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Mariacristina Piva and Marco Vivarelli

Maastricht Economic and social Research institute on Innovation and Technology (UNU-MERIT)

email: info@merit.unu.edu | website: <http://www.merit.unu.edu>

Maastricht Graduate School of Governance (MGSoG)

email: info-governance@maastrichtuniversity.nl | website: <http://www.maastrichtuniversity.nl/governance>

Boschstraat 24, 6211 AX Maastricht, The Netherlands

Tel: (31) (43) 388 44 00

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IS INNOVATION DESTROYING JOBS? FIRM-LEVEL EVIDENCE FROM THE EU^o

Mariacristina Piva

(Università Cattolica del Sacro Cuore, Piacenza, Italy)

Marco Vivarelli*

(Università Cattolica del Sacro Cuore, Milano, Italy;
UNU-MERIT, Maastricht, The Netherlands and IZA, Bonn, Germany)

ABSTRACT

Using a unique firm-level database comprising the top European R&D investors over the period 2002-2013 and running LSDVC estimates, this study finds a significant labour-friendly impact of R&D expenditures. However, this positive employment effect appears limited in magnitude and entirely due to the medium-and high-tech sectors, while no effect can be detected in the low-tech industries. From a policy point of view, this outcome is supporting the EU2020 strategy, but – taking into account that most European economies are specialised in low-tech activities – is also worrying in terms of future perspectives of the European labour market.

Key words: R&D; innovation; employment; firm-level analysis; EU

JEL codes: O33

* Corresponding author:
Professor Marco Vivarelli
Università Cattolica del Sacro Cuore
Milano
Italy
Email: marco.vivarelli@unicatt.it

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1. Introduction

The fear of mass technological unemployment is back.

During the first industrial revolution, English manufacturing workers destroyed machinery under the charismatic lead of Ned Ludd, while their agricultural counterparts did the same against the threshers under the command of Captain Swing (see Hobsbawm, 1968; Hobsbawm and Rudé, 1969).

Nowadays, ICT automation, the intensive use of robots across all manufacturing sectors, the introduction of self-driving autonomous cars and the widespread usage of 3D printing machines have raised the fear of imminent pervasive technological unemployment. Moreover, not only manufacturing employment seems at risk, but also employees in services – including cognitive skills – are no longer guaranteed. Examples are IBM Watson Explorer displacing legal advisors and medical tasks or open online university courses – provided by the top US universities – displacing university professors all over the world.

In this context, Brynjolfsson and McAfee (2011 and 2014) think that the root of the present employment problem is a structural adjustment (“Great Restructuring”) characterised by an exponential growth in ICT applications and computers’ processing speed having an even larger impact on jobs, skills and the whole economy¹. Consistently, Frey and Osborne (2013) – using data from the US Department of Labor – predict that almost half of the occupational categories are at risk of being automated, including a wide range of white-collar/cognitive tasks in administration, logistics and transportation, retailing, legal services, etc.

Under this scenario, the aim of this paper is twofold. On the one hand, the economic insights about the employment impact of technological change will be disentangled and previous empirical studies will be discussed (Section 2); on the other hand – using a unique dataset – a microeconomic empirical test will be provided, in order to shed some light on the recent evolution of the relationship between R&D expenditures and employment in Europe both on the aggregate and disentangling firms according to their R&D intensity (Sections 3 and 4).

¹ For a recent assessment of the impact of ICT on the Italian economy, see Bonanno, 2016.

2. The literature

2.1 Theory

The assessment of the impact of innovation on employment is both a well-debated and a controversial issue for theoretical economists. On the one hand, technological unemployment is considered a direct worrisome consequence of labour-saving process innovations; on the other hand, economic theory pinpoints both the existence of indirect effects able to compensate for the reduction in employment due to process innovation, and the key role of product innovation that generally shows a labour-friendly nature.

Strictly speaking, the direct impact of process innovation is to destroy jobs: process innovation means to produce the same amount of output using a lesser amount of production factors, in particular labour. However, the economic thought - since its very beginning - has shown the existence of economic forces which can compensate for the reduction in employment determined by technological progress.

Indeed, in the first half of the XIX century, classical economists designed a theory that Marx later called the “compensation theory” (see Marx, 1961, vol. 1, chap. 13 and 1969, chap. 18). This theory is articulated in different market compensation mechanisms which can counterbalance the initial labour-saving impact of process innovation (for extensive surveys on the subject, see Petit, 1995; Vivarelli, 1995, chaps. 2 and 3; Vivarelli and Pianta, 2000, chap. 2; Pianta, 2005; Coad and Rao, 2011; Vivarelli 2013 and 2014).

First of all, process innovation leads to a decrease in the unit costs of production and, if market competitive forces are at work, this effect is translated into a decrease in prices. The decreasing prices stimulate a new demand for products and, in turn, additional production and employment (see Say, 1964). This compensation mechanism “via decrease in prices” has been largely put forward in the history of economic thought and in the recent debate (see Pigou, 1962; see Neary, 1981; Stoneman, 1983, chaps. 11 and 12; Hall and Heffernan, 1985; Dobbs et al., 1987; Nickell and Kong, 1989; Smolny, 1998; Harrison et al., 2008).

However, compensation mechanisms can be partially damaged by the existence of severe drawbacks which are often either undervalued or even neglected by the economic conventional wisdom.

As far as the mechanism “via decrease in prices” is concerned, classical authors (Malthus 1964, Sismondi 1971 and Mill 1976) pointed out that the very first effect of a labour-saving technology is a decrease in the aggregate demand due to the cancellation of the demand coming from the dismissed workers. This shows that market clearing starts from a decreased demand that has to be more than counterbalanced. Moreover, the effectiveness of this mechanism depends on the hypothesis of perfect competition. If an oligopolistic regime is prevailing, the whole compensation is strongly weakened since cost savings are not necessarily translated into decreasing prices (see Sylos Labini, 1969). Finally, demand elasticity plays a crucial role in making this compensation mechanism more or less effective.

However, in case the gap between costs and prices enlarges and the competitive convergence is not instantaneous, extra-profits may be accumulated by the innovative entrepreneurs. According to the proponents of the compensation theory, these profits might be invested and, therefore, they might generate new output and new job (see, originally, Ricardo, 1951 vol. I, p. 396, and Marshall, 1961 p. 542, and more recently Hicks, 1973, and Stoneman 1983). This is the case of the compensation mechanism “via profits”.

Turning our attention to the critique of the compensation “via new investments”, it is obvious that this mechanism relies on the unacceptable Say’s law assumption that the accumulated profits due to innovation are entirely and immediately translated into additional investments. In contrast, pessimistic expectations (“animal spirits” in Keynesian thought) may imply the decision to delay investments even in the presence of cumulated profits obtained by innovation. A substantial delay in compensation may in turn generate structural technological unemployment. Additionally, the intrinsic nature of the new investments does matter: if these are capital-intensive and embody labour-saving process innovations, compensation can only be partial.

However, technological change cannot be reduced to process innovation: the other side of the coin is product innovation. Obviously enough, the introduction of new products and the related emergence of new markets (see, for instance, the personal computer in the last decades of the XX century) involve a substantial job-creation effect (see Say 1964, p.88, as well as Marx 1961, vol. I, p.445). In the current debate, various studies (Freeman et al., 1982; Freeman and Soete, 1987; Freeman and Soete, 1994; 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 development of either entire new goods and/or markets. However, 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 products and sectors) has to be compared with the “substitution effect”, namely the displacement of mature products² (see Katsoulacos, 1984 and 1986; Harrison et al., 2008; Hall et al., 2008).

To sum up, the economic theory available on the relationship between innovation and employment should be considered as a complex and multi-faceted framework, where the direct labour-saving impact of process innovation, the compensation mechanisms, the drawbacks which can weaken the effectiveness of such mechanisms and the labour friendly nature of product innovation can combine in various ways, thus generating different and somehow unpredictable employment outcomes.

In fact, in different historical periods and different institutional and social contexts, the relative balance between the direct labour-saving effect of process innovation and the counterbalancing impacts of compensation forces and product innovation can considerably vary³ (Freeman et al., 1982; Freeman and Soete, 1987; Freeman and Soete, 1994).

On the whole - albeit theoretical economists have developed articulated models about the employment impact of innovation - the economic theory does not have a final clear-cut answer about the final employment effect of R&D and innovation and the attention should be turned to the empirical analyses⁴.

2.2 Empirical studies

Some macroeconometric studies have tested the validity of the compensation mechanisms discussed in the previous section: for instance, Sinclair (1981) concluded that

² For example, the actual MP3 music format is a product innovation currently displacing the end of the XX century compact disk which, in turn, displaced the vinyl (XX century).

³ 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).

⁴ The empirical studies analysing the link between technological change and employment have mainly focused on industrialised high-income countries, particularly OECD countries (basically because of better data availability); among the few recent articles dealing with DCs, see Meschi et al., 2011, for an application to the Turkish case and Mitra and Jha, 2015, for an application to the Indian case.

a positive employment impact is assured if demand elasticity and the elasticity of factor substitution are sufficiently high; by the same token. Layard and Nickell (1985) stated that the crucial parameter was the elasticity of the demand for labour in response to a variation in the ratio between real wages and labour productivity (this elasticity should be high enough to fully compensate initial job losses). Vivarelli (1995) - running 3SLS regressions based on Italian and US data - found that the most effective compensation mechanism turned out to be that “via decrease in prices” in both countries. More recently, Feldmann (2013) - using data on 21 industrial countries over the period 1985-2009 – found that technological change significantly increases unemployment over a three year period, with this impact fading away in the long run.

On the whole, the (few) macroeconomic studies available on the subject reveal that technological progress can display its labour-friendly nature when markets are characterised by competition, higher demand elasticities (both in the product and in the labour market) and by a higher degree of substitutability between the production factors. However, while country-level studies allow to fully explore the different direct effects and compensation mechanisms at work in the aggregate, they are often severely constrained by the difficulty to find a proper aggregate proxy for technological change at the national level. Moreover, the employment national trends are co-determined by overwhelming institutional and social determinants difficult to disentangle and to control for.

In this context, the firm-level dimension is a particularly important setting for investigating the employment impact of technological change. Indeed, microeconomic studies have the great advantage to grasp the very nature of firms’ innovative activities and to allow a direct and detailed firm-level mapping of innovation activities (innovation dummies, R&D expenditures, R&D employees, patents; etc.).

For instance, Van Reenen (1997), in the case of UK, found evidence – using data from the SPRU innovation database covering the period 1976–1982 – of a positive employment impact of innovation. This outcome turned out to be robust after controlling for fixed effects, dynamics and endogeneity.

In the case of Italy, Piva and Vivarelli (2004 and 2005) found evidence in favour of a positive effect of gross innovative investment on employment, although particularly small in magnitude (on the Italian case, see also Hall et al. (2008) finding a positive employment impact of product innovation, but no evidence of any employment

displacement due to process innovation).

Turning our attention to the German case, Lachenmaier and Rottmann (2011) - using a panel dataset of manufacturing firms over the period 1982-2002 - found a significantly positive effect of different innovation measures on employment, but - partially in contrast with the theoretical expectations and previous empirical evidence - the authors found a higher positive impact of process rather than product innovation.

Moving to Spain, Ciriaci et al. (2016) - using matched waves of the annual Spanish Community Innovation Survey (CIS) - run quantile regressions based on a comprehensive longitudinal sample of 3.304 Spanish firms over the period 2002–2009. Their results provide evidence that innovative, smaller and younger firms are more likely to show high and persistent employment growth episodes than non-innovative firms.

Some recent studies are characterised by a multi-country approach. For instance, Bogliacino et al. (2012) analysed a longitudinal sample of European manufacturing and service firms over the period 1990-2008 and found a positive and significant employment effect of R&D expenditures in high-tech manufacturing and services but not in the more traditional (low- and medium-tech) manufacturing sectors.

Using CIS data from four European countries, Harrison et al. (2014) showed that process innovation was responsible of employment displacement (although compensation mechanisms were at work), while product innovation was fundamentally labour-friendly.

Finally, Van Roy et al. (2015) - using data on almost 20,000 European firms covering the period 2003-2012 - found that technological change (proxied by forward-citation weighted patents) reveals to be labour-friendly. However, this positive employment effect of innovation was found to be statistically significant only for firms in the high-tech manufacturing industries, consistently with Bogliacino et al. (2012, see above).

On the whole, previous firm-level studies provide a consistent evidence of a positive link between innovation and employment; however, this impact is particularly obvious when R&D and/or product innovation are adopted as proxies of technological change and when high-tech sectors are considered.

3. Data and econometric setting

3.1 The data

The original and unique dataset used in this study has been built on the basis of data provided by the Joint Research Centre (JRC) of the European Commission, located in Seville (Spain). In more detail, the starting point has been the *JRC Scoreboard* database comprising the top one thousand European (EU) R&D investors - both in manufacturing and services - over the period 2002-2013 (see JRC-IPTS, 2015).

The *JRC Scoreboard* contains the following information:

- Company identification and sectoral classifications (both Industry Classification Benchmark (ICB) and NACE Rev.2 are available);
- Basic economic data, including the crucial information for this study, namely: net sales, capital formation, R&D expenditures and employment. However, with regard to the cost of labour - missing in the *JRC Scoreboard* - we had to use information (where available) downloaded from the Orbis database (Bureau Van Dijk; see below).

It is important to underline that the number of years available for each company depends on the company's history; more specifically, a firm enters the database when it first publishes a public financial statement and exits from it in case of bankruptcy, or because it exits from the relevant market or due to M&A. Thus, the longitudinal database is unbalanced in nature.

Once we had acquired the rough original *Scoreboard* data, we proceeded to construct a consistent longitudinal database, adequate for running panel estimations intended to test the relationship between R&D and employment. We adopted the following step by step procedure.

First step: data extraction

We established the following criteria to guide the extraction of the data from the original *Scoreboard* files:

- We extracted information concerning net sales, capital formation, R&D expenditures and employment. Only firms with complete information were kept. At this stage, the sample was composed by 710 companies and 6,170 observations.
- We expressed all the value data in the current national currency. As all data within the *Scoreboard* are presented in Euro (applying the last available exchange rate for non-Euro countries), we transformed them back into nominal and national currency values.

Second step: deflation of current nominal values

Nominal values were translated into constant price values through GDP deflators (source: <http://stats.oecd.org/>) centred on the year 2010. For a tiny minority of firms reporting in currencies different from the national currency (i.e. 1 Belgian, 11 Dutch, 9 Irish and 11 from Luxembourg reporting in US dollars), we opted for deflating the nominal values through the national GDP deflator as well.

Third step: values in PPP dollars

Once we had obtained constant 2010 price values, all figures were converted into US dollars using the PPP exchange rate at year 2010 (source: <http://stats.oecd.org/>)⁵. 1 company from Malta was excluded, due to the unavailability of PPP exchange rates from the OECD. The 8 companies reporting in Euro but located in non-euro countries (Denmark, Sweden and UK) were excluded as well. The 58 European companies reporting in US dollars were - instead - kept as such.

Fourth step: the final format of the panel data

The obtained unbalanced database comprises 701 companies, 2 codes (country and sector) and 4 variables (net sales, capital formation, R&D expenditures and employment – cost of labour will be added as the very last step) over a period of 12 years (2002-2013).

⁵ This procedure is consistent with that suggested by the Frascati Manual (OECD, 2002) in order to adjust R&D expenditures correctly for differences in price levels over time (*i.e.* intertemporal differences requiring deflation) and between countries (*i.e.* interspatial differences requiring a PPP equivalent). In particular “...the Manual recommends the use of the implicit gross domestic product (GDP) deflator and GDP-PPP (purchasing power parity for GDP), which provide an approximate measure of the average real ‘opportunity cost’ of carrying out the R&D” (*ibidem*, p. 217). PPP dollars were chosen, since the US dollar is commonly considered the reference currency for global transactions, such as those carried out by the investigated firms, which are top world champions in terms of R&D investment.

Since we are interested to test the labour impact of R&D expenditures both in the aggregate and according to different technological levels, we endogenously ranked firms on the basis of their R&D intensity (R&D/net sales), defining firms as High-tech when their R&D intensity is larger than 5%; Medium-tech if R&D intensity is between 1% and 5%; Low-tech if the R&D intensity is less than 1% ⁶.

Since the following econometric exercise is based on a standard dynamic specification of the demand for labour and given the unbalanced nature of our longitudinal database, the inclusion of the lagged dependent variable in the estimated specification involved both a reduction in the number of firms (retaining only those firms with at least two consecutive employment data) and a further decrease in the number of observations (we lost 27 companies in this step).

Therefore, we ended up with 674 companies for a total of 5,222 observations. Since the consideration of the labour-cost variable would have implied a dramatic decrease in terms of the number of information (see below), we have opted for firstly running our regressions without the wage control and then to include the additional variable and test again the extended specification.

The following Table 1 reports the distribution of the retained firms across the different European countries⁷.

⁶ This classification is fully consistent with the JRC-IPTS Scoreboard report (see JRC-IPTS, 2015, which uses the same approach), and allows to properly rank also companies belonging to service sectors which turn out to be very heterogeneous in their R&D intensity. Indeed, the Scoreboard dataset is not representative from a sectoral point of view, since it only comprises top world champions in terms of R&D investment, irrespective of their sectoral belonging; in this context, a traditional sectoral classification turns out to be inadequate to test the possible different job-creation impact of different level of R&D investment. Moreover, a sectoral splitting may result highly biased when, for instance, a low-tech sector might be entirely represented by few R&D global leaders. However, our endogenous classification is sufficiently consistent with the sectoral Eurostat classification, since the resulting HT firms are especially concentrated in Electronic & Electrical Equipment, Health Care Equipment & Services, Pharmaceuticals & Biotechnology, Software & Computer Services, Technology Hardware & Equipment. Firms codified as MT are mainly present in Automobiles & Parts, Chemicals, Construction & Materials, Electronic & Electrical Equipment and Industrial Engineering. In the case of LT firms, the most represented industries are: Construction & Material, Food Producers, Forestry & Paper, Oil & Gas Producers.

⁷ Bearing in mind that all the included firms are quoted, some countries (such as the UK) where stock exchange quotation is more common, turn out to be over-represented.

Table 1: Sample composition

COUNTRY	FIRMS	OBS.
AUT	25	189
BEL	23	197
CZE	1	6
DEU	142	1,016
DNK	20	174
ESP	18	147
FIN	40	379
FRA	101	855
HUN	1	8
IRL	17	132
ITA	37	239
LUX	11	37
NLD	37	261
POL	2	5
POR	4	25
SVN	2	12
SWE	58	454
UK	135	1,086
EU	674	5,222

As mentioned above, we tried to go beyond the *Scoreboard* data limitations (in order to properly test the eq.1 below,) implementing a proxy for the cost of labour.

In particular, we have proceeded to match the *Scoreboard* dataset with the Orbis database (Bureau van Dijk), in order to get the cost of labour as reported in the balance sheets of the available companies.

Unfortunately, this merging has implied an important loss in terms of number of firms and information: Orbis information was accessible for only 360 *Scoreboard* companies, for a total of 2,708 observations, over the shrunken period 2006-2013. The methodological steps discussed in details above were applied to the wage variable, as well.

3.2 Econometric strategy

Since our dependent variable (employment) is highly persistent, as common in the literature using longitudinal data (since Van Reenen 1997 onward, see Section 2), we adopt a

dynamic employment equation, where employment is autoregressive and depends on the cost of labour, output, investment and R&D expenditures, which is our direct measure for innovation. Therefore, the estimated equation is a dynamic labour demand, augmented with technology:

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

where i, j, t indicate, respectively, firm, country and year; E is employment, W is the cost of labour per employee, Y is net sales, I is capital formation, R&D is straightforward, 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 ⁸.

We expect a positive and high coefficient for the lagged term, a negative α_1 capturing the standard labour demand inverse relationship between wages and employment, and a positive α_2 capturing the role of final demand. A priori, α_3 has no obvious sign, since capital formation is labour-expanding through its expansionary effect, and labour-saving through process innovation embodied in the new machineries (see Section 2.1). Finally, our main interest is in α_4 , linking R&D with employment: consistently with the previous literature 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 Section 2).

As well known, the dynamic specification (1) cannot be properly estimated either by Pooled Ordinary Least Squares (POLS) or by the Within Group (fixed effects, WG) estimator. Indeed, a common problem with this kind of dynamic specification concerns the endogeneity of the lagged dependent variable, leading to overestimate it in the POLS case and underestimate it in the WG case. To control for this problem and to obtain consistent estimates, it is necessary to rely on instrumental variable (IV) techniques. In particular, Arellano and Bond (1991) introduced the GMM-DIF estimator as a suitable methodology for

⁸ The set of country dummies control for the possible impact of different national macroeconomic climates, and specific economic policies, while the set of time dummies capture both the economic business cycle and possible supply side effects in the European labour market.

dealing with the endogeneity of the lagged dependent variable⁹, while Blundell and Bond (1998) improved the DIF-estimator, developing the GMM-SYS estimator, more appropriate in the case of high persistency of the dependent variable and when the cross-section dispersion of the data is overwhelming their time-series variability.

However, the recent econometric literature has come to the conclusion that both the GMM-DIF and the GMM-SYS estimators perform poorly when the longitudinal dataset in use is characterised by a low number of individuals. This is indeed our case, since we start from a relatively small number of firms (674), dropping to a very small sample size when dealing with companies split by R&D intensity (see Table 3) and even less when we implement data on the cost of labour (see Table 4).

Therefore, we have used the Least Squares Dummy Variable Corrected (LSDVC) estimator, proposed by Kiviet (1995), Judson and Owen (1999) and Bun and Kiviet (2003) as a suitable methodology in the case of panels characterised by a low number of individuals, where GMM cannot be used efficiently. The procedure is initialised by a standard panel estimate (in our case the GMM-SYS one, given the high persistency of our dependent variable), and then relies on a recursive correction of the bias of the baseline fixed effects (FE) estimator.

An important methodological extension, allowing the LSDVC methodology to be applied to unbalanced panels - such as the one used in this study - has been provided by Bruno (2005a and 2005b). The author tested the behaviour of unbalanced small samples through Monte Carlo experiments and highlighted the fact that the LSDVC estimator has to be preferred to both the LSDV estimator and the GMM estimators, when the number of individuals is small and the degree of unbalancing is severe (Bruno, 2005a), two conditions which are verified in our database.

Finally, consistently with Bun and Kiviet (2003) who have shown that estimated asymptotic standard errors may prove to be poor approximations in small samples, the statistical significance of our LSDVC coefficients has been tested using bootstrapped standard errors (running 50 iterations; see also Bruno, 2005a).

⁹ Indeed, the demand for labour - which is the baseline for our specification (1) - was put forward by Arellano and Bond (1991) as the key example of a dynamic specification where the GMM-DIF methodology is necessary.

4. Results

The dynamic specification (1) has been initially estimated dropping the variable concerning the cost of labour, since it is missing in the original *Scoreboard* dataset.

Table 2 reports the econometric results from POLS, FE and LSDVC regressions, run on the whole sample. As discussed in the previous section, our attention will focus on the most reliable LSDVC estimates; POLS and FE estimates are reported for completeness¹⁰.

Table 2: Dependent variable: number of employees in log scale

	(1) POLS	(2) FE	(3) LSDVC
log(E_{ijt-1})	0.909*** [0.006]	0.547*** [0.108]	0.604*** [0.016]
log(Y_{ijt})	0.058*** [0.007]	0.319*** [0.069]	0.307*** [0.014]
log(I_{ijt})	0.005 [0.004]	0.043*** [0.008]	0.045*** [0.009]
log(R&D_{ijt})	0.010*** [0.003]	0.034*** [0.012]	0.029*** [0.008]
T	Yes	Yes	Yes
C	Yes		
N Obs	5,222	5,222	4,793
Initial estimator			GMM-SYS

Notes: robust standard errors in brackets. E stands for number of employees, Y for Net Sales, R&D for Research and Development expenditures and I for capital formation. *, ** and *** stars indicate significance respectively at 10, 5 and 1 percent. In the LSDVC estimate bootstrapped standard errors are reported in brackets (50 iterations). Due to the instrumentation procedure and the unbalanced nature of the sample, there is a reduction of observations in the LSDVC estimate.

¹⁰ Moreover, we can test whether the LSDVC coefficient of the lagged dependent variable correctly lies between the FE coefficient (characterised by a downward bias) and the POLS coefficient (characterised by an upward bias). As can be seen in Table 2, this is the case; this outcome is reassuring about the adopted econometric methodology.

As can be seen, the results are in line with the theoretical expectations and with most of previous econometric outcomes discussed in the Section 2.2: the demand for labour appears to be auto-regressive and positively and significantly affected by both output and investment¹¹.

Turning our attention to the key regressor, R&D expenditures positively and significantly (99%) affect employment levels, with an elasticity equals to 2.9%. Interestingly enough, these results are very in line with the previous literature, even in terms of the magnitude of the R&D coefficient (see Bogliacino et al., 2012, p.58, Table 1, first column).

Using the R&D intensity grouping criterion discussed in Section 3.1, we were then able to run our estimates for high-, medium- and low-tech firms separately. Results are presented in the following Table 3.

Table 3: Dependent variable: number of employees in log scale

	(1) LSDVC HT	(2) LSDVC MT	(3) LSDVC LT
log(E_{ijt-1})	0.608*** [0.023]	0.351*** [0.028]	0.914*** [0.025]
log(Y_{ijt})	0.254*** [0.026]	0.516*** [0.044]	0.050 [0.054]
log(I_{ijt})	0.047*** [0.008]	0.038** [0.019]	0.059*** [0.032]
log(R&D_{ijt})	0.089*** [0.025]	0.066** [0.032]	0.010 [0.022]
T	Yes	Yes	Yes
N Obs	1,867	1,851	1,075
Initial estimator	GMM-SYS	GMM-SYS	GMM-SYS

Notes: bootstrapped standard errors in brackets (50 iterations). E stands for number of employees, Y for Net Sales, R&D for Research and Development expenditures and I for gross fixed capital formation. *, ** and *** stars stay for a statistical significance respectively at 10, 5 and 1 percent.

¹¹ Therefore, at least in the empirical context of this study, the labour-expanding expansionary effect seems to dominate a possible labour-saving impact due to the implementation of process innovation embodied in capital formation.

Interestingly enough - while the other three coefficients do not exhibit substantial differences across firms of different technological intensity - the key employment/R&D elasticity turns out to be highly significant (99%) and larger in magnitude (8.9%) in the HT firms, smaller (6.6%) and less significant (95%) in the MT companies and even not significant at all in the low-tech firms. This means that the overall labour-friendly nature of R&D expenditures shown in Table 2 is totally due to the high- and medium-tech firms, while no significant employment impact is detectable in the low-tech companies. This outcome is consistent with what obtained by some recent studies (see Evangelista and Savona, 2002; Bogliacino and Vivarelli, 2012; Bogliacino et al., 2012; Van Roy et al., 2015).

Table 4 reports the results using the shrunken dataset obtained by the merging of the *Scoreboard* database with the Orbis one (see Section 3.1). As can be seen, the estimates about the controls are confirmed, while the additional wage term turns out to be negative and highly significant, as expected. Interestingly enough - notwithstanding the important decrease in terms of number of observations - R&D expenditures keep on having a job-creation impact (elasticity equal to 3.4% at the 99% level of significance for the whole sample). However, this labour friendly effect is limited to the sole High-tech companies, where the relevant elasticity keeps its 99% level of confidence and raises to a magnitude equal to almost 17%; in contrast, R&D expenditures do not significantly affect employment levels either in the medium- and in the low-tech firms.

Table 4: Dependent variable: number of employees in log scale

	(1) LSDVC WHOLE SAMPLE	(2) LSDVC HT	(3) LSDVC MT	(4) LSDVC LT
$\log(E_{ijt-1})$	0.588*** [0.026]	0.518*** [0.033]	0.765*** [0.039]	0.623*** [0.046]
$\log(W_{ijt})$	-0.177*** [0.010]	-0.178*** [0.019]	-0.109*** [0.021]	-0.393*** [0.043]
$\log(Y_{ijt})$	0.299*** [0.018]	0.225*** [0.038]	0.313*** [0.040]	0.357*** [0.045]
$\log(I_{ijt})$	0.033*** [0.008]	0.026*** [0.010]	0.016 [0.015]	0.045*** [0.015]
$\log(R\&D_{ijt})$	0.034*** [0.009]	0.168*** [0.037]	0.034 [0.025]	0.005 [0.012]
T	Yes	Yes	Yes	Yes
N Obs	2,708	978	1,037	693
Initial estimator	GMM-SYS	GMM-SYS	GMM-SYS	GMM-SYS

Notes: bootstrapped standard errors in brackets (50 iterations). E stands for number of employees, Y for Net Sales, R&D for Research and Development expenditures, W for cost of labour per employee and I for gross fixed capital formation. *, ** and *** stars stay for a statistical significance respectively at 10, 5 and 1 percent.

5. Conclusions, policy implications and caveats

The economic theory about the relationship between technological change and employment reveals that process innovation should imply a labour-saving effect, while product innovation should foster job creation; however, together with their labour-saving impact, process innovations involve decreasing prices and increasing investments and these in turn boost an increase in demand and production that can compensate the initial job losses.

On the other hand, these compensation mechanisms can be hindered by the existence of severe drawbacks (such as imperfect competition or negative expectations) and their efficacy depends on crucial parameters (such as the demand elasticity and the degree of substitutability

between the production factors) and on the different institutional and socio-economic contexts.

Therefore, in different historical periods and institutional frameworks, the balance between the direct labour-saving effect of process innovation, the counterbalancing impacts of compensation forces and the job-creation impact of product innovation can be substantially different; therefore the actual employment outcome of technological change becomes a relevant matter for empirical studies.

As far as previous microeconomic studies are concerned (see Section 2.2), the extant literature provides consistent evidence of a positive link between innovation and employment, which is more significant when R&D and/or product innovation are adopted as proxies of technological change and when high-tech sectors are singled out.

Consistently with what obtained by the previous literature, this study also finds a significant labour-friendly impact of R&D expenditures; however, this positive employment effect appears limited in magnitude and entirely due to the medium- and high-tech firms, while no effect could be detected in the low-tech companies.

From a policy point of view, this outcome proves that the aim of the EU2020 strategy (see European Commission, 2010) - that is to develop an European economy based on R&D, knowledge and innovation - points in the right direction also in terms of job creation. Indeed, the evidence provided in this study supports the view that R&D expenditures are beneficial not only to European productivity and competitiveness, but also to European job creation capacity, at least at the firm-level.

However, this policy implication should be qualified at least in three important respects. Firstly, this study is conducted at the firm level and so results cannot be easily extended at the macroeconomic/aggregate level, also taking into account the data limitations in terms of country coverage and the representativeness of our sample, which is unbalanced in favour of the top European R&D performers.

Secondly, in this study we use only one (although relevant) indicator to proxy innovation, namely R&D expenditures. Since this proxy is mostly related to labour-friendly product innovation, this study underscores the alternative mode of technological change that is labour-saving process innovation (see Section 2.1).

Thirdly, what emerges clearly from the empirical analysis is that the job-creation impact of R&D expenditures is not equally detectable across the different companies. More

specifically, it is obvious for high- and (to a lesser extent) medium-tech firms, but absent in the low-tech ones. Taking into account that most of EU economies are specialised in traditional activities, this is somehow worrying in terms of the future perspectives of European employment.

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