Employment effects from digitalisation: Evidence from Spanish manufacturing firms.

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ABSTRACT

This study examines the relationship between digitalisation and employment for profit-maximising firms. Using a representative panel of Spanish firms from 2001 to 2014, we contribute to the literature by measuring the extent of digitalisation using a multidimensional index that maps several dimensions of digital transformation. We estimate both the direct effect, which combines both a demand effect and a potential replacement effect, and the productivity effect of digitalisation on labour demand. In addition, we examine the differential impact of two dimensions of digitalisation, namely ICT and automation. Overall, our results show that digitalisation has both a positive and significant direct effect and a significant productivity effect on firms' employment demand, as determined by the ICT index. Automation, on the other hand, appears to have only a productivity effect. Moreover, digitalisation has a negative direct effect on the share of unskilled workers, but not on their total number. Employment in SMEs benefits from the direct and productivity effects of digitalisation, while large companies only experience a productivity effect.

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1. Introduction

In the past few centuries, technological revolutions, from the steam engine to electricity and the ICT revolution, have significantly transformed our economy and society (Barbieri et al., 2019). Today, we are witnessing the birth of the fourth industrial revolution, marked by rapid advances in robotics and artificial intelligence (AI). Unlike its predecessors, this new wave of technological innovation holds the potential for even greater disruption. Bessen (2019) estimates that automation could threaten between 9% and 47% of jobs in this era, raising the crucial question: To what extent will machines replace humans in the workforce? With this in mind, our study aims to provide evidence specific to Spanish manufacturing firms and examine the impact of digital technologies (DTs) on labour demand.

During a testimony before the US House of Representatives in November 2021, Daron Acemoglu highlighted the transformative impact of automation before the mid-1980s. He explained that automation initially increased worker productivity and created new opportunities. Since then, automation has accelerated while the creation of new jobs has slowed sharply, resulting in a net loss of jobs and a negative impact of automation on overall employment[2]. In contrast, the Asian Development Bank presents an alternative perspective, suggesting that robots have the potential to enhance employment rather than destroy it. The increased efficiency resulting from automation generates greater demand, which ultimately offsets the job displacement caused by digitalisation. However, concerns have arisen in light of recent articles suggesting that the COVID-19 pandemic has accelerated the automation of jobs, especially jobs with non-manual routine tasks[3]. Nevertheless, the fact that some 30 million jobs are unfilled in OECD countries argues against this theory. Moreover, there is very little evidence of a decline in employment, and this even for routine jobs compared to other types of jobs[4]. Similarly, Spain faces a similar situation, as the recent pandemic has accelerated job automation. Although the creation of new jobs may compensate for the loss of certain tasks, critics argue that those who are displaced often lack the necessary preparation or training for these emerging positions.

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[2] https://www.ft.com/content/59321a73-5f88-4e94-9aa2-62e4927783b1
[3] https://www.theguardian.com/business/2020/dec/15/more-than-half-of-uk-furloughed-jobs-at-risk-of-automation-report
[4] https://www.economist.com/finance-and-economics/2022/01/22/economists-are-revising-their-views-on-robots-and-jobs

The ongoing debate surrounding the impact of automation and digitalisation on employment reveals a lack of consensus among scholars. Some argue that these advancements will lead to increased employment (Gregory *et al*., 2016; Aghion *et al*., 2020), while others contend that it will result in job shrinkage (Chiacchio *et al*., 2018; Acemoglu and Restrepo, 2020). Additionally, certain scholars suggest that the outcome depends on factors such as the level of routineness, skill, industry, or occupation (Gaggl and Wright, 2017; Akerman *et al*., 2015; Cirillo *et al*., 2021).

Furthermore, the impact of digitalisation varies depending on the characteristics of the workers involved. While there is a consensus that digitalisation tends to benefit high-skilled workers, its effects on the employment of low-skilled workers remain uncertain. Some scholars argue for a positive effect (Dutz et al., 2018, Aghion et al., 2020), while others provide evidence of a negative effect (see e.g., Akerman et al., 2015; Humlum, 2019). In the context of manufacturing jobs, several studies suggest a negative association with digitalisation (Dauth et al., 2017; Mann and Puettman, 2017; Dottori, 2021), while others find no significant effect at all (Gaggl and Wright, 2017). Nevertheless, there is very limited evidence on fixed-term and permanent contracts (Doménech et al., 2018). Therefore, it is crucial to assess the potential consequences for both types of workers, especially in countries like Spain, where the share of workers on fixed-term contracts is relatively high compared to other European countries and the costs associated with dismissing fixed-term workers are comparatively lower.

Most studies analysing the impact of the digital transformation on employment use single indicators for the phenomenon of digitalisation, which can only partially capture the degree of penetration of (certain) DTs and hardly reflect the rapid pace at which the digital transformation has developed. In doing so, they ignore the fact that digitalisation is a complex phenomenon that is difficult to capture with a single indicator. To overcome these drawbacks, we follow Calvino et al. (2018) and construct a synthetic index of digitalisation at the firm level that takes into account the multi-layered phenomenon of digital transformation.

The ultimate aim of this study is to analyse the relationship between the digital transformation in Spanish manufacturing firms and its impact on manufacturing employment. To this end, we follow Ortiz and Salas Fumás (2020), and estimate a demand for labour by profit-maximising firms. Furthermore, we assume an endogenous Markov process, where the digitalisation index can influence the future productivity of firms. Thus, we can empirically assess not only the direct impact of DTs on employment, but also an impact via TFP called the productivity effect. The direct impact will combine two effects caused by the use of DTs. One is the demand effect, as these technologies allow firms to access a larger market, and the other is the potential substitution (or replacement) of these technologies.

We will also distinguish the role of automation from other DTs, referred to collectively as ICTs. To do so, we use two distinct indices to capture these two different components of digitalisation. The first component is the ICT index, which covers the technological components, digital-related human capital, and how firms use DTs to interact with stakeholders. The ICT index is expected not only to increase productivity, but also to act as complement to workers and thus increase employment beyond the demand-scale effect. In contrast, the impact of automation may be more uncertain, since, for example, robots are thought to boost productivity but also replace workers in certain tasks. In this case, employment would increase if the productivity effect dominates the displacement effect. However, while ICTs may lead to the fragmentation of value chains and the outsourcing of labour-intensive task, thus reducing employment, automation is likely to induce "reshoring" of some tasks previously outsourced, therefore leading to more employment at home.

Our results suggest that digitalisation has a positive and significant direct impact on firms' employment, as the demand-scale effect outweighs the potential replacement effect, and there is also a positive productivity effect. Furthermore, SMEs' employment is positively related to digitalisation, through both the direct and productivity effect, whereas no statistically significant direct effect is detected for larger firms. Digitalisation also has a positive effect on the number of different categories of workers. However, when we analyse the impact of digitalisation on the composition of employment, we find that digitalisation has a positive impact on the share of skilled workers but a negative effect on the share of unskilled workers. There is both a negative direct and productivity effect on the share of unskilled workers, and on the share of manufacturing workers. In contrast, we find no direct effect of digitalisation on the proportion of temporary contract workers, who still benefit from a productivity effect.

The rest of the paper is structured as follows. First, we review the existing literature analysing the impact of new technologies on employment. We then describe the methodology before introducing the data and some descriptive statistics. Finally, we present the empirical results and discuss the findings, implications, and limitations of this study.

2. Literature Review

New technologies based on digitalisation and automation can either be labour saving in some tasks and productivity-enhancing in other tasks, leading to lower prices and higher demand (Dottori, 2021), and potentially create new jobs in non-automated tasks (Autor, 2015), as well as create new tasks (Acemoglu and Restrepo, 2019). Dosi *et al.* (2021) even argue that the demand enhancing effect can extend to other markets for both goods and services. As a result, DTs can either act as a substitute for labour (referred to as a displacement effect), reducing employment, or, on the contrary, as complementary, increasing employment (Zator, 2019). Indeed, digitalisation and automation enable to allocate tasks to factors in a more flexible manner, resulting in higher value added and, as a result, an increase in labour demand for non-automated tasks and an increase in overall employment (Acemoglu and Restrepo, 2019). However, automation has also the potential to reduce the labour share, as machines replace workers in some tasks. The question is whether the net new jobs created by new technologies and their productivity effect can offset the displacement effect and the jobs that have been replaced by machines and robots. Depending on a plethora of factors, such as the industry or the skills of the workers, one effect may be stronger than the other and thus alter the net effect on employment. For example, it is argued that robots are more likely to perform routine tasks than tasks requiring higher skills, resulting in a loss of employment in routine tasks performed by medium-skilled workers. Hence, the literature suggests that there is a certain job polarization, by which high-skilled workers stand to gain the most from the digital transformation, followed by low-skilled workers, who will still benefit, but less. In contrast, medium-skilled workers stand to lose the most (Michaels *et al.*, 2014).

Nevertheless, most studies seem to agree that digitalisation has a net positive impact on employment. According to the survey conducted by Barbieri *et al.* (2019), the impact of digitalisation at the micro level is generally positive for employment, implying the creation of new jobs as a result of the ICT revolution. However, the results are quite different when disaggregated by skills. While there seems to be a positive relationship between skilled workers and new technologies, the relationship weaker or even non-existent when low-skilled or particularly, medium-skilled workers are considered. The survey also seems to concur that middle-skilled occupations may suffer more from technology adoption than other occupations. This implies that if we classify occupations by wages, the upper end of the distribution, i.e., professional occupations, would grow, the lower end of the distribution, i.e., elementary occupations, would grow but to a lesser extent, and the middle of the distribution, i.e., machine or electronic equipment operators, for example, would suffer a decline in employment. This polarization may be due to the fact that not only the dimensions of education and occupations are relevant in the analysis, but also the dimension of routine and how easily a particular task could be performed by a machine or robot.

The empirical literature on the impact of digitalisation on labour market outcomes can be divided into three strands, depending on the level of analysis. First, studies using local labour markets and regional data, then industry-level data, and finally firm-level data. Table A.1 in appendix A shows a summary of the key findings of these studies.

At the level of analysis of the local labour markets, Gregory *et al.* (2016) find that routine-replacing technological change has increased labour demand by up to 11.6 million jobs in Europe. Dauth *et al.* (2017) suggest that job losses from the use of robots in the manufacturing sector are offset by job creation in the service sector, suggesting reallocation rather than elimination. Mann and Püttmann (2017) confirm this intuition, confirming a decline in manufacturing jobs caused by automation and offset by the expansion of employment in the service sectors. However, Chiacchio *et al.* (2018) reach a different conclusion, finding a negative impact of robots on employment rates, especially for workers with intermediate education levels, i.e., with at least upper secondary education, but no impact on wages. Similarly, Acemoglu and Restrepo (2020) find a negative effect of robotization on both employment and wages. More specifically, one additional robot per 1000 workers would reduce employment by 3.3 workers and annual wages by $200. In contrast, Dottori (2021) points out that the introduction of robots may benefit to a greater extent blue-collar workers rather than white-collar workers, while this effect is reversed for wages. In addition to these results, Dottori (2021) cannot identify any negative impact of robotization on employment at the local labour market level, except for a very weak negative effect in manufacturing, estimating that exposure to robots could account for about 1/6 of the employment decline in these industries.

In terms of industry-level data, Michaels *et al.* (2014) evidence that ICT growth is associated with a significant increase in the demand for highly-skilled workers relative to medium-skilled workers as well as a significant, but smaller, increase in demand for low-skilled workers relative to medium-skilled workers. Similarly, Falk and Biagi (2017) find a positive relationship between the share of workers with a university degree and several ICT applications, such as enterprise resource planning, automatic data exchange, and electronic invoicing. Moreover, the share of the skilled workforce is also positively associated with the share of broadband-enabled workers and workers with mobile internet access. However, ICT appears to have a negligible impact on unskilled workers, but a strong and negative effect on the relative demand for workers with intermediate education. Graetz and Michaels (2018) find no effect of robotization on total employment, and only a negative effect for low-skilled workers. They also identify a positive and significant effect on wages. According to Klenert *et al.* (2020), there is a positive correlation between robots and total employment. Moreover, they find no evidence that robots are reducing the share of low-skilled workers in Europe.

In studies using firm-level data, Gaggl and Wright (2017) find that ICT increases employment in the wholesale trade, retail trade, and financial sectors, but has no effect on manufacturing. This effect also appears to differ between firms within the same industry. Akerman *et al.* (2015) point to a positive and significant effect of Internet technologies on the employment of skilled workers, whereas the effect is negative for unskilled workers. They point to a complementarity effect between the adoption of broadband technologies and skilled workers in non-routine tasks and a substitution effect between unskilled workers and routine tasks. Dutz *et al.* (2018) point out that the adoption of ICT at the firm level in Argentina, Chile, Colombia, and Mexico is associated with an increase in total employment, even among low-skilled workers. This can be explained by the fact that the productivity effect outweighs the substitution effect, and thus the replacement of low-skilled jobs by technologies or by high-skilled jobs is overcome by the increase in total employment of low-skilled workers. Dixon *et al.* (2019) suggest that investment in robotics is associated with an increase in total employment within the firm. However, companies that employ many low-skilled workers suffer more from the consequences of the substitution effect caused by digitalisation (Zator, 2019). In this line, Humlum (2019) evidences that robot adopters shift from low-skilled to high-skilled labour. Babina *et al.* (2020) find that firms investing more in artificial intelligence experience faster employment growth. Aghion *et al.* (2020) also find a positive effect of automation technologies on overall employment and low-skilled employment. More recently, Cirillo *et al.* (2021) suggest that digitalisation has a small positive and significant effect on employment, implying that employment tends to increase in highly digitalized jobs. However, when digitalisation is paired with routineness, the effect on employment becomes negative. This means that there could be a substitution effect of technology on employment for tasks that are highly digitalized but also highly routinized. In this context, they use the Routine Task Intensity index (RTI), an index which classifies tasks into three main categories, routine tasks, non-routine cognitive tasks and non-routine manual tasks.

Overall, most of these studies suggest a positive impact of DTs, including robots, on firms' demand for labour (Cusolito *et al.*, 2020), and instead of eliminating jobs, they would be reallocated from one industry to another (Bessen, 2019). Overall, however, it seems complicated to assess any trend concerning the existing literature. Indeed, the impact of digitalisation on employment is ambiguous, sometimes positive, sometimes negative, and even non-existent. However, most studies seem to agree that the impact on manufacturing employment is negative, implying a decrease in the demand for labour by manufacturing firms and a loss of jobs in these sectors. Nevertheless, the recent results for Spain, based on the ESEE dataset are not entirely clear. Camiña *et al.* (2020) suggest a negative effect of automation technologies on employment in Spanish manufacturing firms. This effect is slightly weakened, but still negative, when considering only the 2000-2016 period. Automation has a positive effect on long-term employment only when paired with human capital. In contrast, Stapleton and Webb (2020) demonstrate a positive effect, although weak, of the introduction of robots on employment. However, this effect is not robust for all specifications. They also find that robot adoption doubles the number of engineers and college graduates and increases production employment by 80%, while it does not affect college graduates and administrative workers. Finally, Koch *et al.* (2021) show that Spanish manufacturing firms that adopt robots increase employment compared to a non-adopter firm belonging to the same industry, implying that we assist in a reallocation of productivity and employment in favour of robot adopters. Those who adopt robots can expect their employment to increase by about 10%.

Moreover, there is no negative impact of robotization on low-skilled workers, i.e., workers who do not have a 5-year college degree.

Our contribution to the literature is manyfold. Most of the studies listed in this review use indicators that capture only one phenomenon of the digital transformation, such as robotization or automation, or use only ICT applications, whereas we include 13 components of the digital transformation into a synthetic index to better capture the degree of digitalisation. Second, we analyse both the direct effect of digitalisation on employment and the productivity effect using a model that considers profit-maximizing firms and allows for imperfect competition in product markets (Ortiz and Salas Fumás, 2020). Under profit-maximization, the labour demand depends on product demand factors, such as market power, that are not relevant under cost minimization, which is the standard approach. Finally, we explore the impact of digitalisation on different types of employment.

3. Methodology

To examine the effects of digitalisation on firms' labour demand, we adopt a model of a profit-maximizing firm (see Milner and Wright, 1998; Ortiz and Salas Fumás, 2020). We follow Ortiz and Salas Fumás (2020) and assume that the firm's output demand function is $Q = Dp^{-\varepsilon}$, where Q is the quantity demanded at unit price p, D is a parameter directly depending on digitalisation, which enlarges the potential size of the market at this price. DTs enable firms to reach more customers and thus expand their market size. The parameter ε is the (assumed) constant price elasticity of demand. From this, we obtain the inverse demand function $p = D^{1/\varepsilon}Q^{-1/\varepsilon}$. Therefore, total revenue is given as $R = pQ = BQ^{\mu}$, where $B = D^{1/\varepsilon}$ and $\mu = \frac{\varepsilon-1}{\varepsilon}$. These parameters allow us to consider an imperfectly competitive product market. This contrasts with previous literature assuming a perfectly competitive product market, where $\varepsilon = \infty$ and $\mu = 1$ (Van Reenen, 1997).

We consider a Cobb-Douglas production function:

$$Q_{it} = A_{it}K_{it}^{\alpha}L_{it}^{\beta}M_{it}^{\gamma} \quad (1)$$

where K is capital, L is labour, and M is intermediate inputs. α, β, and γ are output elasticities parameters with respect to each input that take values between 0 and 1. The sum of the three output elasticities is equal to δ. If δ is greater than 0, there are increasing returns to scale, if it is lower than zero, decreasing returns to scale, and if it is equal to zero, constant returns to scale. We assume that A the parameter representing the technical efficiency of the production process can be modelled as $A=exp(\omega_{it}, e_{it})$, where ω_{it} is the firm's TFP, which is assumed to be observable by the firm but not by the analyst; and e_{it} is the error term. Moreover, we assume that digitalisation enables firms to source inputs more efficiently as well as to innovate (Tambe and Hitt, 2014). Hence, accounting for the potential role of digitalisation in enhancing TFP, implies modelling productivity as a first order endogenous Markov process that depends on the firm's degree of digitalisation and a random shock, such that:

$$\omega_{it} = g(\omega_{it-1}, DIG_{it-1}) + \xi_{it} \tag{2}$$

where g(.) is an unknown function, and ξ_{it} is an unexpected innovation shock. The problem of profit-maximization of the firm can be formulated as follows:

$$Max_{K,L,M}\pi_{it} = BQ_{it}^{\mu} - rK_{it} - wL_{it} - cM_{it} \tag{3}$$

$$s.t.: Q_{it} = AK_{it}^{\alpha}L_{it}^{\beta}M_{it}^{\gamma}$$

where r, w and c represent the cost of capital, labour and intermediate inputs, respectively. From the profit maximization problem (see, Ortiz and Salas Fumás, 2020), we can derive the first order condition for labour:

$$\frac{\partial\pi_{it}}{\partial L_{it}} = \frac{B\mu\beta\left(AK_{it}^{\alpha}L_{it}^{\beta}M_{it}^{\gamma}\right)^{\mu}}{L_{it}} - w = 0 \tag{4}$$

Similarly, we obtain the optimal solutions for capital and intermediate inputs, and substitute these solutions into equation (4). Moreover, taking logs, and given that $B = D^{1/\varepsilon}$ and $\alpha + \beta + \gamma = \delta$, we can rearrange to obtain the reduced form of the labour demand[5]:

$$lnL_{it} = \frac{1-\mu}{1-\mu\delta} lnD + \frac{1}{1-\mu\delta} ln\mu + \frac{\mu}{1-\mu\delta} lnA + \frac{1-\mu(\alpha+\gamma)}{1-\mu\delta} ln\left(\frac{\beta}{w}\right) + \frac{\alpha\mu}{1-\mu\delta} ln\left(\frac{\alpha}{r}\right) + \frac{\gamma\mu}{1-\mu\delta} ln\left(\frac{\gamma}{c}\right) + u_{it} \quad (5)$$

where u_{it} is the error term. Moreover, w is the cost of labour, which enters as a denominator in the equation, meaning that the higher the real wages, the lower the demand for labour.

Digitalisation affects the labour demand in equation (5) through three components. The first is through the demand-*scale* effect. As previously stated, D is a parameter of the size of the potential market for a given price, which depends directly on digitalisation, $D = f(DIG)$. An increase in digitalisation that raises D will increase the demand for labour (except in price-taking firms, where $\mu = 1$). The second is the *productivity* effect, which is assumed to have a positive impact on the demand for labour. Given that we assume $A = exp(\omega_{it}, e_{it})$, and as shown in equation (2), digitalisation is allowed to impact on productivity through an endogenous Markov process $\omega_{it} = g(\omega_{it-1}, DIG_{it-1}) + \xi_{it}$. Finally, the *complementarity or substitution* effect of digitalisation can be captured through the effect of the price of digital capital, which is contained in the user cost of capital (r), on the labour demand. However, we have no information on the user cost of capital, nor on the prices of specific capital assets (i.e., the price of robots, price of computers, etc.). Instead, we use the capital stock (K) and the digitalisation index (DIG). This is consistent with the assumption that (digital) capital is a quasi-fixed input in the short-term[6] (Berman *et al.*, 1994), and in line with the empirical literature examining employment effects of technological change (Van Reenen, 1997; Pantea *et al.*, 2017; Goaied and Sassi, 2019). Additionally, using the capital stock instead of the user cost of capital, allows us to avoid possible problems related to the measurement of the price of capital, for which there is no reliable data at firm level.

[5] More details about how the labour demand is obtained can be found in the appendix B. A meaningful economic solution requires $1 < \varepsilon <$ infinite ($0 < \mu \leq 1$) and $0 < \delta\mu < 1$ (Ortiz and Salas Fumás, 2020).
[6] Assuming that capital is quasi-fixed in the short term implies that, for yearly variations, even if the cost of capital changes in a significant way, firms will have difficulties to adjust its stock of capital in the short term (Pantea *et al.*, 2017).

For the empirical analysis, we rearrange terms and estimate the following linear specification:

$$l_{it} = \theta_1 DIG_{it} + \lambda_1 \omega_{it-1} + \alpha_1 w_{it-1} + \beta_1 k_{it-1} + \gamma_1 c_{it-1} + \zeta_1 \mu_{it-1} + \sigma_1 X_{it-1} + d_t + d_j + \varepsilon_{it} \quad (6)$$

where labour depends on the parameter θ_1, which combines both the demand-scale effect and the potential supply-replacement effect of the digital transformation (DIG_{it-1}). A priori, the sign of this coefficient will depend on whether the positive scale effect dominates or not the negative potential replacement effect. Labour demand also depends positively on the productivity effect of digitalisation (ω_{it-1}) and negatively on real average wages (w_{it-1}). It does depend also on the capital stock[7] (k_{it-1}), and on the price of intermediate inputs (c_{it-1}), with the direction of these effects depending on the complementarity or substitutability between these inputs and labour. Finally, it will be determined by the extent of market power of the firm, (μ_{it-1}). Similar to previous studies on the employment effect of technological change, we control for a set of lagged control variables (R&D propensity and export propensity) included in the vector X_{it-1}. d_t and d_j are a set of time and industry effects respectively, and ε_{it} is the idiosyncratic error term accounting for the effect of other time- and firm-specific unobservable determinants.

3.1. The Impact of Digitalisation on the Workforce Composition

To examine the impact of digitalisation on the workforce composition, we use shares of workers categories as a dependent variable, under the same specification as in equation (6):

$$s_{it}^{EMP} = \theta_2 DIG_{it} + \lambda_2 \omega_{it-1} + \alpha_2 w_{it-1} + \beta_2 k_{it-1} + \gamma_2 c_{it-1} + \zeta_2 \mu_{it-1} + \sigma_2 X_{it-1} + d_t + d_j + r_{it} + \varepsilon_{it} \quad (7)$$

[7] Lower capital letters refer to variables in logs.

where the dependent variable s_{it}^{EMP} represents the following shares: i) unskilled employment, ii) skilled employment, iii) manufacturing employment, iv) permanent workers, and v) temporary workers. The expected impact of digitalisation on each is discussed in greater detail below.

The first employment share we consider is the share of unskilled workers on total employment, which is expected to be negatively related with the digitalisation index. This is because unskilled labour is more likely to perform routine tasks, thus it may be more easily replaced by DTs, in particular by robots. In contrast, robots and other DTs may act as a complement to skilled employment. In the case of the share of unskilled employment, the replacement effect is expected to outweigh the scale effect, while the opposite is true for skilled employment. This implies that we expect the coefficient θ_2 to be negative for the unskilled employment share. Hence, the share of unskilled workers is expected to decrease with the increase of digitalisation (Graetz and Michaels, 2018) through the parameter θ_2, but still, we expect to find a positive productivity effect through λ_2. Indeed, Autor and Salomons (2017) suggest that productivity growth has contributed to job polarization, implying an increase in skilled and unskilled labour demand at the expense of middle-skilled workers. The same logic can be applied to the analysis of the share of manufacturing workers. According to Dottori (2021), robots could account for about 1/6 of the employment decrease in manufacturing industries. The direct effect of digitalisation on the share of temporary workers is more uncertain, and we find no evidence from the existing literature. However, we hypothesize that temporary workers are more likely to be unskilled and much easier to be replaced due to the lower cost of firing compared to permanent workers. Thus, we expect that digitalisation will have a negative direct impact on the share of temporary workers, while having a positive impact on the share of permanent workers.

3.2. Estimation Methods

To estimate the parameter θ, which informs about the direct impact of digitalisation on firms' employment, we must account for the potential endogeneity of the digitalisation index. In order to do so, we use two different procedures for equations (6) and (7) due to the nature of the dependent variable (i.e., a continuous variable versus a share).

The instrumental variable (IV) approach to estimate equation (6) is based on a two-stage least-squares (2SLS) estimation procedure. We first instrument the digitalisation index with its second lag, which we assume is correlated with the digitalisation index but not with the error term. It is common to use lagged variable as instruments in the literature (e.g., Cameron *et al.*, 2005). In the first stage, we regress the digitalisation index on its second lag and the rest of the control variables using a fixed effect (FE) specification. In the second stage, the model-estimated values from the first stage are then used instead of the original values of the digitalisation index to estimate a FE-OLS model and thus avoid any simultaneity issues.

The dependent variable in equation (7) is instead the share of different categories of workers on total employment. This implies that the values of the dependent variable are bounded between 0 and 1. Therefore, a linear regression model like OLS is not appropriate (Kölling, 2020). Instead, we use a fractional response model for panel data (Papke and Wooldridge, 2008; Wooldridge, 2010). In addition, to control for the potential endogeneity of the digitalisation index in equation (7), we follow Kölling (2020) and apply a control function (CF) approach and treat it as an omitted variable problem (Wooldridge, 2015). The CF consists of two steps. On the first step, we regress the digitalisation index on the second lag of the digitalisation index and the covariates of the empirical model in a FE model. On the second step, the residual of the first step regression, $residual_{it}$, is used as an additional covariate in equation (7) to account for the factors that may cause correlation between the digitalisation index and the error term. Our identification strategy lies in the fact that the extent of digitalisation two periods ago does not influence the current firms' decisions on employment and its components, except through digitalisation.

As a robustness check, instead of using the second lag of the digitalisation index, we build a new instrument. This consists of the mean of the digitalisation index by industry, region, size, year, R&D propensity and export status, but excluding the focal firm. Knowing that the firm in question is excluded, we assume that the instrument is exogenous to the firm's labour demand. We then proceed estimating the model with a 2SLS model, as explained above.

3.3. TFP Methodology

To estimate the productivity effect of digitalisation on employment in equations (6) and (7), we first estimate a production function. Thus, for each two-digit industry, we estimate firm level TFP with the following Cobb-Douglas production function:

$$y_{it} = \beta_l l_{it} + \beta_{NIT} k_{it}^{NIT} + \beta_{IT} k_{it}^{IT} + \beta_m m_{it} + \omega_{it} + e_{it} \tag{8}$$

where y_{it}, l_{it}, k_{it}^{NIT}, k_{it}^{IT}, and m_{it} stand for the logarithms of real gross output, labour, non-ICT capital, ICT capital and materials, respectively. ICT and non-ICT capital are considered as fixed inputs whereas labour and materials are regarded are freely variable. Finally, ω_{it} is the firm's productivity, which we cannot observe but it is assumed that the firm can, and e_{it} is the error term[8].

To estimate the production function, we specify a Markov process for productivity, in which productivity at time *t+1* depends on the productivity a firm can expect given its information set at time *t* and on the innovation term ξ_{it+1}, which it is assumed uncorrelated with the state variables. We follow Doraszelski and Jaumandreu (2013) and assume an endogenous (first-order) Markov process, in which the digitalisation index is also allowed to impact firm's future productivity:

$$\omega_{it+1} = g(\omega_{it}, DIG_{it}) + \xi_{it+1} \tag{9}$$

Using OLS to estimate equation (8) yields biased and inconsistent estimates due to the fact the firm chooses its inputs, especially the freely variable inputs, depending on firms' productivity ω_{it}. We address this problem by using a control function approach following (see Olley and Pakes, 1996; Levinsohn and Petrin, 2003) which will allow us to estimate equation (8) consistently. More precisely, we follow Wooldridge (2009)[9] and use a GMM estimation. In doing so, we assume that the demand for

[8] The estimated errors are robust to heteroscedasticity and autocorrelation.
[9] The method distinguishes between state variables, in our case both types of capital, and flexible variables, here labour and materials. The realization of the state variables in period *t* is decided based on the information in *t-1*, and thus they are not affected by the productivity shock arriving t, while flexible variables are determined in response to the shock.

materials is a function of the state variables and productivity, and under certain conditions it can be inverted. Hence, we obtain: $\omega_{it} = m_t^{-1}(k_{it}^{IT}, k_{it}^{NIT}, m_{it}) = h_t(k_{it}^{IT}, k_{it}^{NIT}, m_{it})$. Finally, substituting this expression into equation (8) leads to the first equation to estimate:

$$y_{it} = \beta_l l_{it} + \beta_{NIT} k_{it}^{NIT} + \beta_{IT} k_{it}^{IT} + \beta_m m_{it} + h_t(k_{it}^{IT}, k_{it}^{NIT}, m_{it}) + e_{it} \quad (10)$$

However, from equation (10), we cannot identify the coefficients of both capitals and materials since h_t is an unknown function[10]. Therefore, to identify these coefficients, we need an additional equation that deals with the law of motion of productivity (Wooldridge, 2009), Hence, we assume that productivity depends on the endogenous Markov process as in equation (9). Knowing that $\omega_{it} = h_t(k_{it}^{IT},\ k_{it}^{NIT},\ m_{it})$, equation (9) becomes $\omega_{it} = f(h_t(k_{it-1}^{IT}, k_{it-1}^{NIT}, m_{it-1}), DIG_{it-1}) + \xi_{it} = g_t(k_{it-1}^{IT}, k_{it-1}^{NIT}, m_{it-1}, DIG_{it-1}) + \xi_{it}$; and then plug it into equation (8) to obtain the second equation we will estimate:

$$y_{it} = \beta_l l_{it} + \beta_{NIT} k_{it}^{NIT} + \beta_{IT} k_{it}^{IT} + \beta_m m_{it} + g_t(k_{it-1}^{IT}, k_{it-1}^{NIT}, m_{it-1}, DIG_{it-1}) + u_{it} \quad (11)$$

where we proxy $g_t(.)$ with a third-degree polynomial in its arguments. The composed error term is $u_{it} = \xi_{it} + e_{it}$.

We follow Wooldridge (2009) to estimate equations (10) and (11) jointly by GMM, using the appropriate set of instruments[11]. This is done for each of the 10 industries considered. Thus, we obtain industry-specific output elasticity estimates and firm-specific TFP estimates. These results are presented in Table 1 and show that the elasticity of the ICT capital is significant across all the 10 industries, being the lowest (0.008 and 0.009) in the textile, leather and shoe industry, and in the non-metallic minerals industry, respectively, and the highest (0.043) in the electrical goods industry. The labour elasticity is the highest in the textile, leather and shoes industry (0.331) and the lowest in the food, drink and tobacco

[10] We proxy $h(.)$ by a third-degree polynomial in its arguments.
[11] We follow Doraszelski and Jaumandreu (2013) and De Loecker (2013) and do not account for sample selection by modelling a firm's exit decision.

industry (0.107); non-ICT capital elasticity is the highest in the non-metallic minerals and food, drink and tobacco industries (0.090) and the lowest in the timber and furniture industry (0.033); and the intermediate inputs elasticity is the highest in the metals and metal products industry (0.733) and the lowest in the textile, leather and shoes industry (0.485).

<Table 1 here>

In order to have evidence of the productivity effect of digitalisation on employment, the digitalisation index must have, first, a significant effect on TFP[12] and, second, the TFP's coefficient must be significant in the labour demand equation. To verify the first condition, we consider a linear specification of the Markov process described by equation (9):

$$\omega_{it} = \beta_1 \omega_{it-1} + \beta_2 DIG_{it-1} + \gamma' z_{it-1} + \alpha_j + \alpha_t + \alpha_i + \epsilon_{it} \tag{12}$$

where ω_{it} is firm's TFP that is a function of its lagged value, the lagged digitalisation index and other control variables that may influence the evolution of productivity, including a vector of observed firm characteristics (z_{it-1}), sector dummies (α_j), year dummies (α_t), and firm fixed effects (α_i). Positive and significant estimates of β_2 are interpreted as an enhancing effect of digitalisation on TFP.

<Table 2 here>

Equation (12) is estimated by the two-step system-GMM estimator for dynamic models (Arellano and Bover, 1995; Blundell and Bond, 1998), which accounts for unobserved heterogeneity and the endogeneity bias[13]. All the specifications provide suitable results for the Hansen test of overidentifying restrictions[14] (testing for instruments validity) and for the non-serial correlation of the error terms[15]. As

[12] To control for the impact of outliers, we winsorize the resulting distribution of TFP at the 1st and 99th percentile.

[13] Eq. (12) -in dynamic form with additional lagged values of productivity-is estimated using the two-step XTABOND2 system GMM approach (Arellano and Bond, 1991) implemented in STATA.

[14] The null hypothesis of the Hansen test is that all overidentifying restrictions are jointly valid. As the p-values of the Hansen test are greater than 0.1, we cannot reject the null and this implies that the instruments are valid.

[15] The optimal lag length of the dependent variable is selected until no serial correlation is achieved in residuals. For the disturbances to be not serially correlated, there should be evidence of significant negative first order serial correlation and no evidence of second order serial correlation in the differenced residuals. Hence, according to the Arellano-Bond test for serial correlation presented in Table 2, all models show evidence of significant first-order

shown in Table 2, digitalisation has a positive and significant impact on TFP and TFP growth. When we look at the impact of the automation and ICT indices, we find that only ICT has an enhancing TFP effect. When looking at column (4), we can notice that for every standard deviation increase of the digitalisation index, TFP would increase by more than 0.7%. We also find a learning by trading effect (De Loecker, 2013) when considering the whole sample of firms.

4. Data and Descriptive Statistics

4.1.Data

The data are drawn from the Survey on Business Strategies (ESEE, henceforth) for the years 2001-2014. This is a yearly panel database that began in 1990 and is financed by the Spanish Ministry of Industry, Tourism and Trade, and supervised by the SEPI foundation. Firms in the survey are representative by two-digit NACE-Rev.1 manufacturing industries and size categories. The ESEE provides data on firm's activity, including employment, products and manufacturing processes, customers and suppliers, costs and prices, markets, technological activities, foreign trade, and accounting data. Because some of the variables used to build the digitalisation index first appeared in 2001, the period of analysis spans from 2001 to 2014.

Concerning the sampling of the ESEE survey, firms with less than 10 employees were initially ruled out from answering the questionnaire. Then, firms between 10 and 200 employees were randomly samples, representing around 5% of the population in 1990. Firms with more than 200 employees were surveyed on a census basis, achieving a participation rate of around 70%. Attrition has been minimized and new firms have been introduced every year in the survey with the same sampling criteria as in 1990. Thus, this dataset keeps being representative over the years.

Our initial sample consists of an unbalanced panel of 24,112 observations corresponding to 3,353 firms that have been observed in at least two consecutive periods between 2001 and 2014.

serial correlation in differenced residuals, and none show evidence of second-order serial correlation in the differenced residuals, suggesting the overall consistency of our estimates.

4.2. The Digitalisation index

Following Añón Higón and Bonvin (2023), and based on the work of Calvino et al. (2018) at the sector level, we construct a firm level index of digitalization for the period 2001 to 2018.[16] This index is designed considering that digitalisation is a complex phenomenon that cannot be captured by a single indicator. Moreover, this index considers the interconnectedness of DTs and the potential synergistic effects they have on each other.

To construct this index, we use four dimensions that represent the extent of digitalization on the period of analysis: 1) the technological components (measured by ICT capital, computer programming services, and the implementation of software programs either hired or developed by the company); 2) the digital-related human capital (measured by personnel training in software and information technology); 3) the extent of automation (measured by the use of robots, computer-aided design, flexible systems, and LAN); and, 4) the company's interactions with its stakeholders through digitalization (this includes ownership of an Internet domain and website, and the use of b2b, b2c, and e-buying). In total, the synthetic index captures information on 13 components measured in different ways that contain relevant information about the firm's extent digitalization. In addition, the analysis distinguishes the role of automation from other digital technologies referred to as ICT. Therefore, we construct an automation index that captures the extent of automation, measured by the third component of the general index. The other dimensions are part of the ICT index.

4.3. Descriptive Statistics

Table 3 shows the descriptive statistics for the dependent variable, the main variables of interest, and the remaining control variables. It is interesting to note that most workers in the sample do not have a college degree, are employed full-time, and have a permanent contract. However, it is important to

[16] Data for some of the dimensions included in the Digitalisation Index have only been available in the ESEE since 2001. We refer the reader to the study by Añón Higón and Bonvin (2023) for details about the construction of the index.

highlight that the Spanish labour markets presents relatively high unemployment rates and a high proportion of temporary workers (Ortiz and Salas Fumás, 2020).

<Table 3 here>

First, we plot the evolution over time of the degree of digitalisation (through the composite digitalisation index and its two components, namely ICT and automation) and overall employment, as well as the various categories of employment (workers' education level, contract type, etc.). At the outset, it is important to note that all-time series plotted in this section have been normalized so that the first year (2001) equals 100, since we are interested in analysing trends.

In the left panel of Figure 1, we show how total employment in manufacturing firms and the digitalisation index evolve over the 2001-2014 period, while on the right side we break down the digitalisation index into the two sub-indices, the automation index and the ICT index. While the extent of digitalisation has increased by more than 30% over the period, manufacturing employment has declined by around 6%. This increase in digitalisation is due to both an increase in ICT and a steep automation process, particularly relevant since the second half of the 2000s. Although not shown, the behaviour of total effective hours is very similar to that of employment. In the econometric specification, we will then test whether the employment decline is due to the displacement effect of digitalisation.

<Figure 1 here>

<Figure 2 here>

In Figure 2, we show how the share of workers with different skills has evolved over the years. The share of unskilled workers seems to have decreased by about 7%, while the share of skilled workers has increased by 60%. This is in line with one strand of the literature that states that workers with low skill levels suffer more from digitalisation than workers with higher skill levels, as DTs would replace the former and complement the latter (Akerman *et al.*, 2015).

<Figure 3 here>

In Figure 3, we divide employment into different categories: temporary and permanent contract workers on the left panel, and part-time and full-time workers on the right panel. While the employment of workers with permanent contracts remained fairly stable over the 2001-2014 period, the employment of workers with temporary contracts decreased by slightly more than 10%. Workers on fixed-term contracts suffered a sharp decline in 2008, due to the impact of the Great Recession. Turning to the right panel, although the share of workers with part-time contracts in Spain is relatively low compared to other European countries, the graph shows that their number increased by about 70% over the period analysed, particularly before 2008. In contrast, the number of full-time employees declined slightly between 2001 and 2014, and thus appears to be negatively correlated with digitalisation.

<Figure 4 here>

Finally, Figure 4 shows the evolution of R&D and industrial plants employment and the digitalisation index over the 2001-2014 period. R&D employment decreased by about 3-4% in 2014 compared to 2001. In the case of industrial plants employment, this decline is smaller with a decrease of just over 5%. Whether this decline is the result of digitalisation will be analysed below.

It is important to remember that these graphs cannot prove any causal impact of digitalisation on the employment variables. To go beyond correlations and intuitions, we need to estimate the models presented in equation (6) and (7).

5. Results

We now turn to assess the impact of digitalisation on the labour demand of profit-maximizing firms in the Spanish manufacturing sector. To do so, we first estimate equation (3.6) using OLS fixed effects and an instrumental variable approach via 2SLS, controlling for the potential endogeneity of digitalisation. We first discuss our main results before delving deeper into the effect of digitalisation on the composition of employment.

5.1. Baseline Results

The main results are displayed in Table 4. In column (1), we estimate an OLS fixed effects model as a benchmark, in which we ignore the potential endogeneity of the digitalisation index. In column (2), we report the same specification but using the same sample as for the IV strategy[17]. Digitalisation appears to be positively and significantly related with employment regardless of the sample size. Columns (2) and (5) are the equivalents of columns (1) and (4) respectively, aside from the fact that we disentangle the digitalisation index into its two sub-indices, the ICT and automation indices. The θ coefficient, which captures the combined demand-scale effect and the potential substitutability of DTs, is very similar across models in columns (1) and (2), and (4) and (5).

To account for the potential endogeneity of digitalisation, we use an IV-2SLS estimation procedure. The results are presented in columns (3) and (6). In column (3), we use the digitalisation index (DIG) and instrument it with its second lag, whereas the ICT and automation indices in column (6) are also instrumented with their respective second lags. We begin by discussing the first stage of the IV regression, which is reported at the bottom of the table. As shown in column (3), the instrument is positively and significantly correlated with the digitalisation index in the first stage. In column (6), giving that we have two instruments for two endogenous variables, it implies that we have two first stages. Both the second lag of the ICT index and that of the automation index are positively and significantly related to the variable they instrument. Moreover, the instruments appear to be relevant as they pass both first-stage tests for weak instruments. Both the Kleibergen-Paap weak identification rk Wald F-statistic and the Cragg-Donald Wald F-statistic surpass the Stock-Yogo 10% critical values fixed at 16.38 and 7.03 for columns 3 and 6, respectively (Stock and Yogo, 2005).

<Table 4 here>

While the direct effect of digitalisation on employment is already sizeable in the OLS-FE models, it is nearly doubled when using a 2SLS model, reflecting the downward bias of the OLS estimates. More precisely, a one standard-deviation increase in the digitalisation index corresponds to a

[17] The IV strategy uses the second lag of the digitalisation index as an instrument, therefore it has less observations.

4.4% increase of total employment within the firm. That digitalisation has a positive direct effect on firms' labour demand may be because the demand-scale effect offsets the potential displacement effect, and thus results in net job creation. It could also be because the positive demand effect is coupled with a positive supply effect arising from potential complementarities between DTs and labour.

To assess if different DTs may have a different impact on employment, we disentangle the digitalisation index into the ICT and automation indices. The IV results are presented in column (6) of Table 4. It appears that the previous positive effect of digitalisation on employment is caused by the ICT index, which has a positive and significant effect on employment, and not by the automation index, which has a positive but not significant effect. The results show that for every one standard-deviation increase of the ICT index, firms' employment is boosted by approximately 5.7%. Overall, these findings imply that automation technologies may be substitutes for employment, but their replacement effect is cancelled out by a positive demand-scale effect. On the contrary, ICT, as suggested by its positive impact on employment, has not only a positive demand-scale effect, but also may complement labour, and thus further increases employment.

The impact of digitalisation on employment goes beyond the direct impact due to the combined scale and replacement effects. There is also a productivity effect of digitalisation on employment captured by the coefficient of the TFP variable. The results in column (3) in Table 4 show that TFP has a positive and significant impact on employment, indicating that a 1% increase in TFP leads to an increase in employment by almost 0.4%. This result coupled with the fact that, as shown in Table 2, the digitalisation index has a positive and significant effect on TFP, confirms that digitalisation impacts employment in a positive way through the productivity effect. Our findings seem to contradict previous studies suggesting that digitalisation has a negative effect (Mann and Püttmann, 2017; Dottori, 2021)[18] or no effect (Gaggl and Wright, 2017) on manufacturing jobs. However, it appears to go in line with studies by Stapleton and Webb (2020) and Koch *et al.* (2021), which using the ESEE dataset, show evidence of a positive effect of robotization on manufacturing employment[19].

[18] The level of analysis of Mann and Püttmann (2017) and Dottori (2021) is at the local labour markets level whereas we use firm-level data

[19] In contrast, Camiña *et al*. (2020) find a negative effect of automation technologies on manufacturing employment.

Regarding the rest of the other control variables, the markup appears to have a negative and significant effect on employment. As expected, an increase in firms' market power leads to a decline in the labour demand. Real average wages are also negatively associated with employment. According to the law of demand, the higher the price, the lower the quantity demanded (Marshall, 1920). This implies that increasing the price of the workforce, i.e., the wage, would decrease the quantity of labour demanded by employers. The coefficient of the capital stock shows positive and significant, as firms that expand their businesses tend to hire more employees[20]. Firms doing R&D are also larger. According to Bogliacino *et al.* (2011), R&D has a positive effect on employment, which is perceptible in high-tech manufacturing but absent in the more traditional manufacturing sectors. Export propensity also has a positive and significant effect on employment since an increase in export participation raises labour demand upwards (Orbeta, 2002). Producing more goods in order to export them should translate into job creation, as suggested by Tandoğan (2019) for the case of Turkey. Finally, although strikingly, the price of materials appears to be positively related to employment. The higher the price of materials, the lower their demand, which could in turn increase the labour demand in order to compensate for this lack of materials in the production process. This could be explained if the firm back-shores or integrates vertically the production process as a result of an increase in the prices of intermediates.

5.2. Heterogenous Employment Effects from Digitalisation

To gain a better understanding of the impact of digitalisation on different categories of employment, we estimate equation (6), but this time using other employment-related variables as dependent variable. Results are presented in Table 5. To estimate the model, we use a fixed effects IV-2SLS approach, in which the digitalisation index is instrumented by its second lag. We formally test for the validity of the instrument. Thus, the Kleibergen-Paap Wald test and the Cragg-Donald F-statistic indicate that the instrument is not weak across all specifications.

[20] Although we do not differentiate between ICT and non-ICT capital, our results are in line with Stehrer (2022), who show that non-ICT capital has a positive impact on employment growth, while ICT capital has no effect. Giving that capital in our study considers both non-ICT and ICT, the magnitude of the overall effect on employment is coherent with the results obtained by Stehrer (2022).

In columns (1) and (2) of Table 5 we show that the digitalisation index is positively related to both skilled and unskilled employment. A one standard-deviation increase in the extent of digitalisation is associated to a 5.4% rise of skilled employment, whereas unskilled employment would increase by 4.6%. Similar to Michaels *et al.* (2014), the demand for skilled workers seems to experience a greater increase than the demand for unskilled workers in response to the digital transformation. Concerning the productivity effect of digitalisation on employment, the tendency is the reversed. For a 1% increase of TFP, skilled employment raises by almost 0.2%, whereas this proportion is almost doubled for unskilled employment.

<Table 5 here>

In column (3) of Table 5 we present the results for manufacturing employment. The results show that digitalisation exerts both (positive) direct and productivity effects. Manufacturing employment increases by 4.5% for every one standard-deviation increase in the digitalisation index, and increases by nearly 0.4% for every 1% increase in TFP. Columns (4) and (5) consider the impact of digitalisation on the demand of permanent and temporary salaried workers, respectively. The results show that permanent salaried staff would increase by 3% for every standard-deviation increase of the digitalisation index, whereas the effect on temporary salaried staff is not significant. However, permanent and temporary salaried staff benefit from the productivity effect of digitalisation. Increasing firm's TFP by 1% leads to a rise in the number of permanent and temporary workers of around 0.4% and 0.3% increase, respectively. The effect of wages on temporary employment is the strongest when looking at all the sub-categories of employment. For every standard-deviation increase of the real average wage, temporary employment would decrease by more than 8%, whereas permanent employment would only decrease by 2.6%.

Finally, we consider the impact of digitalisation on total employment in SMEs (column (6)) and large firms (column (7)). The results show that digitalisation has a direct positive and significant impact on the labour demand of SMEs, whereas there is no effect on large firms' employment. For every standard-deviation increase of the digitalisation index, SMEs' employment is expected to raise by 5.7%. However, the productivity effect is stronger for large firms, which translates into a 0.6% increase in labour demand for every 1% increase in TFP. For SMEs, this effect remains positive and significant, but is halved compared to their larger counterparts.

5.3. Impact of Digitalisation on the Shares of Workers' Composition

To complement the previous analysis, we examine here the impact of digitalisation on the share of employment-related variables. In doing so we estimate equation (7). As previously stated, we use a Generalized Linear Model (GLM) to account for the bounded nature of the dependent variable (Papke and Wooldridge, 2008), and a CF approach to account for the potential endogeneity of the digitalisation index. Therefore, in a first step we regress the digitalisation index on its second lag value in a FE model. We then estimate equation (7) using the disturbance values from the first step. The results are presented in Table 6 in terms of average marginal effects.

From the previous results shown in Table 5, digitalisation had a positive and significant impact on both the demand for skilled and unskilled employment, through both the direct and productivity effect. However, this is not the case when looking at their employment shares. Indeed, in column (1) of Table 6, we have evidence of a negative direct impact of digitalisation on the share of unskilled employment. For every one standard-deviation increase of the digitalisation index, the share of unskilled employees would decrease by almost 2.5%. Column (2) shows that this negative effect is transmitted from both the ICT and automation indices. The productivity effect of digitalisation also appears negative, with a 1% increase in TFP leading to a decrease in the share of unskilled employment by 0.02%. Although not reported in Table 6, digitalisation, also through the ICT and automation indices, has a positive and significant impact on the share of skilled employment, both through the direct and productivity effects. Hence, digitalisation appears to be biased towards skilled employment, which goes in line with previous studies (Akerman *et al.*, 2015; Graetz and Michaels, 2018; Humlum, 2019; Zator, 2019). Despite benefiting both skilled and unskilled workers in absolute values, the share of the latter is negatively related to digitalisation, while the opposite is true for the former.

The results in columns (3) and (4) show that digitalisation has no direct effect on the share of temporary workers. It seems that the negative replacement effect is offset by the positive scale effect. However, when we break down the digitalisation index, we observe that ICT has a positive direct impact, whereas automation has a negative effect on the proportion of temporary workers. This may be due to the fact that ICTs may have a larger scale effect on demand than automation technologies, or the fact that automation technologies may have a larger replacement effect, or a combination of both. Nevertheless, the productivity effect on the share of temporary workers is positive. A 1% increase in TFP leads to an increase in the share of temporary workers of 0.05%.

Finally, in columns (5) and (6) we focus on the proportion of manufacturing employment[21]. First, we observe that the direct effect of digitalisation is negative. The digitalisation index, as well as ICT, display negative and significant coefficients. In contrast, automation has no significant impact. Results in column (5) suggest that for every one standard-deviation increase of the digitalisation index, the share of manufacturing employment decreases by nearly 1.5%. There is also a negative productivity effect. A 1% increase of TFP reduces the share of manufacturing employment by 0.02%. This result is similar to that on the share of unskilled workers.

<Table 6 here>

5.4. Robustness Checks

In this section, we perform a series of robustness checks based on the models from columns (3) and (6) in Table 4 (i.e., the IV-2SLS approach).

<Table 7 here>

The first robustness check, the results of which are presented in columns (1) and (2) of Table 7, consists of introducing more controls to check for omitted variable bias. This additional firm level controls are foreign ownership, whether the firm faces recessive and expansive markets, the number of market competitors, and the internal and external financial health. The results show that the direct and productivity effects are similar to the baseline specification. For every one standard-deviation increase of the digitalisation index, total employment increases by 4.7%, compared to 4.4% in column (3) of

[21] The share of manufacturing employment is the number of workers employed at manufacturing establishments divided by the total number of workers employed by the firm.

Table 4. Concerning the productivity effect, employment is boosted by 0.37% for every 1% increase of TFP, compared to 0.36% previously.

In the baseline results presented in Table 4, the endogeneity issue was addressed using as instrument for the digitalisation index its second lagged value. As a second robustness check, in columns (3) and (4) of Table 7, we use as instrument the mean (excluding the value of digitalisation of the focal firm) of the digitalisation index by industry, region, size, year, R&D, and export status. We assume that this instrument is exogenous to the firm's labour demand. We expect a positive correlation between the average digitalisation of firm's peers and the degree of firm's digitalisation. We formally test for the validity of the instrument. The instrument shows significant (although at 10%) in the first stage of the 2SLS procedure and with the expected sign, as shown in Table A.2 in appendix A. However, the results of the Kleibergen-Paap and the Cragg-Donald tests for weak instruments, shown at the bottom of Table 7, do not support the validity of this instrument in this case.

As a third robustness check, to control for the fact that TFP has been estimated in a first step, we perform an IV-2SLS regression but bootstrapped standard errors with 250 replications. The results are reported in columns (5) and (6) of Table 7 and the significancy of the digitalisation index and TFP appears to persist. Indeed, the results obtained are comparable to columns (3) and (6) of Table 4.

Finally, to control for the bias induced by potential outliers, we trim the log of employment (i.e., the dependent variable) by removing values below the 1st and above the 99th percentiles. Again, the impact of digitalisation and TFP is not altered by removing extreme values and the results appear to be robust.

6. Conclusion

A large number of studies have examined the impact of digitalisation on employment with mixed results. Indeed, DTs can act as a substitute for labour, for example, by replacing manual routine tasks with robots, resulting in a reduction in employment, a phenomenon known as the displacement effect. Alternatively, DTs can be used to complement labour, increase productivity, and result in higher value added and employment. Digitalisation enables firms to access a broader market, increasing demand and thus employment. This is referred to as the demand-scale effect. Which effect dominates will determine the direction of the impact of digitalisation on employment.

In this study, we examine the direct and productivity effects (via TFP) of DTs on firms' employment decisions. In doing so, we use a sample of Spanish manufacturing firms between 2001 and 2014 drawn from the ESEE dataset. To uncover the productivity effect of digitalisation on employment, we assume an endogenous Markov process in which the digitalisation index is allowed to influence firm's productivity. Our findings suggest that the productivity and demand scale effects outweigh the negative displacement effect. As a result, digitalisation leads to net job creation in manufacturing firms both directly and through productivity.

Nonetheless, these results can vary when we consider the workforce composition. In terms of skills, we find that skilled and unskilled workers benefit directly and indirectly, via the productivity effect, from digitalisation, as well as manufacturing workers and permanent contract workers. As for temporary contract workers, they only benefit from digitalisation via the productivity effect. In terms of size, SME's facing an increase in their digitalisation are expected to raise their employment, as they benefit from a direct and productivity effect of digitalisation. In contrast, digitalisation exerts only a productivity effect on the labour demand of large firms.

However, when analysing employment shares, the above conclusions become more nuanced. For instance, if digitization were to increase, the share of unskilled workers in total employment would decrease, both due to the direct effect and productivity effect. The same can be said for the share of manufacturing workers. Both of these results are quite similar, which goes in line with the hypothesis that manufacturing workers are more likely to be unskilled. This confirms the intuition given by previous studies that digitalisation is biased towards skilled employment (Akerman *et al.*, 2015; Graetz and Michaels, 2018; Humlum, 2019; Zator, 2019). This bias could increase the demand for high-skilled workers in a disproportionate way, making these workers more valuable, and therefore increase wages inequalities favouring high-skilled workers with respect to low-skilled workers. According to Juhn *et al.* (1993), an increase in the demand for skills could cause the return to skills to rise, and thus wages inequalities between low- and high-skilled workers to intensify.

From a managerial perspective, our findings offer interesting insights. First, we find no evidence of DTs hindering the employment prospects in SMEs or large firms, and this conclusion holds regardless of the skill level. The implementation of DTs may upgrade the workers' autonomy and communication with managers without raising concern about having to dismiss employees. Nevertheless, some jobs (or tasks) will most likely be replaced by machines, but only to create new jobs probably requiring the same type of skills. According to our findings, unskilled jobs will not disappear, but will grow at a slower rate than skilled jobs, which will account for a larger proportion of total jobs in manufacturing.

In addition, the results provided by this study can help policymakers to design better policies without being reluctant to promote the use of new technologies in Spanish firms with the fear that this will increase unemployment. DTs have helped Spanish firms to remain competitive in foreign markets and, as our results here show, they also lead to more employment. This points to the need to foster policies around the provision of incentives to encourage firms to adopt DTs. These incentives could take the form of subsidies or tax breaks and would help to lower unemployment as well as increase the competitiveness of Spanish firms. As we have previously explained, this is especially true for SMEs. From the side of the employees, training courses could be offered and financed by the state, in order to prepare the Spanish labour force to the potential shift towards more digital-intensive tasks. In these terms, the Next Generation EU[22] program has put in place initiatives by which the Commission funds online training courses to improve the digital skills of the European population and helps SMEs increase their online presence. More specifically, The *Digital Europe Programme* is also a new EU funding program focused on bringing digital technology to businesses, citizens, and public administrations. It aims to shape the digital transformation of Europe's society and economy, benefiting everyone, but in particular SMEs[23].

Nevertheless, our study is not without limitations. First, although the digitalisation index captures many important dimensions of the digital revolution, it does not cover new uprising DTs, such as artificial intelligence, machine learning, blockchain, the Internet of Things, or 3D printing

[22] As reflected in the Next Generation EU program, the digital transformation is one of the two large-scale challenges of our time for Europe along with the green transformation.
[23] https://digital-strategy.ec.europa.eu/en/activities/digital-programme

penetration. Second, an alternative instrument to the twice-lagged digitalisation index could render more robust results. Third, we also lack data on assets' prices, which would allow us to disentangle the direct effect of digitalisation on employment into two different effects, the displacement effect and the demand-scale effect. Currently, we are only able to identify the combination of these two effects. Furthermore, our data do not allow us to distinguish between different occupations or levels of routineness of labour tasks, which, according to previous studies (Cirillo *et al.*, 2021), is a key element that would allow us to discern which types of employment may be threatened by digitization.

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APPENDIX A

Table A.1: Literature review

Authors	Sectors/countries	Period of analysis	Measurement of technical change	Findings (Employment)
Local Labour Markets (LLM)				
Gregory *et al.* (2016)	238 regions in 27 EU countries	1999-2010	Routine-replacing technological change (RRTC)	- RRTC has increased labour demand by up to 11.6 million jobs. - Capital replaces labour, thus RRTC has decreased labour demand by 9.6 million jobs. - It has been overcompensated by product demand and spillover effects which have together increased labour demand by 21 million jobs.
Dauth *et al.* (2017)	402 LLM in Germany	1994-2014	Robots	- No evidence that robots cause total job losses. - Every robot destroys two manufacturing jobs. This loss is offset by additional jobs in the service sector. - Negative impact on medium-skilled workers in machine-operating occupations, while high-skilled managers benefit.
Mann and Püttmann (2017)	722 LLM in the USA	1976-2014	Automation and non-automation patents	- Automation increases jobs in service but decreases them in manufacturing.
Chiacchio *et al.* (2018)	Regional data from Finland, France, Germany, Italy, Spain, and Sweden	1995-2007	Industrial robots	- Negative effect of robots on employment. - One additional robot per 1000 workers reduces the employment rate by 0.16-0.20 percentage points - The negative effect of robots on employment is prominent for workers of middle education.
Acemoglu and Restrepo (2020)	722 LLM in the USA	1990-2007	Industrial robots	- Robotization reduces employment. - One additional robot per 1000 workers reduces aggregate employment to population ratio by 0.18-0.34 percentage points - Negative employment effects of robots for routine manual occupations and blue-collar occupations. - No positive effect for high-skills workers
Dottori (2021)	784 LLM in Italy	1991-2016	Robots	- No negative effect of robotization on overall employment. - Very weak negative effect on manufacturing industries.

Industry-Level				
Michaels *et al.* (2014)	Industry-level data from the USA, Japan, and 9 European countries	1980-2004	ICT capital divided by value-added	- ICT growth is associated with a significant increase in the demand for high-skilled workers relative to medium-skilled workers. - And with a significant, but smaller, increase for low-skilled workers relative to medium-skilled workers.
Falk and Biagi (2017)	Industry-level data from Denmark, Finland, France, Netherlands, Norway, Sweden and the UK	2001-2010	Broadband-enabled employees, mobile internet access, enterprise resource planning (ERP) systems and electronic invoicing	- For manufacturing industries, new technologies are positively related to the share of high-skilled workers. - For service industries, only the use of mobile internet is significant. - Across manufacturing, the increased usage of ERP systems accounts for 30% of the increase in the share of highly skilled workers.
Graetz and Michaels (2018)	Sectoral-level data from 17 developed countries	1993-2007	Industrial robots	- Robots do not reduce total employment. - Robots appear to reduce the share of hours worked by low-skilled workers relative to medium-skilled and high-skilled workers
Bessen (2019)	Industry-level (textile, steel and auto) data from the USA	1810-2011	Automation	- Automation does not cause aggregate unemployment. - Reallocation of employment rather than elimination.
Klenert *et al.* (2020)	Industry-level data of 28 EU countries	1995-2015	Robots	- Robot use is correlated to an increase in aggregate employment. - No evidence of robots reducing the share of low-skilled workers.
Dosi *et al.* (2021)	Sectoral-level data of 19 European countries	1998-2016	Disembodied and embodied technological change	- Technology positively affects employment. - Demand-enhancing effects may extend to other connected markets for goods and services.
Firm-Level				
Akerman *et al.* (2015)	Firm-level data from Norway	2001-2007	Broadband internet	- Broadband adoption in firms complements skilled workers in executing non-routine abstract tasks - Broadband acts as a substitute for unskilled workers in performing routine tasks.
Gaggl and Wright (2017)	Firm-level data from the UK	2000-2004	ICT investment	- ICT raises employment in wholesale, retail and finance industries. - No impact on manufacturing industries. - ICT leads to a rise in the demand for nonroutine, cognitive tasks.

				- A modest tendency of ICT to replace routine- cognitive work while manual work seems unaffected.
Dutz *et al.* (2018)	Firm-level data from Argentina, Chile, Colombia and Mexico	Argentina: 2010-2012 Chile: 2007-2013 Colombia: 2008-2014 Mexico: 2008-2013	Argentina: investment in ICT capital Chile: complex software use Colombia: high-speed internet use Mexico: internet use	- A positive effect of technologies on overall employment. - Positive effects of ICT on both high- and low-skilled workers.
Dixon *et al.* (2019)	Firm-level data from Canada	2000-2015	Robots	- Investments in robots are associated with an increase in total employment within the firm - However, it can reduce middle-skilled workers employment, whereas it increases employment for low-skilled and high-skilled workers
Humlum (2019)	Firm-level data from Denmark	1995-2015	Robots	- Robot adopters shift from low-skilled to high-skilled labour
Zator (2019)	Firm-level data from Germany	1993-2017	Digitalisation and automation	- New technologies reduce employment - Negative effects in industries such as manufacturing, retail and hospitality, but in industries such as finance and education and health, technology seems to complement workers and lead to increased employment - Both digitalisation and automation increase the share of high-skill workers while the substitution effect of new technologies affects mostly unskilled workers
Aghion *et al.* (2020)	Firm-level data from France	1994-2015	Automation	- Positive effect of automation on employment - No significant effect of automation on employment when considering firms with low exposure to international competition
Babina *et al.* (2020)	Firm-level data from the USA	1999-2007	Investment in AI technologies	- Firms investing more in AI experience faster growth in employment
Cusolito *et al.* (2020)	Firm-level data from 82 developing countries	2002-2019	Email and website adoption	- DTs adoption increases firms’ demand for labour
Cirillo *et al.* (2021)	Occupation-level data from Italy	2011-2016	Digital use index: use of computers and emails	- Employment tends to increase in highly-digitalized jobs

			Digital tasks index: software programming or database administration for instance	- Negative effect for jobs that are both highly digitalized and routinized.
Evidence for Spain				
Camiña *et al.* (2020)	Manufacturing firm-level data from Spain	1991-2016	Robots, flexible production systems, data-driven control	- Negative effect of automation on employment, but weaker since the 2000s. - Automation technologies, when paired with human capital, increase employment in the long-term.
Stapleton and Webb (2020)	Manufacturing firm-level data from Spain	1990-2016	Robot adoption	- Weak positive impact on total employment. - Adoption doubles the number of engineers and graduates and increases production employment by 80%. - No effect on the number of non-graduates or administrative workers.
Koch *et al.* (2021)	Firm-level data from Spain	1990-2016	Robot adoption	- Adoption leads to net job creation. - Adopting firms increase employment compared to non-adopters in the same industry. - Positive effects on employment for high-skilled workers, but also low-skilled workers and those employed in the firm's manufacturing establishments.

Table A.2: Robustness (first stage)

Additional Controls (1)			
First Stage	DIG	ICT Index	Automation Index
DIG_{t-2}	0.285***		
	(0.013)		
ICT $Index_{t-2}$		0.204***	0.053**
		(0.015)	(0.025)
Automation $Index_{t-2}$		0.006	0.347***
		(0.006)	(0.011)

Alternative IV (2)			
First Stage	DIG	ICT Index	Automation Index
Average DIG	0.029*		
	(0.016)		
Average ICT		0.021	0.024
		(0.016)	(0.033)
Average Auto.		0.017*	-0.011
		(0.009)	(0.023)

Bootstrapped s.e. (3)			
First Stage	DIG	ICT Index	Automation Index
DIG_{t-2}	0.306***		
	(0.020)		
ICT $Index_{t-2}$		0.235***	0.059*
		(0.021)	(0.035)
Automation $Index_{t-2}$		0.012	0.336***
		(0.008)	(0.020)

Top/Bottom 1% excluded (4)			
First Stage	DIG	ICT Index	Automation Index
DIG_{t-2}	0.284***		
	(0.014)		
ICT $Index_{t-2}$		0.205***	0.052**
		(0.015)	(0.026)
Automation $Index_{t-2}$		0.007	0.343***
		(0.006)	(0.011)

Notes: This table consists of the first stages of the 2SLS regressions performed in Table 7. In the first specification some more controls have been added. The other specifications include the same controls as column (3) of Table 4. In the second specification, we use the average (excluding the firm) of the digitalisation index by year, industry, region and R&D status are used as instruments for DIG in *t*. In the third specification, we report block bootstrapped standard errors (s.e.) at the firm level in parentheses (250 replications). In the last specification, the dependent variable is trimmed at the 1st and 99th percentiles. *Significant at 10%, **Significant at 5%, ***Significant at 1%.

APPENDIX B

The Labour Demand Function

The labour demand presented in equation (5) comes from a profit maximization problem which is formulated as follows (subscripts for firms *i* and for time *t* are suppressed for clarity reasons):

$$Max_{K,L,M}\ \pi = BQ^{\mu} - rK - wL - cM \tag{B.1}$$
$$Subject\ to\ Q = AK^{\alpha}L^{\beta}M^{\gamma}$$

where *K* is capital, *L* is labour, and *M* is intermediate inputs. α, β, and γ are output elasticities parameters with respect to each input and *c, w*, and *i* are the costs of each input, respectively. Moreover, ε is the (assumed) constant price elasticity of demand. The inverse demand function is $p = D^{1/\varepsilon}Q^{-1/\varepsilon}$. Thus, total revenue is given as $R = pQ = BQ^{\mu}$, where $B = D^{1/\varepsilon}$ and $\mu = \frac{\varepsilon-1}{\varepsilon}$. The optimal solutions of (B.1) are:

$$L = B^{\frac{1}{1-\beta\mu}}\ \mu^{\frac{1}{1-\beta\mu}}\ \beta^{\frac{1}{1-\beta\mu}}\ A^{\frac{\mu}{1-\beta\mu}}\ K^{\frac{\alpha\mu}{1-\beta\mu}}\ M^{\frac{\gamma\mu}{1-\beta\mu}}\ w^{\frac{-1}{1-\beta\mu}} \tag{B.2}$$

$$K = B^{\frac{1}{1-\alpha\mu}}\ \mu^{\frac{1}{1-\alpha\mu}}\ \alpha^{\frac{1}{1-\alpha\mu}}\ A^{\frac{\mu}{1-\alpha\mu}}\ L^{\frac{\beta\mu}{1-\alpha\mu}}\ M^{\frac{\gamma\mu}{1-\alpha\mu}}\ r^{\frac{-1}{1-\alpha\mu}} \tag{B.3}$$

$$M = B^{\frac{1}{1-\gamma\mu}}\ \mu^{\frac{1}{1-\gamma\mu}}\ \gamma^{\frac{1}{1-\gamma\mu}}\ A^{\frac{\mu}{1-\gamma\mu}}\ K^{\frac{\alpha\mu}{1-\gamma\mu}}\ L^{\frac{\beta\mu}{1-\gamma\mu}}\ c^{\frac{-1}{1-\gamma\mu}} \tag{B.4}$$

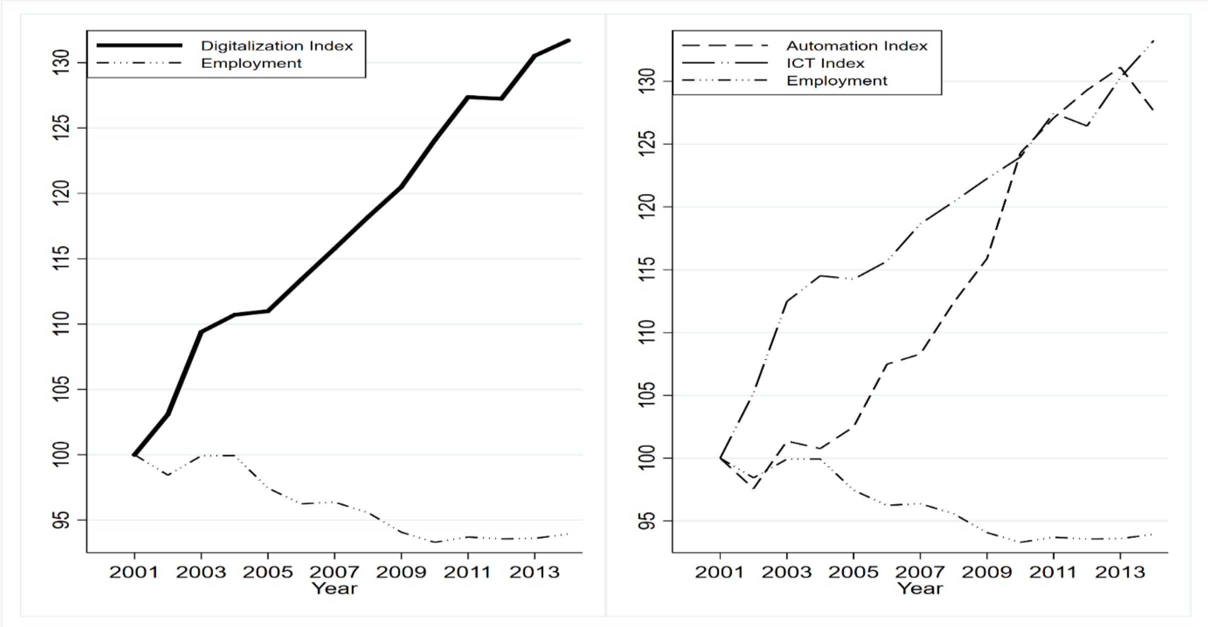
Equations (B.2), (B.3) and (B.4) give the profit-maximizing demand for labour, capital inputs and intermediate inputs respectively. Then substituting (B.3) into (B.2) and (B.1), we obtain:

$$L = B^{\frac{1}{1-\mu(\beta+\gamma)}}\ \mu^{\frac{1}{1-\mu(\beta+\gamma)}}\ \beta^{\frac{\mu\gamma-1}{\mu(\beta+\gamma)-1}}\ A^{\frac{-\mu}{\mu(\beta+\gamma)-1}}\ K^{\frac{-\alpha\mu}{\mu(\beta+\gamma)-1}}\ w^{\frac{1-\mu\gamma}{\mu(\beta+\gamma)-1}}\ c^{\frac{\mu\gamma}{\mu(\beta+\gamma)-1}}\ \gamma^{\frac{-\mu\gamma}{\mu(\beta+\gamma)-1}} \tag{B.5}$$

$$K = B^{\frac{1}{1-\mu(\alpha+\gamma)}}\ \mu^{\frac{1}{1-\mu(\alpha+\gamma)}}\ \alpha^{\frac{\mu\gamma-1}{\mu(\alpha+\gamma)-1}}\ A^{\frac{-\mu}{\mu(\alpha+\gamma)-1}}\ L^{\frac{-\beta\mu}{\mu(\alpha+\gamma)-1}}\ r^{\frac{1-\mu\gamma}{\mu(\alpha+\gamma)-1}}\ c^{\frac{\mu\gamma}{\mu(\alpha+\gamma)-1}}\ \gamma^{\frac{-\mu\gamma}{\mu(\alpha+\gamma)-1}} \tag{B.6}$$

Finally, substituting (B.6) into (B.5), knowing that $B = D^{1/\varepsilon}$ and $\alpha + \beta + \gamma = \delta$, and taking logs, we obtain equation (5), which is the labour demand.

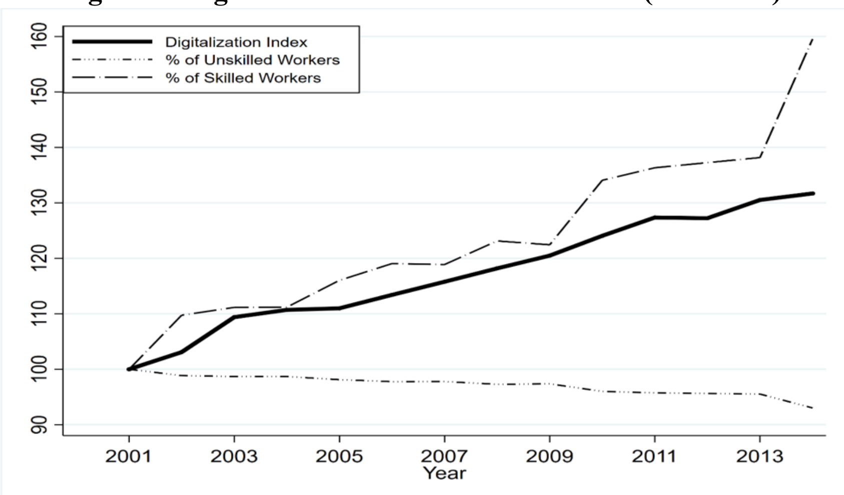
Figure 1: Digitalisation index vs. total employment (2001=100)



Source: ESEE Dataset

Note: The automation index takes into account the use of robots, computer-aided design (CAD), local area network (LAN) and flexible systems whereas the ICT index considers ICT capital, ICT training, computer programming services, implementation of software programs, and whether the firm has its own internet domain, has its webpage in the company's servers, purchases to suppliers through internet, sells to final consumers and/or companies through internet.

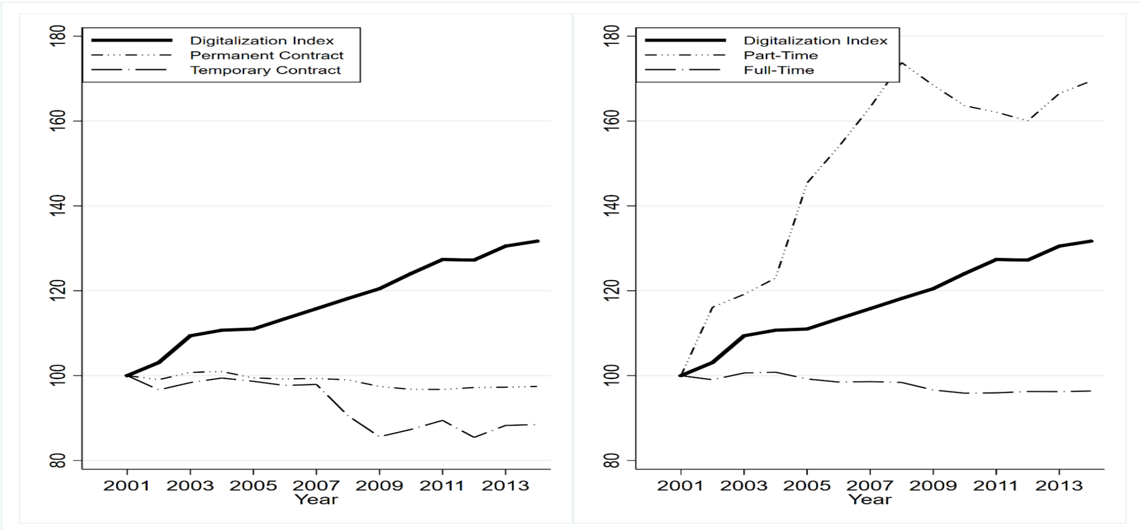
Figure 2: Digitalisation index vs. level of skills (2001=100)



Source: ESEE Dataset

Note: Skilled workers are workers who have at least graduated from a 3-year course, a 5-year course, and engineers.

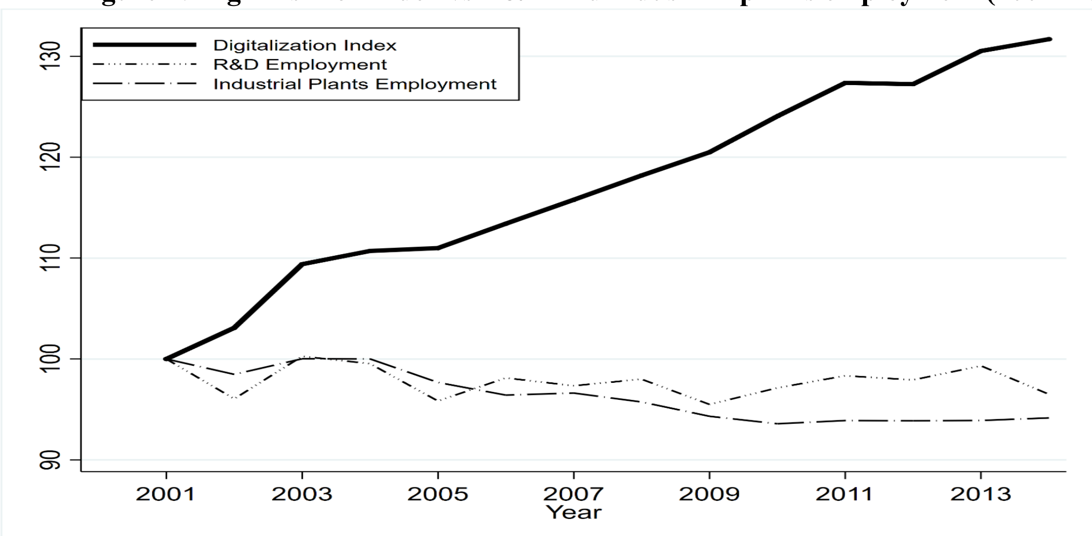
Figure 3: Digitalisation vs. temporary/permanent contracts, and part-time/full-time employment (2001=100)



Source: ESEE Dataset

Note: The ESEE provides information about the number of temporary contract workers, that we then subtract to total employment to obtain permanent contract workers. Part-time and full-time salaried workers are directly given in the dataset. All the variables are taken in logs and normalized.

Figure 4: Digitalisation index vs R&D and industrial plants employment (2001=100)



Source: ESEE Dataset

Note: R&D employment is measured as the number of workers in the R&D department. The number of industrial plants workers is the result of subtracting from total employment the number of non-industrial plants workers, which is provided in the dataset. All variables are taken in logs and normalized.

Table 1: Results of the estimation of the production function

Industry	l	k^{NIT}	k^{IT}	m	Observations
1. Metals and metal products	0.200***	0.048***	0.010***	0.733***	2,486
	(0.008)	(0.008)	(0.003)	(0.011)	
2. Non-metallic minerals	0.230***	0.090***	0.009*	0.660***	1,133
	(0.011)	(0.013)	(0.005)	(0.021)	
3. Chemical products	0.199***	0.062***	0.017***	0.694***	2,010
	(0.009)	(0.009)	(0.003)	(0.022)	
4. Agric. and ind. machinery	0.205***	0.045***	0.017***	0.695***	1,029
	(0.012)	(0.015)	(0.005)	(0.023)	
5. Electrical goods	0.207***	0.056***	0.043***	0.681***	1,064
	(0.011)	(0.011)	(0.004)	(0.017)	
6. Transport equipment	0.184***	0.062***	0.014***	0.718***	1,232
	(0.011)	(0.012)	(0.005)	(0.017)	
7. Food, drink and tobacco	0.107***	0.090***	0.016***	0.675***	2,468
	(0.007)	(0.008)	(0.003)	(0.024)	
8. Textile, leather and shoes	0.331***	0.086***	0.008*	0.485***	1,419
	(0.014)	(0.018)	(0.004)	(0.043)	
9. Timber and furniture	0.220***	0.033***	0.021***	0.679***	1,309
	(0.010)	(0.009)	(0.004)	(0.020)	
10. Paper and printing products	0.251***	0.082***	0.010***	0.599***	1,330
	(0.011)	(0.009)	(0.003)	(0.023)	

Notes: Estimates of the input coefficients from equation (12) are shown for different industries using the GMM estimation proposed by Wooldridge (2009). The dependent variable is the log of gross output. Each row represents a separate regression. Robust standard errors are reported in parenthesis. *Significant at 10%, **Significant at 5%, ***Significant at 1%.

Table 2: The effect of the digitalisation index on TFP

Dependent variable:	TFP	TFP	TFP	TFP	TFP	TFP growth
	(1)	(2)	(3)	(4)	(5)	(6)
TFP_{t-1}	0.544***	0.443***	0.436***	0.446***	0.359***	-0.554***
	(0.187)	(0.147)	(0.127)	(0.101)	(0.095)	(0.101)
DIG_{t-1}	0.107**	0.098***		0.074**		0.074**
	(0.043)	(0.035)		(0.033)		(0.033)
$Automation_{t-1}$			0.014		0.009	
			(0.011)		(0.012)	
ICT_{t-1}			0.119***		0.100**	
			(0.043)		(0.039)	
Trade $status_{t-1}$				0.034*	0.033*	0.034*
				(0.020)	(0.020)	(0.020)
Firm controls	No	No	No	Yes	Yes	Yes
Time & Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,458	12,458	12,458	12,456	12,456	12456
Firms	1,984	1,984	1,984	1,983	1,983	1,983
No. of instruments	59	95	134	189	224	189
AR(1) test (p-value)	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) test (p-value)	0.423	0.797	0.719	0.828	0.618	0.828
Hansen-J (p-value)	0.711	0.531	0.247	0.172	0.143	0.172

Notes: The dependent variable in columns (1) to (5) is the log of TFP, whereas in (6) it is the difference of the log of TFP from *t*-1 to *t*. All explanatory variables are included with one-period lag. All specifications include the second lag of TFP, industry dummies, and year dummies. Firm controls include employment, firm's age and foreign ownership. Estimates are obtained through the two-step system GMM estimator with robust standard errors corrected for finite sample bias (Windmeijer, 2005). AR(1) and AR(2) values report the p-values of the tests for first and second order serial correlation in the differenced residuals, respectively. In column (1) DIG is considered exogenous, while in the rest it is considered endogenous. We use levels of TFP, DIG, Automation, ICT, trade status and employment dated (*t*-3) to (*t*-5) as instruments in the difference equation, and differences dated (*t*-2) as instruments in the levels equation, as well as age, foreign ownership, industry dummies and year dummies. Year FE only enter in the equation in levels. * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table 3: Descriptive statistics

	Mean	St. Dev.	Min.	Max.	Obs.
DIG	0.39	0.19	0.01	1.00	16,825
ICT	0.41	0.19	0.01	1.00	16,825
Automation	0.34	0.33	0.00	1.00	16,825
Log Employment	4.28	1.40	0.00	9.04	16,825
Log Total Effective Hours	4.85	1.38	0.69	9.62	16,825
TFP	3.55	0.71	2.58	5.77	16,825
Markup	1.09	0.55	0.82	18.61	16,825
Log Real Average Wage	10.40	0.40	8.72	13.46	16,825
Log Total Capital	14.62	2.02	8.35	21.10	16,825
Log Skilled Employment	2.42	1.58	0.00	8.25	13,952
Export Propensity	0.70	0.46	0.00	1.00	16,825
Import Propensity	0.69	0.46	0.00	1.00	16,825
R&D Propensity	0.39	0.49	0.00	1.00	16,825
Log Price of Materials	0.00	0.00	-0.03	0.01	16,825
% of Non-Graduated	86.29	14.76	0.00	100.00	16,797
% of Graduated after a 3-Year Course	7.37	9.78	0.00	100.00	16,797
% of Engineers and Graduates	6.35	8.49	0.00	100.00	16,797
Log Part-Time Workers	1.20	1.21	0.00	6.56	5,893
Log Full-Time Workers	4.05	1.51	0.00	9.04	15,770
Log Permanent Contract Workers	4.13	1.44	0.00	9.04	15,800
Log Temporary Contract Workers	2.42	1.50	0.00	7.36	10,439
Log Employment in R&D	1.82	1.26	0.00	7.75	5,914
Log Employment in Non-Industrial Plants	2.90	1.77	0.00	8.33	3,848

Source: ESEE, 2001-2014. The sample are firms that are at least observed for two consecutive years and for which an estimate of TFP can be obtained.

Table 4: The impact of digitalisation on labour demand. Baseline results

	(1)	(2)	(3)	(4)	(5)	(6)	
	OLS-FE	OLS-FE	IV-2SLS	OLS-FE	OLS-FE	IV-2SLS	
Second stage:							
Dependent variable:			*Employment (logs)*				
DIG	0.234***	0.228***	0.438***				
	(0.043)	(0.044)	(0.158)				
ICT				0.231***	0.226***	0.565***	
				(0.043)	(0.045)	(0.179)	
Automation				0.035*	0.036*	0.046	
				(0.020)	(0.019)	(0.067)	
TFP_{t-1}	0.377***	0.368***	0.366***	0.374***	0.365***	0.356***	
	(0.042)	(0.043)	(0.042)	(0.042)	(0.042)	(0.042)	
$Markup_{t-1}$	-0.073***	-0.066***	-0.065***	-0.072***	-0.065***	-0.062***	
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.020)	
Real Average $Wage_{t-1}$	-0.345***	-0.341***	-0.342***	-0.345***	-0.342***	-0.345***	
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	
Capital $Stock_{t-1}$	0.194***	0.186***	0.181***	0.193***	0.186***	0.177***	
	(0.021)	(0.022)	(0.022)	(0.021)	(0.022)	(0.022)	
R&D $Propensity_{t-1}$	0.077***	0.075***	0.073***	0.077***	0.075***	0.071***	
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	
Export $Propensity_{t-1}$	0.045***	0.043***	0.040**	0.045***	0.042***	0.037**	
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	
Price of $materials_{t-1}$	6.498**	6.679**	6.633**	6.377**	6.568**	6.266*	
	(3.126)	(3.168)	(3.161)	(3.136)	(3.179)	(3.220)	
Observations	14,540	12,964	12,964	14,540	12,964	12,964	
No. of firms	2,317	1,905	1,905	2,317	1,905	1,905	
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	
KP (F-stat.)[a]			452.731			102.343	
CD (F-stat.)[b]			905.021			244.393	
First Stage							
Dependent variable:			DIG			ICT	Automation
DIG_{t-2}			0.285***				
			(0.013)				
ICT_{t-2}						0.205***	0.049*
						(0.015)	(0.025)
$Automation_{t-2}$						0.007	0.345***
						(0.006)	(0.011)

Notes: All the specifications include year dummies. All variables, except the DIG, ICT and Automation indices, are included with one-period lag. Columns (1) and (4) consists of a fixed effects OLS model. Columns (2) and (5) also but using the sample as columns (3) and (6) where we use an instrumental variable (IV) in a 2SLS procedure. The IVs models were estimated using the Stata command ivreg2. In columns (1) and (4), robust standard errors are displayed in parenthesis. In columns (2), (3), (5) and (6), robust clustered standard errors are displayed in parenthesis. The coefficients of the instruments in the first stage can be found at the bottom of the table. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.

[a] KP stands for the heteroscedasticity-robust Kleibergen-Paap Wald F test for weak instruments.

[b] CD stands for the standard non-robust Cragg-Donald Wald test for weak instruments.

Table 5: Sensitivity analysis. Heterogeneous employment effects from digitalisation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Second Stage:							
Dep. Variable:	Unskilled Emp.	Skilled Emp.	Manufact. Emp.	Perm. Workers	Temp. Workers	Emp. in SMEs	Emp. in Large Firms
DIG	0.464**	0.543**	0.448***	0.302*	0.549	0.570***	0.279
	(0.180)	(0.261)	(0.169)	(0.169)	(0.567)	(0.218)	(0.218)
TFP_{t-1}	0.379***	0.192***	0.372***	0.424***	0.292**	0.304***	0.604***
	(0.045)	(0.058)	(0.043)	(0.048)	(0.144)	(0.045)	(0.096)
$Markup_{t-1}$	-0.063***	-0.048**	-0.063***	-0.068***	-0.055*	-0.048**	-0.208***
	(0.021)	(0.020)	(0.021)	(0.021)	(0.032)	(0.019)	(0.067)
Real Average $Wage_{t-1}$	-0.369***	-0.116**	-0.348***	-0.265***	-0.819***	-0.318***	-0.427***
	(0.036)	(0.045)	(0.031)	(0.032)	(0.120)	(0.034)	(0.053)
Capital $Stock_{t-1}$	0.182***	0.183***	0.168***	0.185***	0.104	0.143***	0.319***
	(0.024)	(0.033)	(0.021)	(0.024)	(0.065)	(0.023)	(0.047)
R&D $Propensity_{t-1}$	0.061***	0.099***	0.066***	0.069***	0.059	0.077***	0.047**
	(0.016)	(0.028)	(0.014)	(0.015)	(0.047)	(0.016)	(0.023)
Export $Propensity_{t-1}$	0.033	0.073**	0.032*	0.038**	0.081	0.032*	0.093**
	(0.020)	(0.035)	(0.017)	(0.018)	(0.057)	(0.017)	(0.046)
Intermediate $Inputs_{t-1}$	6.859*	8.402	7.786**	4.624	15.930	4.993	12.728**
	(3.557)	(5.252)	(3.140)	(4.283)	(14.171)	(3.780)	(5.871)
Observations	12,943	12,964	12,964	12,544	7,854	9,340	3,624
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
KP (F-stat.)[a]	451.466	452.731	452.731	454.225	284.197	284.602	155.196
CD (F-stat.)[b]	904.246	905.021	905.021	904.104	540.179	580.837	300.878
First Stage	Digitalisation index (DIG)						
DIG_{t-2}	0.285***	0.285***	0.285***	0.286***	0.285***	0.273***	0.303***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.017)	(0.016)	(0.024)

Notes: All the specifications include year dummies. All variables, except the digitalisation index, are included with one-period lag. All columns include the same controls as column (3) of Table 4. In all columns, we use an instrumental variable (IV) in a 2SLS procedure. The first stage can be found at the bottom of the table. *Significant at 10%, **Significant at 5%, ***Significant at 1%.

[a] KP stands for the heteroscedasticity-robust Kleibergen-Paap Wald F test for weak instruments.

[b] CD stands for the standard non-robust Cragg-Donald Wald test for weak instruments.

Table 6: The impact of digitalisation on the shares of workers' composition

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Unskilled	Unskilled	Temp. Workers	Temp. Workers	Manufact. Emp.	Manufact. Emp.
DIG	-0.243***		0.005		-0.146***	
	(0.034)		(0.039)		(0.027)	
ICT		-0.194***		0.085*		-0.250***
		(0.052)		(0.051)		(0.036)
Automation		-0.058***		-0.027*		0.012
		(0.013)		(0.016)		(0.011)
TFP_{t-1}	-0.023**	-0.022**	0.054***	0.051***	-0.024***	-0.017***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.007)	(0.007)
Residual Dig.	0.192***		0.023		0.111***	
	(0.042)		(0.048)		(0.033)	
Residual ICT		0.130**		-0.073		0.207***
		(0.060)		(0.059)		(0.040)
Residual Auto.		0.059***		0.041**		-0.012
		(0.016)		(0.020		(0.014)
Observations	13,161	13,161	12,584	12,584	13,165	13,165
Time & Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mundlak Means	Yes	Yes	Yes	Yes	Yes	Yes
CF	Yes	Yes	Yes	Yes	Yes	Yes

Note: All the specifications include year and industry dummies. All variables, except the digitalisation index, are included with one-period lag. All columns include the same controls as column (3) of Table 4 plus import status and the age of the firm. In all columns, we use an instrumental variable (IV) control function approach and therefore, the regressions include the residual of the first-stage estimation. Following Wooldridge (2005), within-means of the control variables are also included in the regressions (i.e., Mundlak means). CF stands for control function. *Significant at 10%, **Significant at 5%, ***Significant at 1%.

Table 7: Robustness checks

	Additional Controls		Alternative IV		Bootstrapped s.e.		Top/Bottom 1% excluded	
Dependent Variable:	*Employment (Logs)*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DIG	0.472***		4.852*		0.465**		0.387***	
	(0.156)		(2.873)		(0.184)		(0.149)	
ICT		0.556***		3.891		0.679***		0.459***
		(0.181)		(2.449)		(0.209)		(0.168)
Automation		0.069		-2.146		0.004		0.054
		(0.066)		(3.785)		(0.078)		(0.064)
TFP_{t-1}	0.374***	0.364***	0.337***	0.229	0.407***	0.390***	0.346***	0.339***
	(0.047)	(0.048)	(0.074)	(0.145)	(0.056)	(0.055)	(0.043)	(0.043)
Observations	12,492	12,492	12,180	12,180	12,988	12,988	12,699	12,699
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
KP (F-stat)[a]	461.803	99.529	3.447	0.292	452.731	102.343	438.636	99.252
CD (F-stat)[b]	866.894	230.240	7.797	0.755	905.021	244.393	882.594	237.807

Notes: All the specifications include year dummies. All variables, except the DIG, ICT and automation indices, are included with one-period lag. In columns (1) and (2), some more controls have been added. Columns (3), (4), (5), (6), (7) and (8) include the same controls as column (3) of Table 4. In all columns, we use an instrumental variable (IV) in a 2SLS procedure. *Significant at 10%, **Significant at 5%, ***Significant at 1%.

[a] KP stands for the heteroscedasticity-robust Kleibergen-Paap Wald F test for weak instruments.

[b] CD stands for the standard non-robust Cragg-Donald Wald test for weak instruments.