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WORKING PAPER

How vulnerable is Spanish employment to the digital revolution?

R. Doménech / J. R. García / M. Montañez and A. Neut

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Abstract

This paper profiles Spanish workers according to the automation risk of their current jobs, drawing on the automation risk of different occupations, as estimated by Frey and Osborne (2017), and the microdata from Spain's 2011-2016 annual Labour Force Survey. The results show that on aggregate 36% of current jobs are at high risk of automation, although this risk falls significantly for jobs that involve a higher degree of responsibility, higher educational requirements, more involvement in training activities, or the adoption of new ways of working. To mitigate these risks on current workers and to take better advantage of the benefits of the digital revolution, it is essential to face these challenges proactively through efficient educational, employment and redistributive policies.

Key words: technological change, automation, education, employment, public policies

JEL classification: E24, J24, J31, J62, O33

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1. Introduction

As with previous industrial revolutions, which destroyed jobs and spawned new ones, the process of digital transformation that is underway has once again aroused fears over the labour market's ability to adapt and the possibility that society may be heading toward a situation of mass technological unemployment at some point in the future.

It is hard to predict what new jobs automation, computerisation, the internet of things, artificial intelligence and the use of big data will bring about. This makes it difficult to anticipate what the net result of such a process will be in terms of jobs or hours worked. By taking the right precautions, however, it becomes easier to try to assess how workers in current jobs could be affected. This paper specifically uses the probabilities of automation for different occupations that were obtained by Frey and Osborne (2017), together with the microdata from the 2011-2016 annual Labour Force Survey (EPA) samples, to profile those workers whose current occupations are at risk of being replaced by present-day technological disruption..

This article is structured as follows. Section two presents an overview of the effects of previous industrial revolutions on the labour market and discusses the extent to which the current process of technological transformation could have different effects from those experienced in the last two centuries. Section three examines the decisive factors behind the risks of job automation in Spain and evaluates which characteristics determine the vulnerability of workers to the digital revolution. Section four discusses the policies for managing technological change, especially educational, employment and redistributive policies. Finally, section five presents the main conclusions.

2. International empirical evidence

From the dawn of the first industrial revolution, technological advances have inspired both enthusiasm and fear: enthusiasm for progress that brings about greater well-being, but also the fear of an increased concentration of wealth and the possibility of a segment of workers being excluded from the economic and social fabric. Despite the fears, the past two centuries of technological change have confirmed the most optimistic of visions in the long term. As a result, today's average wage-earner in the United States would only have to work for 17 weeks to earn the average real wage of a century ago (Autor, 2015). Moreover, without being dismissive of the immediate harm associated with job replacement/destruction, the fact is that, on aggregate, the creation of new jobs has more than made up for the obsolescence of certain trades, particularly "middle-skill" ones (Katz and Margo 2014). This means that the 20th century ended with a broad consensus regarding the benefits (at least in overall terms) of technological progress for the economy in general and the labour market in particular (Woirol, 1997).

However, this consensus reflects an empirical fact rather than a fundamental law of economic theory. This is why alarm bells are sounding again with the spread of digitisation, automation and artificial intelligence. Will this revolution be similar to or different from those brought about by the steam engine or the advent of electricity? Will it reinforce or

diminish the growing inequality (Atkinson, 2009) seen in the past 30 years in developed countries? Which will be the jobs that are the least complementary and which skills will be encouraged the most? How will the nature of work change in terms of its value, intensity, flexibility, security and institutionality?

We should not forget that, despite the long-term benefits, technological revolutions have as a rule disrupted the labour market, destroying jobs and even entire professions and trades in the short term. Mokyr, Vickers and Ziebarth (2015) highlighted the damage done by the first industrial revolution to a whole generation of workers in key sectors of the economy (e.g., textiles), not so much in terms of employment as in lower wages, less job security (the Luddite riots were more of a cry for better working conditions than for keeping jobs) and an increasing fear of worker alienation[2]. Despite this, Mokyr has clung firmly to the conclusions of the consensus on the benefits of technological progress: in the long run, the gloomy predictions made at the time by Marx, Wicksell, Mills, Keynes and Leontieff were repeatedly refuted, as technological progress emerged as an inexhaustible source of new productive sectors and unprecedented occupations.

Evidence from around the world points to a new disruption in its early stages. From the '80s onwards, there was a break with the major trends and regular features that had characterised the labour market for a good part of the 20th century. Educational level lost its significance as a predictor of wage inequality (Autor, Katz and Kearny, 2008) and the "college or education premium" lost the stability that it had had up to that point[3] (Acemoglu and Autor, 2011). In several developed countries, labour's share of national income began to fall back from the historic level of two thirds to around 60% (Karabarbounis, 2014), while wage inequality rose (OECD 2011). Moreover, in some sectors new work-related dynamics began to be established, such as the so-called "superstar economies" (a phenomenon that has been linked to technological development and the increase in the average size of firms, Rosen, 1981; Gabaix and Landlier, 2008) or the "*gig economies*", which still form a marginal sector, but one that digital platforms are empowering, as Katz and Krueger (2016) have asserted.

Nonetheless, it is still unclear what lies behind the trends of recent decades. Specifically, even though the rise in income inequality is a phenomenon that already extends to most developed countries, it is still not obvious whether this is as a result of automation, globalisation, institutional reforms or greater business concentration, all of which are phenomena that have been around since the '80s. It should also be pointed out that the chain of causality does not necessarily have to run from technology to the labour market, as is evidenced by the increase in automation resulting from the ageing of the population (Acemoglu and Restrepo, 2017a).

Given such uncertainty about the diagnosis of recent trends, it is no surprise that there are conflicting views on the impact that digitisation, automation or artificial intelligence will have on the future of the labour market. Taking the shorter-term forecasts first, few economists expect any significant impact within the next ten years. In fact, the major

2: Worker alienation refers to their estrangement on account of both their jobs and their social milieu (the image of workers who perform repetitive tasks that have no connection with a social context and who are even unaware of the ultimate purpose of their work). Paradoxically, a similar debate is now taking place, although this time about self-employed workers linked to digital platforms (Howard, 2017).
3: The model proposed by Tinbergen (1974) offered a satisfactory explanation for the education premium as a function of the increasing supply of qualified labour, on the one hand, and education and skills-biased technological progress on the other (Goldin and Katz, 2008). This "race" between technology and the labour supply played out in such a way that the wage premium ended up by increasing during the 20th century in spite of the sustained increase in the supply of highly qualified labour.

concern for the last few decades has not been job automation but the developed economies' lack of productivity. This productivity shortfall has provided the grist for some studies to postulate that digitisation and automation are likely to be some way from representing a new industrial revolution and that, very much to the contrary, the nub of the problem is the decreasing return on innovation (Gordon, 2017; Bloom et al, 2017). In contrast to this hypothesis, there have been a lot of studies that make sense of the low productivity observed with the emergence of a new wave of automation. The main arguments used range from a problem of increasingly underestimating production and consumption (as Goolsbee and Klenow [2006] showed by observing the gap between the cost and time invested on the internet) to the existence of major time lags in the effective spread of new technologies (Brynjolfsson, Rock and Syverson, 2017). It is important to also remember that, at least over the last decade, the meagre increase in productivity has been notably tainted by the effects arising from the great recession (Adler, Romain, Davide, Celik, Koloskov and Poplawski, 2017).

Estimates diverge even more when we are dealing with longer term forecasts. Some evidence points to automation already having a net positive effect on local labour markets. Yet there is also evidence that warns of major risks that may persist in the longer run. In the first group, some studies find strong positive "*spillovers*" within the urban centres of developed countries, spillovers that work through the increase in aggregate demand that results from the rise in unearned income (capital gains associated with automation). For 27 European countries, it is estimated that the demand *spillovers* from the automation/destruction of routine employment generated a positive net balance of 11 million jobs in the first decade of this century (Gregory, Salomons and Zierahn, 2016), while for urban areas in the United States it is estimated that at the end of the 20th century each new high-tech job led to the creation of 4.9 jobs in non-tradable sectors (Moretti, 2010). In the second group, there is evidence that some dimensions of automation have already led to a persistent adverse effect in employment: in the first 15 years of this century, it is estimated that robotization destroyed net employment and brought down the average local wage in urban areas of the United States (with a net destruction of 6.2 jobs per additional robot and a 0.7% reduction in the local wage per "additional robot per 1,000 inhabitants", Acemoglu and Restrepo, 2017b).

Despite the current uncertainty over the aggregate net effect in the longer term, one thing is sure: the effective destruction of many existing occupations; thus the importance of identifying those jobs at risk in order to evaluate potential policies that could soften the blow of any transition. Of note here is the paper by Frey and Osborne (2017), in which they deduced that 47% of jobs in the United States have a high risk of being "digitised" in the next decade. It should be pointed out that this significant reference is seen by many as an upper boundary, among other reasons because it assumes that the skill-set required to work in any job involves a constant degree of automation.[4] Also, as Autor (2013) stressed, it is important to distinguish between the first-round risk of automation due only to technology (technological feasibility of automation) and the second-round risk that also considers market forces (economic convinience of automating). The reference by Frey and Osborne to 47% relates to the former risk, without going into economic/pricing considerations.

4: Arntz *et al.* (2016) broke with the assumption that there is a "profile of representative skills" for each job. In analysing the difference in skills used by workers in the same job, they concluded that only 9% of jobs in the United States (and other OECD countries) are at risk of being automated. It should be noted that to exploit intra-occupational differences, Arntz *et al.* had to sacrifice the high level of job disaggregation exploited by Frey and Osborne (2017).

3. Determinants of the risk of automation: the case of Spain

This section aims to identify what characteristics determine the vulnerability of current Spanish workers to the digital revolution. Specifically, it identifies the factors that influence the probability of an individual having a job that is liable to be automated. For the purpose of making international comparisons, the methodology proposed by Frey and Osborne (2017) was used to calculate the likelihood of computerisation. To do this, the job classification used by Frey and Osborne (SOC2010) needed to be matched up with its Spanish counterpart (CNO2011).[5]

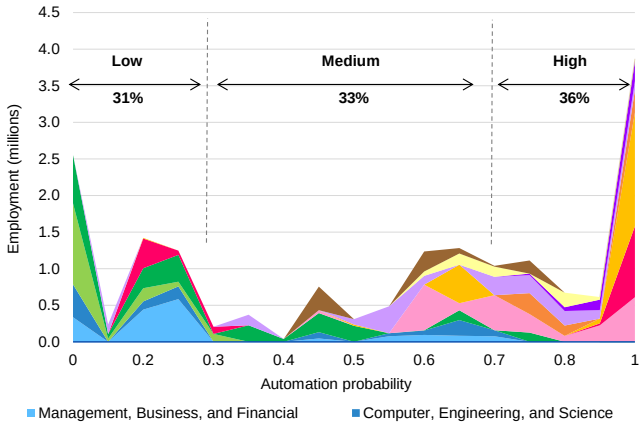
Using the three-digit information in the CNO2011 classification (163 jobs) and assigning to each person with a job in the Labour Force Survey (EPA) the probability of the job they perform being automated (calculated by Frey and Osborne (2017)), we found that 36% of jobs in Spain have a high associated risk of digitisation[6]. Although the results showed a similar scenario to that estimated by Frey and Osborne (2017) for the United States, Spain's productive bent, where certain services weigh more on employment, could be bringing down the percentage of those in work who are vulnerable to computerisation. Prominent among such services are specialist administrative work, reception duties in hotel establishments and domestic workers.

In line with the evidence for other countries[7], it is noticeable that the distribution of employment in Spain is polarised according to its probability of automation (see Figure 1). At one end, we have jobs associated with management, engineering, teaching and healthcare, which are barely exposed to a substitution effect. At the other end, there are tasks that are more routine, such as administrative work, sales and the primary sector, which could be integrally performed by machines.

Although the percentage of workers in jobs at risk in Spain is comparable to Finland[8] (35%) and less than Germany[9] (59%), the recent trend in employment leaves no room for complacency. In particular, in the job destruction phase experienced between 2011 and 2013, the biggest drop came in jobs with either a medium or high probability of automation. However, the jobs created since then are for the occupations that are the worst-placed in regard to technological advances (see Figure 2).

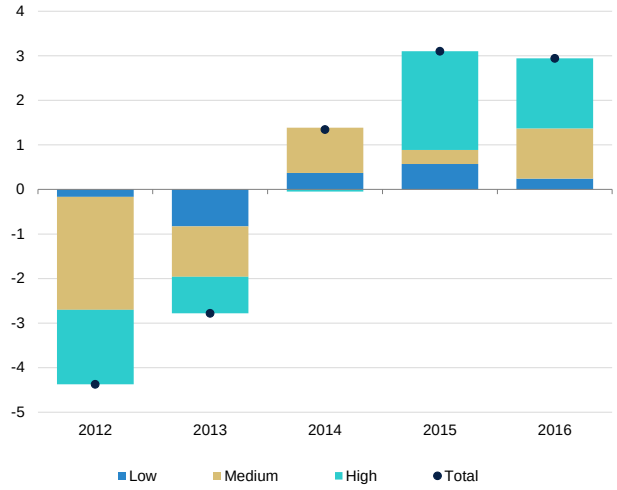
5: This was done using a double-matching scheme. The first match was between the classification currently used in the United States (SOC2010) and the ISCO2008 classification, and the second between the latter and CNO2011.
6: These results were similar to those obtained by Morron (2016).
7: See Dauth (2014) and Autor and Dorn (2013).
8: See Pajarinen and Rouvinen (2014).
9: According to estimates by Brzeski and Burk (2015).

Figure 1 Spain: Distribution of employment by occupation and probability of automation (average for 2011-2016)



Source: Source: BBVA Research based on Frey and Osborne (2017) and INE

Figure 2 Spain: Evolution of employment by probability of automation (contribution to annual change; pp)



Source: BBVA Research based on INE

3.1 Characterisation of workers by risk of job automation

Who are those in work who are most vulnerable to the advance of automation? To establish the types of workers most likely to have their occupations substituted by new technologicies, we used the microdata from the annual EPA samples for 2011 to 2016.

The descriptive analysis suggests that the likelihood of automation falls with educational level, the degree of responsibility[10] and the performance of activities associated with either education or healthcare[11]. This is in line with existing evidence[12] that shows that a higher educational level allows skills to be acquired in areas where human abilities are still ahead of machines, which works in favour both of capital and labour being complementary and of creating new job opportunities. Also, the risk of automation is greater for workers who do not participate in non-formal training activities. Given that the impact of technology is likely to shorten the useful life of workers' skills and that the new business models will involve constant changes in the abilities that are in demand[13], the importance of continuing education (both formal and non-formal) as a way to alleviate the risk of digitisation will grow in the future.

The analysis using the LFS data also suggests that automation risk is comparatively high among the young, but that there is almost no difference between the genders. Here, the literature tells us that jobs in decline "grow old", i.e., the risk of computerisation rises with the average age of the workforce in that kind of employment because older workers have less of an incentive to change their job type (or it is harder for them to do so). As regards gender, empirical evidence[14] tells us that, in spite of the fact that they are less likely to be found in STEM professions (OECD, 2017b), women are better-placed than men to deal with the risk of digitisation, given their current preference for performing skilled work relating to healthcare or education.

10: In line with Arntz et al (2016).
11: Baumol (2012) showed that societies that are better-off demand more intensive services in specialised work.
12: See Autor and Dorn (2009).
13: See WEF (2016).
14: See Autor and Dorn (2009), Anghel, De la Rica and Lacuesta (2013) or OECD (2017b), among others.

Finally, it can be seen that the probability of automation is higher among wage-earners (especially those with a temporary contract or who work in the private sector), workers in agriculture, manufacturing, catering, commerce or household and administrative activities, and those who are searching for another job or were previously unemployed.

3.2 Factors determining the probability of automation

To pick out which characteristics have an influence on a worker's being employed in a job with a greater risk of automation, a regression analysis was performed. Specifically, the model proposed that the probability of a worker's job being computerised depends on personal characteristics (gender, age, education level, etc.), work-related factors (professional status, type of contract, time in service at the company, degree of responsibility, etc.) and on the firm where they work (size and sector of activity).[15]

For the purposes of gauging the importance of the type of contract, two equations were used: one for wage-earners and one for self-employed workers[16]. Given that the dependent variable (p) has values between 0 and 1, a generalised linear model (GLM) was estimated using maximum likelihood estimation, which assumes a logistic distribution of p[17].

Table 1 gives the results of the estimates. Each diagram shows the marginal effects of the response categories for a variable with respect to its mean. The regressions confirm some of the intuitive elements noted in the descriptive analysis and refute others.

The variable that had the biggest effect on a worker's risk of automation was position in the hierarchy. Table 1 shows that the probability of digitisation decreases with the degree of responsibility. Therefore, the risk of a corporate manager being replaced by a machine is 30 points less, *ceteris paribus*, than the mean for all wage-earners and almost 10 points lower for the self-employed.

In line with the results in the descriptive analysis and empirical evidence[18], it emerges that education level is one of the key variables for explaining the differences in the probability of computerisation. Better educated workers (particularly those with a university degree in subjects relating to education, healthcare and the social services) and those who have taken part in non-formal training activities[19] are at less risk of losing their current job to machines. When differentiating by gender, it can be seen that the probability of automation is greater for female wage-earners than for males regardless of education level. Among self-employed workers, only less educated women (i.e., those who did not complete their upper secondary education) have less of a risk of digitisation than men.

Regardless of individual characteristics, the sector of activity makes a substantial difference to the workers' probability of computerisation. Generally speaking, those in the service sector are at a lower risk of being replaced by machines than those in industry or agriculture. The diversity in the tertiary sector is notable, however. As Table 1 indicates, the probability of automation is comparatively low for wage-earners in activities relating to education, healthcare and the

15: We should make a subtle point of importance here: although the model estimates the probability of a worker with certain characteristics being employed in a job that has a certain risk of automation, this does not mean that there is a causal relation in the strictest sense.
16: For further details, see the appendix to this document.
17: After Papke and Wooldridge (1996).
18: Autor and Dorn (2009), Arntz *et al.* (2013) or Gallego (2017).
19: The risk of automation for wage-earners falls when they pursue non-formal studies associated with their current employment. On the other hand, the probability of computerisation for self-employed workers is lower than for those who are engaged in non-formal studies geared to a change of job.

social services, as well as for those working in the civil service and the ICT, energy, and scientific and technical sectors. At the other extreme are those who work in agriculture, commerce, transport, catering, manufacturing, finance and real estate. In qualitative terms, the differences between the sectors as regards the risk of digitisation are similar for self-employed workers, except in commercial activity, which shows a negative effect.

Beyond the sector of activity, occupations that allow for new ways of working are less exposed to to automation[20]. Therefore, the likelihood of a salaried employee who is telecommuting being replaced by a machine is 15 points lower than the probability for one who works on-site. The effect is also positive for self-employed workers, though not to such a great degree.

The other variables have less of an effect on the probability of automation. In regard to the worker's characteristics, we find that the risk of digitisation is relatively high for salaried employees aged under 27 (31 in the case of self-employed workers) and low for those aged over 57[21]. Employed workers aged between 28 and 34 also exhibit less likelihood of automation.

Unlike with age, the risk of being replaced by a machine grows with a salaried employee's length of service with the firm, but decreases in the case of a self-employed person. The literature[22] suggests that the higher probability of computerisation for wage-earners who have been with the company longer could reflect the fact that they have fewer incentives to adapt to technological change, which leads them to remain in jobs that are in decline. In contrast, for self-employed workers, the link between time on the job and the risk of digitisation could be due to a certain degree of self-selection: self-employed workers who have managed to re-orient their business toward activities that are less prone to being automated have longer working careers. This result is complemented by the role played by the size of the firm. The chances of being replaced by a machine are lower in smaller set-ups, especially if the worker is self-employed.

A worker's satisfaction with his or her current job (estimated by job searches) has a bearing on the probability of computerisation. Therefore, salaried employees who seek a more stable job that fits in better with their education level are at greater risk of digitisation in their present job. Similarly, it is considered that having a temporary contract increases the probability of automation by around one point. In contrast, the risk is higher among workers who are looking for a better-paid job and less demanding work hours. These results make it possible to segment workers into two sub-groups. The first would comprise those who have job insecurity and an occupation that has a high likelihood of being automated (and who are therefore trying to find a new job). The second would consist of workers who have stable jobs with a low risk of computerisation and are trying to improve their pay conditions and increase their leisure time.

Finally, it can be seen that a worker's original job situation has an effect on the probability of automation. Salaried employees who were students a year earlier are therefore at less risk than the mean of being replaced by machines[23], while those who had previously been unemployed are relatively more vulnerable. This is likely to be another one of the numerous 'scarring effects' of unemployment[24].

20: In line with evidence provided by WEF (2016).
21: Arntz *et al.* (2016) also found that the role played by age was not very significant.
22: See Anghel, De la Rica and Lacuesta (2013).
23: Based on the 2014 European Social Survey, Gallego (2017) finds a similar result.
24: On the scarring effects of unemployment, see Arulampalam (2001).

Table 1 Marginal effect on the mean of the probability of being in a job that is highly prone to automation

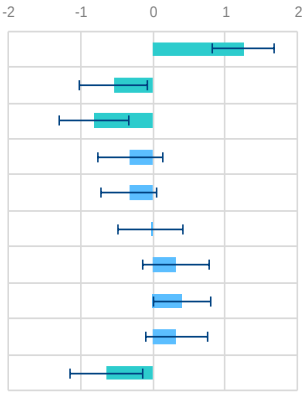
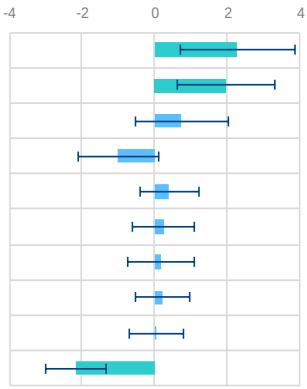
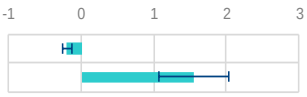
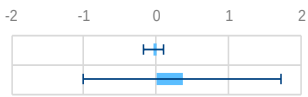
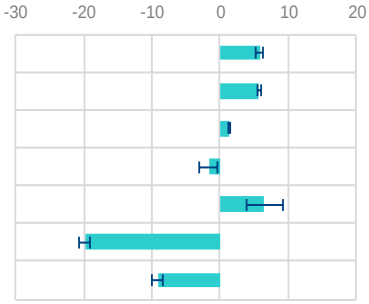
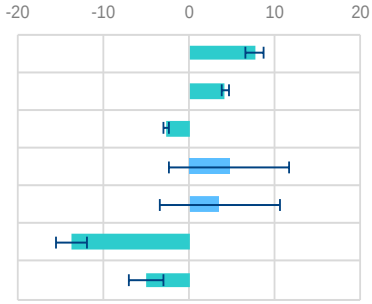
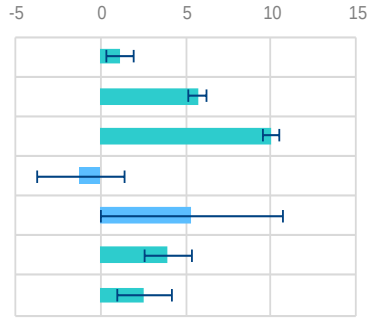
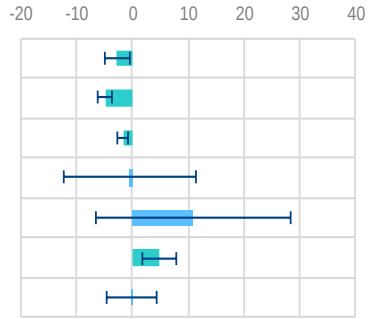
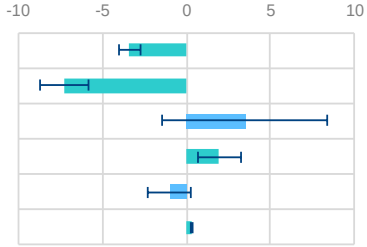
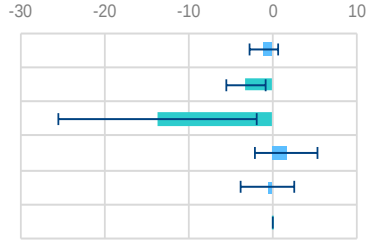
	Wage-earners	Self-employed
Worker characteristics		
Age (years)		
16-27		
28-31		
32-34		
35-38		
39-41		
42-44		
45-47		
48-51		
52-56		
57-86		
Gender		
Male		
Female		
Education level (maximum attained)		
Primary		
1st stage secondary		
2nd stage secondary or higher education in other sectors		
2nd stage secondary in education, health or social services		
2nd stage secondary in STEM areas*		
Higher education in education, health or social services		
Higher education in STEM areas*		
Female and education level		
Primary		
1st stage secondary		
2nd stage secondary or higher education in other sectors		
2nd stage secondary in education, health or social services		
2nd stage secondary in STEM areas*		
Higher education in education, health or social services		
Higher education in STEM areas*		
Non-formal courses (last four weeks)		
Linked to current job, firm participates		
Linked to current job, firm does not participate		
Linked to future job, firm participates		
Linked to future job, firm does not participate		
Out of personal interest		
No		

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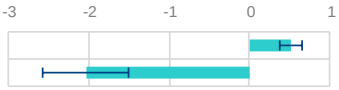
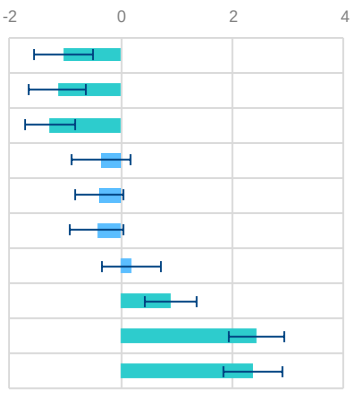
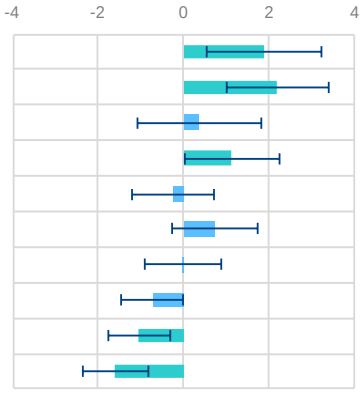
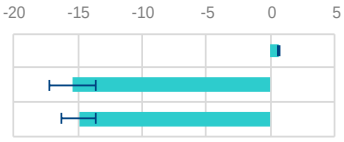
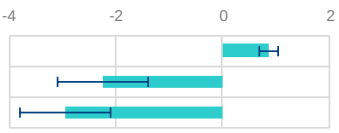
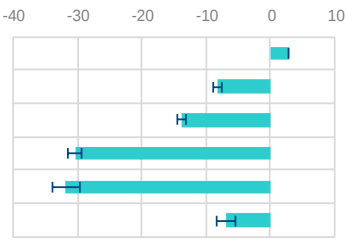
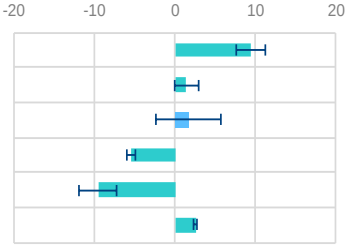
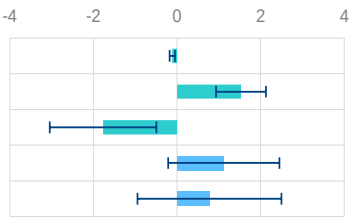
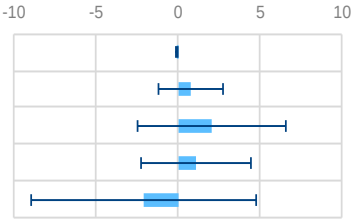
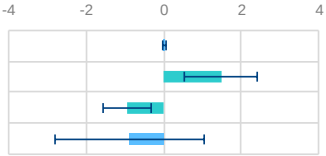
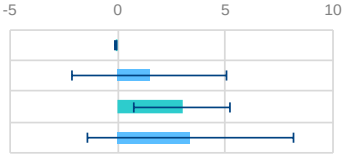
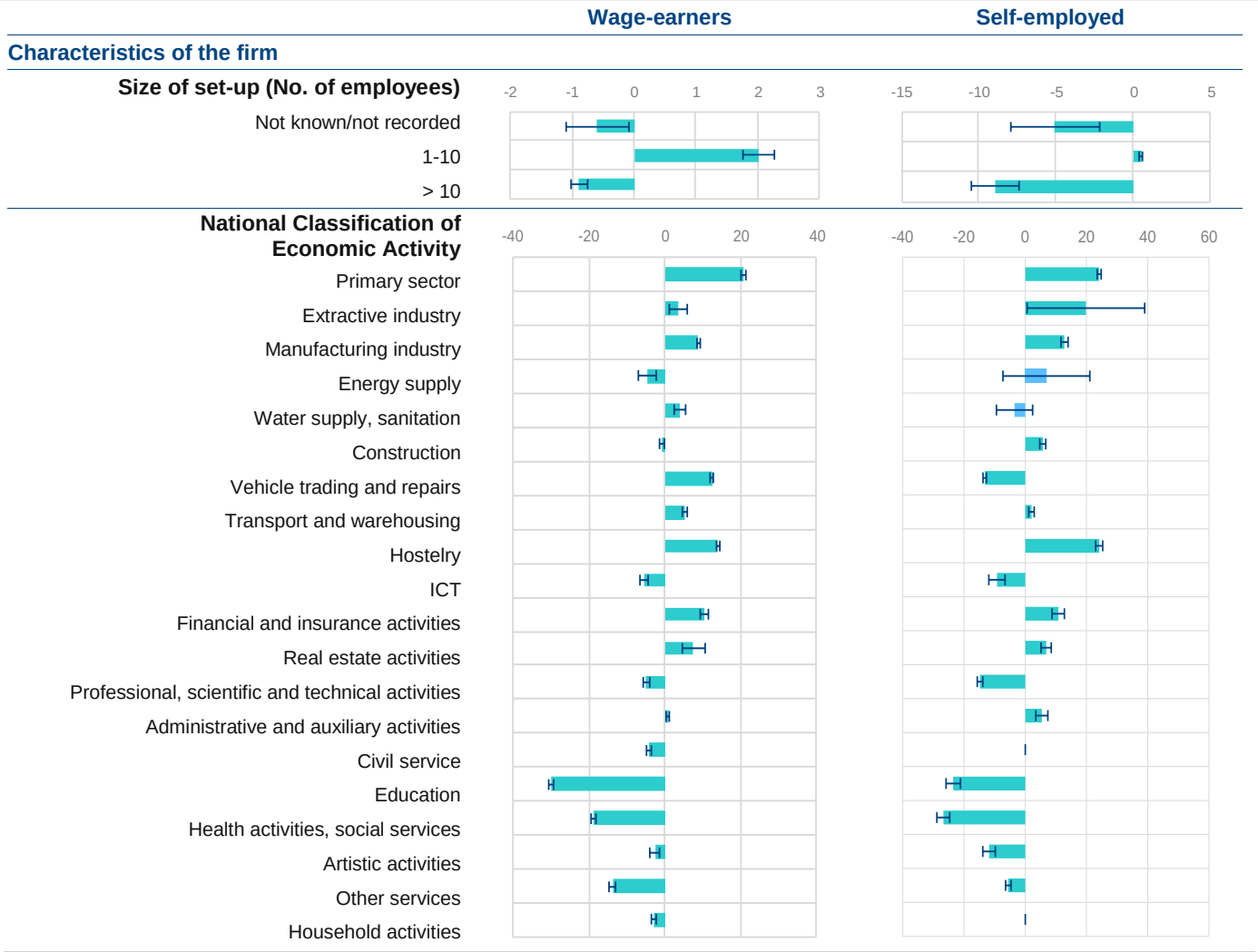
Table 1 Marginal effect on the mean of the probability of being in a job that is highly prone to automation

	Wage-earners	Self-employed
Characteristics of the job		
Employment status		
Private sector wage-earner		
Public sector wage-earner		
Type of contract		
Permanent		
Temporary		
Tenure (years)		
0		
1		
2-3		
4		
5-7		
8-9		
10-13		
14-18		
19-26		
27-60		
Working from home		
Not telecommuting		
Occasionally		
Over half of days worked		
Workers supervised		
None		
Manager, workshop manager, foreman or similar		
Middle manager		
Small company, departmental or branch manager		
Large or medium-sized company manager		
Independent worker (with no managers or subordinates)		
Job status 1 year ago		
Employed		
Unemployed		
Studying		
Inactive		
Other		
Searching for a job		
Not searching		
Yes, more stable and better-suited to education		
Yes, better pay and hours		
Yes, other reasons		

Continued on the next page

Table 1 Marginal effect on the mean of the probability of being in a job that is highly prone to automation



Note: green shading indicates the significance of the variable at a confidence level of 95%.
*STEM: *Science, Technology, Engineering and Mathematics*
The model includes regional and temporal dichotomous variables.
Source: BBVA Research

4. Policies for managing technological change

The effects of technological change on employment, productivity, polarisation, inequality and, in short, social welfare will depend on the Spanish economy's ability to frame policies that respond appropriately to the challenges and manage the changes indicated in the previous sections. It is vital for society as a whole (the public sector, firms and workers) to anticipate and manage these changes pro-actively with a broad set of policies that match the labour supply to the demand, facilitate the creation of jobs that fit the new technologies, improve labour market efficiency, guarantee equal opportunities, boost the long-term positive effects of inclusive technical progress and keep down the individual and social costs of the transition to new production models, processes and organisational structures.

In addition to the process of technological and digital transformation, globalisation and world production chains require an approach that marries long-term strategies with a global outlook. The effects of technological change are not uniform among workers, firms, sectors and countries and they give rise to winners and losers. It is possible for the same changes that boost productivity, wages and employment in aggregate terms in some countries to have diametrically opposite effects in others. Whether these effects are to be positive in net terms will basically depend on how change is managed in three broad areas, namely education, employment policy and inclusive growth.

4.1 Education and continuing education policies

The empirical evidence on the widening of the wage gap among workers by qualification level in at least the last two decades highlights the inadequacy of the labour supply to meet the growing demand from occupations that require higher levels of education and training. This race between education and technology (Goldin and Katz, 2008) can also be seen in economies like Spain's, where there are high structural unemployment rates. The existence of a mismatch between the supply and demand for work not only coexists with high unemployment rates, it is even one of its determining factors, as is borne out by the labour market search models (see, for example, Pissarides [2000] or Mortensen and Pissarides [2001]).

Moreover, investing in human capital is crucial to workers achieving skills for which technical progress is complementary rather than substitutive, even for less skilled tasks. For example, in the United States, the evidence suggests that between 1980 and 2012 the share of overall employment in jobs that require high levels of social interaction and are difficult to automate grew by 12 percentage points (see Deming, 2017). Over this same period, the share of the jobs involving the intensive use of mathematics, but no social skills fell by 3.3 percentage points, whereas the growth of employment and wages was especially strong for occupations that called for both high levels of mathematical and social skills.

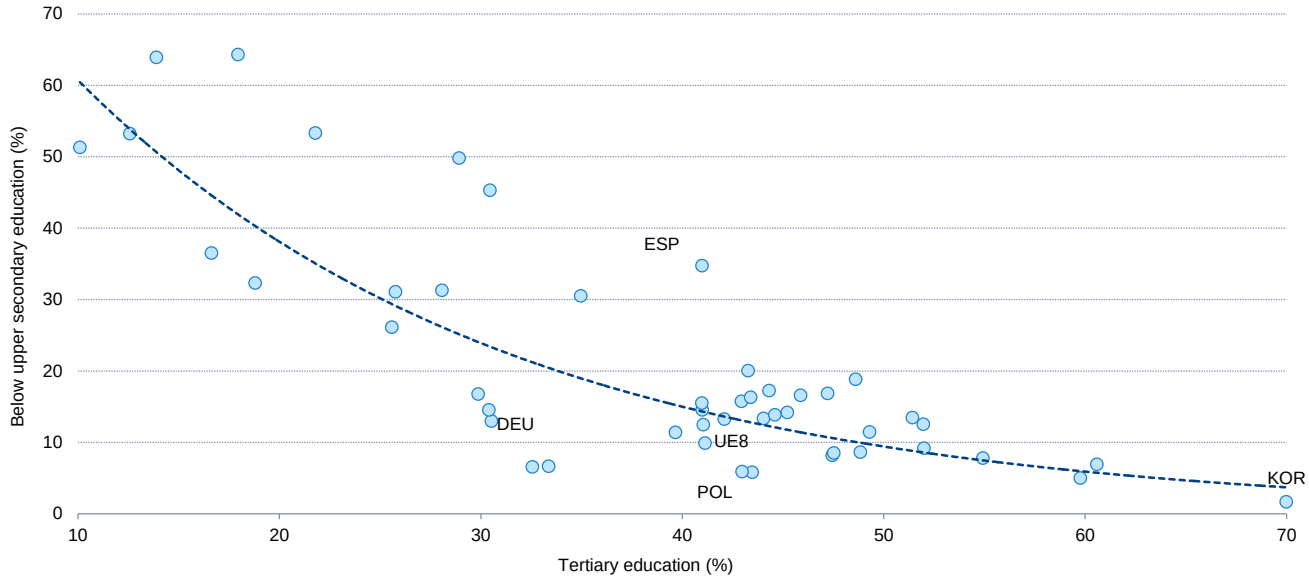
The use of social skills compared to more routine, more easily automated skills is greater in numerous jobs in the service sector, for example in hotels and catering, the restaurants and care services. It is often the case that such jobs are looked down on and pigeon-holed unjustly by a broad section of public opinion as insecure occupations that are not very productive. Improving the training and qualifications for such jobs is crucial. Many of these tasks can be performed with low or high added value, depending on the expertise and skills with which they are performed. Pissarides (2017) specifically asserted that, as the demand for these jobs grows in the coming decades, it is essential to both destigmatise the social perception and improve the quality of jobs in the service sector to make them more socially respectable and appealing, and more productive at the same time. In addition to social and personal skills, improving the quality of these services also calls for improving certain types of knowledge, such as languages, and the managerial skills needed to address society’s growing needs. All the above is exactly what will set two individuals apart who, even if employed in the same job, will present differing degrees of automation and ability to adapt to change.

As technical progress brings with it a simultaneous increase in life expectancy, with the resulting rise in the number of years spent in professional careers, and more frequent and permanent changes of tasks and jobs, further education and professional retraining will be essential. It is easy to predict that the training acquired within the education system prior to entering the job market will prove inadequate to deal with future needs, so it will become necessary to acquire new knowledge and diversified skills depending on the new social demands. Heavier investment in continuing education will present a challenge for workers, firms and government departments. The last of these will have to constantly adapt their policies for training and getting unemployed people back to work again. Firms will have to be one step ahead of their employees' training needs and invest in training efficiently. Workers will have to get used to the fact that their professional careers are unlikely to consist of one single job over several decades, so they will have to maintain a particularly active outlook when it comes to anticipating the opportunities presented by new jobs and the skill levels that these might call for.

Skills-biased technical progress and the future appearance of new jobs that might be hard to picture at the present time not only require more but, above all, better and more flexible training. Unfortunately, Spain presents evident weaknesses on both fronts compared to other countries. Within the EU, it is the country that has the highest rates of academic failure and dropping out of the education system. This fact produces a great deal of duality in terms of human capital, as Figure 3 illustrates. In 2016, the percentage of the population in the 25 to 34 age band who had completed higher education was 41%. But, at the same time, some 35% of the population in this age band had an education level below upper secondary. This percentage is on a par with emerging economies like Brazil, Colombia and Argentina. Besides its consequences for income inequality going forward, the dual bimodal distribution of education levels in Spain implies that roughly one-third of the younger population is not qualified for the challenges posed by the digital revolution. In fact, BBVA Research (2015) has found that education level is one of the factors that best explains the penetration of digital technologies among consumers. Poland and other Eastern European countries have a percentage of population with higher education that is comparable to Spain's, but much smaller percentages at lower education levels.[25]

25: Spain's relative weakness in terms of the years spent in education by the younger population is accompanied by indicators that reflect lower quality in education skills, such as those in the PISA or PIAAC programmes, although in these areas Spain's relative position is not as unfavourable as it is for years of schooling, as Andrés and Doménech (2015) have suggested.

Figure 3 Percentage of the population aged between 25 and 34 by education level in 2016



Source: BBVA Research based on the OECD (2017c)

This burden on the initial conditions is even more important if we bear in mind that what is learned while in the education system during one's youth will not be enough for later professional development. Education will not only be ongoing, but the curriculum will have to be more geared toward preparing individuals from a very early age to acquire abilities outside the education system that allow them to develop new knowledge and skills in communication, team-work, research and creativity over decades. In short, it will be necessary to significantly improve the ability of human capital to adapt to the effects of technological change and seize the new opportunities that this affords.

4.2 Employment policy

Human capital is a factor that significantly enhances the employability of workers, although it is not the only one. The efficiency of the labour market is just as, if not more, important. Bearing in mind the high rate of structural unemployment in the Spanish economy, it is vital to press ahead with reforms that remove barriers to job creation, investment and corporate growth, facilitate the financing of start-ups, and simplify the regulation of the labour market and bring about both more efficient and fairer regulation of it and a tax structure that is oriented toward job creation.

The public sector plays a key role in creating a business climate that will boost the employment rate. The government must be fully engaged in a process of continuing improvement of its efficiency level, and cutting the administration costs and charges that firms find themselves obliged to meet. It is therefore vital that the public sector not only avoids becoming a dead-weight on this process but also spearheads society's technological and digital transformation, providing more and better services to its citizens and firms.

One area in which this challenge is especially important is active and passive labour market policies. The effectiveness of these policies in Spain, which has been palpably open to improvement up to now[26], calls into question their future repercussions on the chances of finding a job and the time workers spend without a job while transitioning from obsolete occupations into new ones arising from technological change. To cut the transition costs for such a process, the coverage of benefits will have to be improved for the time during which workers are jobless, while also making these benefits conditional on actually searching for new jobs.

The transition period between old and new jobs can and should be reduced and already available technology brought to bear to improve the process of matching job vacancies with the unemployed using public platforms that take advantage of big data on the needs of companies and worker profiles, as proposed by Boscá *et al.* (2017). These new technologies and platforms can also be used to anticipate trends in the future needs of companies and the qualifications that workers will require, as well as to learn about the performance of training and education centres as regards the employability of and the salary levels attained by the students and workers who have passed through them.

The tax structure used to finance the public sector also has a significant effect on the level of employment. As taxes produce distortions and disincentives, they end up affecting economic activity, investment and employment (see Boscá, Doménech and Ferri, 2017). A tax on capital income could discourage investment in new technologies in the same way that income tax and social security contributions distort the supply of and demand for labour.

Another important area for action in the public sector has to do with the adaptation and modernisation of labour regulations. A sizable portion of these regulations (for example, collective bargaining) originated from the changes brought about following the second industrial revolution and the need to organise labour in production centres. As Harris and Krueger (2015) pointed out, it is now necessary to address the needs of the 21st century, as new forms of labour organisation have appeared, featuring the phenomenon of the independent worker and in which new intermediaries and collaborative working platforms are becoming increasingly important.

4.3 Redistribution policy

Improving human capital and employment policies are necessary conditions for ensuring inclusive growth, but they might not be sufficient. Even if technological change means greater welfare for everybody in the long run, it might involve substantial transition costs for many segments in the short to medium term, meaning that the winners and the losers will coexist. In principle, these asymmetric effects should not be a problem, provided that they are properly managed. Insofar as the net social benefits are positive, the challenge consists of designing efficient mechanisms so that the winners compensate the losers and the latter also benefit from the process and do not oppose change. Although feasible in theory, it is hard to put such compensating mechanisms into practice, as we have seen in some countries in the past two decades, due to the interaction between globalisation and technological change. Rising inequality has created large-scale opposition to such changes, an increase in populism and a loss of political legitimacy for the institutions that have attempted to manage such processes (see Andrés and Doménech, 2017).

26: See the evidence collected by Cardoso *et al.* (2016).

The challenge is to constantly design, implement and evaluate public policies that guarantee fairness at the lowest possible price in terms of employment and investment in research, development and innovation. For example, it makes no sense to redistribute by creating new taxes on automation (with the inherent difficulties of defining the criteria whereby certain machines or robots have to be taxed differently to others), artificial intelligence or *big data*, which might slow down progress substantially. The goal is to distribute new wealth rather than hinder its creation.

Before implementing new methods of redistribution, such as a universal basic income, it is essential to enhance the efficiency of the current welfare state first. In keeping with the arguments advanced by Doménech (2017) and the OECD (2017a), in an economy like Spain's, where the average unemployment rate has topped 15% since the beginning of the '80s, and where regulation and the welfare state still have considerable room for improvement before they can approach the level of international best practices, it seems hard to justify designing and efficiently implementing proposed redistribution schemes that are unprecedented in countries with far lower levels of unemployment and inequality. A rigorous ex ante and ex post assessment of all public policies and programmes still remains one of the most significant pending challenges for the Spanish government apparatus.

5. Conclusions

All industrial revolutions have had substantial effects on the labour market, and the present one is no exception. The ongoing process of digital transformation and advances in robotics and artificial intelligence will create new jobs, both in innovative sectors and in those that benefit from the income effect of technological change. However, the Fourth Industrial Revolution will also hasten automation for numerous tasks, which could leave as many as 36% of Spain's current jobs at risk.

Although such a process of creative destruction does not represent a unique aspect of present-day technological change, the speed that innovative activity is reaching threatens to shorten the path to a new equilibrium between labour supply and demand. As a result, identifying the workers who are most vulnerable to the digital revolution is a necessary condition for minimising individual and social transition costs.

Based on the probabilities of automation for different occupations that were obtained by Frey and Osborne (2017), we used the microdata from the 2011-2016 annual Labour Force Survey (EPA) samples to determine which personal and job characteristics influence the risk of a worker in Spain being replaced by a machine. The results from the estimates show that the probability of automation decreases with the degree of responsibility, education level, willingness to take part in training activities and the adoption of new ways of working (such as telecommuting), and is comparatively low for those employed in education, healthcare, social services, ICT, energy and scientific and technical activities. The other characteristics of workers, such as gender, age, time on the job, type of contract and previous employment, as well as the attributes of the firm, such as size, play only a minor part in explaining the risk of digitisation.

To lessen the negative repercussions of technological progress on present and future employment, it is vital for economic agents (both public and private) to manage the challenges of the digital revolution. To achieve this, action must be taken on three fronts: education, the labour market and redistributive policies.

Firstly, it is essential to invest both more and more efficiently in human capital so that population can acquire knowledge, especially in STEM areas, and cognitive and non-cognitive skills that complement technological progress. In addition, in a context of longer professional careers and technological change, backing continuing education is a must for individuals, firms and the public sector. To achieve this, it is necessary to anticipate training needs and enhance the efficiency of the education system.

Secondly, reforms should place greater emphasis on seeking to remove barriers to corporate investment and growth, and facilitating job creation. It is also essential to step up the effectiveness and efficiency of labour market policies. For the purposes of optimising employment match-ups and cutting the time spent unemployed, public employment services should use already available technology to make the most of big data on the needs of firms and the characteristics of workers. At the same time, given the proliferation of platform-based business models and new forms of recruiting, it is advisable to reconsider current labour regulations.

Finally, it is impossible to ignore the need to design mechanisms that will compensate for those adversely affected by the digital revolution. Comparative analysis reveals that there is ample scope for improving the coverage and efficiency of the Spanish welfare state. Against this backdrop, improvements in ex ante and ex post evaluation of public policies becomes a must.

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Appendix

To gauge the relative importance of the employment situation for individuals, a model was first specified that included the complete sample of wage-earners and the self-employed (1). Having confirmed the differences, two further equations were specified: one for wage-earners (2) and one for the self-employed (3). Given that the dependent variable *(ρ)* takes on values between 0 and 1, regressions were estimated using maximum likelihood estimation of a generalised linear model (GLM), which assumed a logistic distribution of *ρ*.

The probability of automation for each individual recorded in the 2011-2016 annual Labour Force Survey subsamples were determined by a set of variables that sought to distinguish each employed person by characteristics, including those of a personal nature and those which concerned the job and firm where the individual worked. The variables to be included in each of the equations would therefore be identical, except for those relating to job characteristics. In the case of the complete model (1), a variable was included that precisely defined the person's professional situation. On the other hand, the model that referred to wage-earners (3) included information on the person's employment situation and contract type, unlike that specified for the self-employed (2).

Furthermore, all the equations included a fixed effect for each region, a fixed effect for each year and an independent error term.

The following table gives details of the variables and the results of the regressions.

Table A.1 Factors determining the probability of a job being automated

		Employed				Wage-earners				Self-employed			
		Coef.	Std. Error.	p-value		Coef.	Std. Error.	p-value		Coef.	Std. Error.	p-value	
Worker characteristics	**Age (ref. 16-27 años)**												
	28-31	-0.084	0.016	0.000	***	-0.087	0.016	0.000	***	-0.014	0.049	0.772	
	32-34	-0.098	0.016	0.000	***	-0.100	0.017	0.000	***	-0.073	0.049	0.139	
	35-38	-0.095	0.016	0.000	***	-0.076	0.016	0.000	***	-0.157	0.048	0.001	***
	39-41	-0.094	0.015	0.000	***	-0.077	0.015	0.000	***	-0.090	0.044	0.043	**
	42-44	-0.087	0.016	0.000	***	-0.062	0.017	0.000	***	-0.097	0.045	0.029	**
	45-47	-0.074	0.016	0.000	***	-0.046	0.017	0.006	***	-0.100	0.046	0.028	**
	48-51	-0.078	0.015	0.000	***	-0.041	0.016	0.010	**	-0.099	0.045	0.027	**
	52-56	-0.085	0.016	0.000	***	-0.045	0.017	0.007	***	-0.106	0.045	0.017	**
	57-86	-0.170	0.017	0.000	***	-0.093	0.018	0.000	***	-0.213	0.046	0.000	***
	Nationality (ref. Spanish)												
	Foreign	0.047	0.013	0.000	***	0.085	0.014	0.000	***	0.019	0.037	0.602	
	Gender (ref. Male)												
	Female	-0.012	0.019	0.551		0.053	0.019	0.006	***	-0.124	0.055	0.023	**
	Education level (ref. Primary)												
	1st stage secondary	-0.084	0.014	0.000	***	-0.105	0.015	0.000	***	-0.126	0.032	0.000	***
	2nd stage secondary or higher education in other sectors	-0.417	0.014	0.000	***	-0.402	0.016	0.000	***	-0.494	0.033	0.000	***
	2nd stage secondary in education, health or social services	-0.298	0.057	0.000	***	-0.294	0.059	0.000	***	-0.171	0.238	0.473	
	2nd stage secondary in STEM areas*	-0.099	0.067	0.142		-0.059	0.071	0.409		-0.392	0.165	0.017	**
	Higher education in education, health or social services	-1.272	0.032	0.000	***	-1.254	0.036	0.000	***	-1.162	0.072	0.000	***
	Higher education in STEM areas*	-0.738	0.026	0.000	***	-0.717	0.028	0.000	***	-0.633	0.067	0.000	***
	Female & education level (ref. female wiht primary education)												
	1st stage secondary	0.184	0.021	0.000	***	0.218	0.022	0.000	***	-0.102	0.060	0.089	*
	2nd stage secondary or higher education in other sectors	0.409	0.021	0.000	***	0.412	0.022	0.000	***	0.047	0.059	0.428	
	2nd stage secondary in education, health or social services	-0.036	0.061	0.557		-0.107	0.062	0.084	*	0.102	0.283	0.720	
	2nd stage secondary in STEM areas*	0.317	0.133	0.017	**	0.203	0.135	0.132		0.620	0.413	0.133	
	Higher education in education, health or social services	0.199	0.037	0.000	***	0.141	0.040	0.000	***	0.378	0.099	0.000	***
	Higher education in STEM areas*	0.122	0.040	0.002	***	0.064	0.042	0.123		0.117	0.121	0.334	
	Non-formal courses over the last four weeks (ref. Linked to current job, firm participates)												
	Linked to current job, firm does not participate	-0.182	0.017	0.000	***	-0.177	0.018	0.000	***	-0.053	0.043	0.214	
	Linked to future job, firm participates	-0.348	0.031	0.000	***	-0.364	0.035	0.000	***	-0.158	0.060	0.009	***
	Linked to future job, firm does not participate	0.094	0.118	0.425		0.156	0.125	0.211		-0.701	0.336	0.037	**
	Out of personal interest	0.093	0.032	0.004	***	0.081	0.034	0.016	**	0.075	0.089	0.403	
	No	-0.077	0.030	0.010	**	-0.063	0.032	0.052	*	-0.031	0.081	0.702	
Characteristics of the job	**Employment status (ref. Wage-earner)**												
	Self-employed	-0.110	0.019	0.000	***								
	Sector (ref. Private sector wage-earner)												
	Public sector wage-earner					-0.123	0.016	0.000	***				
	Type of contract (ref. Permanent)												
	Temporary					0.072	0.014	0.000	***				
	Tenure (ref. <1 year)												
	1	-0.006	0.017	0.719		-0.005	0.018	0.773		0.015	0.045	0.742	
	2-3	-0.031	0.015	0.043	**	-0.012	0.016	0.459		-0.073	0.050	0.141	
	4	0.003	0.017	0.883		0.033	0.021	0.115		-0.036	0.044	0.409	
	5-7	-0.003	0.016	0.868		0.031	0.020	0.110		-0.102	0.043	0.019	**
	8-9	0.002	0.016	0.916		0.029	0.020	0.151		-0.055	0.043	0.197	
	10-13	0.019	0.017	0.278		0.060	0.021	0.005	***	-0.091	0.042	0.031	**
	14-18	0.028	0.016	0.094	*	0.094	0.021	0.000	***	-0.125	0.040	0.002	***
	19-26	0.077	0.017	0.000	***	0.170	0.021	0.000	***	-0.141	0.041	0.001	***
	27-60	0.073	0.017	0.000	***	0.167	0.022	0.000	***	-0.167	0.042	0.000	***
	Working from home (ref. Not telecommuting)												
	Occasionally	-0.362	0.022	0.000	***	-0.766	0.045	0.000	***	-0.148	0.024	0.000	***
	Over half of days worked	-0.428	0.020	0.000	***	-0.743	0.035	0.000	***	-0.183	0.024	0.000	***
	Workers supervised (ref. None)												
	Manager, workshop manager, foreman or similar	-0.544	0.016	0.000	***	-0.520	0.017	0.000	***	-0.374	0.055	0.000	***
	Middle manager	-0.774	0.018	0.000	***	-0.778	0.018	0.000	***	-0.362	0.107	0.001	***
	Small company, departmental or branch manager	-1.185	0.020	0.000	***	-1.649	0.034	0.000	***	-0.706	0.045	0.000	***
	Large or medium-sized company manager	-1.534	0.046	0.000	***	-1.735	0.070	0.000	***	-0.916	0.075	0.000	***
	Independent worker (with no managers or subordinates)	-0.695	0.020	0.000	***	-0.463	0.035	0.000	***	-0.323	0.044	0.000	***
	Job status 1 year ago (ref. Employed)												
	Unemployed	0.077	0.016	0.000	***	0.080	0.016	0.000	***	0.040	0.049	0.414	
	Studying	-0.056	0.031	0.073	*	-0.080	0.032	0.013	**	0.099	0.110	0.368	
	Inactive	0.055	0.032	0.086	*	0.060	0.034	0.075	*	0.056	0.082	0.498	
	Other	0.009	0.044	0.828		0.043	0.043	0.316		-0.099	0.170	0.562	
	Searching for a job (ref. Not searching)												
	Yes, more stable and better-suited to education	0.077	0.024	0.001	***	0.071	0.024	0.004	***	0.074	0.088	0.397	
	Yes, better pay and hours	-0.026	0.016	0.099	*	-0.048	0.016	0.003	***	0.146	0.056	0.008	***
	Yes, other reasons	0.002	0.045	0.958		-0.045	0.048	0.344		0.165	0.117	0.159	

Continued on the next page

Table A.1 Factors determining the probability of a job being automated (continued)

		Employed				Wage-earners				Self-employed			
		Coef.	Std. Error.	p-value		Coef.	Std. Error.	p-value		Coef.	Std. Error.	p-value	
Characteristics of the firm	**Size of set-up (ref. 1-10 employees)**												
	Not known/not recorded	-0.156	0.014	0.000	***	-0.127	0.015	0.000	***	-0.270	0.074	0.000	***
	> 10	-0.169	0.009	0.000	***	-0.141	0.009	0.000	***	-0.467	0.043	0.000	***
	Sector (ref. Primary)												
	Extractive industry	-0.934	0.077	0.000	***	-0.850	0.057	0.000	***	-0.196	0.435	0.652	
	Manufacturing industry	-0.704	0.015	0.000	***	-0.605	0.019	0.000	***	-0.497	0.029	0.000	***
	Energy supply	-1.318	0.052	0.000	***	-1.204	0.053	0.000	***	-0.743	0.302	0.014	**
	Water supply, sanitation	-0.974	0.033	0.000	***	-0.823	0.036	0.000	***	-1.182	0.132	0.000	***
	Construction	-1.000	0.016	0.000	***	-1.037	0.020	0.000	***	-0.792	0.025	0.000	***
	Vehicle trading and repairs	-0.828	0.014	0.000	***	-0.437	0.019	0.000	***	-1.629	0.021	0.000	***
	Transport and warehousing	-0.899	0.017	0.000	***	-0.771	0.022	0.000	***	-0.946	0.023	0.000	***
	Hostelry	-0.322	0.017	0.000	***	-0.354	0.020	0.000	***	0.001	0.033	0.975	
	ICT	-1.376	0.026	0.000	***	-1.243	0.030	0.000	***	-1.439	0.066	0.000	***
	Financial and insurance activities	-0.672	0.027	0.000	***	-0.524	0.031	0.000	***	-0.582	0.045	0.000	***
	Real estate activities	-0.717	0.045	0.000	***	-0.665	0.071	0.000	***	-0.745	0.039	0.000	***
	Professional, scientific and technical activities	-1.420	0.021	0.000	***	-1.215	0.028	0.000	***	-1.708	0.030	0.000	***
	Administrative and auxiliary activities	-1.050	0.016	0.000	***	-0.967	0.019	0.000	***	-0.804	0.045	0.000	***
	Civil service	-1.402	0.018	0.000	***	-1.184	0.026	0.000	***				
	Education	-2.588	0.023	0.000	***	-2.396	0.028	0.000	***	-2.211	0.081	0.000	***
	Health activities, social services	-1.997	0.019	0.000	***	-1.828	0.023	0.000	***	-2.439	0.084	0.000	***
	Artistic activities	-1.291	0.026	0.000	***	-1.118	0.031	0.000	***	-1.561	0.054	0.000	***
	Other services	-1.587	0.022	0.000	***	-1.606	0.029	0.000	***	-1.271	0.026	0.000	***
	Household activities	-1.232	0.018	0.000	***	-1.129	0.021	0.000	***				
	Constant	1.915	0.023	0.000	***	1.692	0.029	0.000	***	1.748	24.550	0.000	***
	Regional dummies	Yes				Yes				Yes			
	Time dummies	Yes				Yes				Yes			
	Observations	220023				180418				39605			
	AIC	435.2675				437.2736				389.4602			
	Log pseudolikelihood	-47884334.88				-39445915.64				-7712192.056			

*STEM: *Science, Technology, Engineering y Mathematics*

Significance: * p<0,1, **p<0,05, ***p<0,01.

Source: BBVA Research based on INE

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