Innovating for the good or for the bad.

An EU-wide analysis of the impact of technological transformation on the labour market

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Abstract

This article investigates the impact of technological transformation on two labour market outcomes: within sector job polarisation and unemployment. We define the technological transformation as the relationship between different innovation inputs that increase the stock of knowledge within companies and innovation outputs. Hence, the labour market outcomes of the technological transformation derive from two types of effects: the direct effect of innovation inputs or their effect mediated by innovation outputs. We consider two innovation inputs (digital technologies adoption and use and the learning capacity of the organisation) as well as four innovation outputs (product, process, organisational or marketing innovations). We build an EU wide database that integrates, at the sector-country level, four data sources (two employer-level and two employee-level surveys), and we implement a Structural Equation Model (SEM). We find that investments in *Digital technology adoption and use* and in the *Learning capacity of the organisation* influence labour market outcomes differently. The effect of the first innovation input is fully mediated by innovation outputs while mediation is either partial or nil for the second one. In particular, the *Learning capacity of the organisation* provides direct protection against unemployment and, in the longer run, against occupational downgrading. Furthermore, innovation outputs play an important role in determining the labour market outcomes of the technological transformation. Depending on its type, innovation outputs can be either beneficial or detrimental to employees. Product innovation is for the good as it mediates positively the relationship between innovation inputs and labour market outcomes. Marketing innovation is for the bad as its mediation effect is opposite.

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1 Introduction

Periods of radical changes such as those happening during technological revolutions usually raise concerns about the widespread substitution of machines to labour and the rise of wages inequalities. The current digital revolution has stretched once again the fear of massive skills and job destruction due to automation, robotics and Artificial Intelligence (Brynjolfsson and MacAfee, 2014; Frey and Osborne 2017). Moreover, emerging digital technologies seem to affect workers across all different occupational ranks and not only in manufacturing industries (Bailey, 2022). Nevertheless, each technological revolution also generates new goods and services, which by raising demand, may create new jobs that use new skills.

This paper steps into this debate and offers an original empirical analysis exploiting an innovative EU-wide dataset that combines complementary employer and employee sources of information by aggregating data at the sector-country level. We first enrich the approach of the technological transformation by considering that innovation strategies and choices made by companies in how they embed digital technologies into the production process are key. Indeed, simply introducing a new technology into the production process is not enough to bring about a technological transformation. The company must find a use of the new tool that produces new knowledge and helps to generate innovations. Nor is technology the only factor involved in this process of knowledge production embedded in the company's production process. Research & Development (R&D), traditionally considered in the economics of innovation, also plays an important role, as does the learning capacity of the organisation, which is less often considered in empirical studies because it is more difficult to measure. Overall, the technological transformation is the result of technological (product and process) and non-technological (organisational and marketing) innovations generated by a combination of investments in R&D, digital technologies and in the learning capacity of the organisation (Greenan and Napolitano, 2023).

We provide empirical evidence of the relationship between this enriched approach to technological transformation and two labour market outcomes that are rarely considered simultaneously, although they provide complementary information. The first one is the job polarisation trend. We capture it through indicators of the evolution of the shares of employment, at the sector-country level, in low-paid, middling and high-paid occupations with respect to a wage ranking fixed in a base year (2011). An increase in the shares of employment in low-paid and high-paid occupations, to the detriment of middling jobs, would identify a job polarisation trend. The second one is the unemployment rate at the sector-country level, which refers to the employment loss of people who were employed in a specific sector, but who, despite being available for work and having taken specific steps to find a job, have not been recruited in their former sector or in another one.

We analyse econometrically the relationship between the technological transformation and the selected labour market outcomes implementing structural equation models (SEM) that allow simultaneously estimating multiple relations between the innovation inputs and outputs and between the inputs, the outputs and the labour market outcomes. It also allows conducting a mediation analysis, which assumes that the relationship between inputs and outcomes is mediated by a third variable, the innovation outputs of our model.

This paper is organised as follows: Section 2 reviews the literature about innovation and the labour market, section 3 presents the conceptual framework and develops our hypotheses, sections 4 present the data and the empirical strategy, section 5 shortly discusses the results and section 6 concludes.

2 Literature review

Innovation is a conflicting mantra. Although economists and policy makers recognise innovation as one of the main sources of the wealth of nations, economic analysis, both theoretical and empirical, has shown that the effect of innovation on the labour market is difficult to discern. With regard to technological innovation, the literature has widely examined its impact on the labour market, and regular waves of studies are produced in the attempt to rule out (or to fuel) the destructive impacts that cyclically, at each technological breakthrough, populate the collective imagination (see for instance the very recent wave on the impact of chat GPT in Felten *et al*., 2023; Eloundou *et al*., 2023). By contrast, the effects of non-technological innovation, a concept developed with the tertiarisation of the economy, are way less investigated, even if, since 2005, the Community Innovation Survey provides data on the introduction of organisational and marketing innovation.

On the negative side of the story, technological transformation may determine labour displacement and increase wage inequality, while on the bright side we find the literature showing an overall positive effect of innovation on the labour market because of the expansion of the production possibilities and the creation of new markets. Empirically, contrasting findings are mainly found at different level of data aggregation and different disentanglement of the concept of innovation (Calvino and Virgillito, 2018).

Quantitative studies that directly focus on the effects of innovation on unemployment rather than on employment creation or destruction are scanter and usually macroeconomic. Among the analyses focused on European countries, Feldmann (2013) finds a negative but temporary effect of technological change on unemployment between 1985 and 2009. Matuzeviciute et al. (2017) examine a panel of 25 EU countries between 2000 and 2012 and find no significant relations between technological innovation and unemployment. Yildirim et al. (2022) analyse a panel dataset of 12 European countries from 1998 to 2015 and find that technological developments increase unemployment rates, both in high and relatively low innovative countries, but with higher rates in less innovative regimes.

The micro and meso-economic literature offer some deeper insights. Employment at the firm level is positively affected (Pohlmeier and Entorf, 1990; Brouwer et al., 1993; Smolny, 1998; Greenan and Guellec, 2000; Harrison et al. 2014), and this is usually confirmed when aggregating at the sectoral level. However, important differences are observed depending on the level of innovativeness, the technological characteristics (Vivarelli, 2014) and the learning processes within the sectors (Pianta, 2022). Indeed, the sectoral level analysis allows taking into consideration that the aggregate effect of innovation on employment does not equal the average firm-level effect, as competition between firms within the same sector plays a role (Harrison et al., 2014).

When scholars open the black box and treats the different components of innovations separately, the analysis show that not all innovations are equal. In particular, the suspect of a labour displacement effect deriving from process innovation becomes visible, especially at the sectoral level. This is because the labour substitution induced by gains in productivity at the firm level (Van Reenen, 1997; Pianta, 2004; Vivarelli, 2014) may be compensated by a market expansion enabled by a price reduction, which may stimulate the demand of old products. However, at the sectoral level, it may be easier to discern whether the firm-level compensation mechanisms consist in a pure market expansion or rather in a market erosion from non-innovative firms, the so-called "business stealing", or in firms' entry and exit flows (Harrison et al., 2014).

The effect of product innovation on employment is less ambiguous, at both the firm and sectoral level. At the firm level, new products tend to create employment via a demand increase allowed by an expanding market (Van Reenen, 1997; Bogliacino and Vivarelli, 2012; Vivarelli, 2014;

Marcolin et al., 2016), despite a possible counterbalancing effect of the "cannibalisation" and replacement of old products (Pianta, 2005). At the sectoral level, product innovation has a prevailing market expansion effect, thanks to job reallocation patterns within the sector (Greenan and Guellec, 2000) and especially in highly innovative industries (Mastrostefano and Pianta, 2009; Bogliacino and Pianta, 2010).

As mentioned, while the effect of non-technological innovation is rarely studied, it is mainly addressed using microeconomic data at national level and focusing on the combination of technological and non-technological innovations (Tavassoli and Karlsson, 2015). Despite a growing literature examining the impact of organisational and marketing innovation on firms' performances, very few studies have focussed on the impact on the labour market. Evangelista and Vezzani (2011) clarified the difference between direct impact and indirect effects (compensation mechanisms) of product, process, and organisational innovation on unemployment, as well as between analyses undertaken at macro and micro-level. They proposed an analysis of unemployment by classifying firms according to the prevailing form of innovation and find negative effects for manufacturing firms combining process and organisational innovation only.

Marketing innovation, although widely discussed in the management literature, is the least studied type of innovation in the economics literature. The few studies that have examined marketing innovation as a distinct component have, again, mainly done so to link it to economic performance (see for example Vasileiou et al., 2022). In the management literature, D'attoma and Ieva (2020) separate the four components of marketing innovation (design, price, promotion, and placement) and demonstrate that they can have opposite impacts on innovation success. To the best of our knowledge, there are no study analysing specifically the impact of marketing innovation on the labour market.

Beyond historical fears of machines stealing human jobs, technological progress has been blamed for the increase in wage inequalities. Freeman and Katz (1994) have developed one of the hypotheses fostering this allegation. They suggested that technology is a complicated matter that only skilled workers can handle. In their view, technical change is intrinsically skill-biased, as it favours the creation of jobs requiring higher intellectual abilities. The implication of that is quite straightforward: technology pushes up the demand for skilled workers, hence contributing to increased wage inequality, a phenomenon known as job upgrading.

However, skill-biased technical change is not the only hypothesis developed around the effect that technology might have on wages. Taking into account the tasks performed rather than the job qualification, Autor et al (2003) proposed a two-dimensional categorisation of the structure of employment, dividing the classic skilled/non-skilled categories into routine and non-routine jobs on the one hand, and manual and cognitive jobs on the other. Routine manual tasks are those for which workers have been constantly replaced by machines since the first industrial revolution, while routine cognitive tasks are those that are increasingly entrusted to computers. At the same time, non-routine tasks are mainly performed by the highly skilled workers mentioned in the Freeman and Katz hypothesis (non-routine cognitive tasks) but they are also a part of jobs consisting of flexible manual activities (non-routine manual tasks).

Goos and Manning (2007) take the view of the structure of employment embedded in Autor et al.'s (2003) theory and endeavour to show that technological change mainly affects jobs consisting of routine tasks - which are not the least paid - while the impact on jobs involving non-routine tasks remains marginal. The authors suggest that labour market polarisation is the result of the impact of technological progress on workers earning average wages, resulting in a shrinking middle class and they manage to show this empirically using UK data for the years 1975-1999. Autor et al. (2006) and Acemoglu and Autor (2010) have reached similar conclusions for the American labour market. Goos et al. (2009) expanded the analysis to Europe by using data from the European Labour Force Survey for the years 1993-2006. In their article, the authors stress the importance of studying the phenomenon of labour market polarisation in different countries, as the impact of technological change on wage inequality is likely to be influenced by the structure of employment, which varies considerably in different national contexts. They then enriched their analysis by adding considerations on offshoring (Goos et al., 2014). Despite significant national differences and non-uniform impacts of technological change and offshoring on routine tasks, they observe a fairly consistent pattern of labour market polarisation across Europe.

Fernández-Macías (2012) strongly criticised these European findings and proposed a more nuanced analysis of what happened in the EU-15 over 1995-2007[1]. According to this author the previous analyses have neglected the fundamental role played by the institutional framework and its change over time in the process of structural change in employment. Mishel and Bivens (2021) have stressed the same central institutional role for the US job market.

[1] See also Fernandez-Macias and Hurley (2017) in which the authors present findings more in line with an upgrading effect due to cognitively intense jobs.

A more marginal stream of literature suggests that polarisation occurs first in the direction of job upgrading, a source of inequality that is naturally followed by a higher demand for unskilled workers providing services to the better-off (Mazzolari and Ragusa, 2013), hence generating a kind of polarisation cycle.

Many of the previous studies have looked at the evolution of the structure of jobs according to their position in the wage hierarchy and have inferred a link between this evolution and technological change, identifying it with the observed time trend rather than measuring it directly. More recently, the literature has started to disentangle the different factors that drive labour market polarisation. By using OECD, WIOD and EU Klems data, Breemersch et al. (2019) focused on R&D intensity, ICT capital use, offshorability and China net import penetration and analysed their impact on job polarisation at the sector level. The authors show that polarisation is a phenomenon that is mostly happening within industries as the reallocation of employment from unpolarised industries toward industries with relatively more low- and high-skill jobs only explains one-third of it. They also estimate that ICT use generates about one third of the polarisation happening within manufacturing industries, while Chinese net import competition plays a marginal role.

As one can guess by reading the literature presented above, the debate on the impact of technological change on labour market is far from being settled. While many disagree on the foundation of the issue itself (skill-biased technical change vs routine replacement positions, business stealing vs sales growth), some others stress the importance of identifying further drivers and compensation mechanisms (Calvino and Virgillito, 2018). Moreover, the methodologies adopted to analyse the phenomena range from taking technological change from granted to proxy it as a black box, from using only one figure for innovation to combinations of innovations form, from using micro data while focussing on one country to aggregated data at international level. Finally vast majority of studies on polarisations considers wages as the core dimension of the quality of jobs, while some authors make use of multidimensional indicators of “good jobs" (Oesch & Piccitto,2019).

In this study, we look at the relationship between technological transformation and the labour market, using sectoral level data that allows capturing the compensation mechanisms described in the literature review. The measures of technological transformation, job polarisation trend and unemployment rates that we use allow considering that strategic choices made by organisations in terms of technological and organisational changes are among the determinants of worker vulnerability on the labour market (Greenan et al., 2017). Moreover, our data allow us to look inside the innovation black box while considering the evolutionary nature of technological change (see Section 2 for the input output part of the analysis). In particular, in line with Bailey (2022), we believe that the digital transformation occurring nowadays in firms is not homogenous. A firm equipping with new laptops is not the same that firms using 3D printing or cloud computing, which again is not comparable to a firm buying a quantum computer. Emerging technologies continuously create opportunities for a large range of new uses, and for this reason, their adoption has no deterministic or uniform consequences. The innovation strategies and choices made by companies in how they embed digital technologies into the production process are key in determining their impact on the labour market. This is why we approach digital technologies taking into account their evolutionary features and the technological transformation as a relationship between inputs, including the learning capacity of the organisation, and innovation outputs. Because of the limited definition of the technological transformation in this literature and because relevant data come from sources at the employer and employee or household levels, approaches and results focusing on innovation, technological change, job polarisation and unemployment have remained separate although they are complementary for a comprehensive understanding of the phenomena at stake. Our conceptual and measurement framework on the technological transformation and its consequence on the labour market allows integrating and combining them.

3 Conceptual framework

In this paper, we apply the framework proposed by Greenan et al. (2023), which conceptualises the technological transformation as a relationship between inputs of a knowledge production function and innovation outputs. Inspired by the Crépon, Duguet and Mairesse (1998) model and its following expansions (Polder et al., 2010; Hall et al., 2013; Venturini, 2014; Mohnen et al., 2018), we consider that companies invest to increase the stock of productive knowledge. Key investments reside in R&D, in the adoption and use of digital technologies and in the improvement of the learning capacity of the organisation. The learning capacity is a distinct argument of the knowledge production function of enterprises that captures the implementation of those management tools concerned with the improvement of individual and organisational learning (Greenan and Napolitano, 2023). Innovation outputs refer to the introduction of technological (product or process innovation) or non-technological innovations (organisational or marketing).

[Insert Figure 1]

In our model (Figure 1), investments in digital technologies and in the learning capacity of the organisation may have direct and/or indirect effects on labour market outcomes because associated innovation outputs may play a mediating role. The learning capacity of the organisation protects employees in the labour market from negative impacts for two main reasons: it favours enterprises adaptability to rapidly changing environments and hence prevents employment destruction and it supports employees in developing their skills and tailoring them to the business requirements. If digital technologies adoption and use may also have a direct impact on the labour market, its sign is less straightforward than for the learning capacity of the organisation. On the one hand, the adoption and use of digital technology may lead companies to replace workers performing routine tasks, but it may also make it necessary to acquire new skills.

Looking further at figure 1, all inputs also have a positive impact on the four different forms of innovation, and this relationship may have an indirect effect on the labour market through mechanisms that affect economic performance. Indeed, we know from the theoretical and empirical literature that innovation may generate new markets, increase product attractiveness or spur efficiency gains. Although we do not directly measure such mechanisms, we know that each innovation form can trigger one or more of these features and consequently have a positive impact on the labour market via economic growth and value creation or a negative one via business stealing. The literature has explored extensively the labour market consequences of product and process innovation. Hence, we know that at the sector level, product innovation has a positive impact and process innovation a mixed one. The empirical evidence lacks for organisational and marketing innovation but because we assume a labour market impact that happens through efficiency gains and higher product attractiveness, we consider that the effects of these two forms are likely to be close to that of process innovation.

Accordingly, we develop the following hypotheses:

- *Hypothesis 1.* Higher levels of learning capacity of the organisation at the sector level directly protect employees against adverse labour market outcomes of the technological transformation through the development of workers' skills and the organisation's ability to adapt.

- *Hypothesis 2.* Higher rates of digital technologies adoption and use at the sector level have a direct role that depends on the balance between the substitution effect and upskilling effects.
- *Hypothesis 3*. Different forms of innovation have different impact on the labour market according to the effects that they trigger on economic performance and product market dynamics:
    - *Hypothesis 3.1* Product innovation has a positive impact on the labour market via the creation of new markets. The growth effect dominates the business stealing effect (or cannibalisation effect) due to higher product attractiveness. It mediates positively the impacts of innovation inputs.
    - *Hypothesis 3.2* Process, organisational and marketing innovation have mixed impacts on the labour market as increased demand associated with efficiency gains and/or higher product attractiveness may harm competitors. The sign of the mediation will depend on the balance between the growth and the business stealing effects.

4 Methods

4.1 Data sources

To test our hypothesis, we construct a cross-country and cross-sector dataset with a EU-wide coverage that combines data from complementary surveys targeted to employers and employees. Table 1 provides a summary of the key sources of information, the key measures they provide and the selected years of interest.

[Insert table 1]

The technological transformation is computed gathering data from different data sources (see Greenan and Napolitano, 2023 for more details): the Community ICT usage and e-commerce in enterprises (CICT, Eurostat), which provides direct measures about the use of specific digital technologies and e-commerce in enterprises and on which we build a synthetic indicator of *Digital technology adoption and use*; the Community Innovation Survey (CIS, Eurostat), which provides information on different types of innovation outputs, defined on the basis of the conceptualisation provided by the Oslo Manual (OECD/Eurostat, 2005); the Statistics on

Business enterprise expenditure on R&D (BERD by NACE Rev. 2 activity), which provides data about R&D expenditures. The three mentioned data sources provide aggregated data at the country and sector level and cover enterprises with more than 10 employees.

In the absence of an employer level surveys providing information about investments into the learning capacity of the organisation, we add a fourth data source, at the employee level: the European Working Condition Survey (EWCS, Eurofound), which provides data about forms of work organisation and management tools that favour employees' innovative work behaviours and promote the circulation of knowledge among workers. We use this data source to construct the composite indicator of the *Learning capacity of the organisation*, using the information relative to workers in enterprises with more than 10 employees.

We use employee level data from the Labour Force Survey (LFS, Eurostat) as source of information to measure the labour market outcomes of the technological transformation: the sector level evolutions in the shares of employment in low-paid, middling and high-paid occupations with reference to a wage ranking constructed in 2011 and unemployment rates.

To combine the different data sources, data have been harmonised and aggregated (when necessary) through a "common cell" constructed on key variables similarly defined in all the datasets: country, sector and year. The final dataset covers enterprises with more than 10 employees in 26 EU Member States (Sweden is not covered[2]) plus UK. Despite the aim was to obtain the finest grained information about sectors, we face some limitations that are discussed in Greenan and Napolitano (2023). For this study, the main limitation comes from the LFS, as information about the sector in which workers are employed is available only at the 1-digit level of detail of the NACE Rev. 2 classification. The covered sectors go from C (manufacturing) to N (administrative and support service activities), with data on sectors D (electricity, gas and steam) and E (water, sewerage and waste) aggregated in a unique cell (because this is how Eurostat release data from the CICT survey). The dataset covers three periods where we carefully identify the time path between innovation inputs, innovation outputs and labour market outcomes. Investments in innovation inputs are measured at t-2 (2010, 2012 or 2014) and innovation outputs are introduced into the production process between t-2 and t (hence, between 2010 and 2012, 2012 and 2014 or 2014 and 2016). We then compute the outcomes for the period following the innovation outputs with two variants, t+2 and t+3 because we do not

[2] For Sweden, the information about the income deciles in the LFS is not available. As this was key to construct the measure the indicators of job polarisation, the country is not included in our final dataset.

know exactly after which time lapse they are observed on the labour market. Hence, unemployment rates are computed at t+2 (2014, 2016 or 2018) or t+3 (2015. 2017, 2019) and the job polarisation indicators are computed as evolutions between t and t+2 (hence, between 2012 and 2014, 2014 and 2016 and 2016 and 2018) or between t and t+3 (hence, between 2012 and 2015, 2014 and 2017 and 2016 and 2019).

4.2 Key measures

4.2.1 Input and output variables

As described in further details in Greenan and Napolitano (2023), we construct a synthetic indicator of *Digital technology adoption and use* with employer level data from the CICT survey that Eurostat releases yearly at a sector-country aggregated level. The indicator is composed of five sub-dimensions: e-commerce technologies, connection technologies, web and social media technologies, e-business technologies and cloud computing. The final indicator takes into account the use of digital technologies, by considering the percentage of enterprises in a sector within a country using a specific technology, as well as the novelty of this technology, by weighing them using the inverse of the European diffusion rate of each technology in 2010 which proxies its technological intensity.

The overall *Digital technology adoption and use* index equals the normalised sum of the weighted rates of technology diffusion at the sector-country level for each of the five sub-dimensions of digital technologies. It varies from 3,04 to 95,22 (table 2) and hence shows a huge variability between industries and countries. We also observe that from 2010 to 2014 there has been a rapid adoption of technologies at the EU-level, with the overall indicators varying from 40.0 in 2010 to 55.7 in 2014.

[Insert table 2]

Greenan and Napolitano (2023) further propose a measurement frame to approach the *Learning capacity of the organisation* with a composite indicator. It measures the ability of an organisation to develop management tools and organisational practices aimed at improving individual and organisational learning. A learning organisation encourages workers to adopt innovative work behaviours by facilitating the creation, acquisition, transfer and distribution of knowledge among its members. It is adaptive, as it is able to solve the trade-offs between exploration/innovation/change and exploitation/standardisation/continuity, without disrupting its structure and ensuring its sustainability (Greenan and Lorenz, 2010; Teece, 2018; Greenan and Napolitano, 2021; Greenan and Napolitano, 2023).

We implement this approach using individual level data from the EWCS 2010 and 2015. The composite indicator of the *Learning capacity of the organisation* comprises eight sub-dimensions: preservation of the cognitive dimension of work; training opportunities; autonomy of worker in cognitive tasks; motivation backed by the organisation; autonomous teamwork; social support; supportive supervisory style and direct participation. It equals the normalised sum of the eight sub-dimensions, where each dimension has the same weight. Then, we aggregate data at the sector-country level so that the final indicator is the average *Learning capacity of the organisation* observed through the responses of workers employed in enterprises with more than 10 employees. As the EWCS provides two points in time (2010 and 2015), we imputed the *Learning capacity* indicator's values for 2012 as the midpoint between the two. We observe in table 2 that the *Learning capacity of the organisation* varies from 29.6 to 88.9. It has remaining stagnant between 2010 and 2015.

Employer level data from the CIS provide information about enterprises' innovations, defined based on the third Oslo Manual (OCDE/Eurostat, 2005). While previous versions of the Oslo Manual focused on technological product and process innovation, from the fourth CIS edition (covering 2002-2004), measures of non-technological innovation (organisation and marketing) were introduced to account for service innovations that significantly improved user experiences without necessarily having a technological component.

The survey asks whether the enterprise introduced a product innovation, defined as a new or significantly improved good or service with respect to its capabilities, user friendliness, components or sub-systems; a process innovation, defined as improved production process, distribution method, or supporting activity; an organisational innovation, defined as a new organisational method in your enterprise's business practices (including knowledge management), workplace organisation or external relations that has not been previously used by your enterprise; a marketing innovation, defined as the implementation of a new marketing concept or strategy related to product design or packaging, product placement, product promotion or pricing. The reference period is of three years, so, for example, the CIS2012 refers to innovations introduced between 2010 and 2012. We use the aggregated data released by Eurostat, at the sector-country level. Descriptive statistics for each innovation type are given in table 2.

4.2.2 Labour market outcomes

We construct four variables of labour market outcomes using employees-level data from the LFS, then aggregated at sector-country level to be combined with available data from the other data sources. Three variables measure within sector polarisation and the forth one unemployment.

To build our within-sector indicators of polarisation, we take inspiration from the methodology applied to develop the European Jobs Monitor and used in Fernández-Macías (2012) and Fernández-Macías and Hurley (2017). We use data from the 2011 LFS, which provides information about the monthly take-home pay from the main job in deciles. In our combined dataset, 2011 represents the reference year of analysis[3].

We select the population of workers in enterprises with 10 employees and more, limited to full-timers (those working at least 30 hours per week and who self-describe as full-timers). In this population, we construct in each country a matrix of jobs, where a job is defined as an occupation (ISCO-08 at the 2-digit level) in a sector (NACE Rev 2.0, at 1-digit level).

We select 2011 as base year for ranking jobs according to their average wage level. For each interviewed individual, the LFS gives the country-based decile of the monthly take-home pay from the main job. For each job, we calculate the weighted average of the deciles by using sampling weights. Then, we rank each job from the highest to the lowest score of the deciles' average, and we compute the weighted cumulated population of this distribution. By using the midpoint of the weighted cumulated population, we create terciles (where the lowest-paid occupations are assigned to tercile 1 and the best-paid occupations to tercile 3), so that each tercile represents 33% of the population.

We then select our target years, allowing for a 2-year lag (2014, 2016 and 2018) or for a 3-year lag (2015, 2017 and 2019) with the innovation output variables of the model. In both cases, we ensure that all jobs in our target years appear in the base year, and vice versa, by dropping unmatched cases. We assign each occupation in a sector-country cell to the same job-wage tercile as the one determined with the LFS 2011. Hence, the occupation-to-tercile assignment of 2011 applies for each sector-country cell across time. We then compute, by sector-country level, the shares of employment in occupations belonging to each tercile of the wage ranking distribution, obtaining the shares of employment in low-paid, middling and high-paid occupations.

[3] As our final dataset cover the period 2010-2018, we aimed at using 2010 as reference year to construct the job polarisation indicators. This was not possible because the ISCO-08 classification of occupations was not yet available in 2010.

We are finally able to assess the evolution in the employment structure by computing the difference between the shares of employment in occupations in a given tercile at two different dates. An increase in the shares of employment in low-paid and high-paid occupations would identify a job polarisation trend. The descriptive statistics presented in table 3 show that this is not an average trend within the sectors: whether the difference relates to two or three years, we observe a decrease in the share of low-paid occupations and an increase that is greater in high-paid occupations than in intermediate occupations, which rather indicates a job-upgrading trend.

For a full labour market assessment, we also need to know whether part of the workforce willing to work does not find a job. Unemployment rates provide this information. The fourth labour market outcome that we consider measures the share of unemployed individuals at sector-country level. First, we identify the active population through the employment status of individuals. Then, we select the sector of activity for the employed workers, while, thanks to the questions about the previous job characteristics, we select the sector of activity of the previous job for those that are currently unemployed. In doing so, we focus on a particular measure of unemployment, which refers to the loss of employment of people who were employed in a specific sector, but who, despite being available for work and having taken specific steps to find a job, have not been recruited in their former sector or in another one. Table 3 reports summary statistics for the unemployment rates two and three years after innovation took place. It is on average 6.67% and 6.01% respectively.

[Insert table 3]

4.2.3 Control variables

We include a set of control variables in our model: dummies for year, for secondary or tertiary sectors and the log average size of enterprises in each sector-country cell. We also include dummies to assign each country to a welfare regime (see appendix A1), according to the classification of the typology of welfare regimes proposed by Esping-Andersen (1990) and progressively extended in terms of geographical coverage (Sapir, 2006; Fenger, 2007; Kammer et al., 2012).

4.3 Data analysis

We implement a Structural Equation Model (SEM) to analyse econometrically the relationship between the technological transformation and the selected labour market outcomes at the sector-country level. SEM allows taking into account the multiple relations of our conceptual framework. The clear time ordering of the data structure (as described in Section 4.1) also allows assuming that the relationship between the inputs of the knowledge production function, the innovation outputs and the labour market outcomes goes in one direction only, without feedback loops. We thus implement a mediation analysis, by assuming that a third set of variables, the innovation outputs of our model, mediates the relationships between inputs and outcomes as shown in figure 3.

[Insert figure 3]

Following the approach developed by Baron and Kenny and adjusted by Iacobucci et al. (2007) for use with SEM, complete mediation occurs when the size of the effect that the independent variable has on the dependent variable is no longer significant after the mediator has been introduced. Partial mediation occurs when the size of the effect that the independent variable has on the dependent variable is reduced but not nullified after the mediator has been introduced. When partial mediation occurs, it is possible to compute the effect size of the indirect effect as the Ratio of the Indirect effect to the Total effect (RIT). The RIT can be interpreted as the percentage of the effect of the independent variable (e.g. learning capacity) on the dependent variable (unemployment rates) mediated by the mediator variable (e.g. product innovation) (MacKinnon et al., 2007).

Our system includes the following equations:

$$
\begin{cases}
Product\_Inno_{ijt} = \beta_0 + \beta_1 R\&D_{ijt-2} + \beta_2 Tech_{ijt-2} + \beta_3 Learn_{ijt-2} + \varepsilon_{1\_ijt} \\
Process\_Inno_{ijt} = \beta_0 + \beta_1 R\&D_{ijt-2} + \beta_2 Tech_{ijt-2} + \beta_3 Learn_{ijt-2} + \varepsilon_{2_{ijt}} \\
Organisation\_Inno_{ijt} = \beta_0 + \beta_1 R\&D_{ijt-2} + \beta_2 Tech_{ijt-2} + \beta_3 Learn_{ijt-2} + \varepsilon_{3_{ijt}} \\
Marketing\_Inno_{ijt} = \beta_0 + \beta_1 R\&D_{ijt-2} + \beta_2 Tech_{ijt-2} + \beta_3 Learn_{ijt-2} + \varepsilon_{4\_ijt} \\
\Delta low\_paid\_occ_{ijt+2} = \beta_0 + \beta_1 Tech_{ijt-2} + \beta_2 Learn_{ijt-2} + X(Inno)_{ijt} + \varepsilon_{5\_ijt+2} \\
\Delta high\_paid\_occ_{ijt+2} = \beta_0 + \beta_1 Tech_{ijt-2} + \beta_2 Learn_{ijt-2} + X(Inno)_{ijt} + \varepsilon_{6\_ijt+2} \\
Unemp_{ijt+2} = \beta_0 + \beta_1 Tech_{ijt-2} + \beta_2 Learn_{ijt-2} + X(Inno)_{ijt} + \varepsilon_{7\_ijt+2}
\end{cases}
$$

Where i represent sectors according to the NACE Rev. 2 classification at 1-digit level, j represents countries and t time.

The first set of regressions describes the technological transformation. We specify a parsimonious model, as needed by the SEM methodology. However, Greenan and Napolitano (2023) obtained very stable results across different specifications.

We include the R&D expenditures, the *Digital technology adoption and use* indicator and the *Learning capacity of the organisation indicator* as inputs of the knowledge production function and we consider the sector level share of enterprises in a given country that introduced product, process, organisational and marketing innovations. In a second set of regressions, we test the relationship between inputs and innovation outputs and the selected labour market outcomes: evolutions in the share of employment in low-paid and high-paid occupations and unemployment rates. As we found that R&D expenditure was not significantly related to labour market outcomes, we do not introduce it in the last regression of the system. We then test the direct and mediated effects of the *Digital technology adoption and use* and of the *Learning capacity of the organisation* indicators. All specifications include as controls time dummies, welfare regime dummies (see appendix A1), a dummy distinguishing between tertiary and secondary sectors and the log of the average size of enterprises in each sector-country cell.

5 Results

Results of the SEM at t+2 are displayed in table 4, followed in table 5 by an assessment of the mediation effects based on the analysis of the RIT.

[Insert table 4 and table 5]

The results from the first set of equations in the first four columns of table 4, which specifies the relationship between innovation inputs and outputs, are in line with those of Greenan and Napolitano (2023). Slight changes come from the reduced coverage of the combined dataset enriched with the LFS (29 countries instead of 32) and a different specification where we include country group dummies according to welfare regimes rather than country dummies. Nonetheless, the overall interpretation of results remains unchanged.

In line with the CDM research tradition (Crépon et al., 1998), we find that across European industries, investments in R&D are powerful drivers of all forms of innovation but are especially impactful for the share of product innovative enterprises. Unsurprisingly, sectors with higher average enterprise size are more innovative and the tertiary sector proves more innovative than the secondary one for all types of innovation except process innovation.

Industries that invest in *Digital technologies adoption and use* show more innovativeness of all types, with stronger impacts first for product innovation and then for marketing innovation. The *Learning capacity of the organisation* that builds on the creative capabilities of the whole workforce appears as a third vital force of the innovativeness of industries, with a stronger influence on organisational innovation, followed by product innovation. The weakest effect concerns marketing innovation for which the effect of the learning capacity is significant at the 10% level only. The implication of these results is that we are likely to find some indirect effects of these two inputs of the knowledge production function on labour market outcomes if innovation strategies of enterprises affect economic performances and competitive dynamics of product markets, as we assume they do.

Results in the last three columns of table 4 provides empirical evidence about labour market outcomes.

Our first hypothesis states that we expect a direct positive effect of the *Learning capacity of the organisation* on labour market outcomes. If our job polarisation indicators show no significant relationship with the *Learning capacity of the organisation*, we find a highly significant and positive impact on unemployment rates. A one-unit increase in this indicator leads to within sector unemployment rates that is lower by 0.083 percentage points (pp). This result is consistent with previous findings at the individual level based on PIAAC (Greenan et al., 2017), showing that working in a discretionary learning organisation significantly decreases the probability of employees to make a transition out of employment compared with other forms of work organisations.

Our second hypothesis concerns the direct influence of *Digital technology adoption and use*. We assume that it depends on the balance between the substitution and the upskilling effect of the adoption of digital technologies into the production process. As we find no significant direct influence of our indicator on the three labour market outcomes, we conclude that these effects cancel each other out.

We test Hypothesis 3 by assessing and analysing the impacts of innovation outputs on labour market outcomes. We find three significant influences. Two concern product innovation and one concerns marketing innovation.

Hypothesis 3.1 states that product innovation has a positive effect on labour markets via the creation of new markets and that it mediates positively the impacts of innovation inputs. The third line of table 4 aligns with this assumption, as a higher share of product innovative enterprises is associated with a reduction of low-paid occupations and with lower unemployment rates. A rise of 1 point in the share of product innovative enterprises reduces the share of employment in low-paid occupations by 0.071 pp and lowers the unemployment rate by 0.056 pp. Hence, the share of product innovative enterprises mediates positively the labour market outcomes of innovation inputs. The RIT test results (table 5) show that the share of product innovative enterprises fully mediates the effect of *Digital technology adoption and use* when it mediates partially that of the *Learning capacity of the organisation* (30% for the effect on evolution of the share of low-paid occupations, 9% for the effect on unemployment).

Hypothesis 3.2 claims that process, organisational and marketing innovation have mixed impacts on the labour market. They appear to cancel out each other as far as process and organisational innovations are concerned, as we find no significant effects. This is not the case for marketing innovation, since a one-point increase in the share of marketing innovators leads to a 0.091 pp rise in the unemployment rate. Thus, the business stealing effect of marketing innovation clearly dominates value creation. The RIT test results (table 5) show again that marketing innovation fully mediates the effect of *Digital technology adoption and use* with a negative influence towards higher unemployment, when it only attenuates the direct protective influence of the *Learning capacity of the organisation* (a result with weaker significance).

We have already emphasised that the time frame for impacts on the labour market is uncertain. This is why we have repeated our SEM analysis, considering impacts at t+3. We display results in table 6 with an assessment of the mediation effects based on the analysis of the RIT in table 7.

[Insert tables 6 and 7]

Results concerning the knowledge production function in the first four columns of table 6 are as expected, very stable as the time frame of this first part of the analysis is unchanged. We just note that the influence of the *Learning capacity of the organisation* on the share of marketing innovative firms is now positive at a 5% level of significance.

Results concerning labour market impacts observed at t+2 are strengthened at t+3 as coefficients keep the same sign and increase and/or become more significant. Furthermore, RIT tests provided in table 7 confirm that mediation effects are most of the time complete for the *Digital adoption and use* indicator and partial or nil for the *Learning capacity of the organisation*. Our first conclusions thus remain valid one year later. Three additional results appear if we consider a 10% level of significance. We believe that it is useful to present them, given that the size of our sample is limited (498 observations) and that they are consistent with our hypotheses.

First, we find a new direct effect of the *Learning capacity of the organisation*, in line with Hypothesis 1 as it corresponds to a decrease of the employment share of low-paid occupation. The protective direct effect of this innovation input thus extends to our first labour market outcome, counteracting a potential polarisation trend.

Second, a higher share of product innovative enterprises increases the share of high-paid occupation confirming a job-upgrading trend associated with lower unemployment when this form of innovation prevails.

Third, a higher share of marketing innovating enterprises increases the share of low-paid occupations, confirming a job-downgrading trend associated with higher unemployment when this form of innovation prevails.

6 Conclusions and discussion

This research investigates the links between the technological transformation and two labour market outcomes. It is based on a methodology with two essential characteristics. Firstly, by mobilising information from both employers and employees, it takes advantage of the richness of two different and complementary sources of information. Secondly, because the data is aggregated at the meso level, i.e. at the level of the sector within a country, it provides information from a specific perspective. This one takes into account two elements we cannot assess by focusing on data at the individual level: differences due to market structures, political factors and macroeconomic patterns that shape the technological transformation on the one hand; reallocation and selection effects between companies in the same sector on the other.

Inspired by the knowledge production function in the CDM model (Crépon et al., 1998), we describe the technological transformation in the digital age as the relationship between different innovation inputs able to increase the stock of knowledge within companies and innovation outputs. On the input side, we consider the role of R&D expenditure and we develop a synthetic indicator of *Digital technologies adoption and use* that accounts for the heterogeneity of ICTs and digital technologies and their constant renewal. Then, we add a new argument, the *Learning capacity of the organisation*, which proves to be a distinct and impactful dimension of the knowledge production function. It captures the adoption of management tools and organisational practices concerned with the improvement of individual and organisational learning. On the output side, we consider an extended measure of innovation in the digital age that includes technological innovation (product and process innovation) and non-technological innovations (organisational and marketing innovation).

We then move towards the analysis of the nexus between the technological transformation and labour market outcomes. We step into the debate about the fear of massive skills and job destruction due to automation, robotics and AI in the current digital revolution. Emerging digital technologies seem to affect workers in all industries and across different occupational ranks. Nevertheless, each technological revolution also generates new goods and services, which by raising demand, create new jobs that use new skills.

We focus on two specific outcomes. The first one is the job polarisation trend with indicators that account for the change in the share of employment at the sector-country level for occupations belonging to the first, second or third terciles of a wage ranking distribution with respect to a base year (2011). The second one is the unemployment rate at the sector-country level, which thus refers to the job loss of people who were employed in a specific sector, but who, despite being available for work and having taken specific steps to find a job, have not been recruited in their former sector or in another one.

Our results show that investing in the *Learning capacity of the organisation* and in *Digital technology adoption and use* stimulates innovativeness in enterprises as all types of innovation are favoured. However, these two types of investments influence labour market outcomes differently. The effect of investments in *Digital technology adoption and use* are fully mediated by innovation outputs while mediation is either partial or nil for investments in the *Learning capacity of the organisation*. In particular, this latter investment provides direct protection against unemployment and, in the longer run against occupational downgrading.

This result aside, innovation plays an important role in determining the labour market outcomes of the technological transformation. We find that, depending on its characteristics, innovation can be either beneficial or detrimental to employees.

Product innovation is for the good as it mediates positively the relationship between the innovation inputs and labour market outcomes. Higher levels of investments are related with less unemployment and occupational downgrading as well as more occupational upgrading in the longer run. This result suggests the dominance of market creation or expansion effects in sectors where a larger share of firms introduce goods or services that are new or significantly improved with respect to their characteristics or intended uses.

Marketing innovation is for the bad as its mediation effect on labour market outcomes is opposite. However, it mainly concerns *Digital technologies adoption and use*. For the *Learning capacity of the organisation* we find partial mediation for unemployment rates and for the evolution of the employment share of low-paid occupations. This result suggests the predominance of a business stealing effect in the sectors of companies that introduce significant changes in product design, packaging, placement, promotion or pricing to the detriment of employees in companies that do not.

Overall, we find two main results. First investing into the *Learning capacity of the organisation* appears as a win-win strategy leading to more innovativeness and improved labour market outcomes. Second, even though labour market outcomes depend on the relative shares of product and marketing innovations, the technological transformation over the second decade of the millennium is not associated with increased polarisation. In sectors where innovation inputs lead to a share of product innovative firms, which is larger than that of marketing innovative firms, unemployment rates are lower and the job structure shifts upward in the wage ranking. On the contrary, when marketing innovation dominates, sector level unemployment develops and in the longer run, low paid jobs grow to the detriment of the best-paid ones.

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8 Appendices

Table A1: List of countries by welfare regimes

Scandinavian countries	**Conservative countries**	**Eastern European countries**	**Southern European countries**	**Former USSR countries**	**Liberal countries**
Denmark Finland	Austria Belgium Germany France Luxembourg Netherlands	Bulgaria Czech Republic Croatia Hungary Poland Romania Serbia Slovakia	Cyprus Greece Spain Italy Malta Portugal	Estonia Lithuania Latvia	Ireland UK

FIGURES AND TABLES

Figure 1. Conceptual framework

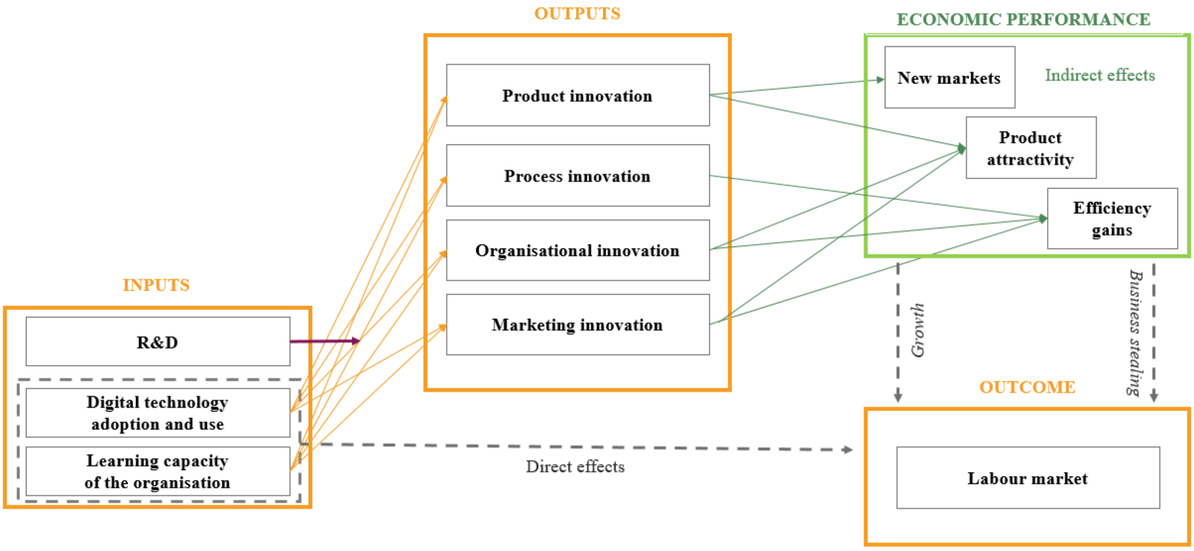

Table 1: Key measures and related sources of data

Data source	Level of information	Measures	Available years
INPUTS at *t-2*			
Statistics on Business enterprise R&D expenditure (aggregated data, Eurostat[4])	Employers	**R&D expenditures**	2010, 2012, 2014
Community survey on ICT usage and e-commerce in enterprises (aggregated data, Eurostat)[5]	Employers	***Digital technology adoption and use***	2010, 2012, 2014
European Working Condition Survey (Eurofound)	Employees	***Learning capacity of the organisation***	2010, (2012 imputed), 2015
OUTPUTS at *t*			
Community Innovation Survey (aggregated data, Eurostat)[6]	Employers	**Innovation outputs**	Δ2010-2012 Δ2012-2014 Δ2014-2016
LABOUR MARKET OUTCOMES			
at *t+2* — Labour Force Survey (Eurostat)	Employee	**Unemployment rates** **Δ low-paid/middling/high-paid occupations**	2014, 2016, 2018 Δ 2012-2014, Δ 2014-2016, Δ 2016-2018
at *t+3* — Labour Force Survey (Eurostat)	Employee	**Unemployment rates** **Δ low-paid/middling/high-paid occupations**	2015, 2017, 2019 Δ 2012-2015, Δ 2014-2017, Δ 2016-2019

Table 2: Descriptive statistics of key measures of input and output variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Digital technology adoption and use	808	47,57	14,12	3,04	95,22
Learning capacity of the organisation	844	55,47	9,05	29,62	88,89
Share of product innovative enterprises	609	20,52	13,44	0,20	66,10
Share of process innovative enterprises	609	22,04	11,73	1,50	75,65
Share of organisation innovative enterprises	609	26,79	12,65	0,00	66,65
Share of marketing innovative enterprises	609	21,93	11,54	0,00	61,55
Average size of enterprises (ln)	591	4,26	0,59	3,10	6,92

[4] https://ec.europa.eu/eurostat/databrowser/view/rd_e_berdindr2/default/table?lang=en
[5] https://ec.europa.eu/eurostat/web/digital-economy-and-society/data/comprehensive-database
[6] https://ec.europa.eu/eurostat/web/science-technology-innovation/data/database

Table 3: Descriptive statistics of key measures of labour market outcomes

Variable	Obs	Mean	Std. Dev.	Min	Max
Δ low-paid occupations (t+2)	836	-0,43	4,58	-19,84	19,42
Δ middling occupations (t+2)	836	0,11	4,71	-19,01	19,12
Δ high-paid occupations (t+2)	837	0,28	4,64	-17,53	15,81
Unemployment rates (t+2)	844	6,67	5,63	0,00	45,07
Δ low-paid occupations (t+3)	829	-0,68	4,86	-17,33	18,40
Δ middling occupations (t+3)	831	0,09	5,03	-16,80	19,77
Δ high-paid occupations (t+3)	831	0,60	4,95	-19,98	19,14
Unemployment rates (t+3)	841	6,01	5,00	0,00	40,44

Figure 2: Path diagram

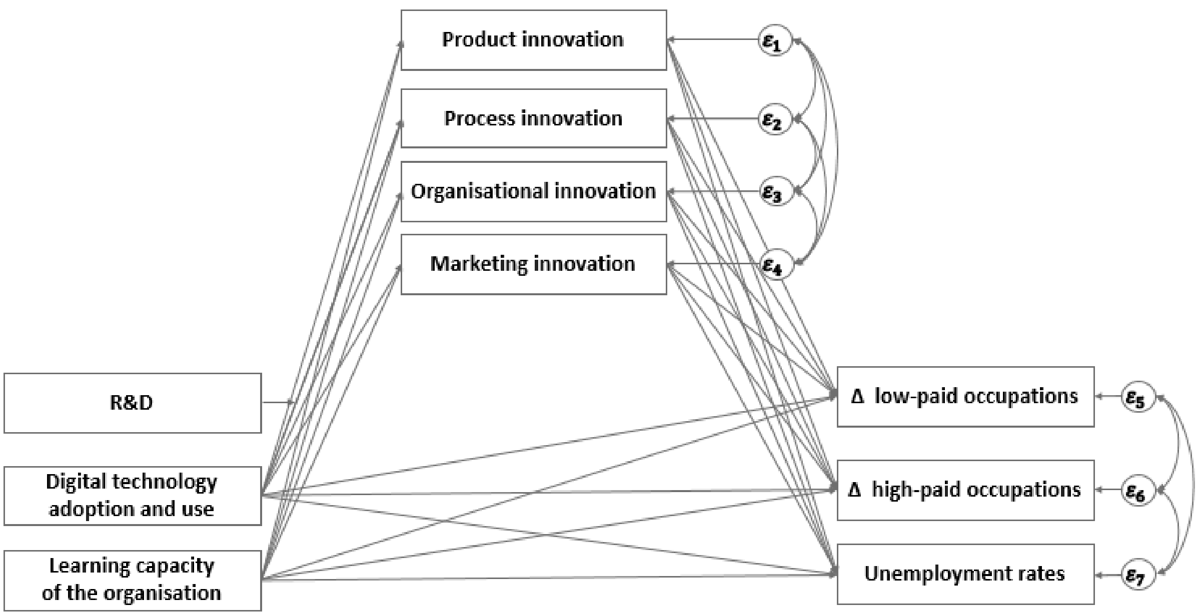

Table 4. Structural Equation Model at t+2

	Share of product innovative enterprises	Share of process innovative enterprises	Share of organisation innovative enterprises	Share of marketing innovative enterprises	Δ low-paid occupations	Δ high-paid occupations	Unemployment rates
R&D exp per employee (ln, th. euro)	2.616***	1.908***	1.598***	1.665***			
	(13.56)	(9.61)	(9.23)	(8.54)			
Digital technology adoption and use	**0.355*** **	**0.143*** **	**0.118*** **	**0.188*** **	-0.008	0.012	-0.022
	(9.00)	**(3.73)**	**(3.72)**	**(5.12)**	(-0.47)	(0.56)	(-1.41)
Learning capacity of the organisation	**0.130*** **	**0.096** **	**0.194*** **	**0.077* **	-0.021	0.003	**-0.083*** **
	(2.83)	**(1.97)**	**(4.51)**	**(1.68)**	(-0.88)	(0.14)	**(-4.19)**
Share of Product Innovative enterprises					**-0.071** **	0.0476	**-0.056** **
					(-2.30)	(1.60)	**(-2.46)**
Share of Process Innovative enterprises					0.016	-0.024	-0.031
					(0.51)	(-0.73)	(-1.16)
Share of Organisation Innovative enterprises					-0.001	0.008	-0.030
					(-0.02)	(0.27)	(-1.33)
Share of Marketing Innovative enterprises					0.004	-0.016	**0.091*** **
					(0.13)	(-0.52)	**(3.20)**
Average size of enterprises (ln)	4.241***	5.553***	5.440***	3.316***	-0.512	0.411	-0.348
	(6.43)	(7.94)	(8.56)	(5.17)	(-1.49)	(1.06)	(-1.09)
Tertiary sector (Ref: secondary sectors)	2.126**	-2.064**	2.683***	4.929***	-0.284	-0.394	-1.562***
	(2.56)	(-2.41)	(3.57)	(5.94)	(-0.83)	(-1.03)	(-3.57)
Groups of countries	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-22.73***	-15.51***	-7.549**	-10.16**	5.646**	-2.496	14.08***
	(-5.60)	(-3.48)	(-1.97)	(-2.39)	(2.49)	(-1.09)	(7.63)

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$
Source: Beyond 4.0 integrated database CIS-CICT-ECWS-LFS (2010-2014, 2012-2016, 2014-2018)
Number of observations: 499; Coverage: EU27 (Sweden excluded) plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C to N, D-E aggregated

Table 5. RIT test from SEM model at t+2

	Share of product innovative enterprises	**Share of marketing innovative enterprises**
Δ LOW-PAID OCCUPATIONS		
Digital technology adoption and use	Complete mediation	-
Learning capacity of the organisation	30%	-
UNEMPLOYMENT RATES		
Digital technology adoption and use	Complete mediation	Complete mediation
Learning capacity of the organisation	9%	9%*

*The Baron and Kenny approach to testing mediation is implemented considering significance levels at 10%.

Table 6. Structural Equation Model at t+3

	Share of product innovative enterprises	Share of process innovative enterprises	Share of organisation innovative enterprises	Share of marketing innovative enterprises	Δ low-paid occupations	Δ high-paid occupations	Unemployment rates
R&D exp per employee (ln, th. euro)	2.585***	1.926***	1.603***	1.644***			
	(13.72)	(10.07)	(9.38)	(8.73)			
Digital technology adoption and use	**0.337*** **	**0.121*** **	**0.097*** **	**0.171*** **	-0.032	0.021	-0.017
	(8.27)	**(3.02)**	**(2.92)**	**(4.53)**	(-1.51)	(0.95)	(-1.19)
Learning capacity of the organisation	**0.153*** **	**0.116** **	**0.212*** **	**0.100** **	**-0.041* **	0.011	**-0.093*** **
	(3.40)	**(2.44)**	**(4.93)**	**(2.19)**	**(-1.68)**	(0.46)	**(-4.94)**
Share of Product Innovative enterprises					**-0.129*** **	**0.0597* **	**-0.062*** **
					(-4.04)	**(1.77)**	**(-2.83)**
Share of Process Innovative enterprises					0.041	-0.030	-0.016
					(1.30)	(-0.78)	(-0.74)
Share of Organisation Innovative enterprises					0.009	0.011	-0.015
					(0.28)	(0.35)	(-0.71)
Share of Marketing Innovative enterprises					**0.056* **	-0.020	**0.086*** **
					(1.81)	(-0.65)	**(3.37)**
Average size of enterprises (ln)	4.528***	5.812***	5.585***	3.461***	-0.419	0.093	-0.454*
	(6.97)	(8.29)	(8.82)	(5.46)	(-1.10)	(0.25)	(-1.65)
Tertiary sector (Ref: secondary sectors)	2.006**	-2.114**	2.627***	4.786***	-0.877**	0.012	-1.177***
	(2.46)	(-2.49)	(3.55)	(5.87)	(-2.35)	(0.03)	(-3.23)
Groups of countries	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-24.57***	-16.72***	-8.299**	-11.33***	6.710***	-2.618	13.01***
	(-6.07)	(-3.79)	(-2.17)	(-2.68)	(2.80)	(-1.24)	(7.67)

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$
Source: Beyond 4.0 integrated database CIS-CICT-ECWS-LFS (2010-2015, 2012-2017, 2014-2018)
Number of observations: 498; Coverage: EU27 (Sweden excluded) plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C to N, D-E aggregated

Table 7. RIT test from SEM model at t+3

	Share of product innovative enterprises	**Share of marketing innovative enterprises**
∆ LOW-PAID OCCUPATIONS		
Digital technology adoption and use	Complete mediation	Complete mediation*
Learning capacity of the organisation	33%*	16%*
∆ HIGH-PAID OCCUPATIONS		
Digital technology adoption and use	Complete mediation*	
Learning capacity of the organisation	Complete mediation*	
UNEMPLOYMENT RATES		
Digital technology adoption and use	Complete mediation	Complete mediation
Learning capacity of the organisation	9%	10%

*The Baron and Kenny approach to testing mediation is implemented considering significance levels at 10%.