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INNOVATING FOR THE GOOD OR FOR THE BAD. AN EU-WIDE ANALYSIS OF THE IMPACT OF TECHNOLOGICAL TRANSFORMATION ON JOB POLARISATION AND UNEMPLOYMENT

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Innovating for the good or for the bad.

An EU-wide analysis of the impact of technological transformation on job polarisation and unemployment

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Abstract

This article investigates the impact of the 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 (R&D, digital technologies and the learning capacity of the organisation) and innovation outputs (product, process, organisational or marketing innovation). We build an EU-wide database that integrates, at the sector-country level, four data sources (two employer-level and two employee-level surveys). Using Structural Equation Modelling, we examine the direct effect of innovation inputs on labour market outcomes as well as the effect mediated by innovation outputs. The findings reveal that the effects on the labour market outcomes of investments in *Digital technology adoption and use* are fully mediated by innovation outputs. By contrast, mediation is either partial or nil for the *Learning capacity of the organisation*. Notably, the *Learning capacity of the organisation* directly protects against unemployment and, in the longer run, against occupational downgrading. In addition, two types of innovation appear to be key determinants of the labour market impacts of the technological transformation, since they will either be beneficial or detrimental to employees. Product innovation is for the good, as it mediates positively the relationship between innovation inputs and labour market outcomes while marketing innovation is for the bad, as its mediation effect is opposite.

Keywords: Technological transformation, digital technologies, innovation, knowledge production function, polarisation, unemployment

JEL codes: O31, O33, J23, J24

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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). However, each technological revolution also generates new goods and services, which by raising demand, may create new jobs that use new skills.

In economics, the concept of technological bias aims to explain these trends. It has recently been revisited following the insights of Autor et al. (2003), who reintroduced the division of labour into production modelling. A new stream of research has thus developed a task-based approach to production, which has now become central in the analysis of the labour market impacts of artificial intelligence and robotics (Acemoglu and Restrepo, 2018). If this approach is based on a more realistic model where production happens through the performance of tasks, the division of labour proceeds directly for the technological characteristics, which are either exogenously determined or fixed by those who develop the technologies, outside the direct context of production.

This paper steps into this debate by adopting a different conceptual frame. Indeed, we refer to the knowledge-intensive direction of technological change (Corrado and Hulten, 2010; Antonelli et al., 2023) and model production, not with a task function embedded into it but rather with a knowledge production function (Crépon et al., 1998). Indeed, the adoption of an emerging technology requires finding ways of exploiting it to generate new knowledge and foster innovation. Technology is not the only factor involved in this process; Research and Development (R&D) also play an important role, as does the learning capacity of the organisation, which is less often taken into account in empirical studies because it is more difficult to measure. The concept of learning capacity of the organisation breaks with the deterministic view of the technology carrying in its blueprint the task content of production. A firm with low learning capacity will probably align with the standard model promoted by the technology provider, whereas a firm with high learning capacity will explore with its employees the full potential of the technology and the new opportunities it opens for the goods and services produced as well as for the whole business process. Overall, following Greenan and Napolitano

(2023), we model the technological transformation as a relationship between investments in R&D, digital technologies and the learning capacity of the organisation and innovation outputs.

We perform an original empirical analysis exploiting an innovative EU-wide dataset that combines complementary information from employer and employee surveys by aggregating data at the sector-country level. This database allows us to enhance our understanding of the technological transformation by capturing firms' innovation strategies and choices regarding the integration of digital technologies into the production process. Furthermore, it makes it possible to explore the links between this enriched approach to the 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 based occupational 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 provide empirical evidence about the relationship between the technological transformation and the selected labour market outcomes analysing it econometrically with Structural Equation Modelling (SEM). Hence, we estimate simultaneously the multiple relations between the innovation inputs and outputs and between the inputs, the outputs and the labour market outcomes. We also conduct a mediation analysis, assuming that the relationship between inputs and labour market outcomes is mediated by innovation outputs.

2 Literature review

The economic literature, both theoretical and empirical, has widely examined the impact of the technological change on the labour market. This exploration seeks to clarify the potentially destructive effects that cyclically capture collective imagination with each technological breakthrough[1].

The literature highlights that the effect of innovation on the labour market is difficult to discern, with contrasting empirical findings at various level of data aggregation and different disentanglement of the concept of innovation[2]. By contrast, non-technological innovation, a concept that emerged with the tertiarisation of the economy, has been way less investigated, although data on organisational and marketing innovation have been available since 2005 through the Community Innovation Survey (CIS, Eurostat).

In particular, the literature shows, at the firm level, that process innovation results in efficiency gains that may lead to unemployment (Van Reenen, 1997; Pianta, 2004; Vivarelli, 2014). The displacement of labour may be compensated by a market expansion effect induced by a price reduction. Analyses at sectoral level make it easier to discern whether the compensation mechanisms result, at economic level, in a pure expansion of the market or whether it is rather a phenomenon of market erosion that prevails, what is known as the "business stealing" effect to the detriment of non-innovative companies (Harrison et al., 2014).

The effect of product innovation on employment is less ambiguous. At the firm level, new products tend to create employment via new demand (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 sectors (Greenan and Guellec, 2000) and especially in highly innovative industries (Mastrostefano and Pianta, 2009; Bogliacino and Pianta, 2010).

However, significant differences are observed depending on the level of innovation, technological characteristics (Vivarelli, 2014; Hötte et al, 2023) and learning processes within sectors (Pianta and Reljic, 2022). A recent study by Ugur (2023), based on data for 32 sectors in 12 OECD countries, points out that when technological innovation increases market power, enabling successful innovators to extract rents, it also has perverse effects on the labour market by reducing employment as well as the labour share in value added.

[1] See for instance the very recent wave on the impact of chat GPT in Felten et al. (2023) and Eloundou et al. (2023).
[2] For a comprehensive review, see Calvino and Virgillito (2018).

As mentioned, the effect of non-technological innovation is rarely studied and mainly addressed using microeconomic data at national level focusing on the combination of technological and non-technological innovations (Tavassoli and Karlsson, 2015). A growing body of literature examines the impact of organisational and marketing innovation on firms' performances, but still few studies focus on labour market. Evangelista and Vezzani (2010) find that all types of innovation create employment by improving firms' performance, and that the introduction of stand-alone organisational innovation is particularly effective in this regard. They also observe a labour displacement effect of process innovation when combined with organisational innovation, but only in the manufacturing sector. Hence, they conclude that employment losses are concentrated among firms characterised by poor knowledge competing on purely cost/price factors, because of a business stealing effect.

Marketing innovation, although widely discussed in management literature, is the type of innovation least studied in economics. The few studies that examine marketing innovation have linked it to economic performance (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 impacts of marketing innovation on the labour market.

Quantitative studies that directly focus on the effects of innovation on unemployment rather than on employment creation or destruction are scanter and usually carried out at macroeconomic level. Among the analyses focused on European countries, Feldmann (2013) provide evidence of 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 relationships between technological innovation and unemployment. Yildirim et al. (2022) analyse a panel dataset of 12 European countries from 1998 to 2015 and observe that technological developments increase unemployment rates, both in high and relatively low innovative countries, but with higher rates in less innovative regimes.

Beyond the longstanding fear of machines stealing human jobs, technological progress raises concerns about increased wage inequalities. Freeman and Katz (1994) suggest that technological change is intrinsically skill-biased, as it favours the demand for well-paid and highly skilled workers while diminishing opportunities for low-paid and less skilled workers, contributing to an occupational upgrading phenomenon. Autor and al. (2003) argue that technological change targets tasks rather than occupational groups. Computer capital is routine-biased in the sense that it automates routine tasks, whether manual or cognitive, while being unable to perform non routine cognitive tasks. Using British data, Goos and Manning (2007) provide evidence of a job polarisation trend characterising the 1975-1999 period: the jobs of occupations located in the middle of the wage hierarchy have been shrinking while low and high-paid jobs have expanded. They argue that the routine-bias hypothesis provides a better explanation of this stylised fact than the skill bias hypothesis. Autor et al. (2006) and Acemoglu and Autor (2011) reach similar conclusions for the American labour market. Goos et al. (2009) expand the analysis to Europe by using data from the European Labour Force Survey for the years 1993-2006 and observe a fairly consistent pattern of labour market polarisation across European countries.

Fernández-Macías (2012) criticises these findings and propose a more nuanced analysis of what happened in the EU-15 over 1995-2007[3]. According to this author, the technological bias hypothesis neglects the fundamental role played by the institutional framework and its evolution over time in the process of structural change in employment. Mishel and Bivens (2021) have come to the same conclusion for the US job market.

In this study, we look at the relationship between the technological transformation and the labour market, using sectoral level data that allows capturing the compensation mechanisms described in the literature review. Moreover, integrating employer and employee level surveys, we combine measures of technology adoption and use, organisational choices, innovation, job polarisation and unemployment that the literature usually treats separately, although they are complementary for a comprehensive understanding of the phenomena at stake.

3 Conceptual framework

In line with Bailey (2022), we believe that the digital transformation occurring nowadays in firms is not homogenous. Emerging technologies continuously create opportunities for a large range of new uses, and for this reason, their adoption has no deterministic consequences. The innovation strategies and organisational 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 the technological transformation as a relationship between inputs of a knowledge production function and innovation outputs, applying the framework

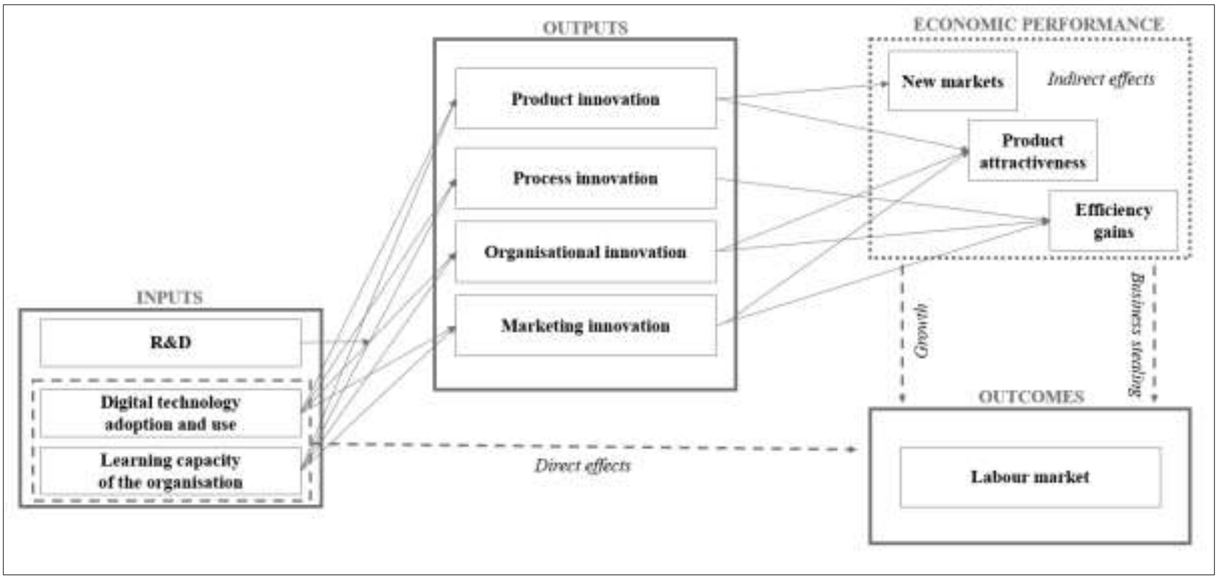
[3] See also Fernández-Macías and Hurley (2017) in which the authors present findings more in line with an upgrading effect due to cognitively intense jobs.

proposed by Greenan and Napolitano (2023). Inspired by the CDM model (Crépon, Duguet and Mairesse, 1998) and its following expansions (Polder et al., 2010; Hall et al., 2013; Venturini, 2014; Mohnen et al., 2018), we consider that firms invest to increase their 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 of the organisation captures the implementation of those management tools concerned with the enhancement of 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). Innovation outputs refer to the introduction of technological (product or process) or non-technological (organisational or marketing) innovations.

In our model (Figure 1), investments in digital technologies and in the learning capacity of the organisation may have direct effects on labour market outcomes and/or indirect ones through the mediating role played by innovation outputs. We expect that the learning capacity of the organisation directly protects employees in the labour market from negative impacts for two main reasons: it prevents employment destruction by favouring enterprises adaptability to rapidly changing environments 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 as it crucially depends on how the firm will take advantage of the new opportunities opened by the use of the technology, both in the organisation of the business process and in the characteristics of the goods and services produced. However, the task-based approach to technological change argues that there are two paths, an automation one or an augmentation one and that the institutional framework, at least in the US, favours the former that has unfavourable effects on the labour market (Acemoglu et al., 2023).

Figure 1. Conceptual framework



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 at the sectoral level. Indeed, we know from the theoretical and empirical literature that innovation may generate new markets, increase product attractiveness or spur efficiency gains (Evangelista and Vezzani, 2010). Although we do not directly measure such mechanisms, we know from the literature 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. As seen, the empirical literature has explored extensively the labour market consequences of product and process innovation but is scant for organisational and marketing innovation. We consider that the effects of these two forms of innovation are likely to be similar 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.
- *Hypothesis 2.* Adoption and use of digital technologies have heterogeneous effect at firm level with no clear sector level impact in our model. According to the task based approach of technological change automation effects are likely to dominate augmenting effects at firm and sector level.

- *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* Higher shares of product innovative enterprises at the sector level are associated with better labour market outcomes via the creation of new markets. The growth effect dominates the business stealing effect due to higher product attractiveness. Product innovation mediates positively the impacts of innovation inputs.

    - *Hypothesis 3.2* Higher shares of process, organisational or marketing innovative enterprises at the sector level 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 depends on the balance between the market growth and the business stealing effects.

4 Methods

4.1 Data sources

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

The technological transformation is described gathering data from different data sources: the Statistics on Business enterprise expenditure on R&D (BERD by NACE Rev. 2 activity), 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*; and 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). These three data sources provide aggregated data at the sector-country 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 third data source, at the employee level: the

European Working Condition Survey (EWCS, Eurofound). It 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[4].

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-based occupational ranking constructed in 2011 and unemployment rates.

We combine the different data sources through a common cell constructed on key variables that have been harmonised across datasets and at which level all variables of interest have been aggregated: country, sector and year. The final dataset covers enterprises with more than 10 employees in 26 EU Member States[5] plus UK. Despite the aim was to obtain the finest grained information about sectors, we face some limitations. The main one comes from the LFS, as information about the sector in which workers are employed is available only at the 1-digit level 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. As we do not know exactly after which time lapse innovation outputs affect the labour market, we compute the outcomes with two variants allowed by the availability of data, t+2 and t+3. Unemployment rates are thus computed at t+2 (2014, 2016 or 2018) and t+3 (2015, 2017, 2019) and the job polarisation indicators are computed as evolutions between t and t+2 (Δ2012-2014, Δ2014-2016, Δ2016-2018) or between t and t+3 (Δ2012-2015, Δ2014-2017, Δ2016-2019).

[4] For more details on the construction of the indicators of *Digital technology adoption and use* and of the *Learning capacity of the organisation*, see Greenan and Napolitano (2023)

[5] Sweden is not included as the information in the LFS about the income deciles, key to construct the indicators of job polarisation, is not available.

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)[6]	Employers	**R&D expenditures**	2010, 2012, 2014
	Community survey on ICT usage and e-commerce in enterprises (aggregated data, Eurostat)[7]	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)[8]	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*				2015, 2017, 2019 Δ 2012-2015, Δ 2014-2017, Δ 2016-2019

4.2 Key measures

4.2.1 Input and output variables

The *Digital technology adoption and use* 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

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

the inverse of the European diffusion rate of each technology in 2010 to proxy its technological intensity.

The overall *Digital technology adoption and use* indicator 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), showing 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.

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

Source: Beyond 4.0 integrated database CIS-CICT-EWCS-LFS
Coverage: EU 27 (Sweden excluded) plus the UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C to N, D-E aggregated.

The *Learning capacity of the organisation* indicator 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, it aggregates 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), the *Learning capacity* indicator's values for 2012 is imputed 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 remained stagnant between 2010 and 2015.

Employer level data from the CIS provide information about firms' innovations, defined on the basis of 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 business practices (including knowledge management), workplace organisation or external relations that has not been previously used by the 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 employee-level data from the LFS that we aggregate at sector-country level to combine them with the other data sources. Three variables measure within sector polarisation and the fourth 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 select the population of workers in firms 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 a matrix of occupations (ISCO-08 at the 2-digit level) for each sector-country cell.

Then, we build a wage-based occupational ranking within each sector using the country-based decile of the monthly take-home pay of the main occupation from the LFS 2011[9]. For each occupation in a country-sector, we calculate the weighted average of the wage decile using sampling weights, rank them from the highest to the lowest decile averages, and compute the weighted cumulated population of this distribution. By using the midpoint of the weighted cumulated population, we cut the distribution in terciles, each representing 33% of the

[9] As our final dataset covers the period 2010-2019, we aimed at using 2010 as reference year for ranking occupations within sector. This was not possible because the ISCO-08 classification of occupations was not yet available in 2010.

population, with the lowest-paid occupations assigned to tercile 1 and the highest-paid to tercile 3.

We subsequently employ this wage-based occupational ranking to assign each occupation in a country-sector in subsequent years (2012 to 2019) to its respective tercile, excluding those occupations that were not ranked in 2011[10]. In so doing, we cover more than 90% of the population of 2012-2019 employed in occupations already identified in 2011. Indeed, the occupation-to-tercile assignment of 2011 remains consistent across time for each country.

Finally, we compute, at the sector-country level, the shares of employment in occupations belonging to each tercile of the wage ranking distribution. We look at the evolution in this employment structure by computing a 2-years difference in the shares of employment in low-paid, middling and high-paid occupations at t+2 (Δ2012-2014, Δ2014-2016, Δ2016-2018) or at t+3 (Δ2012-2015, Δ2014-2017, Δ2016-2019), t being the end year for the implementation of innovation.

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 employment in 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 variable 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

[10] With the exception of a few jobs that appear for the first time in 2012 and that we include in the ranking in order to reduce the number of excluded jobs.

the unemployment rates two and three years after innovation took place. It is on average 6.67% and 6.01% respectively.

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

Source: Beyond 4.0 integrated database CIS-CICT-EWCS-LFS
Coverage: EU 27 (Sweden excluded) plus the UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C to N. D-E aggregated.

4.2.3 Control variables

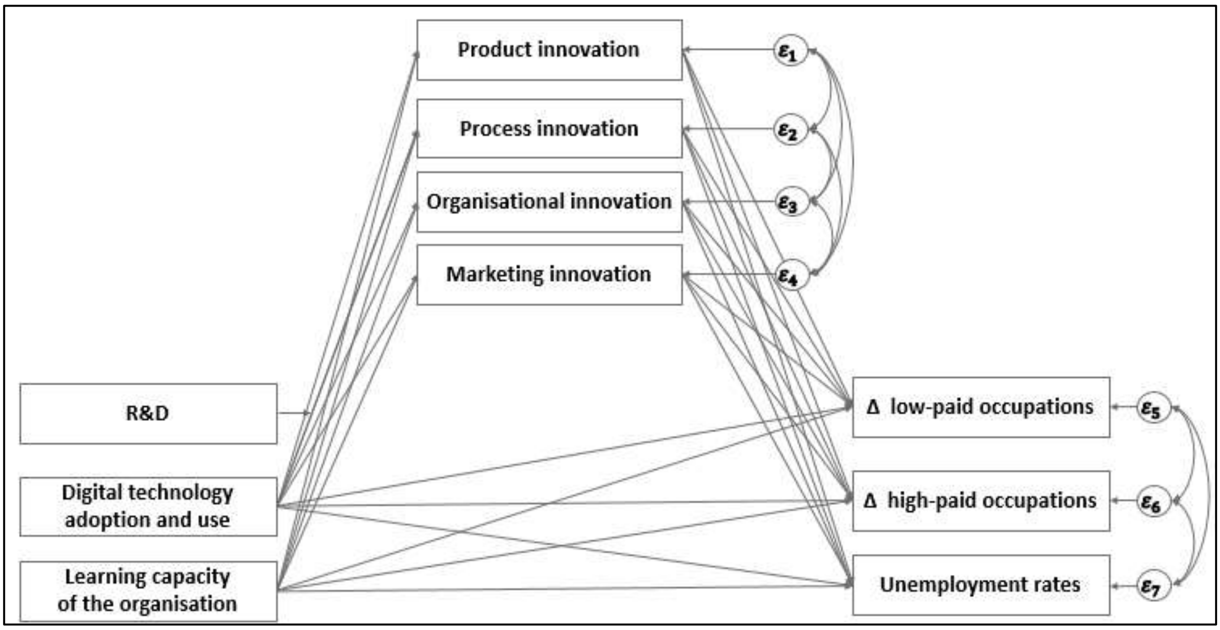
We include a set of control variables in our model: dummies for year, for secondary (sectors C, D-E and F) or tertiary sectors (sectors G to N) and the log average size of enterprises in each sector-country cell. We also include dummies to assign each country to a welfare regime[11], according to the classification 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

To analyse econometrically the relationship between the technological transformation and the selected labour market outcomes at the sector-country level, we implement a Structural Equation Modelling (SEM). 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) 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 the innovation outputs of our model, mediate the relationship between inputs and outcomes as shown in the path diagram (figure 2).

[11] Scandinavian countries are Denmark and Finland. Conservative countries are Austria, Belgium, Germany, France, Luxembourg and the Netherlands. Eastern-European countries post-communist are Bulgaria, Czech Republic, Croatia, Hungary, Poland, Romania, Serbia and Slovakia. Southern European countries are Cyprus, Greece, Spain, Italy, Malta and Portugal. Former USSR (Baltic) countries are Estonia, Lithuania and Latvia. Liberal countries are Ireland and the UK.

Figure 2: Path diagram



Adhering to the approach developed by Baron and Kenny and adjusted by Iacobucci et al. (2007), complete mediation occurs when the size of the effect that the independent variable has on the dependent variable becomes statistically insignificant after introducing the mediator. Partial mediation occurs when the size of the effect after introducing the mediator is reduced, but not nullified. When partial mediation occurs, it is possible to compute the effect size of the indirect effect using 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 of the organisation*) on the dependent variable (e.g. unemployment rates) that is mediated by the mediator variable (e.g. product innovation) (MacKinnon et al., 2007).

Our system includes the following equations:

$$\begin{cases} Product\_Inno_{ijt} = \beta_{01} + \beta_{11}R\&D_{ijt-2} + \beta_{21}Tech_{ijt-2} + \beta_{31}Learn_{ijt-2} + Y_{1ijs} + \varepsilon_{1\_ijt} \\ Process\_Inno_{ijt} = \beta_{02} + \beta_{12}R\&D_{ijt-2} + \beta_{22}Tech_{ijt-2} + \beta_{32}Learn_{ijt-2} + Y_{2ijs} + \varepsilon_{2_{ijt}} \\ Organisation\_Inno_{ijt} = \beta_{03} + \beta_{13}R\&D_{ijt-2} + \beta_{23}Tech_{ijt-2} + \beta_{33}Learn_{ijt-2} + Y_{3ijs} + \varepsilon_{3_{ijt}} \\ Marketing\_Inno_{ijt} = \beta_{04} + \beta_{14}R\&D_{ijt-2} + \beta_{24}Tech_{ijt-2} + \beta_{34}Learn_{ijt-2} + Y_{4ijs} + \varepsilon_{4\_ijt} \\ \Delta low\_paid\_occ_{ijt+2} = \beta_{05} + \beta_{15}Tech_{ijt-2} + \beta_{25}Learn_{ijt-2} + X_5(Inno)_{ijt} + Y_{5ijs} + \varepsilon_{5\_ijt+2} \\ \Delta high\_paid\_occ_{ijt+2} = \beta_{06} + \beta_{16}Tech_{ijt-2} + \beta_{26}Learn_{ijt-2} + X_6(Inno)_{ijt} + Y_{6ijs} + \varepsilon_{6\_ijt+2} \\ Unemp_{ijt+2} = \beta_{07} + \beta_{17}Tech_{ijt-2} + \beta_{27}Learn_{ijt-2} + X_7(Inno)_{ijt} + Y_{7ijs} + \varepsilon_{7\_ijt+2} \end{cases}$$

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 four regressions describes the technological transformation. We specify a parsimonious model, as needed by the SEM methodology. However, Greenan and Napolitano

(2023) obtained 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 the technological transformation and the selected labour market outcomes. As we found that R&D expenditures were not significantly related to them, we do not introduce this variable 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 Y_{1ijs}, a matrix of controls: time dummies, welfare regime dummies, a dummy identifying tertiary 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.

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. While 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 are lower by 0.083 percentage points (pp). This result is consistent with previous findings at the individual level based on PIAAC (Programme for the International Assessment of Adult Competencies) (Greenan et al., 2017), showing that working in a 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 heterogeneous effect at firm level with no clear sector level impact consistent with our non-deterministic approach of the socio-organisational consequences of technology uses. This hypothesis is different from the view promoted by the task based approach and according to which automation effects tend to dominate augmenting effects at firm and sector level. As we find no significant direct influence of our indicator on the three labour market outcomes, we conclude in favour of a non-deterministic relationship between the adoption and use of new technologies and labour market outcomes.

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 fourth line of table 4 aligns with this assumption, as a one-point rise 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* while 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 rates. Thus, the business stealing effect of marketing innovation 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).

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; * $p < 0.10$. ** $p < 0.05$. *** $p < 0.010$. Overall R-squared: 0.90.
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
∆ 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%.

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.

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*, which is in line with Hypothesis 1 as it corresponds to a decrease of the employment share of low-paid occupations. The protective direct effect of this innovation input thus extends to our first labour market outcome, counteracting potential downgrading or polarisation trends.

Second, a higher share of product innovative enterprises increases the share of high-paid occupations 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.

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; * $p < 0.10$. ** $p < 0.05$. *** $p < 0.010$. Overall R-squared: 0.9.
Source: Beyond 4.0 integrated database CIS-CICT-ECWS-LFS (2010-2015. 2012-2017. 2014-2019)
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%.

6 Discussion and conclusion

This research investigates the links between the technological transformation and job polarisation and unemployment. It does so by building a database that combines multiples sources, allowing to carry out an analysis at the sector country level. The meso level allows taking into account differences due to market structures, political factors and macroeconomic patterns that shape the technological transformation as well as reallocation and selection effects between companies in the same sector.

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 three innovation inputs able to increase the stock of knowledge within companies (R&D expenditure, digital technologies and the learning capacity of the organisation) and measures of innovation in the digital age that include technological (product and process) and non-technological (organisational and marketing) innovations.

We then move towards the analysis of the nexus between the technological transformation and labour market outcomes, contributing to the debate about the fear of massive skills and job destruction and increased wage inequalities due to automation, robotics and AI in the current digital revolution. 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.

Innovation hence 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 shares of product innovative enterprises at the sector level 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, this mainly concerns *Digital technologies adoption and use*. As far as the *Learning capacity of the organisation* is concerned, mediation is indeed only partial for unemployment rates and for the share of low-paid occupations.

Overall, we find three 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, digital technologies have no deterministic role in the structural change of occupations and in job destruction. Third, 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 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, share of employment in low paid jobs grow to the detriment of the best-paid ones.

The empirical analysis presented in this paper has required a huge effort in terms of data merging from different sources. Some weaknesses have been identified in data collection at EU level and specific actions would allow for a better use of existing data sources. Effort should be directed towards two aims. First, facilitating the combination of data from multiple sources and, second, enriching the measurement framework of technological change to take account of the constant renewal of technologies and complementary intangible investments in organisational practices.

Practical implications can be drawn from our findings. First, investments into the learning capacity of the organisation contribute to the development of a human-centered technological transformation. However, in most sectors, the level of the *Learning capacity of the organisation* has been stagnating over the last decade and barriers to its development need to be addressed. This opens a new line of research for economics and management scholars, and it also suggests that the different components of the *Learning capacity of organisations* are central ingredients to successful innovation policies and should be publicly supported as such. Second, public policies should discriminate between innovations that are for the good and those that are for the bad. Our results show that marketing innovation is not an innovation like the others: it correlates with business stealing dynamics that have a negative impact on the labour market. While financing innovation with public funding, policy makers should not only target the degree of innovativeness, they need to be aware that some types of innovation may end up generating perverse labour market effects. For instance, public support to marketing innovation via the research tax credit should be assessed in terms of economic and social impacts.

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