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R&D, embodied technological change, and employment: evidence from Italian microdata

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Abstract

This article explores the employment impact of innovation activity, taking into account both R&D expenditures and embodied technological change (ETC). We use a novel panel data set covering 265 innovative Italian firms over the period 1998–2010. The main outcome from the proposed fixed-effect estimations is a labor-friendly nature of total innovation expenditures; however, this positive effect is barely significant when the sole in-house R&D expenditures are considered and fades away when ETC is included as a proxy for innovation activities. Moreover, the positive employment impacts of innovation activities and R&D expenditures are totally due to firms operating in high-tech industries and large companies, while no job creation due to technical change is detectable in traditional sectors and SMEs.

JEL classification: O31, O33

1. Introduction

The historical debate on the relationship between innovation and employment has recently revived due to the widespread diffusion of the technological paradigm (Dosi, 1982, 1988) based on Information and Communication Technologies (ICT) and automation. In particular, the possible "labour-saving" nature of new technologies has raised widespread fears of "technological unemployment" (see Brynjolfsson and McAfee, 2011, 2014; Frey and Osborne, 2017).

Moreover, technological trends have interlinked with the recent financial and economic crises and with the slow recovery afterward, often showing a jobless nature. In the background of this scenario, international organizations—including the United Nations Industrial Development Organization (UNIDO), the Inter-American Development Bank (IDB), and the Organisation for Economic Co-operation and Development (OECD)—are increasingly concerned with the issue of avoiding jobless growth as countries recover from the crisis (see Crespi and Tacsir, 2012; UNIDO, 2013; Arntz, et al., 2016; OECD, 2016).

Moving from the current policy debate to economic theory, the relationship between innovation and employment is a "classical" controversy, where two views are contrasting each other (for a comprehensive discussion, see Freeman et al., 1982; Vivarelli, 1995; Pianta, 2005). One states that labor-saving innovations create technological unemployment, as a direct consequence. The other one asserts the existence of indirect economic effects (through decreasing prices and increasing incomes, both triggered by technological change itself) that can compensate—or even over-compensate—the direct job-destructive effect of process innovation. Moreover, product innovation is seen as the main channel able to effectively counterbalance the displacement of workers due to process innovation (see Katsoulacos, 1986; Freeman and Soete, 1987; Vivarelli et al., 1996; Edquist, et al., 2001).

However, employment compensation by "decreasing prices" may be hindered by price rigidities and noncompetitive practices, while additional incomes due to technical change are not necessarily invested in labor-intensive activities. Even new products may displace older products and so imply a weaker impact in terms of job creation (readers interested in the theoretical analysis of the complex relationship between technical change and employment can refer to recent surveys such as: Sabadash, 2013; Vivarelli, 2014; Calvino and Virgillito, 2018).

Therefore, economic theory does not have a clear-cut answer about the employment effect of innovation, since this depends on the relative weight of process and product innovation; institutional factors such as the degree of competition; price and income elasticities; and on the expectations shaping the amount and the nature of investment activities.

Indeed, in recent times, the attention of the economists interested in the relationship between innovation and employment is focusing, more and more, on empirical studies. Consistently with most of the recent literature (see next section), this article is also empirical in nature and will test the employment impact of technological change using a panel of Italian companies.

Three are the main novelties of this study. First, filling a gap in the extant literature, our analysis takes into account both R&D and the "embodied technological change" (that is process innovation implemented through gross investment; ETC), with the latter usually neglected by previous studies (see Section 3 for a detailed discussion of this issue and for the interpretative methodology adopted in this work). Second, we make use of a unique and novel database, where different waves of Italian CIS (Community Innovation Survey) are merged into a longitudinal panel. Third, together with aggregate estimates, we will be able to disentangle our microeconometric evidence according to sectoral belonging and firm's size allowing a deeper understanding of the peculiarities of the relationship between technological change and employment.

The rest of this article is organized as follows. In the next section an updated survey of the extant empirical literature is provided and critically discussed; Section 3 is devoted to frame our empirical setting and to put forward our testable hypotheses; Section 4 provides a description of the data set and some descriptive statistics; econometric results are discussed in Section 5, while Section 6 briefly concludes.

2. The empirical literature

While theoretical economists have been developing stylized models about the employment impact of process and product innovation, applied economists had to identify adequate econometric specifications to measure process and product innovation and their employment impacts.[1] When considering this issue, a number of critical methodological issues arise.

First of all, it is crucial to clearly identify the level of investigation: whether macroeconomic, sectoral, or microeconomic. Each level of analysis exhibits *pros* and *cons*.

On the one hand, country-level studies allow to fully explore the different direct effects and compensation mechanisms at work in the aggregate (see previous section). While they are attractive from a theoretical point of view, on the minus side they are often severely constrained by the difficulty to find a proper aggregate proxy of technological change and by the fact that the final employment national trends are co-determined by overwhelming institutional and macroeconomic determinants difficult to disentangle and to control for (examples of macroeconomic studies on the link between technology and employment are Sinclair, 1981; Layard and Nickell, 1985; Vivarelli, 1995; Simonetti et al., 2000).

In contrast, microeconometric studies have the great advantage to allow a direct and precise firm-level mapping of innovation variables, both in terms of innovative inputs (R&D and possibly ETC) and/or outputs (innovation dummies, sales from new products, patents; see below). Indeed, only the microeconometric empirical analysis can

1 Starting from Berman et al. (1994), a related stream of literature has investigated the skill-biased nature of new technologies (see also Machin and Van Reenen, 1998; Piva et al., 2005; Acemoglu and Autor, 2011; Bogliacino and Lucchese, 2016). More recently, the focus of this strand of research has moved from skills to tasks, pointing out that new technologies displace routine-based tasks—both in manufacturing and services—leading to a "polarization" both in terms of job opportunities, wages, and incomes (see, among the others, Goos and Manning, 2007; Autor and Dorn, 2009; Michaels et al., 2014; Frey and Osborne, 2017). Although extremely relevant, these issues are out of the scope of the present study.

grasp the very nature of firms' innovative activities and throws some light on the actual ways how new products may generate new jobs and labor-saving process innovation may destroy old ones.

However, there are limitations associated to this level of analysis, as well. First of all, the microeconomic approach cannot take fully into account the indirect compensation effects which operate at the sectoral and country levels. Moreover, 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 rivals, which are crowded out by the innovative firms (this is the so-called: "business stealing effect").[2]

Indeed, sectoral studies may avoid this particular limitation, albeit they suffer from other drawbacks that range from the need to aggregate very heterogeneous micro-behaviors (composition effect) to the inability to take into account inter-sectoral compensation mechanisms (examples of studies investigating the relationship between innovation and employment at the sectoral level are Evangelista and Savona, 2002, Antonucci and Pianta, 2002, Bogliacino and Pianta, 2010; Bogliacino and Vivarelli, 2012; Mitra and Jha, 2015).

In this article, a microeconometric empirical analysis based on longitudinal data will be proposed (see next sections). Therefore, keeping the aim and nature of this article and the above-discussed methodological remarks in mind, our attention can be now turned to the previous microeconometric literature. Former studies can be classified and discussed according to the empirical model adopted and the chosen proxy of technological change.

1. Among the proxies for technological change, dummies for innovation (better if singled out into product and process innovation) capture the existence of the innovation phenomenon in a specific point in time. However, they can only partially depict the overall phenomenon and—as dummies—they suffer obvious limitations. For instance, Blanchflower and Burgess (1998) found a positive link between the innovation dummy and employment, using two different panels of British and Australian establishments. Splitting innovation into its two components, Vivarelli et al. (1996) showed that Italian manufacturing product and process innovation had opposite effects on the demand for labor, in line with what discussed in the previous sections. More recently, Lachenmaier and Rottmann (2011)—using a very comprehensive data set of German manufacturing firms over the period 1982–2002—put forward a dynamic employment equation augmented with proxies (dummies) of current and lagged product and process innovation. Their GMM-SYS estimates showed a significantly positive impact of different innovation measures on employment, but, partially in contrast with expectations and previous contributions, the authors found a higher positive impact of the process dummy rather than the product one. Finally, Ciriaci et al. (2016)—matching eight waves of the annual Spanish CIS—run quantile regressions using a longitudinal data set of 3,304 Spanish firms over the period 2002–2009. Their results showed that innovative (identified through a dummy), smaller, and younger firms are more likely to experience high and persistent employment growth episodes than non-innovative firms.
2. Turning our attention to continuous but discrete measures of technological progress, other studies have used either the number of "relevant innovations" or the number of patents. The advantage of these indicators is twofold: on the one hand, they are proxies of innovation outputs (and so closer to the possible employment impact of innovation); on the other hand, the relevant databases allow for longitudinal studies able to properly take into account methodological issues concerning the role of the unobservable and the occurrence of endogeneity problems. An interesting example of a study using the number of relevant innovations is Van Reenen (1997) who matched the London Stock Exchange database of manufacturing firms with the SPRU innovation database and obtained a firm-level panel over the period 1976–1982. Running GMM-DIF estimates, evidence of a positive employment impact of innovation has emerged from his regressions.

2 An interesting panel analysis has been conducted by Greenan and Guellec (2000) on 15,186 French companies from manufacturing industries over the 1986–1990 period. According to their study, innovating firms create more jobs than non-innovating ones, but the reverse turns out to be true at the sectoral level, where the overall effect is negative and only product innovation reveals to be job creating. This controversial employment impact of innovation at the firm and sectoral level might be due precisely to the "business stealing effect."

Considering patents, it is well known that not all the innovations can be patented, that patenting is a complex and very expensive procedure and so some firms deliberately do not patent and, finally, that patents may have dramatically different economic impacts (that is why most accurate studies use patents weighted by citations). For instance, Van Roy et al. (2015) estimated a dynamic and innovation-augmented labor-demand function using a longitudinal data set—matching different sources—covering almost 20,000 firms from Europe over the period 2003–2012. In their study, technical change is measured by forward-citation weighted patents and reveals its labor-friendly nature, as the outcome of GMM-SYS estimations. However—interestingly enough and consistently with other recent studies—this positive employment impact of innovation is statistically significant only for firms in the high-tech manufacturing sectors, while not significant in low-tech manufacturing and services.

3. Looking at continuous indicators of technological change, in the innovation studies the most commonly used proxy for technological change is the expenditures in R&D (*intra* and/or *extra moenia*). While this is a much more precise indicator and it is often available on an annual basis directly from companies' accounts, its main limitation lies in being a measure of an innovative input that not necessarily generates an innovative output. Moreover, it has to be noticed that R&D is mainly correlated with labor-friendly product innovations; this means that adopting this indicator for innovation implies an "optimistic bias" in terms of assessing the employment impact of innovation. However, Bogliacino et al. (2012)—using a longitudinal database covering 677 European manufacturing and service firms over the period 1990–2008—found that a positive and significant employment impact of R&D expenditures was detectable in high-tech manufacturing and service sectors but not in the more traditional manufacturing sectors.

Another continuous proxy of innovation input is the amount of "total innovation expenditures" as obtainable from CIS surveys (or similar questionnaire analyses). From a methodological point of view, this variable has advantages and disadvantages similar to the ones discussed with regard to the R&D expenditures. Controlling for lagged firms' employment and current sales (and so taking into account the "business stealing effect" discussed above), Piva and Vivarelli (2004, 2005)—applying a GMM-SYS procedure to a panel data set of 575 Italian manufacturing firms over the period 1992–1997—found evidence in favor of a positive (although small in magnitude) effect of gross innovative investment innovation on employment.

Finally, a third continuous measure of innovation is the "sales derived from new products," an information that can be extracted by the CIS surveys. The advantage of this proxy for technological change (differently from the previous two) is that it represents an output of the innovation activity; the disadvantage is that nothing similar is available for process innovation that remains constrained to be measured by a dummy. Using these variables for product and process innovation and firm-level data from CIS in four European countries (Germany, France, the UK, and Spain), Harrison et al. (2005, 2014) have concluded that process innovation tends to displace employment, while product innovation is fundamentally labor-friendly. However, compensation mechanisms are at work, especially in the service sectors, and reveal to be particularly effective through the increase in the demand for the new products. Finally, Hall et al. (2008)—applying the same model to a panel of Italian manufacturing firms over the period 1995–2003—have found a positive employment contribution of product innovation and no evidence of employment displacement due to process innovation.[3]

On the whole—although the previous microeconometric evidence is not fully conclusive about the possible employment impact of innovation—the vast majority of recent investigations provide evidence of a positive link, especially when R&D and/or product innovation are adopted as proxies for technological change and when high-tech sectors are considered. A weaker evidence of a labor-saving impact of process innovation is also detected by some studies, especially when low-tech manufacturing is at the core of the analysis. However, a common shortcoming of the extant literature is that virtually all previous studies have neglected the crucial role of the ETC, exclusively focusing of the other indicators of innovation: R&D, patents, dummies for product and process innovation, etc. The attempt of this study is to fill this gap.

3 Within the related stream of literature devoted to investigate the nature and impact of green technologies (see Crespi et al., 2015), Gagliardi et al. (2016)—also using Italian data—have found that the job creation impact of green product innovation is significantly larger than the one generated by non-environmental product innovation.

Indeed, innovative investments, R&D, and patents are much more correlated with product than process innovation, and this implies a systematic under evaluation of the possible labor-saving effect of process innovation. On the other hand, measuring process innovation through a simple dummy (see above) is very rough and does not take into account the intensity of this innovation activity (obviously compressing both the within and between firms variability).

In fact, most of process innovations are implemented through the so-called ETC, introduced through gross investment. This technological input—which is often dominant in economies and sectors, where small and medium enterprises (SMEs) are prevalent—is generally very difficult to measure because of the complexity in singling out the different components of capital formation (those merely expansionary and those characterized by ETC and by a possibly labor-saving nature). In this context, disentangling ETC is indeed an important novelty of this study (see the next section, where our empirical strategy is described in detail).

3. Methodology and hypotheses to be tested

As mentioned in the previous sections, two are the main sources of innovation: on the one hand, the R&D investment; on the other hand, the "ETC."

R&D expenditures are considered as the main innovative input in the approach originally proposed by Griliches (1979) pointing to the concept of the "Knowledge Production Function" as being a feasible tool for describing the transformation process that runs from innovative inputs to innovative outputs. Indeed, a vast literature has identified a strong and significant link between R&D investment, innovation, and ultimately productivity gains, demonstrating that R&D is a main driver of technological progress both at the macro, sectoral, and micro level (for an articulated model, see Crépon et al., 1998; for comprehensive surveys on this topic, see Mairesse and Mohnen, 2001; Hall et al., 2009; Mohnen and Hall, 2013).

However, the innovation literature suggests that it is product innovation which is significantly based on formal R&D: for instance Parisi et al. (2006) and Conte and Vivarelli (2014) found robust and significant evidence that R&D increases the likelihood of introducing product innovation.

On the other hand, process innovation is much more related to ETC acquired by investment in new machinery and equipment (see Freeman et al., 1982). Indeed, the embodied nature of technological progress and the effects related to its spread in the economy were originally theoretically discussed by Salter (1960) (see also Solow, 1960; Jorgenson, 1966); later, vintage capital models have been put forward to describe how the replacement of old equipment is the main way through which firms introduce process innovation (see Clark, 1987; Hulten, 1992; Greenwood et al., 1997; Hercowitz, 1998; Mukoyama, 2006).

In other words, while R&D is the main vehicle for introducing disembodied knowledge, innovative investment and updated scrapping are the ways how firms introduce more advanced process innovation.

Moreover, sectoral and microeconomic studies show that R&D is crucial in large firms and more advanced sectors, while ETC assumes a dominant role in SMEs, more traditional sectors, and developing countries (see Pavitt, 1984; Acs and Audretsch 1990; Audretsch and Vivarelli, 1996; Brouwer and Kleinknecht, 1996; Conte and Vivarelli, 2014; Haile et al., 2017).

Summing-up, R&D and ETC are the main drivers of technological progress, with the former more related to product innovation and the latter more related to process innovation. Obviously enough, the distinction between product and process innovation is often ambiguous from an empirical point of view (see, for instance, the diffusion of computers and telecommunication devices), and in many cases the two forms of innovation are strictly interrelated. However, from a theoretical point of view, we can conclude that two are the innovative inputs and two are the innovative outputs, with R&D mainly (but not only) related to product innovation and ETC mainly (but not only) related to process innovation. Figure 1 represents what discussed so far pointing to the main links between innovative inputs and innovative outputs (see Vivarelli, 2013).

Turning our attention to the main issue of this article and making value from what discussed so far, Figure 1 also depicts the likely overall impacts of process and product innovation on employment. These are represented in the right panel of Figure 1: on the one hand, process innovation creates a direct labor-saving effect, mainly related to the introduction of machineries that allow producing the same amount of output with fewer workers; on the other hand, product innovation entails a job-creating effect through either the expansion of the existing markets or the emergence of entirely new markets.

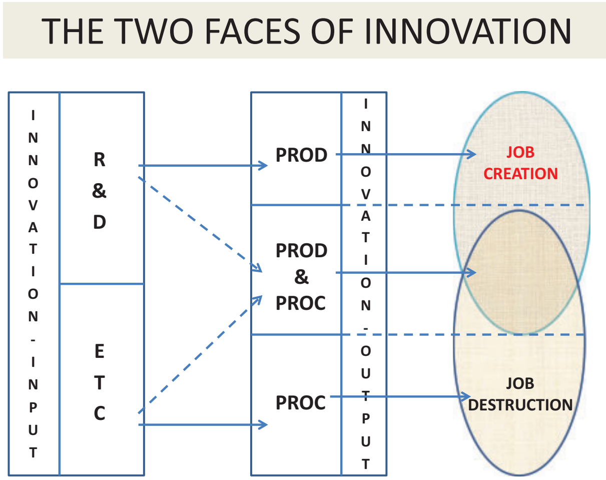

Figure 1. Innovation inputs, innovation outputs, and their likely impacts on employment.

Obviously enough (see also what discussed in Section 2), both R&D and ETC are innovation inputs and so their relationship with the final employment impact is indirect and mediated by the innovation outputs, as sketched in Figure 1. While considering ETC together with R&D is the main novelty of this work, using proxies of innovative inputs is probably its main limitation. However, what discussed above in this section and previous evidences surveyed in Section 2 allow to consider our two key impact variables as proper indicators of different types of innovation activities, structurally linked to different innovation outputs, and likely to different employment impacts.

Therefore, taken into account the discussion above and the extant empirical literature discussed in Section 2, the econometric investigations carried on in the next sections will test the following hypotheses:

H1: Consistently with the previous literature, overall innovation activities and particularly R&D expenditures should be related to an increase in employment at the firm's level.
H2: In contrast, ETC should be related either to a decrease in firm's employment or should display a non significant effect.[4]

In addition, firms' sectoral and size dimensions will be separately investigated, to test whether firm's size and sectoral belonging play a role in affecting the innovation/employment relationship. In this perspective, the previous literature (see Section 2) suggests that the possible job creation effect of innovation is most notably detectable in the high-tech sectors.

In contrast, previous studies taking into account firm's size are virtually absent; however—taking into account what discussed above—it is plausible to assume that basic R&D and radical product innovation are more likely to occur in large firms, which are also dominant in some high-tech sectors, such as chemical, pharmaceutical, space and aircrafts, and electronics. In contrast, SMEs are much more characterized by applied R&D (if any), ETC, process innovation, and incremental product innovation. Therefore, the following two additional hypotheses can be put forward:

H3: Consistently with the previous literature, innovation variables should be more positively related to employment in the high-tech sectors rather than in the low-tech ones.
H4: Innovation variables should be more positively related to employment in large firms rather than in SMEs.

Consistently with the microeconometric literature surveyed in Section 2 and following the most recent approaches adopted in testing the employment impact of innovation using longitudinal firm-level data sets, the hypotheses above will be tested through a stochastic version of a standard labor demand augmented by including innovation (see, for

4 ETC gives rise to a direct job-destructive effect of process innovation; however—as discussed in the Introduction—market compensation forces have to be taken into account in assessing the very final impact of ETC and process innovation in terms of employment levels.

similar approaches: Van Reenen, 1997; Lachenmaier and Rottmann, 2011; Bogliacino et al., 2012; Van Roy et al., 2015).

In particular, for a panel of firms i over time t, our preferred specification should be:

$$l_{i,t} = \beta_1 y_{i,t} + \beta_2 w_{i,t} + \beta_3 gi_{i,t} + \beta_4 innov_i + (\varepsilon_i + \nu_{i,t}) \;\; i = 1, .., n; \;\; t = 1, .., T, \tag{1}$$

where small letters denote natural logarithms, l is labor, y output, w labor cost, gi is gross investments, *innov* denotes our available innovation proxies, ε is the idiosyncratic individual and time-invariant firm's fixed effect, and ν the usual error term.

Unfortunately, the Italian CIS database described in the next section does not allow to properly test the specification reported in Equation (1). In particular, due to an excessive collinearity between value added and capital formation ($\rho = 0.83$) in our data set, we decided to test a simplified version of Equation (1), dropping the investment variable[5]:

$$l_{i,t} = \beta_1 y_{i,t} + \beta_2 w_{i,t} + \beta_3 innov_{i,t} + (\varepsilon_i + \nu_{i,t}) \quad i = 1, .., n; \quad t = 1, .., T\,. \tag{2}$$

4. Data and descriptive statistics

The empirical test of the hypotheses listed above will be developed using a unique and novel longitudinal data set, based on the merge of different Italian CISs, complemented with additional information taken from companies' accounts (see ISTAT and Università Cattolica del Sacro Cuore, 2014[6]).

In more detail, the Italian CIS—as it is the case in all the other EU member states—is submitted to manufacturing and services firms on a regular basis (every 3/4 years), and it is representative at both sectoral and firm size level of the entire population of companies with more than 10 employees.[7] Specifically addressed to measure and to assess technological change occurring at the company level, the CIS collects data on product and process innovation, on resources allocated to innovation activities as well as other information regarding public support to innovation, cooperation activities for innovation, and obstacles to innovation. The collected data are both qualitative and quantitative, with the former referred to the 3-year period covered by the survey and the latter referring to the final year of the covered time span.

In our analysis, we specifically refer to four CIS waves: CIS3 (1998–2000 period), CIS4 (2002–2004), CIS6 (2006–2008), and CIS7 (2008–2010) including, respectively, 15,512, 21,854, 19,904, and 18,328 firms.[8] It has to be noted that CIS is not designed to originate a proper panel structure, addressing more the issue of representativeness at time t rather than the target to track the same firms over time. As a result, the overlapping between the different surveys is extremely limited, accounting for few hundreds of firms, basically concentrated in the manufacturing sectors and characterized by a medium/large average size.

Moreover, CIS data—while being extremely detailed with regard to the innovation activities—do not offer economic information which is extremely relevant to our analysis, such as labor costs, sales, investment, and value added. To overcome this problem, the whole CIS database has been matched with information coming from the Italian Statistical Business Register (ASIA), created by the Italian National Statistical office (ISTAT) and integrating different administrative sources recording all the relevant economic and financial variables at the firm level (number of employees, capital structure, productivity indexes, etc.). Since quantitative variables in each CIS are referred to the

5 Since we had to exclude capital formation from the tested specification (2), the wage variable (here measured as the cost of labor per employee, see Table 1), rather than simply representing the price of the workforce, takes into account the substitution effect in between the two productive inputs: capital and labor.

6 The merge of Italian CIS surveys is the result of a joint research project (launched in 2013 and still in progress) between the Italian National Institute of Statistics (ISTAT, Regional Office for Lombardy) and the Università Cattolica del Sacro Cuore (UCSC) titled: "Social capital, Innovation and Finance: empirical evidences on the manufacturing sector in Italy and in Lombardy region."

7 In particular, the Italian CIS is a sample survey for firms with 10–249 employees and a census survey for firms with more than 250 employees.

8 The unreliable CIS5 has been excluded, since that particular survey was mainly conducted a long time after the relevant 3-year period, resulting in highly incomplete and mainly interpolated data.

Table 1. List of variables

Variables	Description	Source
Employment	Number of employees	CIS
Value added	Value added	ASIA
Labor cost	Cost of labor per employee	ASIA
Total innovative expenditures	All the expenditures devoted to innovation activities, including internal and external R&D, ETC, and other innovative expenditures (technological acquisition, engineering, training, marketing)	CIS
Internal R&D	Intramural (*in-house*) R&D	CIS
ETC	Innovative expenditures devoted to the acquisition of machinery, equipment, and software (excluding expenditures on equipment for R&D)	CIS

Note: All the monetary variables have been deflated using the Italian GDP deflator (2010 = 100)—OECD source.

last year of the 3-year period covered by the survey, firms' economic and financial data were also matched using the same year (i.e., firm's accounting data in 2000 for the CIS3, and so on, so forth).

One of the implications of the matching between the CIS and ASIA database has been the exclusion of companies operating in the service industries: therefore, our analysis will necessarily focus on the manufacturing sector. Moreover, the very limited overlap between the different CIS and the matching procedure has reduced our workable panel to 288 firms over four time periods.

It is important to note that CIS data also include non-innovative firms, while our study is specifically devoted to the employment impact of innovation; therefore, our sub-sample of innovators was then selected identifying innovators as those firms declaring that they had introduced either product or process innovations, or had started innovative projects (then dropped or still-to-complete) in at least a CIS wave (this is also the official procedure adopted by ISTAT in each survey as a filter to single out non-innovators). However, since previous data selections have limited our workable panel to manufacturing medium–large companies, this further step only implied the loss of few firms, ending up with 270 companies.

In a further step, we had to deal with some missing values in accounting data, with particular reference to the output measures (sales and value added); to minimize the loss in terms of available information, we retained value added as a proxy for output. Finally, we dropped the top 5 percentiles in terms of innovative intensity (total innovative expenditures over value added) to exclude non-reliable outliers, ending up with a final unbalanced panel of 265 firms (892 observations).

The following Table 1 reports the variables, their definitions, and the relevant statistical sources.

Our aggregate innovation proxy will be the total innovation expenditures (as a general indicator of the overall firm's innovative efforts), while the hypotheses *H1* and *H2* will be tested using our specific R&D and ETC indicators. In more detail, we will focus on "in house" R&D expenditures on the one hand and, on the other hand, on the embodied technologies measured as those innovation expenditures specifically devoted to the implementation of new machinery, equipment and software.[9] Then, hypotheses *H3* and *H4* will be investigated using the OECD classification (Hatzichronoglou, 1997) splitting manufacturing sectors into high- and low-tech sectors, and the EU threshold of 250 employees splitting firms into SMEs and large ones.

Table 2 reports some descriptive statistics of the variables used in the following econometric analysis (see Section 5).

5. Results

The following Table 3 reports the simple correlation coefficients among the log-transformed variables used in the empirical tests using the data described in the previous section. As can be seen, our dependent variable (employment) is positively correlated with all the independent variables, with a key role played—not surprisingly—by the value added. By the same token, again not surprisingly, R&D and ETC also result to be highly correlated with total innovative expenditures. Obviously enough, this preliminary evidence—pointing to a positive employment impact of

9 Internal R&D and ETC represent—on average—more than three-fourth of the "Total innovative expenditures."

Table 2. Descriptive statistics

N = 892 *n* = 265	Mean	Standard deviation		Minimum	Maximum
Employment	547.3	Overall	648.2	12	4969
		Between	763.3		
		Within	137.9		
Value added	507,633.6	Overall	797,749.3	6029.9	9,707,794
		Between	894,526.7		
		Within	171,915.3		
Cost of labor per employee	478.3	Overall	127.3	95.8	996
		Between	126.1		
		Within	50.9		
Total innovative expenditures	31,541.7	Overall	70,794.6	0	725,490.7
		Between	82,812.6		
		Within	27,281.7		
Internal R&D	13,522.1	Overall	37,217.5	0	469,390
		Between	43,954.1		
		Within	12,430.2		
ETC	10,577	Overall	32,859.9	0	462,330
		Between	29,640.5		
		Within	20,403.8		

Note: Monetary variables are expressed in hundreds.

Table 3. Correlation matrix

Variables	ln(Employment)	ln(Value added)	ln(Cost of labor per employee)	ln(Total innovative expenditures)	ln(Internal R&D)	ln(ETC)
ln(Employment)	1					
ln(Value added)	0.924	1				
ln(Cost of labor per employee)	0.329	0.566	1			
ln(Total innovative expenditures)	0.362	0.379	0.213	1		
ln(Internal R&D)	0.321	0.329	0.223	0.745	1	
ln(ETC)	0.283	0.301	0.116	0.725	0.391	1

innovation—can be entirely due to a firm's size effect or be affected by common unobservable firm's characteristics. Only the following econometric analysis can overcome these problems and properly test the roles of the multivariate relationships affecting employment dynamics.

Given the specification (2), we have run fixed-effects (FE) estimates, so controlling for unobservable firm's characteristics.[10] As reported in the following Tables 4–6, time dummies were also included (generally resulting as jointly significant), heteroscedasticity robust standard errors have been used, and the within-*R*-squared always resulted satisfactory.

The results based on the overall sample and using our three alternative proxies of firm's innovation efforts (total innovation expenditures, internal R&D and ETC) are reported in the following Table 4. As can be seen, the labor-demand controls (value added and cost of labor) always display the expected sign (respectively, positive and negative), a 99% level of statistical significance and a considerable magnitude (showing an employment elasticity around 0.5). These outcomes—further confirmed in the following Tables 5 and 6—are highly consistent with those from the extant empirical literature (see Section 2).

10 The Hausman's tests comparing the FE with the random effects estimations were always in favor of the former (results available from the authors under request).

Table 4. Econometric results—manufacturing sectors—whole sample. Dependent variable: ln(Employment)

Independent variables	Fixed effects—whole sample			
	(1)	(2)	(3)	(4)
ln(Value added)	0.485***	0.487***	0.492***	0.488***
	(0.045)	(0.047)	(0.046)	(0.047)
ln(Cost of labor per employee)	−0.516***	−0.518***	−0.518***	−0.518***
	(0.116)	(0.122)	(0.121)	(0.122)
ln(Total innovative expenditures)	0.005**			
	(0.002)			
ln(Internal R&D)		0.004*		0.003
		(0.002)		(0.003)
ln(ETC)			0.002	0.001
			(0.002)	(0.002)
Time dummies	Yes	Yes	Yes	Yes
Constant	2.820***	2.801***	2.773***	2.810***
	(0.844)	(0.887)	(0.873)	(0.878)
Wald test time dummies (*P*-value)	2.42* (0.066)	2.20* (0.088)	2.61* (0.052)	2.27* (0.081)
R^2 (within)	0.42	0.42	0.42	0.42
Number of observations			*892*	
Number of firms			*265*	

Notes: Robust standard errors in parentheses; *significance at 10%; **5%; ***1%.

Table 5. Econometric results—manufacturing sectors—high-tech and low-tech. Dependent variable: ln(Employment)

Independent variables	Fixed effects—high-tech				Fixed effects—low-tech			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
ln(Value added)	0.412***	0.420***	0.427***	0.420***	0.537***	0.540***	0.541***	0.539***
	(0.065)	(0.065)	(0.065)	(0.066)	(0.059)	(0.062)	(0.060)	(0.061)
ln(Cost of labor per employee)	−0.593***	−0.608***	−0.629***	−0.609***	−0.521***	−0.518***	−0.518***	−0.519***
	(0.154)	(0.155)	(0.151)	(0.156)	(0.138)	(0.145)	(0.142)	(0.143)
ln(Total innovative expenditures)	0.009**				0.004			
	(0.005)				(0.002)			
ln(Internal R&D)		0.007*		0.007		0.002		0.001
		(0.004)		(0.005)		(0.003)		(0.003)
ln(ETC)			0.002	0.0003			0.002	0.002
			(0.003)	(0.004)			(0.003)	(0.003)
Constant	4.416***	4.432***	4.507***	4.437***	2.103**	2.066*	2.055*	2.076*
	(0.821)	(0.817)	(0.846)	(0.850)	(1.063)	(1.122)	(1.089)	(1.106)
Wald test time dummies(*P*-value)	2.47* (0.066)	2.32* (0.080)	3.17** (0.027)	2.32* (0.080)	2.68** (0.049)	2.48* (0.063)	2.95** (0.035)	2.61* (0.053)
R^2 (within)	0.47	0.47	0.46	0.47	0.42	0.42	0.42	0.42
Number of observations		*340*				*552*		
Number of firms		*108*				*157*		

Notes: Time dummies always included; robust standard errors in parentheses; *significance at 10%; **5%; ***1%.

Table 6. Econometric results—manufacturing sectors—SMEs and large firms. Dependent variable: ln(Employment)

Independent variables	Fixed effects—SMEs				Fixed effects—large firms			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
ln(Value added)	0.506***	0.517***	0.499***	0.507***	0.433***	0.432***	0.442***	0.435***
	(0.010)	(0.104)	(0.102)	(0.102)	(0.045)	(0.046)	(0.046)	(0.046)
ln(Cost of labor per employee)	−0.299	−0.303	−0.314	−0.332	−0.505***	−0.512***	−0.501***	−0.514***
	(0.268)	(0.265)	(0.262)	(0.252)	(0.131)	(0.138)	(0.141)	(0.142)
ln(Total innovative expenditures)	0.003				0.005**			
	(0.004)				(0.002)			
ln(Internal R&D)		−0.003		−0.007		0.007***		0.008***
		(0.005)		(0.006)		(0.002)		(0.002)
ln(ETC)			0.007	0.009			−0.001	−0.003*
			(0.005)	(0.006)			(0.002)	(0.002)
Constant	0.633	0.560	0.793	0.826	3.785***	3.852***	3.699***	3.830***
	(2.081)	(2.119)	(2.045)	(2.001)	(0.796)	(0.820)	(0.856)	(0.834)
Wald test time dummies (*P*-value)	1.21	1.19	1.04	1.08	1.88	1.67	2.42*	1.85
	(0.312)	(0.319)	(0.377)	(0.360)	(0.135)	(0.174)	(0.068)	(0.141)
R^2 (within)	0.32	0.32	0.33	0.34	0.47	0.48	0.47	0.48
Number of observations	*315*				*577*			
Number of firms	*99*				*185*			

Notes: Time dummies always included; robust standard errors in parentheses; *significance at 10%; **5%; ***1%.

Turning our attention to the main variables of interest, our general proxy for innovation appears to have a positive and significant (95%) employment impact, although very small in magnitude: according to our estimate, a 100% increase in total innovative expenditures would imply a 0.5% increase in employment. Moreover, this labor-friendly effect is barely significant when the sole *in-house* R&D expenditures are considered and fades away when ETC is included as a proxy for innovation activities. Finally, when jointly included (Column 4), both R&D and ETC do not display any significant impact on employment levels.[11]

Consistently with the previous empirical literature (see Section 2), on aggregate the link between innovation and employment turns out to be positive, but negligible in size. However, when ETC is taken into account, the labor-saving nature of innovation fully counterbalances any possible job creation effect, and the positive employment effect disappears; this is a novel result in comparison with the extant literature that never addressed the role of ETC explicitly.

Therefore, the evidence provided in Table 4 weakly supports our *H1* hypothesis, while partially confirms our *H2* hypothesis pointing out to a not significant—albeit not negative—employment effect of ETC[12].

To test hypothesis *H3*, in Table 5 the results from the separate estimates for firms belonging to high- and low-tech manufacturing sectors are reported. As can be seen, the aggregate outcomes discussed above are entirely due to the

11 R&D and ETC are components of the total innovation expenditures, and this has prevented us from jointly including the three variables in our estimated specification (see also the very high correlation coefficients in Table 3, Column 4).

12 Dealing with only four waves prevents us from running a proper dynamic analysis. However, both as a robustness check and to facilitate the comparison with other studies published in this special issue, Table A1 puts forward an OLS specification where both the dependent variables, value added and the cost for labor, are expressed in annual rates of growth, while the innovative variables—being already annual flows—are kept as in the benchmark specification tested in Table 4. It has to be noticed that the available observations decrease by one quarter (223 observations) due to the availability of ASIA accounting data only from year 2000. A further decrease of 37 observations is due to missing data in years 2003, 2007, and 2009. As can be seen, the results from Table 4 are fully confirmed both with regard to our key variables and the controls.

firms operating in the high-tech. With regard to the low-tech sectors, neither the overall innovative expenditures nor the internal R&D nor the ETC seem to have a significant impact on employment (both when separately and jointly included). In contrast, in the high-tech manufacturing sectors, the positive employment impact of the overall innovative expenditures and of the sole in-house R&D expenditures emerge with the same levels of statistical significance and with higher coefficients in comparison with those obtained in Table 4.

Therefore, *H3* is confirmed: consistently with previous evidence from the extant literature, innovation and employment are positively linked only in the high-tech sectors, where elasticities increase to 0.7% or 0.9%; in contrast, in low-tech manufacturing, innovation (in its various aspects) does not reveal any labor-friendly nature.

Finally, Table 6 reports the estimated coefficients separately for the SMEs (firms with less than 250 employees, accordingly to the European Union (EU) definition) and for their larger counterparts. What emerges is that a robust positive link between innovation (both total expenditures and in-house R&D) is detectable in the large firms, while no significant impacts emerge as far as SMEs are concerned. Interestingly enough, in large manufacturing firms, the R&D expenditures reach their highest level of significance (99%) obtained so far, both when solely included and when inserted jointly with ETC. Moreover, in the last specification, a barely significant negative employment impact of ETC emerges. Therefore, our hypothesis *H4* is strongly confirmed by these regressions, while *H2*—albeit limited to large firms—receives a further support.

Summing-up, the estimates reported in Tables 4–6 seem to confirm a positive—although small in magnitude—employment impact of innovation; however, this labor-friendly effect is statistically significant only when the total innovative efforts and in-house R&D expenditures are considered, while never significant when ETC is used as proxy of innovation (with one exception, however pointing out to a negative effect). Moreover, the detected positive employment impact of innovation is totally due to the firms operating in the high-tech manufacturing and to the larger firms.[13]

6. Conclusions

In Sections 1–3, we discussed the links relevant to the investigated issue, starting from the different ways how technology is implemented into the economy and ending with the discussion of its final possible employment impacts. In this framework, we clarified that R&D expenditures generating product innovation are likely to be labor-friendly, while ETC as a way to introduce process innovation might reveal a labor-destroying nature. However, on the one hand, product and process innovation are often interrelated and, on the other hand, the direct labor-saving impact of process innovation may be—at least partially—compensated by different market mechanisms which may assure the re-absorption of the technological unemployment initially generated by process innovation.

Taken into account what summarized above and the extant empirical literature discussed in Section 2, the econometric investigations carried on in this article have been addressed to test the following four hypotheses, here recalled for reader's convenience:

H1: Consistently with the previous literature, innovation activities, and particularly R&D expenditures should be related to an increase in employment at the firm's level.
H2: In contrast, ETC should be related either to a decrease in firm's employment or should display a non significant effect.
H3: Consistently with the extant literature, innovation variables should be more positively related to employment in the high-tech sectors rather than in the low-tech ones.
H4: Innovation variables should be more positively related to employment in large firms rather than in SMEs.

Our estimates based on the Italian novel data set described in Section 4 allow us to draw the following conclusions.

13 The short nature of our panel does not allow us to properly deal with the possible endogeneity of our key impact variables (in fact a GMM methodology requires at least $t = 6$ for a cautious estimation). However, we run a robustness check instrumenting our three technological variables through their lagged values (the number of observations dropping from 892 to 621). Interestingly enough, our outcomes are largely confirmed with regard both the aggregate regression and the ones split according to firm's size and technological level (results available from the authors upon request).

H1: This hypothesis is weakly confirmed by our estimates; on the whole, a generalized and highly significant labor-friendly nature of innovation is not detectable in the present study. In more detail, our general proxy for innovation (total innovation expenditures) appears to have a positive and significant employment impact, although almost negligible in magnitude. Moreover, this labor-friendly effect is barely significant when the sole in-house R&D expenditures are considered and fades away when ETC is included as a proxy for innovation activities. Finally, when jointly included, both R&D and ETC do not display any significant impact on employment levels.

H2: This hypothesis is confirmed by our estimates: ETC never exhibits a labor-friendly nature and in one case (within larger companies) turns out to generate a (barely) significant labor-saving impact.

H3: This hypothesis is strongly confirmed on the basis of our regressions: the positive employment impact of the total innovation expenditures and the sole R&D expenditures is totally due to the high-tech firms.

H4: This hypothesis is confirmed by our estimates: job creation by total innovation expenditures and R&D is significant within large firms but not significant at all within SMEs.

Our results cannot be entirely generalized due to the limitations of both our data set and our microeconometric specification (see Sections 4 and 5). However, they seem to confirm that a possible job creation impact of innovation is limited to the R&D component of the innovation expenditures, to the high-tech sectors and to the larger firms.

Therefore—from a policy perspective—innovation policies addressed to maximize the positive employment impact of innovation should be targeted to R&D subsidies in favor of large companies operating in the most advanced sectors.

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Appendix

Table A1. Econometric results—manufacturing sectors—whole sample. Dependent variable: employment annual rate of growth

Independent variables	Ordinary least squares—whole sample			
	(1)	(2)	(3)	(4)
Value added (annual rate of growth)	0.167***	0.168***	0.166***	0.168***
	(0.038)	(0.038)	(0.038)	(0.038)
Cost of labor per employee (annual rate of growth)	−0.419***	−0.423***	−0.421***	−0.423***
	(0.071)	(0.071)	(0.072)	(0.071)
ln(Total innovative expenditures)	0.003***			
	(0.001)			
ln(Internal R&D)		0.002**		0.002*
		(0.001)		(0.001)
ln(ETC)			0.002	0.001
			(0.001)	(0.001)
Time dummies	Yes	Yes	Yes	Yes
Constant	−0.019**	−0.010	−0.009	−0.014*
	(0.009)	(0.007)	(0.007)	(0.008)
Wald test time dummies (*P*-value)	0.20 (0.822)	0.17 (0.841)	0.06 (0.944)	0.14 (0.867)
R^2	0.25	0.25	0.25	0.25
Number of observations	*632*			
Number of firms	*265*			

Notes:—Robust standard errors in parentheses;—*significance at 10%;**5%;***1%.