design and manufacturing), DDC (data-driven control) and FPS (flexible production systems) are labour-augmenting Harrod-neutral automation technologies, and $\sigma \in (0,1)$ is the constant elasticity of substitution between labour, capital and human capital.

We assume that robotization, computer-aided design and manufacturing, data-driven control and flexible production systems mainly give rise to an increase in *R, CADM, DDC,* and *FPS*. An increase in *R, CADM, DDC* and *FPS* implies that the same amount of labour services (*RN*), (*CADMN*), (*DDC*) and (*FPSN*) requires less amount of labour (*N*). Assuming that, in perfect competitive environments, real wage (W/P) is equal to the marginal product of labour, and the first-order condition for labour can be written as:

$$\log Q - \log N = +\sigma \log\left(\frac{W}{P}\right) - (\sigma-1)\log R - (\sigma-1)\log CADM - (\sigma-1)\log DDC - (\sigma-1)\log PFS \tag{2}$$

In the same way, in perfect competitive environments, we can assume that the marginal product of capital equals the cost of capital (C). Therefore, the first-order condition for capital can be written as:

$$\log Q - \log K = \sigma \log C \tag{3}$$

Finally, and following human capital theory, we can assume that the marginal product of human capital equals the cost of employee education and training (T). Therefore, the first-order condition for human capital can be written as:

$$\log Q - \log H = \sigma \log T \tag{4}$$

Combining these three expressions, we can obtain our employment demand function:

$$\log N = -\sigma \log\left(\frac{W}{P}\right) + (\sigma-1)\log R + (\sigma-1)\log CADM + (\sigma-1)\log DDC + (\sigma-1)\log FPS + \log K + \sigma \log C + \log H + \sigma \log T \tag{5}$$

Alternatively, the labour productivity function can be expressed as:

$$\log Q - \log N = +\sigma \log\left(\frac{W}{P}\right) - (\sigma-1)\log R - (\sigma-1)\log CADM - (\sigma-1)\log DDC - (\sigma-1)\log FPS \tag{6}$$

where the second equation terms: $-(\sigma-1)\log R$, $-(\sigma-1)\log CADM$, $-(\sigma-1)\log DDC$, $-(\sigma-1)\log FPS$, refer to the total factor productivity based on technological changes (or TFP), and the first equation term $\sigma\log(W/P)$ refers to labour deepening. When the elasticity of substitution between labour, capital and human capital is low ($\sigma < 1$) and for given real wages, labour productivity increases in *R, CADM, DDC* and *FPS*. Consequently, employment decreases as long as output (given level of production) and real wages are remain constant. The decline in employment occurs because the increase in *R, CADM, DDC* and *FPS* implies that less labour is needed to achieve a given level of labour services (*RN*), (*CADMN*), (*DDCN*) and (*FPSN*), and also because the low degree of substitution between labour, capital and human capital implies a small increase in the use of labour services. In contrast, when the elasticity of substitution is high ($\sigma > 1$), labour productivity decreases in *R, CADM, DDC* and *FPS* (for given real wages), and employment increases (for given *Q*). The reason for this is that the decrease in *R, CADM, DDC* and *FPS* implies that more labour is needed to achieve a given level of labour services (*RN*), (*CADMN*), (*DDCN*) and (*FPSN*), and, due to the shift from capital services to labour services, more labour is needed to achieve a given level of labour services.

Following Eq. (5) we can see that, for a given level of capital and human capital, real wages and user cost of capital and human capital, employment increases in *R, CADM, DDC* and *FPS* if the elasticity of substitution is high ($\sigma > 1$), but decreases if the elasticity of substitution is low ($\sigma < 1$). Therefore, the implications of automation technologies on employment are equal to the case of a given level of production (Eq. (6)). Recent empirical evidence supports that the value of σ is below 1 in the case of automation technologies (León-Ledesma et al., 2010; Harrison et al., 2014).

Thus, we can conclude that, for a given capital and human capital stock and/or for a given output stock (i.e. in the short term), the impact of automation technologies on productivity or employment depends on the size of the elasticity of substitution between labour, capital and human capital. But, in the long term, output and capitals are endogenous and it is possible to expect that robotization, computer-aided design and manufacturing, data-driven control and flexible production systems would reduce the marginal costs of production, which could encourage investment, productivity and output. Depending on the elasticity of demand, this improvement in the economic activity could increase employment in the long term. Hence, despite the fact that automation technologies tend to reduce employment in the short term, it may be the case that in the long term this trend will reverse (Acemoglu and Restrepo, 2018b; Autor and Salomons, 2018; Brynjolfsson and McElheran, 2019). If the increase in output is high enough, the net long-term effect of automation technologies on employment could be positive. In this sense, it is possible to postulate that:

Hypothesis 1. Automation technologies increase labour productivity in the long term (non-given capitals and/or non-given output stock). This hypothesis only requires that the elasticity of substitution between labour, capital and human capital is below 1.

Hypothesis 2. Automation technologies increase employment in the long run. This hypothesis suggests significant employment creation in the long term, which would compensate the short-term reduction in jobs.

However, similar to the link established between intangible assets, such as human capital and workplace innovation, and ICT uses in the first digital wave (Venturini, 2015), we expect that automation technologies are related one with each other and their use is linked with different types of firm knowledge flows, especially with human capital and training. Therefore, we extend our basic model to evaluate the complementarity effects of automation technologies on firm productivity and employment. The conditions of (long-term) flexibility of output, capitals, real wages and user costs of capital and human capital are established as in the previous model. It is possible to expect that complementarities among automation technologies reduces the marginal costs of production, reinforces productivity and increases the demand of firm's output (Müller et al., 2018; Dalenogare et al., 2018). In this situation, the displacing effect on employment in the short term would be clearly accelerated by the increases in output and human capital over the long term (Brynjolfsson et al., 2018; Dechezleprêtre et al., 2019; Longo et al., 2017). In order to accomplish this long-term analysis, we propose two additional hypotheses:

Hypothesis 3. The complementarity effect among robotization, computer-aided design and manufacturing, data-driven control and flexible production systems increases productivity in the long term.

Hypothesis 4. The complementarity effect of automation technologies and human capital increases employment in the long term.

3.2. Estimation functions and methods

We estimate the relationship among automation technologies, labour productivity and employment using two types of models. The first model estimates the individual effects of unit labour cost and automation technologies on productivity and employment (together with capital per worker and human capital). The second model estimates the complementarity effects among automation technologies on productivity (together with the individual effect of unit labour cost) and the complementarity effects among automation technologies and human capital on employment (together with the individual effects of unit labour cost and capital per worker).

As we have explained in previous sections, we expect that the effects of automation technologies on productivity and employment depend on time. We estimate long-term effects in log-levels and we assume that firm differences in log-levels reflect the differences in productivity and/or employment in the long term. The stochastic equations of productivity (derived from Eq. (6)) and employment (derived from Eq. (5)) in the long term to explain individual effects take the following form, depicted in Eqs. (7) and (8):

$$q_{it} - \eta_{it} = \beta(w-p)_{it} + \mu R\&D_{it} + \alpha R_{it} + \lambda CADM_{it} + \theta DDC_{it} + \varphi FPS_{it} + \pi_{se} + \pi_{si} + u_{it} \tag{7}$$

$$\eta_{it} = -\beta(w-p)_{it} + \gamma k_{it} + \mu h_{it} + \mu R\&D_{it} + \alpha R_{it} + \lambda CADM_{it} + \theta DDC_{it} + \varphi FPS_{it} + \pi_{se} + \pi_{si} + \varepsilon_{it}, \tag{8}$$

where lower case letters denote logs and π_{se} and π_{si} are sector and size firm dummies. These dummies control for the unobserved heterogeneity in the manufacturing sector and firm size. Remember that R_{it}, $CADM_{it}$, DDC_{it} and FPS_{it} represent the use of industrial robots, computers-aided design and manufacturing, data-driven control and flexible production systems for firm i in period t. Note that $(w-p)_{it}$ refers to the real labour unit cost, and capital (k_{it}) and human capital (h_{it}) are also captured. As a result of the importance of R&D activities as a driver of technological change processes and as an agent for improving firm performance, especially productivity, and additional variable ($R\&D_{it}$) has been incorporated into the functions to be estimated (Coccia, 2009; Hall et al., 2013; Luintel et al., 2014). In Eq. (5) the uses of both the cost of capital (*log C*) and the cost of human capital (*log T*) affect labour demand. But, where there are differences in the user cost of capital and human capital across manufacturing sectors or firm size, these factors are captured by the fixed effects. This implies that their differences are constant over time. Also, u_{it} and ε_{it} are white noise terms.

Eqs. (9) and (10) depict the productivity and employment functions with two complementarity effects. Eqs. (11) and (12) depict the productivity and employment functions with four and five complementarity effects:

$$q_{it} - \eta_{it} = \beta(w-p)_{it} + \mu R\&D_{it} + \alpha_1 RCADM_{it} + \alpha_2 RDDC_{it} + \alpha_3 RFPS_{it} + \alpha_4 CADMDDC_{it} + \alpha_5 CADMFPS_{it} + \alpha_6 DDCFPS_{it} + \pi_{se} + \pi_{si} + u_{it} \tag{9}$$

$$\eta_{it} = -\beta(w-p)_{it} + \gamma k_{it} + \mu R\&D_{it} + \alpha_1 RCADM_{it} + \alpha_2 RDDC_{it} + \alpha_3 RFPS_{it} + \alpha_4 CADMDDC_{it} + \alpha_5 CADMFPS_{it} + \alpha_6 DDCFPS_{it} + \alpha_7 RH_{it} + \alpha_8 CADMH_{it} + \alpha_9 DDCH_{it} + \alpha_{10} RFPSH_{it} + \pi_{se} + \pi_{si} + \varepsilon_{it} \tag{10}$$

$$q_{it} - \eta_{it} = \beta(w-p)_{it} + \mu R\&D_{it} + \alpha AUTOM_{it} + \pi_{se} + \pi_{si} + u_{it} \tag{11}$$

$$\eta_{it} = -\beta(w-p)_{it} + \gamma k_{it} + \mu R\&D_{it} + \alpha_1 AUTOMH_{it} + \pi_{se} + \pi_{si} + \varepsilon_{it} \tag{12}$$

Two-complementarity effects are: *RCADM* (robotization and computer-aided design and manufacturing), *RDDC* (robotization and data-driven control), *RFPS* (robotization and flexible production systems), *CADMDDC* (computer-aided design and manufacturing, and data-driven control), *CADMFPS* (computer-aided design and manufacturing, and flexible production systems), *DDCFPS* (data-driven control and flexible production systems), *RH* (robotization and human capital), *CADMH* (computer-aided design and manufacturing, and human capital), *DDCH* (data-driven control and human capital), and *FPSH* (flexible production systems and human capital). Finally, the four-complementarity and five-complementarity effects in the productivity and employment equations are: *AUTOM* (robotization, computer-aided design and manufacturing, data-driven control and flexible production systems) and *AUTOMH*, which refers to the complementarity effect between the four technologies of automation and human capital.

The provision of an annual series for a long period of time has allowed us to address the estimation of explanatory factors for the manufacturing firms' long-term productivity and employment. With this objective in mind, we have constructed the arithmetic means of the variables and indicators for the two established estimation periods. The first period corresponds to the available set of data and covers from 1991 to 2016. As a result of the progressive adaptation of the information source to the business context, we have built a second estimation period that covers from 2000 to 2016. In this second period, the indicators related to the manufacturing firms' digitization process are incorporated. The estimation of the hypothesized functions has been carried out using Ordinary Least Squares (OLS) regression methods. To capture the effects of automation technologies on some firm results, we have also performed statistical association analysis and multivariate predictive studies (continuous and discrete choice models).

3.3. Information source

The information source used for the analysis is the *Encuesta sobre Estrategias Empresariales* (Business Strategy Survey, ESEE). The ESEE is an annual survey of Spanish manufacturing firms conducted by the Spanish Government's Ministry of Finance and Public Administration. The questionnaire, answered by the general management of the firm, provides detailed information on businesses, especially in the areas of strategic decision-making (prices, costs, markets and investment) and the value process (human capital, organization, innovation, R&D and ICT use). In addition, the most important indicators and ratios from firms' balance sheets and profit and loss accounts are presented. In this context, it is important to stress that the ESEE provides panel data representing Spanish manufacturing businesses covering a broad period from 1990 to 2016 (last available year). Consequently, this panel data permits a very detailed study of the microeconomics of productivity and employment as well as the analysis of changes in Spanish manufacturing firms during various stages of the business cycle (Torrent-Sellens, 2018).

The ESEE contains segmented information for manufacturing firms with more than 200 workers (large firms) and firms with 10 to 200 workers (SMEs). As a result of the data collection, SMEs are classified differently to the European Commission's definition (European Commission, 2012). In the case of the ESEE, the limit used to define an SME is 200 employees, while the European Commission uses a maximum size of 250 workers. This difference is due to the sampling procedure used by the ESEE. In this survey, all large manufacturing firms (more than 200 workers) are included in the sample. However, for SMEs (from 10 to 200 workers), stratified, proportional and systematic sampling is used by industries (national economic activity two-digit classification code, NACE) and size of the firm. The sampling excludes manufacturing micro-firms, i.e. firms with less than 10 workers.

The ESEE also provides detailed information for 20 manufacturing branches of activity: (1) meat industry; (2) food products and tobacco; (3) beverages; (4) textiles and clothing; (5) leather and footwear; (6) wood industry; (7) paper industry; (8) graphic arts; (9) chemical industry and pharmaceutical products; (10) rubber and plastic products; (11) non-metallic mineral products; (12) ferrous and non-ferrous metals; (13) metal products; (14) agricultural and industrial machinery; (15) computer, electronic and optical products; (16) machinery and electrical equipment; (17) motor vehicles; (18) other transport material; (19) furniture industry; and (20) other manufacturing industries.

Appendix A presents detailed information on the structure (size: Table A.1; and industries: Table A.2) of the sample of firms used. The analysis of the panel data over time suggests a growing presence of smaller firms (from 63.3% of SMEs in 1991 to 81.0% of SME in 2016) and a notable reorientation of the industrial branches of activity. While in 1991 six industries each accounted for more than 7% of the number of firms in the sample: textile and clothing (11.3%), food and tobacco (10.4%), metal products (7.6%), chemical and pharmaceuticals (7.4%), non-metallic mineral (7.2%) and machinery and electrical equipment (7.1%), in 2016, specialization had increased significantly and only three industries accounted for 7% or more of the total number of firms: food and clothing (13.5%), metal products (12.7%), and chemical and pharmaceuticals (7.0%).

3.4. Variables and indicators

The dependent variables of the analysis are labour productivity and employment in manufacturing firms, that we have approximated using the logarithm of real added value per hour worked (HPT) and the logarithm of the total staff employed (all contracts) in the firm (EMPL).

To capture the use of automation technologies, we use four dichotomous variables that take value 0 when the firm does not use them, and take value 1 when firm uses them: (1) robotization (R); (2) computer-aided design and manufacturing (CADM); (3) data-driven control (DDC); and (4) flexible production systems (FPS). Despite the obvious restrictions that using dichotomous variables imply, their incorporation to the predictive model allow us to make a relevant contribution: we are able to assess the impact on firm productivity and employment when moving from an scenario where automation technologies are not used to an scenario where these automation technologies are used. Moreover, the analysis of their complementary relationships will allow us to study their combined effects on productivity and employment. In this sense, we have constructed six additional variables that collect the pairs-complementarity between the four automation technologies, and four more variables that include the pairs-complementarity between the technologies of automation and human capital. We have also built a joint indicator of automation technologies (AUTOM) and its complementarity with human capital (AUTOMHC). All these complementarity relationships have been calculated through the multiplication of the input variables, with the objective of capturing which firms use jointly the identified technologies.

Real wages were approximated using an indicator of labour costs per worker (LCW), the capital stock of the firm was approximated using the logarithm of financial assets per worker (KW), and the human capital stock of the firm (HC) was measured using the logarithm of the percentage of employees with tertiary (university) education (bachelor's degree level and higher). R&D activities have been captured through a dichotomous variable (R&D) that takes value 0 when the firm neither performs nor contracts R&D activities, and takes value 1 when the firm carries out and/or contracts R&D activities.

Regarding the sectoral (π_{se}) and size (π_{si}) dummies, we have constructed four additional variables that capture the non-observed heterogeneity in the models. From the average values of productivity, R&D expenditure and proportion of employees with university education we have constructed three dichotomous variables that assign value 1 to the manufacturing sectors with values of productivity, R&D spending and university training of employees above the average, and value 0 otherwise. Once these dichotomous variables were obtained, we have multiplied them by the firm size variable, which takes value 0 for firms with 200 employees or less on average in the reference period, and value 1 in the case of firms with more than 200 employees on average in the reference period.

As a result of these combinations we obtain the following three variables: (1) LAR_EF (large and efficient firms) identifies large firms located in manufacturing sectors with above-average productivities; (2) LAR_HC (large firms with intensity in human capital) identifies large firms located in manufacturing sectors with an above-average number of employees with university education; and (3) SME_R&D (SMEs with R&D intensity) identifies small and medium-sized firms (SMEs) located in manufacturing sectors with above-average R&D expenditure.

All the variables and indicators expressed in nominal terms have been deflated using a Paasche index referred to the prices variation of intermediate consumption. This index has been built on two groups of goods: producer goods and energy and services acquired. Since we did not have the relative weights of producer goods and energy we have added the variation of these two components using a geometric mean with fixed weights. In this sense, the price index of intermediate consumption would take the following form:

$$PI_{INTCON}(t) = \frac{V_{PGE}(t)}{V_{INTCON}(t)} PI_{PGE}(t) + \frac{V_{SER}(t)}{V_{INTCON}(t)} PI_{SER}(t), \tag{14}$$

where $PI_{INTCON}(t)$ is the price index of intermediate consumption in period t (to be calculated); $V_{PGE}(t)$ is the value of the purchases consumed in period t; $V_{INTCON}(t)$ is the value of the intermediate consumption in period t; $PI_{PGE}(t)$ is the price variation of producer goods and energy between t-1 and t obtained as $PI_{PGE}(t) = [(PI_{PG}(t)]^{0,95} x\ [(PI_E(t)]^{0,5}$, where PI_{PG} and PI_E are the price indices of producer goods and energy provided by the firm; $V_{SER}(t)$ is the value of the services acquired in period t; and PI_{SER} is the price index of the services acquired in the period t-1 and t. Appendix B (Table B.1) presents the descriptive statistics of the variables and indicators used in the analysis.

4. Results

4.1. Descriptive statistics

Table 1 and Fig. 1 show some of the main statistics describing the value process and the results for the Spanish manufacturing firms. Firstly, it is important to note the clear diverging trend of productivity and employment in the analysed period. While real worked-hourly productivity grew by 3.2% on average in the period 1991–2016, employment fell by 2.0%. If we index the data in base 100 at the beginning of the period (1991) and calculate their evolution, the results show us that productivity would not have stopped growing (until reaching a

Table 1
ANOVA and crosstab analysis for manufacturing firms, based on the use of industrial robots.

	1991–2016			2000–2016		
Variable/indicator	Non-robotized	Robotized	All	Non-robotized	Robotized	All
Firm outputs						
Sales (thousands of euros)	15,382	83,071	40,341***	19,159	92,524	47,900***
Added value (thousands of euros)	4,171	19,749	9,918***	4,845	20,702	11,057***
Exports (thousands of euros)	4,455	31,824	14,509***	6,282	38,049	18,716***
Firm inputs						
Capital per employee (thousands of euros)	50.5	83.8	62.9***	63.7	99.6	77.9***
Tertiary education of labour (% employees)	10.3	14.2	11.7***	11.9	15.3	13.3***
External exp. training per worker (euros)	–	–	–	57.9	114.1	79.8***
R&D expenditure (thousands of euros)	152.5	1,128	510.6***	229.1	1,285	641.9***
Innovation (% firms)						
Product innovation (%)	23.5	**23.5**	47.0***	19.1	**21.5**	40.6***
Process innovation (%)	35.3	**30.9**	66.2***	32.9	**31.3**	64.2***
Product and process innovation (%)	18.2	**22.3**	40.5***	14.9	**19.9**	34.8***
E-commerce (% firms)						
B2B: digital purchases from suppliers (%)	–	–	–	25.6	**23.7**	49.3***
B2C: sales to end consumers (%)	–	–	–	8.0	**7.5**	15.5***
B2C: sales to firms (%)	–	–	–	8.1	**9.9**	18.0***
Productivity and employment						
Productivity (thousands of euros per worker)	34.7	50.2	40.5***	40.6	55.6	46.5***
Productivity (euros per hour worked)	19.7	28.7	23.0***	23.1	31.8	26.5***
Employees (number)	90.6	338.3	181.3***	88.7	310.1	175.3***
Labour cost (thousands of euros)	2,741	12,211	6.233***	3,219	12,498	6854***
Labour cost per worker (euros)	24,855	31,283	27,225***	28,763	34,329	30,943***
Labour cost / added value (%)	65.7	61.8	62.8**	66.4	60.3	62.0**
N (firms)	3,492	2,019	5,511	2,495	1,604	4,099
% (firms)	63.4	36.6	100.0	60.9	39.1	100.0

Notes: Data in euros and thousands of euros in real terms. The data of robotics use are captured for every 4 years: 1990, 1994, 1998, 2002, 2006, 2010 and 2014. To obtain the 1991–2016 and 2000–2016 means, we have updated the quadrennial data with the information on robotic uses for the new firms incorporated into the panel annually. Statistical association analysis: ANOVA for continuous variables and comparison of means (crosstabs) for discrete or dichotomous variables. * $p < 0.1$; ** $p < 0.05$, *** $p < 0.01$. In bold, the percentage of firms higher than expected using normal distribution: standardized corrected residual for counting ≥ 1.9.

value of 180.3 points in 2016), while employment would have been reduced about half (50.6 points in 2016).

Regarding automation technologies, and with the aim of providing more information to international firm evidence, we have segmented the sample of firms through the uses of industrial robots (robotized firms versus non-robotized firms). In this sense, a very similar evolution of productivity is observed, with a gap that has been reduced during the last ten years. In contrast, employment dynamics have offered ambiguous results. Until 2007, the evolution of employment was clearly less negative in robotized firms. However, during the last decade the robotized firm labour-reducing trend has accelerated, reaching a minimum of less than 300 employees on average in 2016 (compared to more than 600 in 1991). In contrast, non-robotized firms have evolved less negatively in recent years (since 2008 their employment has stabilized at just under 80 employees on average).

As a result of the similar evolution of productivity and the clearly differentiated dynamics of employment, it is possible to point out that the jobless recovery has been much more intense in robotized firms, especially since 2007. The gap between the growth of productivity and employment has sharply accelerated during the last decade, especially for robotized firms (more than 140 percentage points of difference in 2016).

To contrast the existence of significant differences between robotized and non-robotized firms, we have carried out various statistical association tests (ANOVA and Crosstabs). The use of industrial robotics in Spanish manufacturing firms has evolved positively (from 17.7% in 1990 to a mean average of 39.1% in the period 2000–2016). The characterization of robotized firms by size and industries (see Table A.3 of Appendix A) indicates a significant presence in the largest firms and in a few industries, especially food and tobacco, chemical and pharmaceuticals, metallurgy, ICT and electronics and automotive industries.

Secondly, it should also be noted that the use of industrial robots is associated with better firm results. From 1991 to 2016, firms that used robots presented sales levels five times higher than that of firms that did not use robots, as well as an added value and exports clearly higher on average. In the same way, robotized firms stand out for being much better capitalized, having a greater presence of human capital and for clearly higher R&D expenditure.

Thirdly and regarding productivity, robotized firms are more efficient and reward and train the labour factor with greater intensity than firms that do not use robots. Nevertheless, since the 2000s, the acceleration of productivity growth in non-robotized firms has reduced the gap between the efficiency levels of robotized and non-robotized firms. Especially interesting is the analysis of the labour share on added value. Our data also confirm the labour-displacing approach. Between 1991 and 2016, the percentage of the unit labour cost over the real added value of robotized firms stood at 61.8%, below that of non-robotized firms (65.7%). This labour-displacing effect has been accentuated since the 2000s (60.3% for robotized firms and 66.4% for non-robotized firms between 2000 and 2016, respectively). Finally, robotized firms are more intensive in innovation activities and the use of ICT-related technologies. However, since the 2000s, the innovative dynamics have also slowed down.

4.2. Predictive analysis

We have analysed the predictive capacity of the four automation technologies identified: industrial robots, computer-aided design and manufacturing, data-driven control and flexible production systems on some of the main firm results: sales, added value, exports, gross margin, product innovation, process innovation and R&D activities. Following the research methodology on the effects of automation on firm results (Dalenogare et al., 2018; Brynjolfsson and McElheran, 2019; Dechezleprêtre et al., 2019), we have contrasted four estimation models by OLS and three discrete choice estimation models by Binary Logit. The variables to be explained are the indicators of firm performance, expressed in logistic averages (real terms for continuous variables, and dichotomous form for innovation and R&D variables), and the explanatory variables are the four automation technologies and the size and industry dummies. Table 2 shows the results obtained.

OLS regression should be used only if some standard requirements of the data are achieved, such as normality, linearity, and homoscedasticity (Hair et al., 2010). The skewness and kurtosis values (reported in Appendix B: Table B.1) suggest that the variables can be assumed to be normal distributed (below the threshold of 2.58). Multicollinearity diagnoses have been addressed testing tolerance and variance inflation factor (VIF) among the explanatory variables. Given that all these values were below the threshold tolerance = 0.10 and VIF = 10.0, multicollinearity may not be a concern in our regression models (correlation matrix is presented in Table B.2 of Appendix B). Finally, homoscedasticity was visually examined and tested in plots of standardized residuals against predicted value and with Durbin–Watson test ($1.5 < DW < 2.5$). We performed four independent regression models, one for each of the firm results. Four models were significant ($p = = 0.000$) and explained almost 60% of the variance of the firm results variables.

The coefficients obtained suggest significant contributions from robotics, data-driven control and flexible production systems in explaining firm results. The marginal effects on sales, added value and export levels of one more robotized firm are 0.168, 0.151 and 0.140 percentage points, respectively. The marginal effects on sales, added value and export levels of an additional firm using data-driven control technologies are 0.104, 0.098, and 0.041 percentage points, respectively. And, the marginal effects on sales, added value and export levels of an additional firm using flexible production systems are 0.102, 0.109 and 0.077 percentage points, respectively. On the contrary, computer-aided design and manufacturing only has a significant effect on the explanation of added value (0.033 percentage points). The marginal effects of automation technologies on gross margin are much weaker: 0.030 ($p < 0.1$) percentage points for the use of industrial robots, and 0.037 ($p < 0.05$) for the flexible production systems.

In order to test the effects of automation technologies on the innovation and R&D activities, a binary logistic regression analysis was also performed. The goodness of fit of the three models was high, as confirmed by the values and levels of significance reached by the Chi-square statistics and the Hosmer-Lemeshow test ($p < 0.05$). Moreover, the values of Nagelkerke's statistic indicated that the three models had explanatory power. The value of this statistic was 18.1% for the product innovation model, 22.5% for the process innovation model and 32.4% for the R&D activities model.

Regarding automation technologies, we obtain the Odds Ratio (OR) coefficients (or Exp (β)). Formally, it is usually defined as the ratio of the odds of a condition occurring in a population group to the odds of it occurring in another group. It is a measure of the statistical association between dichotomous variables, which has been widely used because it is useful for examining the predictive effect of one variable on another,

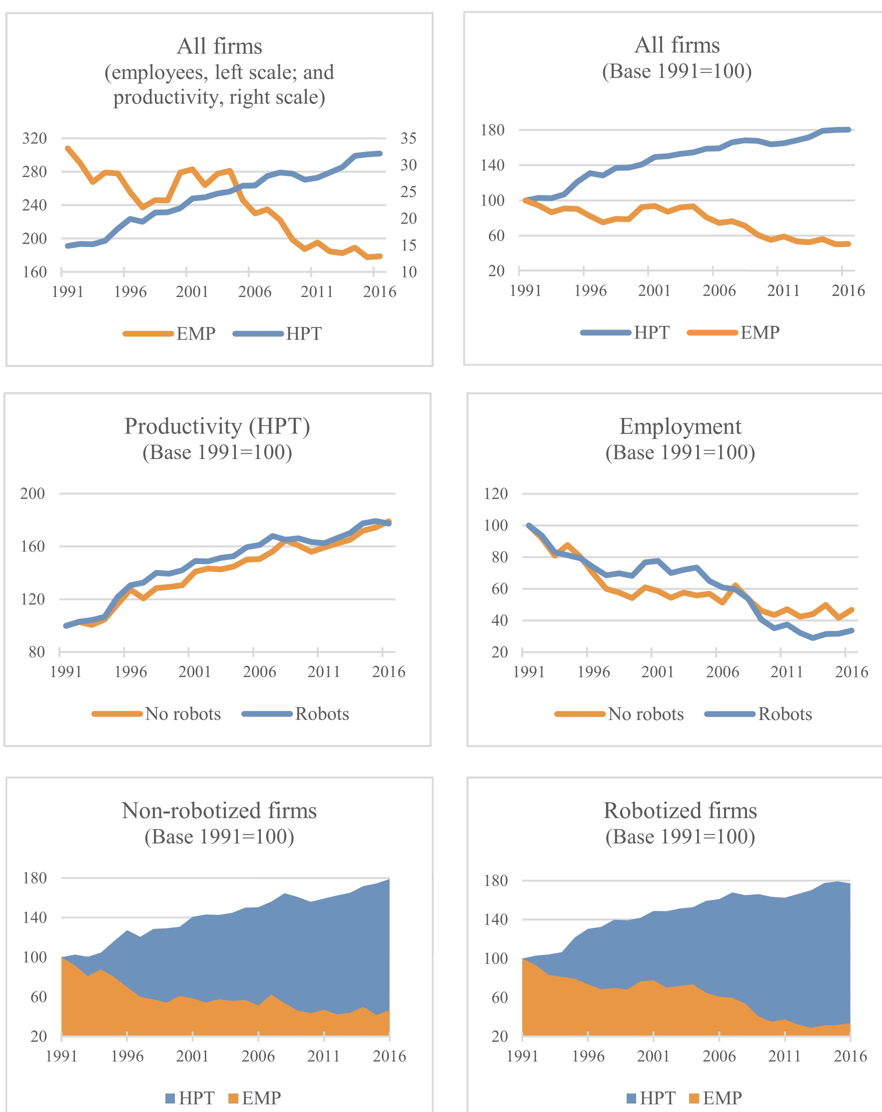

Fig. 1. Productivity (HPT: real added value per hour worked) and employment (EMP: employee average) dynamics in Spanish manufacturing firms. 1991–2016.

while the other variables remain constant (*ceteribus paribus*) in a logistic regression model. The interpretation of an OR analysis is as follows. If the value of the OR is less than 1 and the confidence interval (95% CI) is situated below the unit, the predictive relationship between the two variables analysed is an inverse relationship. If the value of the OR is greater than 1 and the confidence interval (95% CI) is situated above the unit, the predictive relationship between the two variables analysed is a direct relationship. Whenever the confidence interval (95% CI) includes the unit, the predictive relationship between two variables cannot be determined (Green, 2012; Hensher et al., 2015).

The results obtained confirm a high prediction capacity of automation technologies on innovation and R&D activities. The use of robots and flexible production systems show high predictive capacity for product innovation (OR = 1.664 and OR = 1.569, respectively), process innovation (OR = 2.009 and OR = 2.215) and R&D activities (OR = 1.905 and OR = 1.861). Otherwise, computer-aided design and manufacturing shows better predictive capacity for R&D activities (OR = 2.031). Finally, data-driven control predicts process innovation more intensely (OR = 1.595).

4.3. Individual effects on productivity and employment estimation

Concerning the analysis of the explanatory factors (individual and complementary) of productivity and employment for Spanish industries, and following the methodology of recent international research (Acemoglu and Restrepo, 2018b; Autor and Salomons, 2018; Brynjolfsson and McElheran, 2019), we have estimated the effects of automation technologies through multivariate regression analysis by OLS (introduction method). Table 3 presents the individual effects of estimating the long-term trend of productivity level (worked-hourly productivity, HPT). Consistent with Eq. (7), the first column (Model 1) analyses the effects of labour costs per worker on productivity. The second column (Model 2) analyses the effects of R&D activities. In the third column (Model 3), the effects of use of automation technologies (robots, computer-aided design and manufacturing, data-driven control and flexible production systems) are incorporated. And, in the fourth column (Model 4), size and industry dummies are also integrated.

The effects of automation technologies on hourly-worked productivity are mixed. While the uses of industrial robots and flexible production systems have a significant and positive effect, the use of computer-aided design and manufacturing has a negative effect. Data-driven control does not exert a significant effect. These individual effects are robust (increases in the change of adjusted R^2 and models p-value = 0.000) to the inclusion of labour cost per worker, R&D activities and size and industry dummies as explanatory variables. Tests to see if the data met the assumption of collinearity indicated that multicollinearity was not a concern (for all explanatory variables and indicators, Tolerance > 0.10 and VIF < 10; correlation matrix is presented in Table B.2 of Appendix B). Also, the data met the assumption of independent errors (Durbin–Watson values between 1.5 and 2.5).

This is evident through column analysis. Jointly the unit labour cost, R&D activities and the size and industry dummies have significant impacts with the expected signs. However, the unit labour cost and R&D coefficients tend to fall as we incorporate more variables to the regression (Models 3 and 4, compared with Model 1 and 2). In the same way, the automation technologies coefficients tend to decrease when the size and industry dummies are incorporated (Model 4 compared to Model 3).

The reduction in the unit labour cost coefficient is related to the type of investment and efficiency model of the technology-driven firms.

Table 2
Predicted effects of automation technologies in Spanish manufacturing firms. 1991–2016.

	OLS estimation				Binary logistic estimation		
	Sales	Added value	Exports	Gross margin	Product innovation	Process innovation	R&D activities
(Constant)	6.200***	5.735***	5.356***	1.961***	0.372***	0.676***	0.289***
	(0.012)	(0.011)	(0.029)	(0.021)	(0.049)	(0.047)	(0.052)
Use of robots (R)	0.168***	0.151***	0.140***	0.030*	1.664***	2.099***	1.905***
	(0.018)	(0.016)	(0.036)	(0.030)	(0.068)	(0.079)	(0.072)
CAD/CAM (CADM)	0.008	0.033***	0.015	0.007	1.472***	1.363***	1.595***
	(0.018)	(0.016)	(0.036)	(0.029)	(0.067)	(0.073)	(0.070)
Data-driven control (DDC)	0.104***	0.098***	0.041**	0.025	1.243***	2.031***	1.278***
	(0.018)	(0.017)	(0.038)	(0.030)	(0.067)	(0.068)	(0.071)
Flexible production systems (FPS)	0.102***	0.109***	0.077***	0.037**	1.569***	2.215***	1.861***
	(0.018)	(0.016)	(0.036)	(0.031)	(0.068)	(0.078)	(0.071)
Large & efficient ind. (LAR_EF)	0.059***	0.121***	0.058**	0.090***	0.665**	0.686*	0.809
	(0.042)	(0.037)	(0.075)	(0.071)	(0.176)	(0.213)	(0.212)
Large & HC ind. (LAR_HC)	0.548***	0.542***	0.356***	0.028	2.954***	1.798***	5.435***
	(0.031)	(0.027)	(0.056)	(0.051)	(0.134)	(0.161)	(0.167)
SMEs in R&D ind. (SMEs_R&D)	0.018	0.048***	−0.107***	0.092***	0.743*	0.755	0.397***
	(0.039)	(0.035)	(0.071)	(0.066)	(0.167)	(0.206)	(0.227)
Statistics							
N (observations)	5,426	5,414	3,750	4,692	5,492	5,492	5,492
Adjusted R^2	0.564	0.602	0.360	0.111			
Estimation SE	0.549	0.483	0.949	0.864			
F value	1004	1173	301.9	8.748			
p value	0.000	0.000	0.000	0.000			
Durbin-Watson	1.624	1.606	1.736	1.993			
Nagelkerke R^2					0.181	0.225	0.324
Chi^2					802.1	971.6	1526
Prob. > Chi^2					0.000	0.000	0.000
Log-likelihood					6,790	6,052	6,080
p value Hosmer-Lemeshow					0.046	0.017	0.000

The data of automation technologies use are captured for every 4 years: 1990, 1994, 1998, 2002, 2006, 2010 and 2014. To obtain the 1991–2016 and 2000–2016 means, we have updated the quadrennial data with the information on automation technologies use for the new firms incorporated into the panel annually. OLS estimation: Data in real monetary log-levels. Estimated coefficients: Standardized coefficients. Standard errors of the non-standardized effects in brackets. Binary logit estimation: Data in dichotomous form: 1, innovation or R&D activities, and 0 not innovation or not R&D activities. Estimated coefficients: Exp(β) or Odds Ratio (OR). Standard errors of the β effects in brackets.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Automation technologies generate a smaller effect of the labour cost in the productivity explanation, which already starts suggesting that there exists a labour-share-displacing effect. On the other hand, the reduction in the coefficient of R&D activities suggests a certain technological displacement effect. As firms use automation technologies, the role of previous R&D activities as productivity drivers is reduced. In the same way, the introduction of size and industry dummies reflects the heterogeneity of the firm. Large firms located in human capital-intensive industries and SMEs located in R&D-intensive industries tend to be more efficient by themselves, which reduces the effects of labour cost, R&D and automation technology on productivity.

Especially interesting is the comparison of results between the two constructed data series: 1991–2016 and 2000–2016. With this comparison, we capture the differential effects on productivity from the 2000s. For the sake of simplicity we focus on the model that incorporates all the explanatory variables into the analysis (Model 4). The results obtained confirm significant and mixed effects from automation technologies on productivity. From 1991 to 2016, the marginal effect on worked-hourly productivity level of one more robotized firm is 0.057 percentage points, and an additional firm that use flexible production systems boosted worked-hourly productivity by 0.033 percentage points. These results have accelerated since the 2000s. From 2000 to 2016, the marginal effect on worked-hourly productivity level of one more robotized firm is 0.064 percentage points, and an additional firm using flexible production systems boosted worked-hourly productivity by 0.039 percentage points.

Similarly, the contribution of R&D activities has also accelerated since the 2000s (from 0.056 percentage points in the period 1991–2016 to 0.076 percentage points in the period 2000–2016). Contrary to what was expected, the use of computer-aided design and manufacturing, and data-driven control technologies did not have a significant or positive effect on the explanation of productivity (the former with a significant and negative effect that has accelerated since the 2000s, and the latter with a non-significant effect in the two periods analysed). Finally, there was also a greater labour-displacing effect. An additional real euro of labour cost per employee increased worked-hourly productivity by 0.679 percentage points between 2000 and 2016, compared to 0.739 percentage points in 1991–2106.

Table 4 presents the individual effects from estimating the long-term trend of employment level. Unlike the increasing trend in the worked-hourly productivity level, the interpretation of results in the estimation of employment is the opposite. As we have already pointed out in the descriptive results subsection, industrial employment has clearly evolved downwards during the periods analysed. Therefore, a positive coefficient implies a positive contribution to the declining trend of employment (i.e. a positive coefficient implies a decrease in employment), while a negative coefficient implies a negative contribution to the downtrend in employment (i.e. a negative coefficient implies an increase in employment). Consistent with Eq. (8), the first column (Model 1) analyses the effects of labour costs per worker, capital per worker (financial assets per employee) and human capital per worker (percentage of employees with tertiary education) on employment. The second column (Model) 2 integrates the effects of R&D activities. In the third column (Model 3), the effects of automation technologies are incorporated. And, in the fourth column (Model 4), size and industry dummies are also integrated.

Contrary to expectations, the use of automation technologies significantly decreases the employment level (positive contribution to the downtrend in employment). These individual effects are robust (increases in the change of adjusted R^2 and models p-value = 0.000) to the inclusion of labour cost per worker, capital per worker, human capital per worker, R&D activities and size and industry dummies as explanatory variables. The multicollinearity (for all explanatory variables and indicators, Tolerance > 0.10 and VIF < 10; correlation matrix is presented in Table B.2 of Appendix B) and error independence (Durbin-Watson values between 1.5 and 2.5) tests confirm the validity of the proposed model.

Both the unit labour cost and human capital per worker have significant impacts and with the expected signs: the higher the labour cost, the less employment; and the more tertiary education, the greater the employment. However, the capital per worker, R&D activities and the dummies do not behave as expected: the more capital per worker, the less employment, and an additional firm that carries out R&D activities, less employment. Large firms located in efficient and human capital-intensive industries, and SMEs located in R&D-intensive industries tend to be less labour-intensive.

Table 3
Labour productivity (added value per hour worked, HPT), individual explanatory factors in Spanish manufacturing firms. 1991–2016 and 2000–2016.

	1991–2016				2000–2016			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
(Constant)	−3.448***	−3.316***	−3.247***	−3.205***	−3.592***	−3.351***	−3.284***	−3.230***
	(0.050)	(0.052)	(0.054)	(0.056)	(0.071)	(0.075)	(0.076)	(0.079)
Labour cost/worker (LCW)	0.785***	0.759***	0.746***	0.739***	0.738***	0.699***	0.688***	0.679***
	(0.012)	(0.012)	(0.013)	(0.013)	(0.016)	(0.017)	(0.017)	(0.018)
R&D activities (R&D)		0.080***	0.060***	0.056***		0.101***	0.084***	0.076***
		(0.005)	(0.006)	(0.005)		(0.005)	(0.005)	(0.006)
Use of robots (R)			0.062***	0.057***			0.071***	0.064***
			(0.006)	(0.006)			(0.006)	(0.006)
CAD/CAM (CADM)			−0.044***	−0.042***			−0.059***	−0.056***
			(0.006)	(0.006)			(0.006)	(0.006)
Data-driven control (DDC)			0.013	0.014			0.010	0.011
			(0.006)	(0.006)			(0.006)	(0.006)
Flexible production systems (FPS)			0.037***	0.033***			0.041***	0.039***
			(0.006)	(0.006)			(0.007)	(0.007)
Large and HC industry (LAR_HC)				0.072***				0.079***
				(0.008)				(0.009)
SMEs in R&D industry (SMEs_R&D)				0.061***				0.060***
				(0.011)				(0.013)
Statistics								
N (observations)	5,407	5,407	5,407	5,407	4,060	4,060	4,060	4,060
Adjusted R^2	0.616	0.622	0.627	0.632	0.545	0.553	0.560	0.565
Estimation SE	0.177	0.176	0.174	0.172	0.174	0.172	0.171	0.170
Change of Adjusted R^2	0.616	0.006	0.006	0.005	0.545	0.009	0.008	0.005
F value	8,684	4,446	1,517	1,149	4,854	2,514	863.4	654.9
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Durbin-Watson				1.885				1.865

Note: Real monetary data in log-levels. Regression analysis: Ordinary Least Squares with introduction method. Estimated coefficients: Standardized coefficients. Standard errors of the non-standardized effects in brackets. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 4
Employment, individual explanatory factors in Spanish manufacturing firms. 1991–2016 and 2000–2016.

	1991–2016				2000–2016			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
(Constant)	−3.970***	−3.135***	−2.408***	−0.762***	−5.391***	−3.608***	−2.950***	−0.646***
	(0.204)	(0.188)	(0.183)	(0.146)	(0.255)	(0.234)	(0.227)	(0.169)
Labour cost/worker (LCW)	0.406***	0.348***	0.295***	0.169***	0.447***	0.345***	0.301***	0.151***
	(0.056)	(0.051)	(0.050)	(0.040)	(0.066)	(0.060)	(0.058)	(0.043)
Capital/worker (KW)	0.109***	0.057***	0.030**	0.049***	0.099***	0.041**	0.014	0.040***
	(0.018)	(0.016)	(0.016)	(0.012)	(0.020)	(0.017)	(0.017)	(0.012)
Human capital (HC)	−0.222***	−0.245***	−0.227***	−0.228***	−0.188***	−0.242***	−0.217***	−0.277***
	(0.024)	(0.022)	(0.021)	(0.017)	(0.027)	(0.025)	(0.024)	(0.017)
R&D activities (R&D)		0.386***	0.302***	0.182***		0.444***	0.378***	0.207***
		(0.015)	(0.015)	(0.012)		(0.014)	(0.014)	(0.011)
Use of robots (R)			0.195***	0.117***			0.204***	0.098***
			(0.016)	(0.012)			(0.017)	(0.012)
CAD/CAM (CADM)			0.018	−0.002			−0.004	−0.001
			(0.016)	(0.013)			(0.017)	(0.012)
Data-driven control (DDC)			0.009	0.026			0.037*	0.033***
			(0.016)	(0.013)			(0.017)	(0.012)
Flexible production systems (FPS)			0.130***	0.063***			0.087***	0.046***
			(0.016)	(0.013)			(0.017)	(0.012)
Large and efficient industry (LAR_EF)				0.385***				0.011
				(0.023)				(0.028)
Large and HC industry (LAR_HC)				0.319***				0.622***
				(0.026)				(0.020)
SMEs in R&D industry (SMEs_R&D)				0.105***				0.012
				(0.032)				(0.026)
Statistics								
N (observations)	4,479	4,479	4,479	4,479	3,501	3,501	3,501	3,501
Adjusted R^2	0.198	0.335	0.399	0.636	0.213	0.380	0.438	0.708
Estimation SE	0.527	0.481	0.457	0.356	0.170	0.169	0.169	0.169
Change of Adjusted R^2	0.198	0.137	0.064	0.237	0.213	0.168	0.058	0.270
F value	370.4	565.9	372.6	712.8	316.0	538.1	341.8	774.1
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Durbin-Watson				1.844				1.840

Note: Real monetary data in log-levels. Regression analysis: Ordinary Least Squares with introduction method. Estimated coefficients: Standardized coefficients. Standard errors of the non-standardized effects in brackets.

* $p < 0.1$.

** $p < 0.05$.

*** $p < 0.01$.

Comparing Model 1 with Model 2 and Model 3, relevant considerations are obtained. In the explanation of the employment reduction, the coefficients of labour costs per worker and of capital per worker evolve downwards when the technological variables are incorporated into the analysis. In this sense, investment and use of R&D and automation technologies displace the labour and capital returns. However, at the same time, an increase in human capital would indicate greater educational needs for a more appropriate use of R&D and automation technologies. Similarly, the comparison of Models 3 and 4 also provides relevant conclusions. The introduction of size and industry dummies reflects firm heterogeneity. Large firms located in efficient and human capital-intensive industries, and SMEs located in R&D-intensive industries tend to be less labour-intensive by themselves, which reduces the effects of labour cost, human capital, R&D and automation technology on employment.

The comparison of the results obtained for the 1991–2016 and 2000–2016 intervals allows us to evaluate the explanatory factors of the observed destruction of employment and, more particularly, to analyse whether they have been accentuated since the 2000s. Regarding the automation technologies dimension (Model 4), the results obtained confirm significant and negative effects of robotization, data-driven control and flexible production systems on employment. From 1991 to 2016, having one more robotized firm reduced employment levels (increased negative employment trend) by 0.117 percentage points, while an additional firm using flexible production systems decreased employment by 0.063 percentage points.

Nevertheless, these negative effects have moderated since the 2000s. From 2000 to 2016, having one more robotized firm reduced employment levels by 0.098 percentage points, and an additional flexible production systems using firm lessened employment by 0.046 percentage points. In contrast, data-driven control appears as significant in the period 2000–2016, and with a contribution to the fall in employment of 0.033 percentage points. In addition, there are also greater R&D-displacing effect, and a lower labour-displacing and capital-displacing effects. Human capital reinforces its positive contribution to employment creation. An additional firm carrying out R&D activities lessened employment by 0.207 percentage points between 2000 and 2016, compared to 0.182 percentage points in 1991–2016. An additional real euro of labour cost per employee decreased employment by 0.151 percentage points between 2000 and 2016, compared to 0.169 percentage points in 1991–2106. An additional real euro of capital per worker decreased employment by 0.040 percentage points in the 2000–2016 interval, compared to 0.049 percentage points in the 1991–2016 interval. An additional employee with tertiary education increased employment by 0.277 percentage points in the 2000–2016 interval, compared to 0.228 percentage points in the 1991–2016 interval.

4.4. Complementarity effects on productivity and employment estimation

The complementarity effects obtained from estimating the long-term trend of worked-hourly productivity level are presented in Table 5 (two-complementarities, Eq. (9)) and Table 6 (four-complementarities, Eq. (11)). As in the case of individual effects, the four regression models comparison suggests a labour-share-displacing and R&D-displacing

Table 5
Labour productivity (added value per hour worked, HPT), automation technologies' two-complementarity explanatory factors in Spanish manufacturing firms. 1991–2016 and 2000–2016.

	1991–2016				2000–2016			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
(Constant)	−3.448***	−3.316***	−3.268***	−3.222***	−3.592***	−3.351***	−3.313***	−3.249***
	(0.050)	(0.052)	(0.054)	(0.055)	(0.071)	(0.075)	(0.076)	(0.079)
Labour cost/worker (LCW)	0.785***	0.759***	0.751***	0.743***	0.738***	0.699***	0.692***	0.683***
	(0.012)	(0.012)	(0.013)	(0.013)	(0.016)	(0.017)	(0.017)	(0.018)
R&D activities (R&D)		0.080***	0.064***	0.059***		0.101***	0.090***	0.081***
		(0.005)	(0.005)	(0.005)		(0.005)	(0.005)	(0.006)
R x CADM			−0.003	−0.003			−0.028	−0.027
			(0.012)	(0.012)			(0.013)	(0.018)
R x DDC			0.061***	0.059***			0.077**	0.070***
			(0.009)	(0.009)			(0.010)	(0.010)
R x FPS			0.003	−0.001			0.005	0.001
			(0.011)	(0.011)			(0.013)	(0.013)
CADM x DDC			−0.046***	−0.043***			−0.049***	−0.045**
			(0.008)	(0.008)			(0.009)	(0.009)
CADM x FPS			0.008	0.006			0.012	0.009
			(0.010)	(0.010)			(0.012)	(0.012)
DDC x FPS			0.026	0.026			0.024	0.025
			(0.010)	(0.010)			(0.011)	(0.011)
Large and HC industry (LAR_HC)				0.075***				0.083***
				(0.008)				(0.009)
SMEs in R&D industry (SMEs_R&D)				0.062***				0.059***
				(0.011)				(0.013)
Statistics								
N (observations)	5,407	5,407	5,407	5,407	4,060	4,060	4,060	4,060
Adjusted R^2	0.616	0.622	0.628	0.633	0.545	0.553	0.558	0.563
Estimation SE	0.177	0.176	0.174	0.173	0.173	0.172	0.171	0.170
Change of Adjusted R^2	0.616	0.006	0.006	0.005	0.545	0.009	0.005	0.005
F value	8,683	4,446	1,129	912.4	4,854	2,514	639.7	518.1
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Durbin-Watson				1.889				1.873

Note: Real monetary data in log-levels. Regression analysis: Ordinary Least Squares with introduction method. Estimated coefficients: Standardized coefficients. Standard errors of the non-standardized effects in brackets. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

effect and reflects firm heterogeneity. The unit labour cost and R&D coefficients tend to be reduced when incorporating automation technology-based complementarities and size and industry dummies (from Model 1 and Model 2 to Model 3). In the same way, the coefficients of automation technologies complementarities are reduced by introducing the dummies effect (from Model 3 to Model 4). In this sense, automation technologies complementarities also introduce changes into the firm efficiency models, with lower contributions from the labour and R&D factors. At the same time, the location of the firm in large and human-capital-intensive industries or in R&D-intensive SMEs also reduces the contribution of the labour factor, R&D activities and automation technology complementarities.

The complementary effects obtained are robust (increases in the change of adjusted R^2 and models p-value = 0.000) and the complete model does not present problems of multicollinearity (for all explanatory variables and indicators, Tolerance > 0.10 and VIF < 10) or error dependence (Durbin-Watson values between 1.5 and 2.5). Regarding complementarity effects, only two of the six complementarities raised have significant effects on productivity. In addition, with opposite sign: robotization and data-driven control reinforces productivity, and computer-aided design and manufacturing and data-driven control lessen productivity.

The comparison of the coefficients obtained for the two constructed data intervals (1991–2016 and 2000–2016) suggests two interesting results. Firstly, it is possible to confirm that the mixed complementarity effects on productivity have accentuated since 2000s. From 1991 to 2016, having one more robotized and data-driven control firm increased worked-hourly productivity level by 0.059 percentage points. This complementarity has boosted since the 2000s. From 2000 to 2016, having one more robotized and data-driven control firm increased worked-hourly productivity level by 0.070 percentage points. From 1991 to 2016, having one more computer-aided design and manufacturing, and data-driven control using firm decreased productivity by 0.043 percentage points. This complementarity has worsened since the 2000s. From 2000 to 2016, having one more computer-aided design and manufacturing, and data-driven control using firm decreased productivity by 0.045 percentage points. In addition, the contribution of R&D activities would also accelerated since the 2000s (from 0.059 percentage points in the period 1991–2016 to 0.081 percentage points in the period 2000–2016), while there is also a labour-displacing effect (labour-cost per worker coefficients: from 0.743 percentage points in the period 1991–2016 to 0.683 percentage points in the period 2000–2016).

Secondly, we observe that the joint effects of automation technologies (collected through the complementarity between the four identified technologies) on productivity have clearly worsened since the 2000s. While in the 1991–2016 period automation generated a slightly positive and significant effect on productivity (0.019 percentage points with $p < 0.1$), in the 2000–2016 period this effect has become non-significant.

The complementarity effects from estimating the long-term trend of employment level are presented in Tables 7 (two-complementarities, Eq. (10)) and Table 8 (five-complementarities, Eq. (12)). As in the case of employment individual effects, the four regression models comparison suggests a labour-share-displacing, R&D-displacing effect and reflects firm heterogeneity. Hence, in the explanation of the employment reduction, the coefficients of labour costs per worker and R&D activities evolve downwards when the automation technologies and human capital complementarities are incorporated into the analysis (from Model 1 to Model 2 and Model 3). Large firms located in efficient and human capital-intensive industries and SMEs located in R&D-intensive industries tend to be less labour-intensive by themselves, which reduces the effects of labour cost and R&D activities on employment (Model 1 and Model 2 compared with Model 4).

The complementary effects obtained are robust (increases in the

Table 6
Labour productivity (added value per hour worked, HPT), automation explanatory factors in Spanish manufacturing firms. 1991–2016 and 2000–2016.

	1991–2016				2000–2016			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
(Constant)	−3.448***	−3.316***	−3.288***	−3.232***	−3.592***	−3.351***	−3.338***	−3.260***
	(0.050)	(0.052)	(0.053)	(0.055)	(0.071)	(0.075)	(0.076)	(0.078)
Labour cost/worker (LCW)	0.785***	0.759***	0.754***	0.745***	0.738***	0.699***	0.697***	0.685***
	(0.012)	(0.012)	(0.012)	(0.013)	(0.016)	(0.017)	(0.017)	(0.018)
R&D activities (R&D)		0.080***	0.073***	0.065***		0.101***	0.098***	0.086***
		(0.005)	(0.005)	(0.005)		(0.005)	(0.005)	(0.006)
AUTOM (R x CADM x DDC x FPS)			0.026**	0.019*			0.014	0.008
			(0.007)	(0.007)			(0.007)	(0.008)
Large and HC industry (LAR_HC)				0.083***				0.094***
				(0.008)				(0.009)
SMEs in R&D industry (SMEs_R&D)				0.064***				0.063***
				(0.011)				(0.013)
Statistics								
N (observations)	5,407	5,407	5,407	5,407	4,060	4,060	4,060	4,060
Adjusted R^2	0.616	0.622	0.624	0.628	0.545	0.553	0.556	0.561
Estimation SE	0.177	0.176	0.175	0.174	0.174	0.172	0.171	0.170
Change of Adjusted R^2	0.616	0.006	0.002	0.004	0.545	0.009	0.003	0.005
F value	8,683	4,446	2,971	1,805	4,854	2,514	1,677	1,022
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Durbin-Watson				1.885				1.866

Note: Real monetary data in log-levels. Regression analysis: Ordinary Least Squares with introduction method. Estimated coefficients: Standardized coefficients. Standard errors of the non-standardized effects in brackets. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

change of adjusted R^2 and models p-value = 0.000) and the complete model does not present problems of multicollinearity (for all explanatory variables and indicators, Tolerance > 0.10 and VIF < 10) or error dependence (Durbin-Watson values between 1.5 and 2.5).

Contrary to expectations, the complementarity effects of the use of automation technologies decreases the employment level (positive contribution to the downtrend in employment). Regarding two-complementarity effects and from 1991 to 2016, the results obtained confirm significant and negative effects of the majority of interactions raised: robots and data-driven control (0.126 percentage points), robots and flexible production systems (0.043 percentage points), computer-aided design and manufacturing and data-driven control (0.111 percentage points), computer-aided design and manufacturing and flexible production systems (0.050 percentage points) and data-driven control and flexible production systems (0.077 percentage points). Only the complementarity between robots and computer-aided design and manufacturing does not have a significant and negative effect on employment.

In contrast, the complementarities between automation technologies and human capital have positive and significant effects on employment. From 1991 to 2016, having one more robotized and human capital-intensive located firm increase employment trend by 0.058 percentage points, an additional computer-aided design and manufacturing using firm located in human-capital intensive industry expand employment in 0.129 percentage points, an additional data-driven control using firm located in human-capital intensive industry boost employment in 0.097 percentage points, and an additional flexible production systems using firm located in human-capital intensive industry enhance employment in 0.090 percentage points.

This trend would have been reversed after the 2000s. While the complementarities of automation technologies tend to have a lower labour-displacement effect, the complementarities between automation technologies and human capital tend to have a less positive effect on employment. In fact, if the set of complementarities between the four identified automation technologies and human capital is analysed (Table 8), their contribution to employment growth would have increased: from 0.056 percentage points in the 1991–2016 period to 0.069 percentage points in the period 2000–2016. This trend of industrial employment from the 2000s is completed with some labour-displacement and capital-displacement effects slightly lower. On the contrary, the R&D-displacement effects on employment have been accentuated: from 0.189 percentage points in the 1991–2016 period to 0.0211 percentage points in the period 2000–2016.

5. Discussion

This study analyses the relationship among automation technologies for Spanish industrial firms to explain its effect on productivity and employment. Up to this purpose we test four postulated hypotheses using a large and long-term sample: 5,511 manufacturing firms in the period intervals of 1991–2016 and 2000–2016. We aim to capture the differential effects on productivity and employment since the 2000s.

5.1. Discussion of the descriptive results

First, and following the I4.0 literature, we have identified the uses of four automation technologies in the industrial firm: industrial robots, computer-aided design and manufacturing, data-driven control and flexible production systems (Chen and Tsai, 2017; Liao et al., 2017). The results obtained confirm relevant uses, although not yet majority. None of the four technologies analysed reaches already a frequency higher than 50% of firms. Moreover, none of the six relations of two complementarities established between the four automation technologies reaches a third of the industrial fabric. These results suggest the need to study in the future the implementation factors of automation technologies, especially in the manufacturing SMEs (more than three quarters of the analysed sample). The related literature has already pointed out the importance of a complete approach to explain the set of uses of automation front-end technologies (Frank et al., 2019). In the same way, previous research also considers mechanisms including purchase, such as leasing or pay-per-use (Landscheidt et al., 2018). These new mechanisms could facilitate the access of SMEs, to be considered in the future.

The descriptive analysis also highlights the jobless recovery approach in Spanish manufacturing firms (Brynjolfsson and McAfee, 2012; Goos et al., 2014). While real worked-hourly productivity grew, industrial employment fell. The comparison between robotized and non-robotized firms indicates that the jobless recovery was much more pronounced in the former, basically as a result of labour-reducing effects since 2007. In the same way, the analysis of the labour share on added value confirms the labour-displacing approach (Chiacchio et al., 2018; Karabarbounis and Neiman, 2014). However, the reduction of industrial employment linked to automation

Table 7
Employment, automation technologies' two-complementarity explanatory factors in Spanish manufacturing firms. 1991–2016 and 2000–2016.

	1991–2016				2000–2016			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
(Constant)	−2.431***	−1.708***	−1.957***	−0.465***	−2.881***	−2.225***	−2.543***	−0.584***
	(0.166)	(0.162)	(0.168)	(0.128)	(0.218)	(0.211)	(0.218)	(0.172)
Labour cost/worker (LCW)	0.290***	0.236***	0.257***	0.132***	0.282***	0.240***	0.263***	0.124***
	(0.046)	(0.044)	(0.046)	(0.035)	(0.056)	(0.054)	(0.056)	(0.044)
Capital/worker (KW)	0.059***	0.038**	0.040**	0.062***	0.038**	0.017	0.018	0.044***
	(0.015)	(0.014)	(0.014)	(0.011)	(0.017)	(0.016)	(0.016)	(0.012)
R&D activities (R&D)	0.380***	0.293***	0.299***	0.172***	0.421***	0.348***	0.358***	0.200***
	(0.015)	(0.015)	(0.015)	(0.011)	(0.014)	(0.014)	(0.014)	(0.011)
R x CADM		0.092***	0.084***	0.010		0.081***	0.072**	0.039*
		(0.032)	(0.034)	(0.026)		(0.033)	(0.036)	(0.028)
R x DDC		0.094***	0.095***	0.126***		0.155***	0.140***	0.129***
		(0.025)	(0.032)	(0.024)		(0.026)	(0.034)	(0.026)
R x FPS		0.104***	0.074***	0.043**		0.049**	0.032	0.016
		(0.031)	(0.033)	(0.024)		(0.034)	(0.035)	(0.027)
CADM x DDC		−0.038**	0.074***	0.111***		−0.037*	0.065**	0.090***
		(0.023)	(0.031)	(0.023)		(0.024)	(0.033)	(0.025)
CADM x FPS		0.024	0.035	0.050**		−0.003	0.035	0.040*
		(0.028)	(0.032)	(0.024)		(0.031)	(0.035)	(0.027)
DDC x FPS		0.048**	0.044*	0.077***		0.062**	0.073**	0.103***
		(0.027)	(0.034)	(0.025)		(0.030)	(0.038)	(0.029)
R x HC			0.031	−0.058***			0.035	−0.041**
			(0.027)	(0.020)			(0.027)	(0.021)
CADM x HC			−0.108***	−0.129***			−0.116***	−0.119***
			(0.022)	(0.017)			(0.023)	(0.018)
DDC x HC			−0.076***	−0.097***			−0.058**	−0.083***
			(0.019)	(0.015)			(0.020)	(0.015)
FPS x HC			0.028	−0.090***			0.022	−0.089***
			(0.025)	(0.019)			(0.028)	(0.021)
Large and efficient industry (LAR_EF)				0.059***				0.036**
				(0.027)				(0.030)
Large and HC industry (LAR_HC)				0.568***				0.567***
				(0.020)				(0.021)
SMEs in R&D industry (SMEs_R&D)				0.000				0.020
				(0.025)				(0.028)
Statistics								
N (observations)	4,956	4,956	4,956	4,956	3,758	3,758	3,758	3,758
Adjusted R^2	0.337	0.405	0.415	0.673	0.368	0.433	0.443	0.670
Estimation SE	0.489	0.462	0.452	0.334	0.461	0.437	0.430	0.333
Change of Adjusted R^2	0.337	0.069	0.010	0.258	0.368	0.066	0.017	0.220
F value	840.1	376.1	266.8	637.0	731.3	320.3	227.7	478.6
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Durbin-Watson				1.768				1.817

Note: Real monetary data in log-levels. Regression analysis: Ordinary Least Squares with introduction method. Estimated coefficients: Standardized coefficients. Standard errors of the non-standardized effects in brackets.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

technologies could be related to different labour structural changes. In our research, neither indirect (intra-industry and inter-industry) labour-augmenting effects (Autor and Salomons, 2018), nor the terciarization of industrial employment (Dauth et al., 2017), nor the fall in routine employment and offshoring (Acemoglu and Restrepo, 2017; Dechezleprêtre et al., 2019; Dengler and Matthes, 2018) have been considered. All these sets of factors could modify the labour-reducing contribution of automation technologies. Future directions of research include exploring the influence of introducing these new components in the analysis.

5.2. Discussion of the predictive analysis

The results of the predictive analysis indicate a remarkable explanatory capacity of the automation technologies on some of the main firm results (Dalenogare et al., 2018; Müller et al., 2018). The uses of industrial robots, data-driven control and flexible production systems are able to predict sales, value added and exports. In contrast, computer-aided design and manufacturing have much more limited explanatory capabilities. In the same way as for the gross margin, the marginal effects of automation technologies are much weaker, suggesting that more adequate profit models should be based on internal value generation rather than on competitive external forces (such as market power).

Unfortunately, in this paper we have not been able to analyse the uses and effects of those automation technologies that are more closely linked to I4.0, such as IoT, big data, cloud computing or additive manufacturing and 3D printing. Although, the first official data available indicate very minor uses (less than 10% of the business fabric), its accelerated implementation and transformation capacity (Brynjolfsson and McElheran, 2016; Frank et al., 2019) suggests a future line of research for the future.

Additionally, automation technologies have high predictive capabilities on the generation of product and process innovations, and on the realization of R&D activities. The link among automation technologies, R&D activities and innovation is especially relevant for the creation of a competitive advantage. As the literature has repeatedly pointed out (Coccia, 2012, 2017), firms have great incentives to find innovative solutions and to generate monopolistic returns and competitive advantages in contexts dominated by technological dynamism.

Table 8
Employment, automation explanatory factors in Spanish manufacturing firms. 1991–2016 and 2000–2016.

	1991–2016				2000–2016			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
(Constant)	−3.503***	−2.433***	−1.797***	−1.347***	−4.947***	−2.869***	−2.352***	−1.237***
	(0.168)	(0.157)	(0.155)	(0.091)	(0.222)	(0.209)	(0.207)	(0.088)
Labour cost/worker (LCW)	0.371***	0.291***	0.238***	0.098***	0.408***	0.279***	0.242***	0.094***
	(0.047)	(0.043)	(0.043)	(0.033)	(0.055)	(0.054)	(0.053)	(0.043)
Capital/worker (KW)	0.131***	0.065***	0.064***	0.067***	0.109***	0.044***	0.047***	0.056***
	(0.016)	(0.014)	(0.014)	(0.0113)	(0.018)	(0.016)	(0.016)	(0.012)
R&D activities (R&D)		0.387***	0.322***	0.189***		0.460***	0.384***	0.211***
		(0.014)	(0.014)	(0.011)		(0.014)	(0.014)	(0.012)
AUTOM x HC			−0.225***	−0.056***			−0.182***	−0.069***
			(0.016)	(0.013)			(0.017)	(0.014)
Large and efficient industry (LAR_EF)				0.111***				0.083***
				(0.028)				(0.031)
Large and HC industry (LAR_HC)				0.513***				0.530***
				(0.021)				(0.022)
SMEs in R&D industry (SMEs_R&D)				0.010				0.033**
				(0.026)				(0.030)
Statistics								
N (observations)	5,327	5,327	5,327	5,327	4,003	4,003	4,003	4,003
Adjusted R^2	0.219	0.350	0.393	0.643	0.229	0.384	0.412	0.640
Estimation SE	0.531	0.485	0.468	0.360	0.513	0.459	0.449	0.351
Change of Adjusted R^2	0.219	0.132	0.043	0.249	0.229	0.155	0.029	0.227
F value	747.3	958.8	864.6	1369	595.7	831.8	702.5	1015
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Durbin-Watson				1.734				1.780

Note: Real monetary data in log-levels. Regression analysis: Ordinary Least Squares with introduction method. Estimated coefficients: Standardized coefficients. Standard errors of the non-standardized effects in brackets. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

However, in the Spanish context where there exists a growing shortage of public resources for R&D and discrete developments in R&D and firm innovation (Torrent-Sellens, 2018), the role of public policies is decisive, especially for SMEs (Coccia, 2011, 2018). Therefore, public policies become necessary to provide the use of automation technologies and R&D activities as a support of technological transformation. The link between R&D activities, automation and public R&D policies should be studied in greater depth in the future.

5.3. Discussion of estimation results

We observe significant and growing effects of industrial robots and flexible production systems on productivity since the 2000s. But, counterintuitevely, computer-aided design and manufacturing, with a negative and growing marginal effect, and data-driven control, without a significant marginal effect on the explanation of productivity, attenuate the previous positive results (suggesting only partial acceptation of hypothesis 1). Thus, and in the same way previous literature highlights, a mixed trajectory is confirmed (Dalenogare et al., 2018; Müller et al., 2018). While the use of robots 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.

Our analysis of complementarity relationships confirms this mixed trajectory. While the two-complementarity between robots and data-driven control would increasingly boost productivity since the 2000s, the two-complementarity between computer-aided design and manufacturing, and data-driven control, would diminish productivity from the 2000s. In this sense, the results obtained give data-driven control an important complementary role in the explanation of firm productivity. This role should be investigated in greater depth in the future, especially the transition from data control to data-based management (Brynjolfsson and McElheran, 2016; 2019). In any case, the connection between the four automation technologies in the explanation of productivity has not been confirmed in our investigation (rejection of hypothesis 3).

These mixed productivity-augmenting effects, as a result of the introduction of automation technologies, could also be generating an advance in productivity dispersion. As previous evidence suggests (Andrews et al., 2016; Berlingieri et al., 2017), the increase in the productivity gap between leader firms, those in the frontier of automation, and laggard firms, could reveal technological divergence. In this sense, a future line of research is to further study the role that automation technological complementarities play in the explanation of productivity divergences, especially in the case of industrial SMEs.

Regarding employment, individual estimation results confirm significant and negative effects of the use of robots and flexible production systems on employment. However, these negative effects would have been slightly attenuated since the 2000s. In addition, and from the 2000s, data-driven control has been incorporated as a labour-reducing factor. These results, which reject hypothesis 2, are in accordance with previous international evidence (Acemoglu and Restrepo, 2017; Autor and Salomons, 2018; Dauth et al., 2017). Moreover, the two-complementarity effects of automation technologies and human capital boost employment. Similarly, the overall complementarity effect of the four automation technologies and human capital increases employment in the long-term, which confirms hypothesis 4.

Thus, the set of complementary relationships between automation technologies and human capital in the explanation of employment act in a contradictory way. While the use of automation technologies tends to reduce employment, when these technologies are combined with adequate human capital, they tend to increase employment. The weakness of the compensatory effect of automation technologies could be explained in several ways. Firstly, by the productivity model in the Spanish manufacturing firms, which tends to underutilize the competitive potential of automation technologies: the overall effect of automation technologies on productivity is not significant in the period 2000–2016. Secondly, it could be explained by employment structure and demand incentives. Automation technologies generate a counterbalanced effect. Although they increase the importance of human capital, they reduce the unit labour cost coefficient. The need for more trained employees, but with a lower weight of their compensation, would explain the compensation mechanism weakness from the employees' demand.

However, there are also favourable results to be extracted from our research. When the uses of automation technologies are complemented by an adequate level of human capital, especially with a higher level of employee training, the effects on employment are positive. This result, which confirms the well-known complementary relationships between technological change and human capital (Brynjolfsson et al., 2017), highlights the decisive importance of employee training to maximize the effects of automation. An interesting line of future research is to introduce indicators of internal and external expenditure on training and analyse different training modalities.

5.4. Forecasting managerial and policy implications

Finally, the results suggest certain implications for strategic actions and public policies to achieve growth and business acceleration. First of all, it is important to consider the whole set of complementarities that automation technologies can establish among themselves (platform effects). From our results, we can derive that data-driven control could play an important driving role. Through data-drive management the effects of robotics, computer-aided design and manufacturing and flexible production systems on productivity and employment could be increased. However, public support policies become essential in the Spanish context, which is characterized by SMEs with low technological intensity and by an environment that allocates few resources to R&D (Coccia, 2017). Secondly, it is also important to consider the set of knowledge spillover effects that automation technologies generates on firm productivity and employment. Partial public policies or manager actions could be clearly counter-productive. For example, promoting second-wave digital transformation processes, such as IoT or big data technologies, without seizing the technological and training mechanisms linked to them, could also lead to unexpected results.

6. Conclusion

As a result of the implementation of automation technologies in the Spanish industrial firms, we prove the inexistence of overall long-term productivity augmenting, and the existence of overall labour-reducing and human capital-labour-augmenting effects. The bad news, linked to the lack of productivity boost and the reduction in employment, are related to a productivity model that underestimates the competitive potential of automation technology and a structure of employment that, despite human capital advances, reduces labour costs per worker. The good news are linked to the positive effects that the relationship between automation and human capital has on employment. Moving towards data-driven decision management and investment in automation technologies that boost productivity and demand (i.e. machine learning, smart learning systems or big data analytics), should help to maintain this trend in employment (Acemoglu and Restrepo, 2019). In this context, strategic management and public policy should lead efforts to transform firm competitiveness models, human capital and industrial relations into models that emphasize automation skills. The main objective should be to increase and develop automation technology uses to enhance productivity and to transfer productivity improvements to the labour market in a more effective way.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.techfore.2019.119828.

Appendix A

Table A.1, Table A.2, Table A.3

Table A.1
Descriptive and frequency statistics (dimension: value 0, 200 employees or less; value 1, more than 200 employees) of the sample of Spanish manufacturing firms. 1991–2016.

	Descriptive statistics			Frequency statistics (valid%)	
	N	Mean	S.D.	200 employees or less	More than 200
1991	2,059	0.37	0.482	63.3	36.7
1992	1,977	0.34	0.474	66.1	33.9
1993	1,869	0.30	0.460	69.7	30.3
1994	1,876	0.33	0.470	67.1	32.9
1995	1,702	0.33	0.470	67.2	32.8
1996	1,716	0.30	0.460	69.6	30.4
1997	1,920	0.28	0.447	72.4	27.6
1998	1,776	0.29	0.455	70.7	29.3
1999	1,754	0.28	0.448	72.3	27.7
2000	1,870	0.33	0.470	67.0	33.0
2001	1,724	0.32	0.466	68.1	31.9
2002	1,708	0.31	0.464	68.6	31.4
2003	1,380	0.33	0.469	67.3	32.7
2004	1,374	0.33	0.470	67.2	32.8
2005	1,911	0.30	0.460	69.5	30.5
2006	2,023	0.27	0.446	72.7	27.3
2007	2,013	0.28	0.447	72.4	27.6
2008	2,009	0.25	0.431	75.4	24.6
2009	2,015	0.23	0.418	77.4	22.6
2010	2,006	0.20	0.402	79.7	20.3
2011	1,816	0.21	0.405	79.3	20.7
2012	1,869	0.19	0.391	81.2	18.8
2013	1,683	0.18	0.387	81.6	18.4
2014	1,525	0.19	0.393	80.9	19.1
2015	1,666	0.17	0.377	82.8	17.2
2016	1,808	0.19	0.393	81.0	19.0

Table A.2
Frequency statistics (industries: branches of activity; valid percentages) of the sample of Spanish manufacturing firms. 1991–2016.

	91	92	93	94	95	96	97	98	99	00	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16
Meat	2.7	2.7	2.9	3.0	3.1	3.0	2.8	2.8	2.4	2.6	2.6	2.5	2.7	2.7	2.5	2.7	3.0	3.5	3.5	3.7	3.6	4.4	4.2	4.3	4.5	4.8
Food and tobacco	10.4	10.8	11.0	10.6	10.9	10.4	9.4	9.7	9.2	9.3	8.8	9.3	9.3	9.4	9.0	9.1	9.7	9.5	9.9	10.8	11.0	11.6	12.1	12.2	12.8	13.5
Beverage	2.7	2.7	2.6	2.4	2.2	2.2	1.7	1.7	1.6	1.7	1.5	1.5	1.4	1.5	2.2	2.2	2.1	2.1	2.3	2.2	2.1	2.1	2.3	2.2	2.3	2.2
Textiles and clothing	11.3	11.5	11.6	10.9	10.7	10.5	10.4	10.3	10.5	9.6	9.3	9.4	8.5	8.3	8.2	7.5	7.0	6.3	6.2	6.6	6.4	6.2	6.4	6.6	5.9	6.0
Leather and footwear	3.1	3.0	3.2	3.1	2.9	3.7	3.6	3.5	3.2	2.9	2.8	2.8	2.2	2.3	2.6	2.7	2.6	2.5	2.7	2.7	2.8	3.2	3.0	3.2	3.6	3.7
Wood industry	2.4	2.3	2.4	2.1	2.1	2.3	2.3	2.3	2.6	3.5	3.3	3.4	3.3	3.3	3.5	3.9	3.9	3.7	3.8	3.8	4.0	3.4	3.4	3.1	2.8	2.9
Paper industry	2.7	2.4	2.4	2.5	2.5	2.8	2.8	2.9	3.1	3.3	3.3	3.4	3.4	3.3	3.1	3.3	3.2	3.6	3.9	3.9	4.2	4.6	4.7	4.5	4.5	4.3
Graphic arts	5.1	5.2	4.9	4.7	4.6	5.0	5.0	4.7	4.7	5.5	5.5	5.7	5.6	5.5	5.2	5.3	5.3	5.1	4.0	3.9	3.7	3.4	3.6	3.7	3.9	3.9
Chemical and pharmaceuticals	7.4	7.5	7.2	7.5	7.4	6.9	6.5	6.7	6.3	6.2	6.3	6.1	6.6	6.6	7.0	6.6	6.5	6.6	7.0	6.7	6.9	7.3	7.1	7.3	7.1	7.0
Rubber and plastic	4.6	4.4	4.5	4.7	5.1	5.2	5.5	5.5	5.8	5.7	5.9	5.9	5.4	5.5	4.7	4.9	5.1	5.3	5.5	5.6	5.3	5.6	5.5	5.2	5.5	6.0
Non-metallic minerals	7.2	7.2	6.8	6.7	6.8	6.7	6.6	6.5	6.7	6.7	6.7	6.7	7.1	7.1	7.8	8.2	8.0	7.9	7.7	7.5	7.2	6.6	6.5	6.5	6.5	6.4
Ferrous and non-ferrous metals	2.5	2.5	2.6	2.8	2.8	2.7	2.9	3.1	3.4	3.3	3.2	3.3	3.6	3.7	3.2	3.0	3.4	3.6	3.5	3.7	3.4	3.2	3.2	3.3	2.9	2.8
Metal products	7.6	8.4	8.3	9.0	8.9	8.7	9.8	9.7	9.8	10.5	11.7	11.6	12.1	12.1	13.0	13.4	13.3	12.9	13.3	12.4	12.6	13.1	12.9	12.8	13.5	12.7
Agricultural and industrial machinery	6.2	5.8	5.6	5.8	6.2	6.2	5.8	6.0	5.9	6.1	6.0	6.0	6.4	6.4	6.1	6.1	5.9	6.1	5.5	5.4	5.7	5.9	6.2	6.2	6.2	6.4
Computer, electronics & optical	3.6	3.6	3.4	3.5	3.4	3.3	3.4	3.3	3.1	2.9	3.1	2.8	2.4	2.4	2.5	2.4	2.1	2.0	1.8	1.5	1.5	1.7	1.7	1.7	1.8	1.9
Machinery and electrical equipment	7.1	6.6	6.8	6.6	6.6	6.4	6.4	6.1	5.9	5.2	5.2	4.9	4.5	4.6	4.7	4.2	4.3	4.3	4.1	4.2	4.2	4.0	4.0	3.6	3.4	3.1
Motor vehicles	3.4	3.5	3.6	3.9	4.3	4.7	4.9	5.0	5.4	5.5	5.4	5.4	5.3	5.3	5.2	4.8	5.1	5.2	5.3	4.8	4.8	4.7	4.8	4.9	4.4	4.3
Other transport material	2.5	2.5	2.5	2.6	2.6	2.3	2.4	2.6	2.7	2.4	2.1	2.2	2.4	2.4	2.8	2.2	2.3	2.3	2.1	2.1	2.4	1.9	1.8	2.0	1.8	1.8
Furniture industry	4.5	4.6	4.9	4.9	4.2	4.4	5.1	4.8	5.1	4.9	4.8	4.9	5.4	5.4	4.6	5.1	5.0	5.1	5.3	5.3	5.4	4.5	4.2	4.0	4.1	4.2
Other manufacturing industries	2.8	2.7	2.7	2.8	2.6	2.6	2.8	2.7	2.5	2.2	2.4	2.3	2.2	2.3	2.1	2.5	2.3	2.4	2.5	2.7	2.7	2.6	2.6	2.6	2.3	2.2
Total	2,059	1,—977	1,—869	1,—876	1,702	1,176	1,—920	1,776	1,754	1,870	1,724	1,708	1,380	1,374	1,911	2,023	2,013	2,009	2,015	2,006	1,816	1,869	1,683	1,525	1,666	1,808

Table A.3
Frequency statistics (valid percentages) of industrial robots uses in the Spanish manufacturing firms, by size and industry. 1991–2016 and 2000–2016.

	1991–2016			2000–2016		
Variable/indicator	Non-robotized	Robotized	All	Non-robotized	Robotized	All
Firm size*						
200 employees or less	54.2	18.7	72.8	53.1	21.5	74.7
More than 200 employees	9.2	**18.0**	27.2	7.7	**17.6**	25.3
Firm industry*						
Meat	2.4	1.1	3.5	2.6	1.0	3.6
Food and tobacco	6.2	4.0	10.3	6.0	**4.7**	10.7
Beverage	1.1	**1.0**	2.2	0.9	**1.1**	2.0
Textiles and clothing	7.3	1.7	9.0	5.7	1.7	7.4
Leather and footwear	3.3	0.4	3.7	2.9	0.4	3.3
Wood industry	2.3	1.1	3.4	2.3	1.2	3.5
Paper industry	2.1	1.2	3.3	2.2	1.3	3.5
Graphic arts	4.2	1.0	5.2	3.9	0.9	4.8
Chemical and pharmaceuticals	3.8	**2.7**	6.5	3.6	**3.0**	6.6
Rubber and plastic	2.9	**2.5**	5.4	2.8	2.3	5.1
Non-metallic minerals	3.8	**3.2**	7.0	3.7	**3.4**	7.1
Ferrous and non-ferrous metals	1.5	1.2	2.7	1.5	1.2	2.7
Metal products	7.3	4.3	11.5	7.1	4.1	11.2
Agricultural and industrial machinery	3.4	2.1	5.6	3.1	2.0	5.1
Computer, electronics & optical	1.5	**1.3**	2.8	1.2	**1.5**	2.7
Machinery and electrical equipment	2.2	**2.1**	4.3	1.8	**1.7**	3.5
Motor vehicles	1.2	**2.8**	3.9	1.0	**2.9**	3.8
Other transport material	1.0	**0.8**	1.8	0.8	**1.2**	2.0
Furniture industry	3.8	1.3	5.1	3.2	1.4	4.6
Other manufacturing industries	2.7	1.8	2.4	1.6	0.6	2.2
N	3,492	2,019	5,511	2,495	1,604	4,099
Total%	63.4	36.6	100.0	60.9	39.1	100.0

*** $p < 0.01$. In bold, the percentage of firms higher than expected in firms using robots: standardized corrected residual for counting ≥ 1.9.

Appendix B

Table B.1, Table B.2

Table B.1
Descriptive and frequency statistics of the variables and analysis indicators. 1991–2016.

	Descriptive statistics			Frequencies (valid%)		Skewness	Kurtosis
	N	Mean	S.D.	0	1		
Explained variables							
HPT (value added per hour worked)	5,503	1.245	0.28	–	–	−0.254	1.048
EMP (total employment)	5,592	1.749	0.60	–	–	0.572	−0.348
Sales	5,523	6.732	0.83	–	–	0.302	−0.483
Added value	5,511	6.243	0.77	–	–	0.334	−0.422
Exports	3,784	6.042	0.76	–	–	−0.303	−0.456
Gross margin	4,982	2.077	0.87	–	–	−0.632	1.782
Product innovation	5,592	0.466	0.50	53.4	46.6	0.136	−1.982
Process innovation	5,592	0.658	0.47	34.2	65.8	−0.667	−1.556
R&D activities	5,592	0.480	0.50	52.0	48.0	0.080	−1.994
Explanatory variables							
LCW (labour costs per worker)	5,523	4.373	0.21	–	–	−0.509	0.468
KW (capital per worker)	5,439	4.382	0.62	–	–	−0.564	0.539
HCW (% employees tertiary educ.)	4,643	1.017	0.35	–	–	−0.184	0.323
R (robotics use)	5,511	0.366	0.48	63.4	36.6	0.555	−1.593
CADM (CAD/CAM use)	5,511	0.453	0.49	54.7	45.3	0.187	−1.966
DDC (Data-driven control use)	5,511	0.485	0.50	51.4	49.6	−0.349	−1.879
FPS (Flexible production systems use)	5,511	0.395	0.49	60.5	39.5	0.430	−1.815
R x CADM	5,511	0.245	0.43	75.0	25.0	1.158	−0.659
R x DDC	5,511	0.234	0.41	69.4	30.6	1.256	−0.422
R x FPS	5,511	0.306	0.46	76.6	23.4	0.841	−1.293
CADM x DDC	5,511	0.368	0.48	68.2	32.8	0.548	−1.700
CADM x PFS	5,511	0.285	0.45	71.5	28.5	0.954	−1.089
DDC x FPS	5,511	0.319	0.47	68.1	31.9	0.777	−1.397
R x HC	5,398	0.363	0.52	–	–	1.013	−0.511
CADM x CH	5,345	0.465	0.57	–	–	0.663	−1.120
DDC x CH	5,299	0.580	0.57	–	–	0.276	−1.395

(*continued on next page*)

Table B.1 (*continued*)

	Descriptive statistics			Frequencies (valid%)		Skewness	Kurtosis
	N	Mean	S.D.	0	1		
FPS x CH	5,377	0.403	0.56	–	–	0.883	−0.799
Sectoral and size dummies							
LAR_EF (large firms & efficient ind.)	5,713	0.155	0.35	39.6	60.4	1.901	1.750
LAR_UNI (large firms & HC ind.)	5,575	0.225	0.44	60.4	39.6	1.834	2.127
SME_R&D (SMEs & R&D ind.)	5,774	0.110	0.30	66.5	33.5	1.492	1.934

Note: Real monetary data in log-levels. Frequencies of discrete variables in percentages. 0 = no automation technologies use, no innovation, no R&D activities, or no relevance to sectoral and size dummies; 1 = automation technologies use, innovation, R&D activities or relevance to sectors and size dummies.

Table B.2
Correlation matrix. 1991–2016.

	HPT	EMP	SALES	AVAL	EXP	GMA	PINN	PRINN	R&D	LCW	KW	HC	ROB	CADM	DDC	FPS
HPT (Hourly productivity)	1															
EMP (Employment)	0.428**	1														
SALES (Sales)	0.658**	0.915**	1													
AVAL (Added value)	0.703**	0.939**	0.962**	1												
EXP (Exports)	0.462**	0.739**	0.803**	0.773**	1											
GMA (Gross margin)	0.341**	0.044**	0.050**	0.153**	0.025	1										
PINN (Product innov.)	0.157**	0.321**	0.311**	0.313**	0.205**	0.037*	1									
PRINN (Process innov.)	0.227**	0.282**	0.306**	0.307**	0.179**	0.096**	0.398**	1								
R&D (R&D activities)	0.327**	0.500**	0.510**	0.514**	0.405**	0.077**	0.492**	0.382**	1							
LCW (Labour cost per worker)	0.784**	0.455**	0.642**	0.658**	0.491**	0.035*	0.133**	0.180**	0.322**	1						
KW (Capital per worker)	0.713**	0.379**	0.585**	0.562**	0.419**	0.187**	0.147**	0.193**	0.312**	0.661*	1					
HC (Human capital)	0.333**	−0.044**	0.101**	0.088**	0.118**	0.078**	0.113**	0.034*	0.155**	0.371**	0.268**	1				
ROB (Robots use)	0.300**	0.435**	0.452**	0.453**	0.343**	0.069**	0.261**	0.291**	0.330**	0.286**	0.287**	0.031*	1			
CADM (CAD/CAM use)	0.252**	0.312**	0.312**	0.338**	0.233**	0.053**	0.237**	0.253**	0.295**	0.315**	0.204**	0.137**	0.348**	1		
DDC (Data-driven control use)	0.269**	0.302**	0.332**	0.338**	0.214**	0.060**	0.203**	0.306**	0.250**	0.296**	0.235**	0.047**	0.386**	0.417**	1	
FPS (Flexible prod. systems)	0.302**	0.398**	0.407**	0.424**	0.303**	0.074**	0.261**	0.304**	0.337*	0.316**	0.271**	0.110**	0.380**	0.434**	0.365**	1

Notes: Pearson bivariate correlations.

* $p<0.05$.

** $p< 0.01$.

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