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ORIGINAL PAPER

Technological change and employment: is Europe ready for the challenge?

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Abstract The aim of this paper is twofold. On the one hand, the economic insights on the employment impact of technological change are discussed covering both classical theories and updated theoretical and empirical analyses. On the other hand, an empirical test is provided; in particular, longitudinal data—covering manufacturing and service sectors over the 1998–2011 period for 11 European countries—are used to run GMM-SYS and LSDVC estimates. Two are the main results: (1) a significant labor-friendly impact of R&D expenditures (mainly related to product innovation) is found; yet, this positive employment effect appears to be entirely due to medium and high-tech sectors, while no effect can be detected in low-tech industries; (2) capital formation is found to be negatively related to employment; this outcome suggests a possible labor-saving effect due to the embodied technological change incorporated in gross investment (mainly related to process innovation).

Keywords Technological change · Employment · Sectoral analysis · EU

JEL Classification O33

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1 Introduction

In the past decades the emergence and subsequent pervasive diffusion of a 'new technological paradigm' (Dosi 1982, 1988), mainly based on ICT and automation, has led to a dramatic social impact on the employment structure of the industrialized world.

In recent years, the introduction of 3D printing machines, self-driving cars (Tesla, Google, Apple) and agricultural robots has raised again the fear of an upcoming massive technological unemployment. Moreover, not only agricultural and manufacturing employment appears at risk,[1] but employees in services—including those jobs requiring cognitive skills—are no longer protected (see, for instance, how IBM's cognitive computer Watson may displace the majority of legal advices).

In addition, from the macroeconomic point of view, the recent financial and economic crisis has led to a slow recovery characterized by a worrying jobless growth. Indeed, international organizations (UNIDO and OECD) are increasingly concerned about this risk (see Crespi and Tacsir 2012; UNIDO 2013; Arntz et al. 2016; OECD 2016).

In this context, Brynjolfsson and McAfee (2011, 2014) suggest that the current employment problems are only partially caused by the economic crisis. In their opinion, they rather are the expression of a structural adjustment (a 'Great Restructuring') characterized by an exponential growth in computers' processing speed having an even bigger impact on jobs, skills, and the whole economy. By the same token, Frey and Osborne (2017)—using a Gaussian process classifier applied to data from the US Department of Labor—predict that 47% of the occupational categories are at high risk of being automated, including a wide range of service/white-collar/cognitive tasks such as accountancy, logistics, legal works, translation and technical writing.

The aim of this paper is twofold. On the one hand, the economic insights over the employment impact of technological change will be discussed covering both classical theories and updated theoretical and empirical analyses; on the other hand, a sectoral empirical test will be provided, in order to shed some light on the recent evolution of the relationship between innovation and employment in Europe.

Three are the main novel contributions of this work.

Firstly, a comprehensive theoretical setting will be critically discussed, trying to reveal implicit assumptions, possible drawbacks and market failures frequently neglected by the current economic debate often prone to believe that market clearing easily guarantees a return to full employment (Sect. 2).

Secondly, an updated survey of previous empirical studies (at the macro, sectoral and micro level) will be provided (Sect. 3).

Thirdly, we will put forward a dynamic specification able to empirically test the possible employment impact of innovation across different European countries in recent times (Sects. 4, 5).

[1] Atkinson (2015) discusses the changing nature of 'jobs' in contemporary economies.

2 Theory

The assessment of the effects of technological change on employment is a well-known controversial issue for theoretical economists. Indeed, technological unemployment is considered a direct troublesome consequence of labor-saving process innovations. However, economic theory underlines also the existence of indirect compensation mechanisms able to balance the reduction of the number of employees caused by technological progress.

In addition, product innovations, differently from process innovations, generally show a labor-friendly nature.

2.1 Process innovation and 'compensation mechanisms'

The unavoidable direct impact of process innovation is job destruction: by definition, process innovation means producing the same amount of output using a smaller quantity of production factors, i.e. mainly labor. However, since the very beginning, economic theory has pointed out the existence of economic forces that can counterbalance—at least partially—the employment reduction caused by process innovation.

In more detail, at the time of the classical economists, these two opposite views started to compete. On one hand, the working class feared to be dismissed because of innovation (see Ricardo 1951). Indeed, the working class perception was so negative that Ned Ludd guided workers to destroy machines (see Hobsbawm 1968; Hobsbawm and Rudé 1969). On the other hand, the political and academic debate was mainly theoretically dominated by an ex-ante confidence in the existence of market compensation mechanisms for fired workers.

In fact, in the first half of the XIX century, classical economists put forward a theory that Marx called the 'compensation theory' (see Marx 1961; Marx 1969). This theory is based on different market compensation mechanisms which are generated by technological change and which might counterbalance—partially or totally—the initial labor-saving impact of process innovation[2] (see also Petit 1995; Vivarelli 1995; Vivarelli and Pianta 2000; Pianta 2005; Coad and Rao 2011; Vivarelli 2013, 2014; Calvino and Virgillito 2017).

A first channel for compensating the initial job losses can be related to the 'introduction of new machines'. The process innovations displacing workers in the 'user sectors' are able to create new jobs in the capital sectors where these new machines are fabricated (see Say 1964). However, the size of this effect can be only partial as labor-saving technologies affect the capital goods sector as well (see Marx 1969).

A second compensation mechanism depends on the 'decrease in prices'. As process innovations involve the displacement of workers, they easily determine the reduction of the unit costs of production. In a competitive market, this dynamics reduces final prices as well and, in turn, decreasing prices encourage a new demand

[2] Basically this literature refers to process innovations that are general-purpose technologies. For a treatment and an analysis of non-general purpose technologies, see, for instance, Grimalda (2016).

for products and, so, additional production and employment (see Steuart 1966). Nonetheless, two critical issues might reduce the effectiveness of this mechanism. First of all oligopolistic markets or less competitive market structures do not grant the 100% translation of lower costs into lower prices (see Sylos Labini 1969). Secondly, the initial effect of a labor-saving technology is a decline in the aggregate demand from the dismissed workers. Therefore, the mechanism 'via decrease in prices' applies to an already reduced demand and has to more than counterbalance the initial decrease in aggregate purchasing power (see Malthus 1964; Sismondi 1971; Mill 1976). If the delay of this compensation mechanism is crucially relevant, it might create structural unemployment that continues over time.

A third compensation mechanism might depend on the decision to 'support new investments'. Indeed, in case of delay in translating the decline in costs (caused by technological progress) into decrease in prices, positive profits may be accumulated by the innovative entrepreneurs. If these profits are invested, new productions and job opportunities are created with a lag. This proposition has been originally optimistically put forward by Ricardo (1951), but it has also been called forth by neo-classical economists such as Marshall (1961) and, lately, by Hicks (1973) and Stoneman (1983). Nevertheless, pessimistic expectations ('animal spirits' in Keynesian terms) may imply the decision to postpone investments even if cumulated profits obtained by innovation are available. If this is the case, a substantial delay in compensation may generate structural technological unemployment.

A forth compensation mechanism relates to the impact of new technologies on labor market as it might be affected by a 'reduction in wages'. Focusing on the labor-market only, the direct effect of job-destructive technologies may be directly compensated in case of free competition and full substitutability between labor and capital. If these assumptions hold, technological unemployment implies a decrease in wages that would stimulate more labor-intensive and less expensive technologies. The first to adopt this kind of argument were Wicksell (1961) and Hicks (1932).

Finally, a compensation mechanism connected to an 'increase in incomes' has to be considered. This compensation mechanism is directly in contrast with the previous one ('reduction in wages') suggesting that there might be a competition between the two. Under the assumption that economies are dominated by Fordist mass production, unions participate in the distribution of the fruits of technological progress, i.e. a portion of the cost savings due to innovation can be transformed into higher income and, therefore, larger consumption. This demand expansion leads to an increase in employment which may compensate the initial technological unemployment (see Pasinetti 1981; Boyer 1988a, b, 1990). However, nowadays the Fordist mode of production is not so relevant anymore, therefore the distribution of income follows different systems (based more on Phillips' curve than on sharing the productivity gains) and labor markets—depending on institutional factors—have become more competitive and flexible (see Appelbaum and Schettkat 1995).

In sum, economic theory cannot reach a conclusive answer in terms of the final employment impact of process innovation. In order for compensation mechanisms to be effective in counterbalancing the technological displacement caused by process innovations, they have to rely on many simultaneous factors such as the degree of competition and demand elasticity. Depending on institutional, social and economic contexts,[3] compensation can therefore be more or less prompt and victorious in reabsorbing the technological unemployment.

2.2 Product innovation and employment

Of course, technological change cannot be reduced to process innovation: the other side of the coin is product innovation that is also important in terms of its possible employment impact.

As far as product innovation is concerned, obviously enough the introduction of new products and the subsequent emergence of new markets cause a job-creation effect. Indeed, the labor-intensive impact of product innovation was already underlined by classical economists (Say 1964) and even the most rigorous opponent to an optimistic vision of the employment consequences of technological change admitted the positive employment benefits which can derive from the introduction of new products (Marx 1961).

In the current debate, various studies (Freeman et al. 1982; Freeman and Soete 1994, 1987; Vivarelli and Pianta 2000; Edquist et al. 2001; Bogliacino and Pianta 2010) agree that product innovations have a positive impact on employment since they open the way to the production of either entire new goods or differentiated mature ones (Vivarelli 2013, 2014).

Nevertheless, even the job creating effect of product innovation may be more or less effective. In fact, the so-called 'welfare effect' (the creation of new branches of production) has to face the 'substitution effect' (i.e. dispcement of mature products; see Katsoulacos 1984, 1986; Hall et al. 2008; Harrison et al. 2008). For example, the MP3 music format is a product innovation now displacing the compact disk which in turn displaced the vinyl.

Indeed, the balance between the direct labor-saving effect of process innovation and the counterbalancing effects of compensation forces and product innovation can significantly diverge depending on different historical periods and institutional/social frameworks[4] (Freeman et al. 1982; Freeman and Soete 1987, 1994).

Summarizing the economic theory available on the subject, the relationship between innovation and employment can be represented by a very multifaceted picture where the direct labor-saving impact of process innovation, the compensation mechanisms, the impediments and obstacles which can seriously weaken the effectiveness of such mechanisms, and the labor friendly nature of product innovation can combine in very diverse outcomes (see also Vivarelli 2013, 2014).

Hence, although theoretical economists may develop sophisticated models about the employment impact of innovation, the economic theory does not have a clear-cut answer about the final employment effect of innovation. Indeed, the actual employment impact of the new technologies depend on the balance between process

[3] Indeed, also business cycles might have an impact on the innovation-employment nexus as they are 'generated' by innovation à la Schumpeter, but they may also affect propensity to invest à la Keynes (see Guarascio et al. 2015, for an analysis).

[4] For instance, nowadays, the role of green innovation is crucial, also in terms of likely employment impact: see Crespi et al. (2015) and Gagliardi et al. (2016).

and product innovation, the values of the different parameters assessing the efficacy of the different compensation mechanisms and the particular institutional context. Therefore, attention should be devoted to the empirical analyses.

3 Previous empirical evidence

Turning to the empirical analyses[5], only country-studies can fully assess the functioning of all the compensation mechanisms.

However, country-level studies are affected by severe methodological shortcomings. Therefore, even if they allow to explore compensation mechanisms at work in the aggregate, they are often severely constrained by composition biases in the data, the difficulty to find a proper unique proxy for technological change and the fact that the final employment national trends are co-determined by overwhelming institutional and social determinants difficult to disentangle and to control for.

In general, macroeconometric analyses have tested the validity of the compensation mechanisms in a partial or general equilibrium framework.

At the beginning of the '80s and using US data, Sinclair (1981) proposes a macroeconomic IS/LM approach and concludes that a positive employment compensation can occur, especially 'via decrease in wages', if demand elasticity and the elasticity of factor substitution are sufficiently high.

Turning to the UK, Layard and Nickell (1985) derive a demand for labor in a quasi-general equilibrium framework and state that the crucial parameter is the elasticity of the demand for labor in response to a variation in the ratio between real wages and labor productivity. Their hypothesis is that technical change increases labor productivity and—given an adequate elasticity—proportionally the demand for labor and this can be enough to fully compensate initial job losses.

In Vivarelli (1995) the direct labor-saving effect of process innovation and the different compensation mechanisms in US and Italy are estimated through a simultaneous equations model over the period 1960–1988. Running 3SLS regressions, the most effective compensation mechanism turns out to be that 'via decrease in prices' in both countries. In addition, the US technological progress results to be more product oriented than the Italian one. Simonetti et al. (2000) apply the same simultaneous equations macroeconomic model of Vivarelli (1995), running 3SLS regressions and using US, Italian, French and Japanese data over the period 1965–1993. The authors find that the most effective compensation mechanisms are the 'via decrease in prices' and 'via increase in incomes' (especially in Italy and France till the mid-eighties). Finally, product innovation

[5] The empirical studies devoted to the relationship between innovation and employment have mainly focused on high-income countries (see Sect. 3), especially OECD countries (basically because of data availability), meanwhile only recently the phenomenon has been investigated in developing countries (see Meschi et al. 2011, for an application to the Turkish case; Mitra and Jha 2015, for an application to the Indian case and Mendoza Cota 2016, for an application in Mexico where new technological paradigms allow organizational change and offshoring).

significantly reveals its labor intensive potentiality only in the technological leader country in the period, namely the US.

At last, Feldmann (2013)—using data on 21 industrial countries over the period 1985–2009—assesses the impact of innovation (proxied by triadic patents normalized by population) on aggregate unemployment, controlling for a set of macroeconomic factors such as labor market features, tax wedge, employment protection, inflation and output gap. His results suggest that technological change significantly increases unemployment over a 3 year period, but this impact fades away in the long run (compensation mechanisms via decrease 'in prices' and 'wages' seem to be effective).

On the whole, the (few) aggregate studies available on the subject reveal that technological change can display its labor-friendly nature only when markets are characterized by competition and flexibility. Therefore, both the mechanisms 'via decrease in wages' and 'via decrease in prices' turn out to be the most effective ones to compensate the employment displacing nature of technological change.

However, the shortcomings of the county-level studies suggest that the sectoral-level approach is an alternative and particularly important setting for investigating the overall employment impact of innovation. Sectoral-analyses have become more relevant in recent years due to an increasing availability of data. In general, the industrial dimension is not neutral as, especially in manufacturing, new process innovations seem to be implemented mainly through labor-saving embodied technical change, only partially counterbalanced by the market compensation mechanisms.

For instance, Clark (1983, 1987) puts forward a supply-oriented vintage model investigating UK manufacturing and shows that the expansionary effect of innovative investments prevails until the mid '60s, when the rationalizing effect (due to labor-saving process innovation incorporated in investments and scrapping) starts to overcome the expansionary one. However, Nickell and Kong (1989) focus their attention to the operating of the compensation mechanism 'via decrease in prices' in nine UK industries. Putting forward a price equation where cost-saving effects of labor-saving technologies are fully transferred into decreasing prices, results show that in seven sectors out of nine a sufficiently high demand elasticity is able to imply an overall positive impact of technical change on employment.

In the case of Italy, Vivarelli et al. (1996) find evidence that in manufacturing the relationship between productivity growth and employment appears to be negative and, in particular, that product and process innovation have, respectively, positive and negative effects on the demand for labor.

Indeed, at the European level, Pianta (2000) and Antonucci and Pianta (2002) show—using sectoral data based on the European Community Innovation Surveys (CIS)—an overall negative impact of innovation on employment in manufacturing industries across five European countries.

However, more recently, Coad and Rao (2011), focusing only on high-tech manufacturing industries in US over the period 1963–2002, show that innovation and employment are positively linked (especially within the fast growing firms).

Overall, the scenario may also change if services are considered.

Evangelista (2000) and Evangelista and Savona (2002) find—in the Italian case—a positive employment effect of technological change (only) in the most innovative and knowledge-intensive service sectors.

Moreover, taking manufacturing and services jointly into account (again using CIS data), Bogliacino and Pianta (2010) find a positive employment impact of product innovation (which turns out to be reasonable in high-tech manufacturing sectors—see also Mastrostefano and Pianta 2009). By the same token, Bogliacino and Vivarelli (2012)—running GMM-SYS panel estimations covering 25 manufacturing and service sectors for 15 European countries over the time-span 1996–2005—demonstrate that R&D expenditures have a job-creating effect, especially in high-tech industries.

Finally, Bogliacino et al. (2017), based on Bogliacino (2014) formal treatment, explore the impact of innovation and offshoring on wage and employment dynamics, performing an analysis on a panel of 37 industries (1995–2010) across five European countries. Both innovation and offshoring favor mainly high-skill wages and employees, suggesting a heterogeneous impact on different categories of workers (see also Vivarelli 2014).

Summarizing the available sectoral-level evidence, a dominant labor friendly impact has been detected in high-tech manufacturing sectors and knowledge-intensive services, those sectors where product innovation is prevailing and where the demand evolution is more dynamic, while a labor-saving tendency is relevant especially in low- and medium- tech manufacturing.

While the econometric test put forward in this paper will be run at the sectoral level, the literature devoted to the microeconometric investigation of the link between technological change and employment also deserves to be briefly discussed. Indeed, microeconometric studies have the great advantage to grasp the very nature of firms' innovative activities and to allow an accurate and specific firm-level mapping of innovation variables (innovation dummies, R&D, patents, etc.). However, there are limitations associated with this level of analysis, as well. Firstly, the microeconomic approach cannot take fully into account the indirect compensation effects which operate at the sectoral and country levels, therefore the reference to 'compensation mechanisms' is not straightforward. Secondly, a possible shortcoming of this kind of analysis consists in an 'optimistic ex-ante bias': in fact, innovative firms tend to be characterized by better employment performances simply because they gain market shares because of innovation. Even when the innovation is intrinsically labor-saving, microeconomic analyses generally show a positive link between technology and employment since they do not take into account the important effect on the competitors, which are crowded out by innovative firms themselves (a sort of substitution effect commonly named—in this literature—'business stealing' effect).

For instance, van Reenen (1997)—using the SPRU innovation database over the period 1976–1982—finds evidence of a positive employment impact of innovation. This result turns out to be robust after controlling for fixed effects, dynamics and endogeneity.

Interestingly enough, Greenan and Guellec (2000)—using data on French manufacturing firms over the 1986–1990 period—find that innovating firms create more jobs than non-innovating ones, but, conversely, the reverse turns out to be true at the sectoral level, where the overall effect is negative and only product innovation reveals its job-creating nature.

In the case of Italy, Piva and Vivarelli (2004, 2005) find evidence in favor of a positive effect—although small in magnitude—of gross innovative investment on employment (on the Italian case, see also Hall et al. (2008) showing a positive employment contribution of product innovation and no evidence of employment displacement due to process innovation).

More recently, Lachenmaier and Rottmann (2011)—using a comprehensive dataset of German manufacturing firms over the period 1982–2002—find a significantly positive impact of different innovation measures on employment, but, partially in contrast with expectations and previous contributions, the authors find a higher positive impact of process rather than product innovation.

Turning the attention to Spain, Ciriaci et al. (2016)—using matched waves of Spanish CIS—run quantile regressions based on a sample of 3.304 Spanish firms over the period 2002–2009. Their results show that innovative, smaller and younger firms are more likely to experience high and persistent employment growth episodes than non-innovative firms.

Other recent studies were applied to several countries rather than to just one country. For instance, Bogliacino et al. (2012), investigating European manufacturing and service firms over the period 1990–2008, find a positive and significant employment impact of R&D expenditures in high-tech manufacturing and services but not in the more traditional manufacturing sectors.

Finally, using firm level data from four European countries, Harrison et al. (2014) show that process innovation tend to displace employment, while product innovation is fundamentally labor-friendly.

On the whole, the microeconometric literature provides evidence of a positive link between innovation and employment, especially when R&D and/or product innovation are adopted as proxies of technological change and when high-tech sectors are considered.

In the next section, we contribute to the empirical literature running an employment dynamic specification—at the sectoral-level—to empirically test the possible impact of innovation across different European countries in recent years.

4 Data and econometric setting

4.1 The data

We rely on a database including two-digit sectors belonging to manufacturing and services in 11 European countries (Austria, Belgium, Czech Republic, Denmark, Finland, Germany, Hungary, Italy, Norway, Slovenia, Sweden). The database covers the 1998–2011 period and total number of observations is of 3073. We use the statistical source OECD-STAN for most of the information, coupling it with OECD-ANBERD as far as business R&D, our main proxy for innovation, is concerned.

In Table 1 we report the sectors considered and the average R&D intensity for the covered industries, measured as the ratio of R&D expenditures over value added.[6] Since the available classifications are not fully exhaustive,[7] we decided to adopt an endogenous classification based on the revealed R&D intensities, in order to have three homogeneous groups (the outcome is however almost fully consistent with EUROSTAT classification). In particular, sectors are classified as LT if R&D intensity is less than 1%; MT if it is included between 1 and 5%; HT if R&D intensity is larger than 5%. This splitting will allow us to investigate the R&D/employment nexus across the three groups of sectors, in order to test if the outcome (common to the previous empirical studies) of a positive employment impact of innovation is detectable mainly (only) in the high-tech sectors.[8]

4.2 Econometric strategy

Since our dependent variable (employment) is highly persistent,[9] we adopt a dynamic employment equation where employment is autoregressive and depends on output (value added), wages, capital formation and R&D expenditures, which is our direct measure for innovation. Therefore, the estimated equation is a dynamic labor demand, augmented with technology:

$$\begin{aligned} \ln(E_{ijt}) = \rho \ \ln(E_{ijt-1}) + \alpha_0 + \alpha_1 \ \ln(W_{ijt}) + \alpha_2 \ \ln(Y_{ijt}) + \alpha_3 \ \ln(I_{ijt}) + \\ \alpha_4 \ \ln(R\&D_{ijt}) + \beta' C + \gamma' T + \varepsilon_{ij} + u_{ijt} \end{aligned} \tag{1}$$

where i, j, t indicate respectively industry, country and year, E is employment, W is labor compensation per employee, Y is value added, I is gross fixed capital formation, $R\&D$ is the proxy for technology, C is a set of country dummies, T is a set of time dummies, and the last two terms are the components of the error term.[10]

It is well known by scholars of panel theory that the above dynamic specification cannot be correctly estimated either by pooled ordinary least squares (POLS) or by the Within Group (fixed effects, WG) estimator. Accordingly, we use generalized

[6] Value added has been deflated using the sectoral deflators provided by STAN, which take (quality adjusted) hedonic prices into account. All other nominal variables have been deflated using GDP deflators. We have considered 2010 as the base year. We have corrected all the series for purchasing power parities, expressing, at the end, all the monetary values in constant prices and PPP 2010 US dollars (in order to be consistent within our statistical sources, we used information provided by OECD: http://stats.oecd.org/ where deflators, exchange rates and PPP series are available).

[7] See: http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:Hightech_classification_of_manufacturing_industries; http://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf.

[8] An important source of heterogeneity at the sectoral level may be due to the overall difference in innovation strategy (see Bogliacino and Pianta 2016).

[9] Indeed, the estimation of an employment equation is the standard example for which a panel dynamic specification turns out to be the proper econometric strategy (see Arellano and Bond 1991; van Reenen 1997).

[10] The set of country dummies control for the possible impact of different national macroeconomic situations and specific economic policies, while the set of time dummies capture both the economic business cycle and possible supply side effects in the European labor market. However, this specification, while recalling the main economic variables affecting the employment dynamics, does not allow singling out the effects of all the compensation mechanisms.

Table 1 The sectoral splitting

Industries	ISIC Rev. 4	R&D intensity	
Agriculture, forestry and fishing	01–03	0.39	LT
Mining and quarrying	05–09	1.02	MT
Food products, beverages and tobacco products	10–12	0.97	LT
Textiles	13	2.01	MT
Wearing apparel	14	1.53	MT
Leather and related products, footwear	15	1.88	MT
Wood and products of wood and cork, except furniture; articles of straw and plaiting materials	16	0.51	LT
Paper and paper products	17	1.29	MT
Printing and reproduction of recorded media	18	0.46	LT
Coke and refined petroleum products	19	1.13	MT
Chemicals and chemical products	20	5.16	HT
Basic pharmaceutical products and pharmaceutical preparations	21	16.46	HT
Rubber and plastics products	22	2.70	MT
Other non-metallic mineral products	23	1.50	MT
Basic metals	24	2.35	MT
Fabricated metal products, except machinery and equipment	25	1.62	MT
Computer, electronic and optical products	26	22.67	HT
Electrical equipment	27	6.80	HT
Machinery and equipment n.e.c.	28	5.47	HT
Motor vehicles, trailers and semi-trailers	29	9.11	HT
Other transport equipment	30	12.40	HT
Furniture; other manufacturing; repair and installation of machinery and equipment	31–33	2.15	MT
Electricity, gas and water supply; sewerage, waste management and remediation activities	35–39	0.30	LT
Construction	41–43	0.20	LT
Wholesale and retail trade, repair of motor vehicles and motorcycles	45–47	0.30	LT
Transportation and storage	49–53	0.07	LT
Accommodation and food service activities	55–56	0.02	LT
Publishing, audiovisual and broadcasting activities	58–60	1.33	MT
Telecommunications	61	1.71	MT
IT and other information services	62–63	5.18	HT
Financial and insurance activities	64–66	0.43	LT
Real estate activities	68	0.01	LT
Scientific research and development	72	32.85	HT
Administrative and support service activities	77–82	0.11	LT
Public administration and defense; compulsory social security	84	0.00	LT
Human health and social work activities	86–88	0.15	LT

Table 1 continued

Industries	ISIC Rev. 4	R&D intensity	
Arts, entertainment and recreation	90–93	0.06	LT
Other service activities. Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	94–98	0.05	LT

LT low-tech, *MT* medium-tech, *HT* high-tech industries

method of moments (GMM) in the Blundell and Bond (1998) version (GMM-SYS), since our sample is characterized by high persistence and a dominant cross-sectional variability. Furthermore, we compute a robust and Windmeijer (finite sample) corrected covariance matrix.

While in a dynamic employment equation the lagged dependent variable and the wage term are obviously endogenous, high persistence suggests potential endogeneity for the other variables, as well. Therefore, to be on the safer side, we instrument all of them assuming they are endogenous.

We expect a positive and high coefficient for the lagged term, a negative α_1 capturing the standard labor demand inverse relationship between wages and employment, and a positive α_2 capturing the role played by the final demand. A priori, α_3 has no obvious sign, since capital formation is labor-expanding through its expansionary effect, and labor-saving through process innovation embodied in the new machineries (see Sect. 2). Finally, our main interest is in α_4, linking R&D with employment: consistently with the previous literature (see Sect. 3) and taking into account that R&D is more related with product rather than process innovation, we expect a positive sign for α_4 (see Sect. 2).

5 Results

As can be seen from Table 2 and focusing on the more reliable GMM-SYS estimates, the results exhibit very interesting patterns. Pooled ordinary least squares (POLS) and fixed effect estimators (WG) are provided for completeness and for showing that the estimated GMM coefficient for the lagged dependent variable is correctly situated within the upper and lower bounds set by the POLS and WG estimates respectively.

Not surprisingly, the employment variable turns out to be highly auto-correlated and value added is positively linked with employment, while wages tend to inhibit the demand for labor (although this relationship is significant only in the preliminary POLS and WG estimates).

Together with these expected results, capital formation is negatively (and significantly at 95%) related to employment; this result points to a possible labor-saving effect due to the embodied technological change incorporated in the new investment (see Sect. 2). It may well be the case that in most recent years (also

Table 2 Dependent variable: number of employees in log scale

	(1) POLS	(2) WG	(3) GMM-SYS
$\log(E_{ijt-1})$	0.971*** [0.005]	0.755*** [0.016]	0.930*** [0.031]
$\log(W_{ijt})$	− 0.013*** [0.004]	− 0.028** [0.012]	− 0.042 [0.028]
$\log(Y_{ijt})$	0.037*** [0.005]	0.151*** [0.024]	0.096*** [0.029]
$\log(I_{ijt})$	− 0.004* [0.003]	− 0.007 [0.004]	− 0.010** [0.005]
$\log(R\&D_{ijt})$	0.005* [0.003]	0.002* [0.001]	0.005** [0.002]
Constant	− 0.368*** [0.042]	− 0.169 [0.458]	− 0.794*** [0.144]
Country dummies	Yes	No	Yes
Time dummies	Yes	Yes	Yes
N Obs	3073	3073	3073
Hansen			250.20
p value			0.079
N instruments			220
AR(1)			− 6.74
p value			0.000
AR(2)			− 1.78
p value			0.077

Robust standard errors in brackets

In GMM-SYS estimation all the regressors are considered endogenous and instruments include lags from two to four periods

*, **, *** Statistical significance respectively at 10, 5 and 1%

including the worldwide financial crisis and its consequences) the rationalizing component of investment—fostering process innovation—has turned out to dominate its expansionary component.

Turning our attention to our main variable of interest (R&D), the outcome based on the overall estimate is consistent with the previous empirical literature (see Sect. 3): the elasticity between R&D expenditures and employment turns out to be positive and significant (at the 95% level of confidence), albeit very small in magnitude: 0.005.

Therefore, considering all the economic sectors, R&D expenditures (linked to product innovation) show a labor-friendly nature, although their impact is almost negligible: doubling the R&D investment would induce an increase in employment by about 0.5%. In contrast, capital formation (linked to labor-saving process innovation) seem to play a more relevant role: ceteris paribus, an increase of 100% in investment activity in European sectors would imply a decrease of 1% in employment levels.

As a first extension, we have run alternative specifications in which we have replaced capital and R&D flows with their stocks (respectively K and Z); in fact, it may well be the case that current employment is affected not just by the current flows of R&D expenditures and investments, but rather by the cumulated stocks of knowledge and physical capital. The K and Z stocks have been built using the perpetual inventory method (PIM)[11]:

$$K_{ijt} = \begin{cases} (1-\delta_i)K_{ijt-1} + I_{ijt} & if\ t > 0 \\ \dfrac{I_{ijt}}{g_{ij}+\delta_i} & if\ t = 0 \end{cases} \tag{2}$$

$$Z_{ijt} = \begin{cases} (1-\lambda_i)Z_{ijt-1} + R\&D_{ijt} & if\ t > 0 \\ \dfrac{R\&D_{ijt}}{g_{ij}+\lambda_i} & if\ t = 0 \end{cases} \tag{3}$$

where g is the 1998–2003 compound growth rate at the industry level, δ is equal to 6% and λ is equal to 15%; I and $R\&D$ are the flows of capital and R&D, while K and Z are the corresponding stock measures.

As can be seen in Table 3, reporting alternative GMM-SYS estimates, the demand-for-labor coefficients confirm the auto-correlated nature of the employment variable, the positive and highly significant impact of output and the negative effect of wages (although they turn out to be barely significant in these estimates).

The negative impact of capital formation is not only confirmed (third column), but also reinforced by using the stock variable K (columns 1 and 2); indeed, at least in the examined period, the complementarity between capital and labor has been dominated by a labor-saving impact, possibly due to process innovation incorporated in capital formation.

Moving to the R&D flow and stock (Z), its labor-friendly nature is fully confirmed and even reinforced: when Z is considered, the estimated elasticity increases to 0.8/0.9% and its significance rises to 99%.

On the whole, the stock estimates are consistent with the flow ones and point to a labor-friendly nature of R&D and a labor-saving impact of embodied technological change, more or less compensating each-other.

A further extension consists in using the sectoral splitting presented in Table 1, in order to investigate possible sectoral peculiarities in the relationship between innovation and employment, as detected by the previous literature (see Sect. 3). Indeed, the computed R&D intensity is significantly different across sectors (see Table 1) and the balance between product innovation (potentially labor friendly) vs process innovation (potentially labor-saving) is also not uniform across industries.

Since this differentiation significantly reduces the number of available observations for each sectoral group and multiply the number of necessary moment conditions, we have opted for using the least squares dummy variable corrected estimator (LSDVC). Indeed, Bruno (2005a, b) shows that—when the number of

[11] To initialize the PIM it is necessary to input historical capital and R&D growth rates. To avoid losing observations, we have calculated the average compound growth rates over the period 1998–2003 and used them as the growth rates for computing the initial 1998 stocks. Whenever the growth rates were negative we have used zero. As far as depreciation rates are concerned, we have used the reference rates in the literature: 15% for R&D and 6% for physical capital (see Musgrave 1986; Bischoff and Kokkelenberg 1987; Nadiri and Prucha 1996 for physical capital; Pakes and Schankerman 1986; Hall 2007; Aiello and Cardamone 2008 for knowledge capital). For obvious reasons, the literature assumes the obsolescence of knowledge capital to be faster than that of physical capital.

Table 3 Dependent variable: number of employees in log scale (flows and stocks)

	(1) GMM-SYS	(2) GMM-SYS	(3) GMM-SYS
$\log(E_{ijt-1})$	0.931*** [0.031]	0.948*** [0.027]	0.947*** [0.028]
$\log(W_{ijt})$	− 0.042 [0.029]	− 0.043* [0.026]	− 0.046* [0.026]
$\log(Y_{ijt})$	0.096*** [0.028]	0.086*** [0.026]	0.087*** [0.027]
$\log(K_{ijt})$	− 0.009** [0.005]	− 0.012** [0.004]	
$\log(I_{ijt})$			− 0.012** [0.005]
$\log(Z_{ijt})$		0.009*** [0.003]	0.008*** [0.003]
$\log(R\&D_{ijt})$	0.005** [0.002]		
Const.	− 0.764*** [0.218]	− 0.777*** [0.157]	− 0.797*** [0.158]
Country dummies	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes
N Obs	3073	2826	2826
Hansen	2490.90	234.26	225.56
p value	0.116	0.243	0.234
N instr	220	220	220
AR(1)	− 6.56	− 6.61	− 6.62
p value	0.000	0.000	0.000
AR(2)	− 1.76	− 1.70	− 1.70
p value	0.078	0.089	0.090

Z stands for R&D stock and K for capital stock

Robust standard errors in brackets

All the regressors are considered endogenous and instruments include lags from two to four periods

*, **, *** indicate statistical significance respectively at 10, 5 and 1%

individuals is low related to the number of effects to identify and the panel is unbalanced—the LSDVC estimator performs better than the GMM ones.[12]

Table 4 reports the separate LSDVC regressions for the LT, MT and HT sectors. Previous results in terms of path-dependency of the dependent variable, significant positive impact of value added and negative impact of the cost of labor, are fully confirmed.[13]

The sectoral splitting also allows throwing some light on the revealed overall negative relationship between investments and employment: this seems to be entirely due to the traditional low-tech sectors, while the link is not significant in the HT sectors and even positive in the MT ones. Therefore, a possible labor-saving effect due to the embodied technological change incorporated in capital formation

[12] This methodology is based on the within group estimator, but corrected for its asymptotic bias (see Kiviet 1995, 1999; Bun and Kiviet 2003). The procedure must be initialized by a dynamic panel data estimate and we have opted for the less demanding GMM-DIF. Robust standard errors have been obtained through bootstrapping, with 50 iterations.

[13] Interestingly enough, the negative role of wages in affecting employment seems to be limited to the low-tech sectors, where competition is mainly based on cost-saving rather than on innovation.

Table 4 Dependent variable: number of employees in log scale

	(1) LSDVC LT	(2) LSDVC MT	(3) LSDVC HT
$\log(E_{ijt-1})$	0.839*** [0.030]	0.858*** [0.029]	0.726*** [0.030]
$\log(W_{ijt})$	− 0.051*** [0.013]	− 0.001 [0.006]	− 0.015 [0.016]
$\log(Y_{ijt})$	0.139*** [0.020]	0.072*** [0.016]	0.159*** [0.016]
$\log(I_{ijt})$	− 0.013** [0.006]	0.013** [0.006]	− 0.008 [0.005]
$\log(R\&D_{ijt})$	0.001 [0.001]	0.018** [0.008]	0.026** [0.013]
Time dummies	Yes	Yes	Yes
N Obs	1194	732	500
Initial estimator	GMM-DIF	GMM-DIF	GMM-DIF

Bootstrapped standard errors in brackets (50 iterations)

*, ** and *** stay for a statistical significance respectively at 10, 5 and 1%

appears to be specific to the low-tech sectors where competition is reached through decreasing costs (lower wages and process innovation).

This picture is consistent with what was found with regard to our main variable of interest: indeed, R&D expenditures are job-creating in both the medium-tech and the high-tech sectors (with a 95% level of confidence and an elasticity raising to 1.8% in the MT and 2.6% in the HT), but not in the traditional sectors where they turn out to be not significant.

6 Conclusions

The relationship between innovation and employment is far from being a simple one: as detailed in Sect. 2, technological change generates a direct impact and many indirect effects. On the one hand, process innovation implies a labor-saving effect, while product innovation is generally labor friendly. On the other hand, together with their labor-saving impact, process innovations involve decreasing prices and increasing incomes and these, in turn, boost an increase in demand and production that can compensate the initial job losses.

However, these compensation mechanisms can be hindered by the existence of severe drawbacks and their efficacy is dependent on crucial parameters and on the different institutional and socio-economic contexts.

Therefore, in different historical periods and various institutional frameworks, the relative balance between the direct labor-saving effect of process innovation and the counterbalancing impacts of compensation forces and product innovation can be substantially different. Of course, the scenario appears even more complicated—and less optimistic—when these direct and indirect impacts occur within a period of structural crisis as the current one.

Fully consistent with what was obtained by the previous literature, this study also found a significant labor-friendly impact of R&D expenditures, which are particularly related to product innovation; however, this positive employment effect appears to be entirely due to the medium-and high-tech sectors, while no effect could be detected in the low-tech industries.

From a policy point of view, this outcome, which is consistent with previous studies (see Sect. 3), proves that the aim of the EU2020 strategy (see European Commission 2010)—that is to develop a European economy based on R&D, knowledge and innovation—points in the right direction also in terms of job creation. However, this job creation has to be expected solely in the high-tech sectors, while most of European economies are specialized in traditional industries and this is somehow worrying in terms of future perspectives of the European labor market.

Moreover, and partially in contrast with the previous empirical evidence, capital formation (both in terms of flow and stock) was found to be negatively related to employment. This outcome points to a possible labor-saving effect due to embodied technological change incorporated in gross investment. It seems that in the recent years the rationalizing component of investment has turned out to dominate its expansionary component. Moreover, a possible labor-saving effect due to process innovation incorporated in capital formation seems to be specific to the low-tech sectors where competition is reached through decreasing costs. If these results will be confirmed by future research, this is surely matter for thought for the European policy makers.

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