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Digital technologies, employment and skills

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Abstract

The diffusion of digital technologies and their impact on employment and skills is investigated in this article considering six major European countries (Germany, France, Spain, Italy, the Netherlands and the United Kingdom) and 42 manufacturing and service industries over the 2009-2014 period. We analyse two key dimensions of digitalisation – industries' consumption of intermediate inputs from digital-intensive sectors and investment in ICT tangible and intangible assets per employee. We first investigate their effect on total employment finding that job creation in industries is supported by high digital consumption and reduced by high digital investment. We then explore how these variables have shaped the evolution of four professional groups - Managers, Clerks, Craft and Manual workers, defined on the basis of ISCO classes - and the increasingly polarised skill structure of European economies.

JEL classification: J23; J24; J21; O3 **Keywords**: Digital technology, Innovation, Employment, Skills, European industries

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1. Introduction

Digital technologies are reshaping contemporary economies. They can be understood as part of the current technological paradigm based on Information and Communication Technologies (ICTs), which is unfolding in the same way of previous technological revolutions associated to long term cycles of growth (Freeman and Louçã, 2001). The diffusion of digital technologies throughout the economy is deeply changing the structure of advanced economies, the organization of production, the dynamics of employment and the skill composition of labour.

The emphasis on digitalisation has opened the way to studies that tried to conceptualize digitalisation as a single phenomenon, measuring it with various indicators at the country, industry and firm levels that have often adopted an additive approach, i.e. digitalisation is expected to be higher where the combination of different indicators leads to higher outcomes (McKinsey Global Institute, 2015; Calvino et al., 2018). This approach assumes digitalisation to be an undifferentiated phenomenon, with uniform effects on economic performance and employment; this approach reminds the way technological innovation has long been treated by mainstream economic studies, as an undifferentiated driver of progress. In fact, both technological change and digitalisation can develop along different trajectories, resulting from specific strategies adopted by firms and industries, with possible contrasting outcomes in terms of employment. An extensive literature has shown the importance to distinguish strategies of technological competitiveness, relying on product innovations, with employment-friendly outcomes, as opposed to strategies of cost competitiveness, relying on labour-replacing new processes (Pianta, 2000, 2001, 2005; Bogliacino and Pianta, 2010; Bogliacino et al, 2013). In this article we identify different patterns of expansion of digital activities at the industry level showing that they cannot be understood as a single, uniform process. In particular, we identify two different dimensions of digitalisation:

a. industries' consumption of intermediate inputs from digital-intensive sectors; this reflects the diffusion of inputs based on ICT goods and services that have the potential to improve the performance of other industries, being incorporated in product innovations and contributing to higher quality activities. This dimension of digitalisation may contribute to a strategy of technological competitiveness and is expected to support the expansion of output and employment.

b. industries' investment in tangible and intangible ICT assets per employee; this indicates the importance of computers, telecommunication networks, software, etc., which are becoming a key part of the capital stock used for production in all the economy. However, in terms of employment, when industries' demand dynamics stagnates, digital investment may be part of strategies of restructuring, with a potential negative effect on employment, similar to the impact of cost competitiveness strategies.

In this article the two dimensions of digitalisation are set in the context of changes in economic structures, labour markets and educational levels, innovation in products, processes and organisations, offshoring patterns. All these factors contribute to shape the evolution of employment in industries.

Industries are an important level of analysis for understanding the digital transformation. Industries are characterised by specific technological opportunities and trajectories, by their position in interindustry and international flows of goods and services; all these factors affect the potential and impact of digitalisation (Dosi, 1982; Breschi et al., 2000). Moreover, changes in employment at the industry level are jointly shaped by the evolution of technologies and demand patterns, allowing a more comprehensive assessment of the consequences on jobs (Pasinetti, 1981).

The empirical analysis is based on the Sectoral Innovation Database (SID), covering 42 manufacturing and service industries for six major European countries; variables include our indicators of digitalisation as well as innovation survey data (CIS), economic, input-output, offshoring, and employment variables, including information on skills and occupations. The period we investigate is 2009-2014.

An important novelty of this article is the consideration of the impact of digitalisation not only on total employment, but also on different skill groups. The skill composition of employment is analysed for four professional groups - Managers, Clerks, Craft and Manual workers – based on the International Standard Classification of Occupations (ISCO). We rely on previous works that have developed this definition and investigated the employment dynamics of professional groups (Cirillo, 2017; Bramucci et al., 2017; Cirillo et al., 2018). The advantage of an analysis of the skill structure of employment is that it goes beyond definitions based on high vs. low education, on white collar vs. blue collar jobs, or on the task content of jobs (Acemoglu and Autor, 2011) and allows to consider the hierarchy of occupations, reflected in wage differences, as well as in the levels of education and diversity of competences. An important finding we report is the growing polarisation of the skill structure in European industries, with job creation concentrated at the top (the category of Managers, professionals and technicians) and at the bottom (the Manual workers category) of professional groups; in manufacturing Managers are the only category with significant employment growth, followed by Manual workers; in services Manual workers, Craft workers and Managers have the highest increases.

This approach allows us to carry out econometric tests on the determinants of employment change both for total employment and for each professional group, identifying common drivers and the specificities of skill dynamics. Employment change in European industries is explained by a comprehensive set of factors including our digitalisation variables, the importance of university education, the relevance of innovation in products, processes and organisations, the role of offshoring, as well as by the dynamics of demand and wages.

The paper is organized in five sections. The next paragraph locates this contribution within the existing empirical literature dealing with the employment effects of digitalization. Section 3 describes the indicators used in the empirical analysis and provides descriptive evidence on the two dimensions of digitalization and their employment impact. Employment patterns and the evolution of the four professional groups we investigate are also examined. Section 4 presents the model and the econometric strategy adopted. Section 5 shows the results of our tests on the impact of digitalization on employment. We first investigate the effects on total employment finding – among other determinants - that job creation in industries is supported by high digital consumption and reduced by high digital investment. Second, the specificity of manufacturing and services, and of high and low technology sectors, is investigated in order to better assess the structural factors driving employment change. Third, we explore how the model is able to account for the evolution of the four professional groups - Managers, Clerks, Craft and Manual workers - finding a diversity of drivers of employment change in different professional categories.

2. Digitalisation and the future of jobs

The employment impact of digitalization is at the centre of a lively debate and is becoming a topic of policy concern. It is widely acknowledged that the diffusion of digital technologies throughout the economy is deeply changing the structure of advanced economies, the organization of production activities, the dynamics of employment and the demand for skills. The literature dealing with the employment effects of digitalization and automation is however far from delivering a consensual view on current trends and future scenarios. Many contributions are impressionistic in nature and either emphasise the opportunities associated to digitalization, or foresee bleak long term effects. In particular, Frey and Osborne (2017) estimated that within the next 10 to 20 years 47% of jobs could be automated in the United States. The 2019 OECD Employment Outlook states that "technological progress offers new employment opportunities and that a significant risk of high technological unemployment is unlikely"; at the same time it warns that "without immediate policy action, disparities among workers may rise and social cleavages may deepen between those who gain and

those who lose from the ongoing changes in the world of work" (OECD, 2019). In this line are the findings of Arntz et al. (2016), who argue that 9% of jobs in OECD countries are susceptible to be replaced by machines, while Nedelkoska and Quintini (2018) estimate that about 14% of jobs in the OECD countries participating in the PIAAC survey (on adult skills) are highly 'automatable', with a large variance across countries in the possibilities of automation. Graetz and Michaels (2018) did not find a significant negative impact of the number robots on Europe's employment. Additional insights on the possibility of technological unemployment have come from Brynjolfsson and McAfee (2014), while Acemoglu and Restrepo (2017) consider the effects of robots – assumed to be competitors with workers – and find significant negative effects on employment and wages. A survey on these issues is in Balliester and Elsheikhi (2018).

Further efforts have recently been made to provide a better understanding and measures of the process of digitalisation. In most studies digitalization is in fact conceived as the mere acquisition or use of single specific ICTs items (computers, software, internet, robots)¹. Results are consequently highly dependent on the type of ICT indicator taken into account. Important evidence has been produced by Eurostat's "Community survey on ICT usage and e-commerce in enterprises", covering the last fifteen years, collecting data on a broad range of ICT related activities carried out by firms and households, although with strong limitations in coverage and access to disaggregated data.

Other studies have tried to develop "all-in-one" ICT composite indicators (Guerrieri and Bentivegna, 2012; McKinsey, 2015; Calvino et al., 2018), using some of the above sources. Calvino at al. (2018) have proposed a taxonomy of sectors combining data on ICT tangible and intangible (i.e. software) investment, the purchases of intermediate ICT goods and services, the stock of robots, the number of ICT specialists and the share of turnover from online sales and also presenting an overall composite indicator of digitalization that synthesises the main ICT dimensions taken into account. The study shows the existence of a high sectoral heterogeneity of digital patterns but also the presence of very large cross country differences within the same industries in the level of digitalization.

While studies of this type may be informative in highlighting general digital trends, such an approach may lack robustness and fails to identify the diversity of strategies associated to digitalisation and the contrasting effects they may have on economic performances and employment.

In fact, the question of the impact of digitalisation cannot be addressed outside the broader context of the relationships between the use of technology for different innovative strategies and the complex effects that can exert on performance and on the quantity and quality of jobs at the firm and industry levels.

Within the mainstream, studies have mainly followed the *skill biased technological change* approach, where the emergence of ICT technologies is expected to be complementary to higher skills (Berman, Bound and Griliches, 1994; Autor, Katz and Krueger, 1998; Acemoglu, 2002, Acemoglu and Autor, 2011; Arvanitis and Loukis, 2015; some contrary evidence is provided by Giuri et al. 2008). In fact, what is emerging in most countries and industries is a greater polarisation of jobs on the basis of the nature of 'tasks' performed (*routine biased technical change*). *Routine jobs*, such as those of clerks and factory workers are easier to be replaced by ICTs, while *non-routine activities* (such as those of those of managers and manual) are expected to expand in terms of employment shares as found in several empirical studies (Autor, Levy and Murnane, 2003; Autor and Dorn, 2009; Goos and Manning, 2007; Goos, Manning and Salomons, 2014; Oesch and Rodriguez, 2011; Goos et al. 2014; Bogliacino and Lucchese, 2015; Fernández-Macías and Hurley 2016; Eurofound, 2016; OECD, 2017; Breemersch et al, 2019).

¹ Autor et al. (2003; 2013) and Michaels et al. (2014) take into account the role of investment in computer and IT capital; Graetz and Michaels (2018) and Dauth et al. (2017) assess the employment effects of the use of robots. Marcolin et al. (2016) use as ICT intensity indicator the proportion of workers employed in the business functions "ICT services" and "Engineering and related technical services" in a given industry, over the industry total. Data on a broader set of ICT related technologies (including Internet, intranet, broadband, home pages, services offered via home pages, electronic commerce, and electronic data interchange) are used by a study of Böckerman et al. (2019). Evidence on the broad economic impact of digital technologies is in Evangelista et al. (2014). Data on robots are based on IFR (2018).

In order to avoid the limitations of mainstream approaches, the issue of the employment impact of digitalisation should be framed within the context of the long standing debate on of the effects technology on jobs (Freeman and Soete, 1987; Vivarelli, 1995; Vivarelli and Pianta, 2000). A large literature has explored the role of technology in affecting the quantity and quality of jobs at the firm, sectoral and country level (for reviews see Pianta, 2005, 2018; Vivarelli, 2014; Calvino and Virgillito 2018). The main findings suggest that product innovation tends to have a positive employment impact in firms, industries and at the macroeconomic level. Process innovation can improve firms' performance, but their job increases may be 'stolen' from the employment loss of non-innovating firms, with modest or no net job creation. Technological unemployment can be found at the level of industries or the total economy when innovations in processes dominate, reducing jobs faster than the creation of new jobs allowed by the expansion of demand (Pianta, 2018).

Moreover, the offshoring of domestic production has been found to have parallel effects to technology in the reduction of jobs for manual workers in European industries (Bramucci et al., 2017). The connection between technological and organisational change in shaping employment outcomes has also been investigated, finding that European manufacturing firms experienced the worst job losses when process and organisational innovations are combined (Evangelista and Vezzani, 2012).

As to the skill composition of employment, a critique of the mainstream skill-biased and routinebiased views has emerged with the use of ISCO data on professional groups where the hierarchies among occupations – in terms of power relations, educational levels and wages - are made visible (Cirillo, 2016, 2017; Cirillo et al., 2018). These studies have shown the polarisation of professional groups in Europe and the different impact that technological change has on each of them across industries and countries.

Building on this perspective, more conceptually sound and careful in the use of data, this article combines an effort to identify the relevant dimensions of digitalisation in industries with attention to the broader changes in economic structures, labour markets and educational levels, innovation in products, processes and organisations, offshoring patterns. Moreover, the quality of employment is explored by using the ISCO classification of occupational groups, investigating the different effects of digitalisation on each of them.

3. Patterns of digital technologies and jobs

In this article we focus on the industry level for manufacturing and services as industries are characterised by specific patterns of digitalisation, technological change, international production and demand growth.

Digitalisation is a complex phenomenon that should not be reduced to one synthetic index. Building on McKinsey (2015) and on Calvino et al. (2018), instead of searching for a synthetic indicator of digitalisation, on the basis of data availability we identified two robust indicators of digitalisation. The first one is the share of intermediate consumption of ICT goods and services in total intermediate consumption (i.e. *digital consumption*); the second one is total investment in ICTs per employee (i.e. *digital investments*). We expect that they are capturing two different aspects of digital transformation.²

We define digital consumption as the share of intermediate consumption of ICT goods and services in the total intermediate consumption. In contrast with Calvino et al. (2018), we also consider telecommunications services. The numerator of the indicator is calculated as total intermediate

 $^{^2}$ Data constraints limit the scope for more comprehensive measures of digitalisation. We selected our indicators after an extensive examination of a wide range of ICT indicators collected by the Eurostat ICT Business Survey; many other indicators of digitalisation have major problems (a large number of missing data; the industry breakdowns change over time, ICT variables, and countries; data are based on rough dichotomic yes/no questions).

purchases of sector i from ICT producing sectors (k) i.e. Manufacture of computer, electronic and optical products, Telecommunications, Computer programming, consultancy, and related activities.

$$\begin{aligned} \text{Digital consumption}_{ijt}^{k} &= \text{Intermediate consumption}_{ijt}^{k} \ / \ \text{Total intermediate consumption}_{ijt} \end{aligned} \tag{1} \\ & k \in \{\text{ICT producing sectors: } C26, J61, J62-J63\}^3 \end{aligned}$$

where i stands for the industry, j for the country, t for the time and k for ICT producing sectors; in order to reduce dimensionality, we summed up purchases of ICT goods and ICT services.

The second indicator - digital investment⁴ - is defined as investment in tangible and intangible ICT assets, measured on a per-employee basis. We aggregate here three indicators: investment in computer hardware, telecommunication equipment and software and databases.

 $Digital investment_{ijt}^{k} = Gross fixed capital formation_{ijt}^{k} / Total number of employees_{ijt}$ (2) $k \in \{Computer hardware, communication equipment, software and databases\}$

where *i* stands for the industry, *j* for country and *t* for time.

Descriptive evidence

In this section, we provide some basic descriptive evidence on major differences in the level of digitalisation and employment dynamics across sectors, countries and professional groups. In order to keep the sectoral analysis of the data simple and insightful, industries are grouped according to the Revisited Pavitt taxonomy proposed by Bogliacino and Pianta (2010): Science Based (SB), Specialised Suppliers (SS), Scale and information intensive (SI), and Supplier Dominated (SD).

In Figure 1 country-Pavitt groups are positioned on the basis of their digital intensity, measured through our two indexes of digitalisation; we find that:

- i. Science based (SB) industries are at the core of digital transformation in all six countries, as key sectors with high ICT content are included in this group (Manufacture of computer, electronic and optical products; Telecommunications; Computer programming, consultancy, and related activities). They show the highest levels of both digital investment and use of digital inputs;
- ii. Specialized Supplier (SS) industries are characterized by a medium use of digital intermediate inputs (in particular for services: Management consultancy, Engineering, Marketing, Other professional services) and by relatively low ICT investment.
- iii. Scale and information intensive industries (SI) are characterized by medium levels of digital investments (mostly driven by Financial services and Media sectors), and show a relatively low use of intermediate digital inputs;
- iv. Supplier dominated (SD) industries show the lowest levels of digitalisation (except for Postal services associated with a high share of digital inputs).

Figure 1. Positioning of industries based on the level of digital activities

³ Nace Rev. 2 two digits classes.

⁴ ICT investment data was drawn from the EU KLEMS, some sectors where disaggregated in order to match sectoral breakdown available in the WIOD and the Labour Force Survey (Nace Rev. 2).



Note: ICT investment per employee and share of intermediate and consumption of ICT goods and services in total intermediate consumption, were measured as averages over the period 2009-14. We find that country-Pavitt groups positioning in terms of both indicators remain stable over the period 2009-2014.

Is there a relationship between these measures of digitalisation and changes in employment? Figures 2 and 3 show the association with the dynamics of employment in the period 2009-14. The two figures show first of all the poor employment performances experienced by the majority of industrial groups in the period taken into account, a reflection of the long-lasting EU economic crisis, that has proved to be particularly severe in southern EU countries. Concerning the relationship between digitalisation and employment, the two figures show the existence of two distinct patterns. Figure 2 shows a seemingly negative relationship between the level of investment in digital technologies and employment change. Figure 3 seems to show a positive association between the use of digital intermediate inputs and the capacity of industries to create new jobs or to limit employment losses. National specificities in employment performances appear to be relevant in the patterns we have identified.

Looking at more refined patterns, we find that job losses are unevenly spread; manufacturing industries show the heaviest losses, while job gains are concentrated in selected services. Employment falls in Scale and information intensive industries, including Financial services and Media, which are undergoing a major restructuring. The same employment pattern is found for Telecommunications which has the highest digital intensity and is part of the Science based group. Conversely, other highly digital sectors – such as IT Services and Research and development - show high employment growth rates. The descriptive evidence shows, as expected, that digitalisation is a complex phenomenon that cannot be reduced to one dimension only and which may have contradictory effects on economic performance and jobs.

Figure 2. Employment dynamics and digital investments



Note: Employment dynamics is measured as average annual rate of change for Germany, Spain, France, Italy, Netherlands and UK over 2009-2014 period; ICT investment per employee refers to the level in 2009.





Note: Employment dynamics is measured as average annual rate of change for Germany, Spain, France, Italy, Netherlands and UK over 2009-2014 period; Intermediate consumption of ICT goods and services refers to the level in 2009.

The investigation on skills

Aggregate data on employment might hide important differences in the dynamics of the various components of the labour force. Labour markets have been undergoing major structural transformations with relevant changes in the composition of employment driven by digitalisation as well as by the broader process of technological change, globalisation, changes in the educational levels and wages and other factors. It is therefore important to investigate the different dynamics of skill groups which are affected in different ways by such drivers of change.

For this purpose, we rely on the classification of occupational activities provided by the International Standard Classification of Occupation (ISCO), widely adopted in empirical research⁵. The ISCO classification reflects not only the nature of the tasks performed and skill content of labour activities, but also the hierarchical structure of work organizations in terms of power relationships, control and wages. The latter allows us to associate the dynamics of such professions to the intensity of the digitalisation process. Following Cirillo et al. (2018) we define four main macro-professional groups - Managers, Clerks, Craft and Manual workers - by aggregating ISCO 1-digit classes⁶ in the way shown in Table 1.

As shown in previous studies adopting this methodology, these four professional groups are able to summarise in an effective way the diversity of skills characterizing the different industries and their trajectory of evolution. Moreover, these groupings overcome the limitation of studies whose focus is on the routine/non-routine nature of tasks, where the hierarchical position of workers is generally ignored.

Professional groups	ISCO 1 digit classes
	Managers, senior officials and legislators
Managers	Professionals
	Technicians and associate professionals
Clerks	Clerks
CIEIKS	Service and sales workers
Craft	Skilled agricultural and fishery workers
workers	Craft and related trade workers
Manual	Plant and machine operators and
workers	assemblers
workers	Elementary occupations
Source Cirillo	2017

Table 1. The professional groups

Source: Cirillo, 2017

The validity of disaggregating the dynamics of employment across these four professional groups clearly emerges in Figure 4, which shows the presence of distinct patterns of change and the clear process of polarization of skills. Job gains are concentrated in Managers and Manual workers, while the middle-skill groups of Clerks and Craft workers have stagnant employment. This evidence emphasizes the need to understand the dynamics of polarization, which is very different from the expectations of a general upskilling of employment associated with the Skill-biased technological change approach.

⁵ The ISCO classification has been adopted by the studies of Hollanders and ter Weel, 2002; Oesch and Rodriguez Menés, 2011).

⁶ A revision of the International Standard Classification of Occupations (ISCO) took place in 2011, when ISCO-88 was succeeded by ISCO-08, resulting in a break in the occupational series; Germany in 2012 reassigned some ISCO occupations (Eurofound, 2017). To achieve consistency in data for the period of our analysis, we retained the updated classification and estimated 2009 data for professional groups on the basis of their share in total employment in 2011; for Germany the base year is 2012.



Figure 4. Employment dynamics across professional groups

Note: Employment dynamics are measured as compound annual rate of change for Germany, Spain, France, Italy, Netherlands and UK over 2012-2017 period; Source: Our elaboration on Eurostat data

The distinction in Figure 4 between manufacturing and services is important because the latter concentrate most of the employment growth while in the manufacturing industries job creation occurs mainly in the category of managers; an increasingly polarised pattern characterizes both sectors, which has favoured managers, professionals, technicians, and manual workers while penalising clerks and craft workers.

4. The model and empirical strategies

We use industry-level data from the Sectoral Innovation Database (SID), covering manufacturing sectors (10-33 Nace Rev. 2 classes) and service sectors (45-82 Nace Rev. 2 classes) for Germany, France, Italy, Spain, Netherlands and United Kingdom. SID merges information on employment and level of education (WIOD Social accounts and Labour Force Survey), innovation efforts (Community Innovation survey), digital investment (EU KLEMS), digital inputs (Input-Output tables), demand, labour compensation (WIOD Social Accounts).

The model we develop aims to identify the drivers of employment change in European industries, to account for the structural diversities we identified between manufacturing and services, and between high and low technology activities, and to investigate the different patterns shown by professional groups. Many studies investigating employment change relied on a translog cost function (see Berman et al., 1994; Machin and Van Reenen, 1998). We adapt this approach considering rates of change rather than shares. As rates of changes proxy the differences in logs, in this way the sectoral unobservable component is differentiated out. The latter permits us to estimate our model (in equation 4 below) using Ordinary Least Squares (OLS), using the following set of variables:

- i. Employment ($\Delta EMPE_i$): annual compound rate of change over the 2009-2014 period;
- ii. Value added (ΔVA_i): annual compound rate of change of value added over the 2009-2014 period;
- iii. Wage (ΔW_i) : annual compound rate of change of the average wage in the industry over the 2009-2014 period, calculated as labour compensation divided by number of employees;
- iv. Highly educated employees (ΔEDU_i): measures the annual compound rate of change of the number of university graduates in the industry over 2009-2014;

- v. Digitalisation: Digital investments $(DigINV_i)$ are measured as ICT investments per employee; Digital consumption $(DigCONS_i)$ is measured as the share in total intermediate consumption; both indicators refer to 2009.
- vi. Innovation: the type of technological regime characterizing different industries is identified on the basis of the relevance of product and process innovations; new products $(PROD_i)$ are proxied by the share of firms introducing product innovation only, while expenditure in machinery per employee ($\Delta EXPMACH_i$) and the share of firms introducing process innovation only ($\Delta PROC_i$) proxy the relevance of strategies consisting of the introduction new processes. In addition, we also evaluate the role of organisational innovation⁷ (ΔORG_i), measured as the share of firms introducing organisational innovation only. Innovation variables were drawn from the ninth wave of the CIS (Community Innovation Survey); the survey reference period is 2012-2014.
- vii. Offshoring $(\Delta Offsh_i)$: Following Guarascio et al. 2015 the offshoring indicator is computed as the share of intermediate inputs inflowing from foreign low-tech industries (Scale intensive and Supplier dominated), in total intermediate inputs. Previous studies have shown that this is a robust proxy of offshoring displacing domestic production (Bramucci et al., 2017).

 $Offshoring_{ijt}^{k} = Imported intermediate inputs_{ijt}^{k} / Total intermediate inputs_{ijt}$ (3)

 $k \in \{Low - tech foreign industries\}$

where *i* stands for the industry, *j* for country and *t* for time.

Building on the proposed conceptual framework, model (4) is introduced in order to assess the role of digitalisation and of the other drivers of employment change:

 $\Delta EMPE_{i} = \beta_{0} + \beta_{1}\Delta VA_{i} - \beta_{2}\Delta W_{i} + \beta_{3}\Delta EDU_{i} - \beta_{4}DigINV_{i} + \beta_{5}DigCONS_{i} + \beta_{6}PROD_{i} - \beta_{7}PROC_{i} + \beta_{8}ORG_{i} - \beta_{9}Offsh_{i} + \varepsilon_{i}$ (4)

Building on the conceptual framework we proposed and on previous findings (Bogliacino and Pianta, 2010; Cirillo, 2017; Cirillo et al. 2018), we expect that the following relationships may emerge:

- i. the growth of industries' demand is captured by higher levels of value added, which is associated with job expansion;
- ii. the neoclassical negative relationship between wages and employment is expected to emerge;
- iii. on the supply side, a greater share of employees with university degree is expected to be associated with faster employment growth as more dynamic industries tend to be the ones with higher level of knowledge embodied in workers.
- iv. the two digital variables we use digital investments and the acquisition of intermediate digital inputs are expected to capture different dimension of the impact of digitalisation on jobs; large digital investment per employee might be associated to restructuring process and labour saving effects; conversely, higher digital inputs can contribute to improvement in products and may be associated with faster employment dynamics;
- v. the innovation variables we use are expected to capture the different effects that technological and organisational innovations have on jobs; as shown by a large literature, new products may open up new markets, leading to output expansion and creation of new jobs; process innovation is associated to job destruction; organisational innovation may take different forms depending on the prevalence of either technological competitiveness or cost competitiveness strategies and its net effect of employment will be assessed;
- vi. considering the importance of international fragmentation of production, we control for the role that offshoring might have on domestic jobs. Low-tech offshoring is expected to have a negative impact on jobs.

⁷ According to the OECD, 2005, an organisational innovation is defined as the "implementation of a new organisational method in the firms' business practices, workplace organization or external relations organization".

With this model, we aim to integrate a wide range of drivers affecting employment change, ranging from different aspects of digitalisation, different trajectories of technological change, the role of changes in organization and the impact of offshoring as well as the level of human capital measured by employees with a university degree.

The complexity of the relationships these factors have with employment change can be highlighted by this approach, taking into the account demand and wage dynamics. Building on this approach we can therefore shed new light on:

- i. The structural change of the economy, namely the expansion or contraction of industries and the long-term shift from manufacturing to services.
- ii. The dominance of technological trajectories based either on a search for new products and services with a potential job-creating effect, or the search for new processes relying on a cost competitiveness strategy.
- iii. The distinct ways in which industries are affected by digitalisation; on the one hand, large ICT investment can reshape production processes favouring restructuring and job cuts, in a way similar to the impact of process innovation and new machinery; on the other hand, the diffusion of ICTs across industries, in the form of digital inputs that improve products and services, has the potential to expand value added and jobs.

We are also interested in exploring structural differences in the relationships we investigate. In order to access the overall coherence of the relationship and specificities that may emerge model (4) will be tested separately for (i) manufacturing and services, (ii) low-tech and high-tech industries.

We have shown the trends towards a polarised occupational structure and we expect that digital, innovation and educational variables will relate in different ways to changes in different professional groups. Therefore we investigate how the variables from model (4) affect employment dynamics for the four professional groups (Managers, Clerks, Craft, Manual workers), using the following set of equations (5-8):

 $\Delta Manager_{i} = \beta_{0} + \beta_{1} \Delta V A_{i} - \beta_{2} \Delta W_{i} + \beta_{3} \Delta E D U_{i} + \beta_{4} DigINV_{i} + \beta_{5} DigCONS_{i} + \beta_{6} PROD_{i} - \beta_{7} EXPMACH_{i} + \beta_{8} ORG_{i} - \beta_{9} Offsh_{i} + \varepsilon_{i}$ (5)

$$\Delta Clerks_i = \beta_0 + \beta_1 \Delta V A_i - \beta_2 \Delta W_i + \beta_3 \Delta EDU_i - \beta_4 DigINV_i + \beta_5 DigCONS_i + \beta_6 PROD_i - \beta_7 EXPMACH_i + \beta_8 ORG_i - \beta_9 Offsh_i + \varepsilon_i$$
(6)

 $\Delta Craft_{i} = \beta_{0} + \beta_{1} \Delta VA_{i} - \beta_{2} \Delta W_{i} + \beta_{3} \Delta EDU_{i} - \beta_{4} DigINV_{i} + \beta_{5} DigCONS_{i} + \beta_{6} PROD_{i} - \beta_{7} EXPMACH_{i} + \beta_{8} ORG_{i} - \beta_{9} Offsh_{i} + \varepsilon_{i}$ (7)

 $\Delta Manual_{ij} = \beta_0 + \beta_1 \Delta V A_i - \beta_2 \Delta W_i + \beta_3 \Delta EDU_i - \beta_4 DigINV_i + \beta_5 DigCONS_i + \beta_6 PROD_i - \beta_7 EXPMACH_i + \beta_8 ORG_i - \beta_9 Offsh_i + \varepsilon_i$ (8)

The occupational structure varies greatly across the sectors (see Appendix), therefore it is not reasonable to assume that each observation should be treated equally; Weighted Least Squares were employed, using as weight the level of employment of each professional group (Managers, Clerks, Craft and Manuals) in 2009.

5. Results

Total employment

We estimate model (4) for the 2009-2014 period at the industry level for six European countries. Table 2 shows the results of the baseline model explaining the employment dynamics. In Table 3 we split the sample between manufacturing and services and high-tech and low-tech industries. Finally, in Table 4 the regression results for each professional group are shown.

Results of the OLS estimation in Table 2 broadly confirm the relationships we anticipated. In all four specifications of the model, job creation goes hand in hand with the expansion of value added with positive and significant coefficients, while a negative and significant relationship between job growth and wages is found. The importance of human capital, measured as the growth of university graduates in expanding industries is shown by the positive and significant coefficients. As expected, the two types of digital activities taken in into account in our study exert contrasting effects on employment; digital investment has negative and significant effects on total jobs, being likely associated to restructuring processes. Conversely, digital inputs show a positive effect on job creation (except in the last specification); this is likely to be the result of the improved quality of products and services integrating digital inputs. The distinct effect of product and process innovation on employment already pointed out by a large literature (Pianta, 2000; Bogliacino and Pianta, 2010) - are confirmed, with the positive role of new products and services and the negative impact of new processes. Organisational innovation emerges as a positive and significant factor supporting job creation in the first two specifications of the model, while offshoring to low-tech industries has a negative and significant impact on domestic jobs. In the estimations (3) and (4) we introduced dummy variables for manufacturing and Southern European countries (Italy and Spain) in order to control for the robustness of results.

Overall, results appear to be robust to the different specifications. A major novelty of these finding is the coexistence of significant relationships for all the main variables we have considered. Employment in European industries is increasing in the sectors characterized by greater knowledge and higher educational level, greater digital content (in terms of intermediate inputs), greater innovation efforts (introduction of product and organisational innovations). All these factors appear to be complementary aspects of the job creation potential of digital and technological change and it is remarkable that they capture distinct aspects which cannot be reduced to a generic ICT-based technological upgrading. In contrast, employment in European industries is negatively affected by the intensity of digital investment, strategies of cost competitiveness based on job displacing new processes and offshoring of low-tech activities. In addition, demand clearly matters with demand growth allowing employment creation, while industries with greater wage growth show lower employment dynamics.

Table 3 shows the results for model (4) estimated on subsamples of industries. Manufacturing industries are characterized by a weaker set of significant relationships, with employment change being positively driven by value added and product innovation, and negatively by ICT investment and offshoring. In contrast, employment change in service industries is affected by all considered variables (except for organisational innovation that loses its significance). As changes in total employment are mainly driven by the expansion of employment in services, it is not surprising that the same factors emerge with a significant impact.

The last four columns (7-10) of Table 3 present the results for high-tech and low-tech industries. For high-tech sectors (Science based and Specialised suppliers) only few relationships emerge as significant; changes in jobs are mainly explained by higher value added, lower wages and by the relevance of organisational innovation. In these industries the overlapping effect of digital and innovation variables may explain the lack of significance in the case of the all other regressors; moreover, high-tech industries are at the same time key producers of digital technologies and heavy users of the same inputs. In contrast, low-tech industries (Scale intensive and Suppliers dominated) confirm again the significance and the signs of the relationships found in Table 2, with the exception of process and organisational innovation, which lose their statistical significance. For these industries, the impact of digital technologies is typically associated with the effects of adoption.

	(1)	(2)	(3)	(4)
Value added	0.217***	0.222***	0.181***	0.174***
	(0.0480)	(0.0505)	(0.0450)	(0.0459)
Wages	-0.349***	-0.304***	-0.383***	-0.311***
	(0.110)	(0.110)	(0.107)	(0.114)
University graduates	0.116***	0.108***	0.113***	0.104***
	(0.0295)	(0.0292)	(0.0285)	(0.0274)
ICT investment	-0.0618*	-0.0644**	-0.0783**	-0.0862***
	(0.0317)	(0.0317)	(0.0318)	(0.0308)
ICT int. consumption	0.0440***	0.0325*	0.0304*	0.0207
	(0.0161)	(0.0166)	(0.0171)	(0.0168)
Product innovation	0.0482***	0.0518***	0.0382**	0.0573***
	(0.0172)	(0.0166)	(0.0169)	(0.0184)
Process innovation	-0.0778**	-0.0618*	-0.0529*	-0.0311
	(0.0338)	(0.0326)	(0.0310)	(0.0321)
Org. innovation	0.0343*	0.0370**	0.0142	0.0122
	(0.0187)	(0.0178)	(0.0160)	(0.0164)
Offshoring low-tech		-0.0495**	-0.0715***	-0.0498**
		(0.0200)	(0.0204)	(0.0219)
South			-1.587***	-1.327***
			(0.310)	(0.334)
Manufacturing				-0.870**
				(0.354)
Constant	-1.584***	-1.260**	0.335	0.0199
	(0.475)	(0.514)	(0.577)	(0.601)
Observations R-squared	189 0.485	189 0.501	189 0.567	189 0.582

Table 2. Results for the rate of change of employment, 2009-2014

Note: Ordinary Least Square regression. The individual observation is sector in a given country. The dependent variable is the average annual rate of change of employment. South dummy is equal to 1 for Italy and Spain, zero otherwise. Manufacturing dummy equals 1 for manufacturing sectors

(10-33 Nace Rev.2), zero otherwise. Robust standard errors are reported in parentheses, significance levels *** p<0.01, ** p<0.05, * p<0.1.

Table 3. Results for the rate of change of employment in major sectors, 2009-2014

	Manufactur	ing	Services		High-tech		Low-tech	
	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Value added	0.235***	0.205**	0.163***	0.117**	0.277**	0.207	0.208***	0.181***
	(0.0801)	(0.0809)	(0.0593)	(0.0464)	(0.122)	(0.125)	(0.0527)	(0.0470)
Wages	0.0622	0.0480	-0.364***	-0.621***	-0.397**	-0.440**	-0.197	-0.335**

$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.199)	(0.201)	(0.117)	(0.125)	(0.177)	(0.166)	(0.142)	(0.144)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	University graduates	0.0303	0.0393	0.182***	0.191***	0.0915	0.0978	0.108***	0.119***
ICT consumption (0.0542) (0.0545) (0.0378) (0.0343) (0.0477) (0.0484) (0.060) (0.0590) ICT consumption -0.0301 -0.0181 0.0327* 0.0288 0.0104 0.0126 0.106*** 0.0477 Product innovation 0.0885*** 0.0679** 0.0649*** 0.0138) (0.0243) (0.0230) (0.0334) Product innovation 0.0885*** 0.0679** 0.0649*** 0.0439* 0.0328 0.0294 0.0539** 0.0216 (0.0271) (0.0283) (0.0216) (0.0229) (0.0270) (0.0260) (0.0244) 0.0179 Process innovation 0.0244 0.0179 -0.0641* -0.0654** -0.0741 -0.0530 -0.0326 -0.0478 (0.0602) (0.0623) (0.0370) (0.0273) (0.0734) (0.0662* 0.0114 -0.0162 (0.757) (0.0249) (0.0219) (0.0182) (0.0383) (0.0371) (0.0204) (0.0162) Offshoring low-tech -0.0288 -0.0505*		(0.0328)	(0.0337)	(0.0387)	(0.0353)	(0.0564)	(0.0604)	(0.0350)	(0.0316)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	ICT investment	-0.0793	-0.118**	-0.0822**	-0.0861**	-0.0230	-0.0463	-0.149**	-0.119**
.(0.0324)(0.0284)(0.0171)(0.0188)(0.0245)(0.0248)(0.0359)(0.0334)Product innovation0.0885***0.0679**0.0649***0.0439*0.03280.02940.0539**0.0216(0.0271)(0.0283)(0.0216)(0.0229)(0.0270)(0.0269)(0.0229)(0.0244)Process innovation0.02440.0179-0.0641*-0.0654**-0.0741-0.0530-0.0326-0.0478(0.0602)(0.023)(0.0367)(0.0279)(0.0734)(0.0690)(0.0376)(0.0337)Org. innovation0.02060.01460.0238-0.01210.0788**0.0662*0.0114-0.0162(0.0275)(0.0249)(0.0219)(0.0182)(0.0383)(0.0371)(0.0204)(0.0162)Offshoring low-tech-0.0288-0.0505*-0.0838**-0.153***-0.0754-0.0967-0.0312-0.0516**(0.0218)(0.0259)(0.0414)(0.0374)(0.0942)(0.0917)(0.0208)(0.0223)South-1.137**-2.064***-1.074*-1.074**-1.992***(0.441)(0.441)(0.490)(0.487)(0.425)-1.789***0.590(1.103)(1.232)(0.567)(0.808)(1.239)(1.306)(0.669)(0.806)Ubservations909099997070119119		(0.0542)	(0.0545)	(0.0378)	(0.0343)	(0.0477)	(0.0484)	(0.0660)	(0.0590)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	ICT consumption	-0.0301	-0.0181	0.0327*	0.0288	0.0104	0.0126	0.106***	0.0477
No.0271 (0.0283) (0.0216) (0.0229) (0.0270) (0.0269) (0.0229) (0.0244) Process innovation 0.0244 0.0179 -0.0641* -0.0654** -0.0741 -0.0530 -0.0326 -0.0478 Org. innovation 0.0206 0.0146 0.0238 -0.0121 0.0788** 0.0662* 0.0114 -0.0162 Org. innovation 0.0206 0.0146 0.0238 -0.0121 0.0788** 0.0662* 0.0114 -0.0162 Offshoring low-tech -0.0288 -0.0505* -0.0838** -0.153*** -0.0754 -0.0967 -0.0312 -0.0516** South -1.137** -2.064*** -1.074** -1.992*** -1.992*** Constant -3.530*** -2.193* -0.578 1.974** -1.020 -0.0425 -1.789*** 0.590 Constant -3.530*** -2.193* -0.578 1.974** -1.020 -0.0425 -1.789*** 0.590 Cobservations 90 99 99 70 70 </td <td></td> <td>(0.0324)</td> <td>(0.0284)</td> <td>(0.0171)</td> <td>(0.0188)</td> <td>(0.0245)</td> <td>(0.0248)</td> <td>(0.0359)</td> <td>(0.0334)</td>		(0.0324)	(0.0284)	(0.0171)	(0.0188)	(0.0245)	(0.0248)	(0.0359)	(0.0334)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Product innovation	0.0885***	0.0679**	0.0649***	0.0439*	0.0328	0.0294	0.0539**	0.0216
Org. innovation (0.0602) (0.0623) (0.0367) (0.0279) (0.0734) (0.0690) (0.0376) (0.0337) Org. innovation 0.0206 0.0146 0.0238 -0.0121 $0.0788**$ $0.0662*$ 0.0114 -0.0162 (0.0275) (0.0249) (0.0219) (0.0182) (0.0383) (0.0371) (0.0204) (0.0162) Offshoring low-tech -0.0288 $-0.0505*$ $-0.0838**$ $-0.153***$ -0.0754 -0.0967 -0.0312 $-0.0516**$ (0.0218) (0.0259) (0.0414) (0.0374) (0.0942) (0.0917) (0.0208) (0.0223) South $-1.137**$ $-2.064***$ $-1.074**$ $-1.992***$ (0.441) (0.490) (0.487) (0.425) Constant $-3.530**$ $-2.193*$ -0.578 $1.974**$ -1.020 -0.0425 $-1.789***$ 0.590 Observations90909999 70 70 119 119		(0.0271)	(0.0283)	(0.0216)	(0.0229)	(0.0270)	(0.0269)	(0.0229)	(0.0244)
Org. innovation0.02060.01460.0238 -0.0121 0.0788**0.0662*0.0114 -0.0162 (0.0275)(0.0249)(0.0219)(0.0182)(0.0383)(0.0371)(0.0204)(0.0162)Offshoring low-tech -0.0288 $-0.0505*$ $-0.0838**$ $-0.153***$ -0.0754 -0.0967 -0.0312 $-0.0516**$ (0.0218)(0.0259)(0.0414)(0.0374)(0.0942)(0.0917)(0.0208)(0.0223)South $-1.137**$ $-2.064***$ $-1.074**$ $-1.992***$ (0.441)(0.440)(0.490)(0.487)(0.425)Constant $-3.530***$ $-2.193*$ -0.578 $1.974**$ -1.020 -0.0425 $-1.789***$ 0.590 (1.103)(1.232)(0.567)(0.808)(1.239)(1.306)(0.669)(0.806)Observations9099997070119119	Process innovation	0.0244	0.0179	-0.0641*	-0.0654**	-0.0741	-0.0530	-0.0326	-0.0478
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.0602)	(0.0623)	(0.0367)	(0.0279)	(0.0734)	(0.0690)	(0.0376)	(0.0337)
Offshoring low-tech -0.0288 (0.0218) -0.0505^* (0.0259) -0.0838^{**} (0.0414) -0.153^{***} (0.0374) -0.0754 (0.0942) -0.0967 (0.0917) -0.0312 (0.0208) -0.0516^{**} (0.0223)South -1.137^{**} (0.441) -2.064^{***} (0.490) -1.074^{**} (0.487) -1.992^{***} (0.487)Constant -3.530^{***} (1.103) -2.193^{*} (1.232) -0.578 (0.567) 1.974^{**} (0.808) -1.020 (1.239) -1.789^{***} (1.306) 0.669)Observations90909999 70 70 119 119	Org. innovation	0.0206	0.0146	0.0238	-0.0121	0.0788**	0.0662*	0.0114	-0.0162
(0.0218) (0.0259) (0.0414) (0.0374) (0.0942) (0.0917) (0.0208) (0.0223) South -1.137** -2.064*** -1.074** -1.92*** (0.441) (0.490) (0.487) (0.425) Constant -3.530*** -2.193* -0.578 1.974** -1.020 -0.0425 -1.789*** 0.590 (1.103) (1.232) (0.567) (0.808) (1.239) (1.306) (0.669) (0.806)		(0.0275)	(0.0249)	(0.0219)	(0.0182)	(0.0383)	(0.0371)	(0.0204)	(0.0162)
South -1.137** -2.064*** -1.074** -1.992*** (0.441) (0.490) (0.487) (0.425) Constant -3.530*** -2.193* -0.578 1.974** -1.020 -0.0425 -1.789*** 0.590 (1.103) (1.232) (0.567) (0.808) (1.239) (1.306) (0.669) (0.806) Observations 90 90 99 99 70 70 119 119	Offshoring low-tech	-0.0288	-0.0505*	-0.0838**	-0.153***	-0.0754	-0.0967	-0.0312	-0.0516**
Constant(0.441)(0.490)(0.487)(0.425)Constant-3.530***-2.193*-0.5781.974**-1.020-0.0425-1.789***0.590(1.103)(1.232)(0.567)(0.808)(1.239)(0.669)(0.669)(0.806)Observations9099997070119119		(0.0218)	(0.0259)	(0.0414)	(0.0374)	(0.0942)	(0.0917)	(0.0208)	(0.0223)
Constant -3.530*** -2.193* -0.578 1.974** -1.020 -0.0425 -1.789*** 0.590 (1.103) (1.232) (0.567) (0.808) (1.239) (1.306) (0.669) (0.806) Observations 90 90 99 99 70 70 119 119	South		-1.137**		-2.064***		-1.074**		-1.992***
(1.103)(1.232)(0.567)(0.808)(1.239)(1.306)(0.669)(0.806)Observations909099997070119119			(0.441)		(0.490)		(0.487)		(0.425)
Observations 90 90 99 99 70 70 119 119	Constant	-3.530***	-2.193*	-0.578	1.974**	-1.020	-0.0425	-1.789***	0.590
		(1.103)	(1.232)	(0.567)	(0.808)	(1.239)	(1.306)	(0.669)	(0.806)
R-squared 0.522 0.552 0.581 0.684 0.555 0.585 0.474 0.569	Observations	90	90	99	99	70	70	119	119
	R-squared	0.522	0.552	0.581	0.684	0.555	0.585	0.474	0.569

Note: Ordinary Least Square regressions. The individual observation is sector in a given country. The dependent variable is the average annual rate of change of employment. South dummy is equal to 1 for Italy and Spain, zero otherwise. Robust standard errors are reported in parentheses, significance levels *** p<0.01, ** p<0.05, * p<0.1.

Professional groups

Finally, Table 4 shows the determinants of the evolution of each professional group taken into account in this study. We test model (4) on all professional groups (equations 5-8) and aim to identify the persistence and diversity of relationships.

Results in Table 4 reveal that key determinants for employment growth in the case of Managers are the level of ICT investments, the relevance of human knowledge, new products and organisational change, all with positive and significant coefficients, in contrast with the negative effects of process innovation and offshoring. Occupations with the highest skills and competencies are expanding in industries characterized by a "Schumpeterian dynamics", that is by high levels of human capital, the ability to pursue strategies of technological competitiveness (product and organisational innovations), all factors expanding the role of the high-skill occupation. For Clerks, digitalisation appears as the driving force of employment change, with a negative effect of digital investments and a positive one of digital inputs. In the case of Craft workers, low technology offshoring is negatively associated with employment growth, while the only significant positive effect is that of the relevance of university graduates. The expansion of Manual workers is clearly driven by demand: new jobs are created in industries where value added grows faster (services); at the same time jobs for manual workers are lost due to process innovation (mainly in manufacturing).

	Managers (1)	Clerks (2)	Craft workers (3)	Manual workers (4)
Value added	0.200***	0.221***	0.203	0.319**
	(0.0508)	(0.0766)	(0.153)	(0.128)
		15		

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$\begin{array}{ccccccc} (0.0518) & (0.0652) & (0.0814) & (0.0948) \\ \mbox{ICT investment} & 0.148^{***} & -0.122^* & -0.158 & -0.174 \\ & (0.0419) & (0.0635) & (0.191) & (0.193) \\ \mbox{ICT consumption} & -0.0130 & 0.0555^* & -0.0284 & -0.0550 \\ & (0.0134) & (0.0313) & (0.0425) & (0.0645) \\ \mbox{Product innovation} & 0.0478^{**} & -0.0203 & 0.0364 & 0.0631 \\ & (0.0228) & (0.0308) & (0.0365) & (0.0383) \\ \mbox{Expenditure in machinery} & -0.252^{***} & -0.213^{**} & -0.109 & -0.294^{***} \\ & (0.0541) & (0.108) & (0.116) & (0.109) \\ \mbox{Organisational innovation} & 0.0610^{**} & -0.0149 & -0.0188 & 0.0646 \\ & (0.0290) & (0.0568) & (0.0446) & (0.0593) \\ \mbox{Offshoring low-tech} & -0.0855^{***} & -0.0158 & -0.193^{***} & -0.0884 \\ & (0.0305) & (0.0696) & (0.0602) & (0.0723) \\ \mbox{Spain} & -1.115^* & -2.025^{***} & -1.632 & -2.125^{**} \\ & (0.567) & (0.743) & (1.247) & (0.996) \\ \mbox{France} & -2.471^{***} & -2.194^{**} & 3.878^{***} & -0.447 \\ & (0.650) & (0.915) & (1.423) & (1.480) \\ \mbox{Italy} & -2.307^{***} & -3.047^{***} & -3.382^{**} & -0.897 \\ & (0.579) & (0.834) & (1.378) & (1.114) \\ \mbox{Netherlands} & -0.985 & -1.830 & 2.900 & -0.744 \\ \end{array}$
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$\begin{array}{c cccccc} Organisational innovation & 0.0610^{**} & -0.0149 & -0.0188 & 0.0646 \\ & (0.0290) & (0.0568) & (0.0446) & (0.0593) \\ Offshoring low-tech & -0.0855^{***} & -0.0158 & -0.193^{***} & -0.0884 \\ & (0.0305) & (0.0696) & (0.0602) & (0.0723) \\ Spain & -1.115^{*} & -2.025^{***} & -1.632 & -2.125^{**} \\ & (0.567) & (0.743) & (1.247) & (0.996) \\ France & -2.471^{***} & -2.194^{**} & 3.878^{***} & -0.447 \\ & (0.650) & (0.915) & (1.423) & (1.480) \\ Italy & -2.307^{***} & -3.047^{***} & -3.382^{**} & -0.897 \\ & (0.579) & (0.834) & (1.378) & (1.114) \\ Netherlands & -0.985 & -1.830 & 2.900 & -0.744 \\ \end{array}$
$\begin{array}{c ccccc} (0.0290) & (0.0568) & (0.0446) & (0.0593) \\ \hline \\ Offshoring low-tech & -0.0855^{***} & -0.0158 & -0.193^{***} & -0.0884 \\ (0.0305) & (0.0696) & (0.0602) & (0.0723) \\ \hline \\ Spain & -1.115^* & -2.025^{***} & -1.632 & -2.125^{**} \\ (0.567) & (0.743) & (1.247) & (0.996) \\ \hline \\ France & -2.471^{***} & -2.194^{**} & 3.878^{***} & -0.447 \\ (0.650) & (0.915) & (1.423) & (1.480) \\ Italy & -2.307^{***} & -3.047^{***} & -3.382^{**} & -0.897 \\ (0.579) & (0.834) & (1.378) & (1.114) \\ \hline \\ Netherlands & -0.985 & -1.830 & 2.900 & -0.744 \\ \end{array}$
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France -2.471^{***} -2.194^{**} 3.878^{***} -0.447 (0.650)(0.915)(1.423)(1.480)Italy -2.307^{***} -3.047^{***} -3.382^{**} -0.897 (0.579)(0.834)(1.378)(1.114)Netherlands -0.985 -1.830 2.900 -0.744
(0.650)(0.915)(1.423)(1.480)Italy-2.307***-3.047***-3.382**-0.897(0.579)(0.834)(1.378)(1.114)Netherlands-0.985-1.8302.900-0.744
Italy-2.307***-3.047***-3.382**-0.897(0.579)(0.834)(1.378)(1.114)Netherlands-0.985-1.8302.900-0.744
(0.579)(0.834)(1.378)(1.114)Netherlands-0.985-1.8302.900-0.744
Netherlands -0.985 -1.830 2.900 -0.744
(0.786) (1.136) (1.793) (1.912)
United Kingdom -2.992*** -2.433** -0.530 -1.487
(0.741) (0.979) (1.126) (1.041)
Constant -1.022 -0.454 0.633 -0.333
(0.621) (0.987) (1.400) (1.097)
Observations 193 193 173 177
R-squared 0.692 0.520 0.471 0.348

Note: Weighted Least Square estimation. The individual observation is sector in a given country. Robust standard errors are reported in parentheses, significance levels *** p<0.01, ** p<0.05, * p<0.1

Summing up the findings, we can point out that the knowledge embodied in employees plays a positive and significant role in job creation for all four professional groups; similarly, the expansion of demand acts as major driving force (except for Craft workers), as jobs are added in the industries where value added grows faster. The negative relation between wage levels and job creation appear significant only for Managers and Manual workers. Higher digitalisation, in terms of digital capital deepening, is associated with job creation in the case of Managers and with a reduction in the employment of Clerks whose numbers, on the other hand, increase with greater digital intermediate inputs. Innovation strategies consisting of the introduction of new products and organisational changes have a strong positive employment effect only for the high-skilled component of the labour force (Managers). The hierarchical position and the ability to control decisions making processes across professional groups in firms may explain the ability of managers to benefit from both these types of innovation. Offshoring and process innovation again emerge as labour saving strategies; new processes disrupt jobs for Managers, Craft and Manual workers, although with a higher magnitude for the latter; we do not find a significant negative impact of offshoring on Manual workers while a negative effect is found in the case of Craft workers and Managers. From these findings, a complex picture of diversity of the drivers of employment change and specificities of professional groups has emerged.

6. Conclusions

From our investigation a number of key novelties have emerged. First, we have provided original evidence on the diversity of the trajectories of digitalisation and on their contrasting employment impact. Rather than thinking of digitalisation as a one-directional process, where 'given' technologies shape economic change, employment, skills and wages, we have shown that two distinct effects are at work. On the one hand, when industries acquire from digital sectors greater intermediate inputs, they are able to increase performances and jobs. On the other hand, when digital investments per employee increase, a process of restructuring associated to job reduction emerges. While there is a complementarity – up to a point – between digital inputs and investment in the digitalisation strategies of firms, we have found that industries consistently show the contrasting employment effects of the two dimensions of digitalisation. It is therefore important to move beyond the idea that digitalisation is a homogenous process and consider the diversity of digitalisation strategies, with their contrasting economic and employment effects.

Second, we have shown that digitalisation closely interacts with changes in industry structures, demand dynamics, labour market conditions, technologies and organisations in shaping employment outcomes. In particular, our model and tests highlight the complex relations between the two dimensions of digitalisations pointed out above and the other determinants of employment change in industries. An important result is that the acquisition of digital inputs operates in a similar way, and appears to be complementary to product innovations and to changes in organisations. They all contribute to industries' ability to achieve 'Schumpeterian' advantages based on novel products and services incorporating advanced digital technologies. Greater digital inputs and greater product innovation allows firms and industries to grow faster in terms of output and jobs.

Conversely, high levels of digital investments per employee – including computer hardware and software, telecommunication equipment and databases – have a similar impact, and appear to be complementary to innovation in processes, as they allow the restructuring of production activities with greater efficiency, control and flexibility, and with fewer workers. It is important to note that our econometric results show that the parallel effects of technological innovation and digital activities – both when they expand and when they reduce employment – do now overlap, but rather integrate one another, capturing different aspects of industries' strategies aiming either at upgrading production capabilities or at restructuring and downsizing.

Third, we have documented the increasing polarisation of the occupational structure in European industries, clearly shown by the use of ISCO professional groups, and we have highlighted the diversity of drivers affecting the employment expansion of Managers and Manual workers and the job stagnation or contraction of Clerks and Craft workers. This approach allows to move beyond the view of digital technologies mainly replacing 'routine' jobs and identifies the specific drivers of employment change for each professional group. Digitalisation again plays different roles when we consider intermediate inputs and investment, leading to contrasting effects for Managers and Clerks. In addition, the other determinants of employment change and, in particular, the role of innovation in products, processes and organisations and of production offshoring emerge as key explanatory factors for the evolution of professional groups.

These results provide new insights for setting digitalisation in the broader context of technological and economic change and for explaining the evolution of European industries in the last decade.

Far from showing a generalised skill-upgrading and an overall improvement of jobs as a result of digitalisation and technological change, we found that different strategies have contrasting employment effects. Winners and losers in occupational groups can be clearly identified, providing an explanation of the key drivers of the current polarisation in the skill structure of employment.

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Appendix

Table A1. List of sectors

Sectors	Nace Rev. 2 codes	Revised Pavi classification
Manufacture of food products, beverages and tobacco products	C10-C12	SD
Manufacture of textiles, wearing apparel and leather products	C13-C15	SD
Manufacture of wood and of products of wood and cork; manufacture of articles of straw and	C16	SD
plaiting materials	C10	3D
Manufacture of paper and paper products	C17	SI
Printing and reproduction of recorded media	C18	SI
Manufacture of coke and refined petroleum products	C19	SI
Manufacture of chemicals and chemical products	C20	SB
Manufacture of basic pharmaceutical products and pharmaceutical preparations	C21	SB
Manufacture of rubber and plastic products	C22	SI
Manufacture of other non-metallic mineral products	C23	SI
Manufacture of basic metals	C24	SI
Manufacture of fabricated metal products, except machinery and equipment	C25	SD
Manufacture of computer, electronic and optical products	C26	SB
Manufacture of electrical equipment	C27	SS
Manufacture of machinery and equipment n.e.c.	C28	SS
Manufacture of motor vehicles, trailers and semi-trailers	C29	SI
Manufacture of other transport equipment	C30	SS
Manufacture of furniture; other manufacturing	C31-C32	SD
Repair and installation of machinery and equipment	C33	SS
Wholesale and retail trade and repair of motor vehicles and motorcycles	G45	SD
Wholesale trade, except of motor vehicles and motorcycles	G46	SD
Retail trade, except of motor vehicles and motorcycles	G47	SD
Land transport and transport via pipelines	H49	SD
Water transport	H50	SD
Air transport	H51	SD
Warehousing and support activities for transportation	H52	SD
Postal and courier activities	H53	SD
Accommodation and food service activities	I55-I56	SD
Publishing activities	J58	SI
Motion picture, video and television programme production, sound recording and music publishing activities; programming and broadcasting	J59-J60	SI
Telecommunications	J61	SB
Computer programming, consultancy and related activities; information service activities	J62-J63	SB
Financial service activities, except insurance and pension funding	K64	SI
nsurance, reinsurance and pension funding, except compulsory social security	K65	SI
Activities auxiliary to financial services and insurance activities	K66	SI
Real estate activities	L68	SS
egal and accounting activities; activities of head offices; management consultancy activities	M69-M70	SS
Architectural and engineering activities; technical testing and analysis	M71	SS
Scientific research and development	M72	SB
Advertising and market research	M73	SS
Other professional, scientific and technical activities; veterinary activities	M74-M75	SS
Administrative and support service activities	Ν	SD

Table A2.	Variable	definition	and	data	sources
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Variable	Unit	Reference period	Source
Rate of growth of value added	Compound annual rate of growth	2009-14	SID – (WIOD-SEA)
Rate of growth of labour compensation per employee	Compound annual rate of growth	2009-14	SID - (WIOD-SEA)
Rate of growth of employment	Compound annual rate of growth	2009-14	SID – (WIOD-SEA)
Investment in ICT per employee	Thousand euros	2009	SID - (EU KLEMS)
Intermediate consumption of ICT good and services	Share	2009	SID - (WIOT)
Firms introducing new products only	Share	2012-2014	SID – (CIS9)
Firms introducing new processes only	Share	2012-2014	SID – (CIS9)
Firms introducing organisational innovation only	Share	2012-2014	SID – (CIS9)
Expenditure in machinery per emloyee	Thousand euros	2012-2014	SID – (CIS9)
Low-tech offshoring	Share	2009	SID – (WIOT)
Rate of growth of university graduates	Compound annual rate of growth	2009-14	SID – (EU LFS)
Rate of growth of managers	Compound annual rate of growth	2009-14	SID – (EU LFS)
Rate of growth of clerks	Compound annual rate of growth	2009-14	SID – (EU LFS)
Rate of growth of craft workers	Compound annual rate of growth	2009-14	SID – (EU LFS)
Rate of growth of manual workers	Compound annual rate of growth	2009-14	SID – (EU LFS)

Note: In order to reflect actual impact of digital transformation, rather than purely statistical one - by introducing measurement errors related to methodological differences in the calculation of ICT deflators (official statistical vs hedonic), all variables are expressed in current terms. Although, this is not a neutral choice it is supported with a low inflation environment after the financial crisis – which is a reference period of our analysis.

Table A2. Summary statistics

PAVITT groups	Dig. Investment per emp. in 000€	Dig. Consumption (%)	Product innovation only (%)	Process innovation only (%)	Expenditure in machines per emp. in 000 €	Org. innovation only %	Offshoring low tech (%)
Science Based	6,95	19,09	22,35	7,07	2,65	18,89	7,44
Specialised suppliers	2,44	6,36	15,13	7,26	0,85	18,79	8,35
Scale and information intensive	3,90	4,81	12,78	11,10	1,70	18,48	13,16
Supplier dominated	1,18	4,01	8,56	9,68	1,35	13,92	12,94





Note: Employment is measured as compound annual rate of change for Germany, Spain, France, Italy, Netherlands and UK over 2012-2017 period; Source: LFS, own elaborations



Figure A2. Occupational structure by Revised Pavitt industry groups, 2014

Note: Aggregation of Germany, Spain, France, Italy, Netherlands and UK; Source: LFS, own elaborations