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R&D, Embodied Technological Change and Employment: Evidence from Italian Microdata

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November 2016

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Institute for the Study
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ABSTRACT

R&D, Embodied Technological Change and Employment: Evidence from Italian Microdata*

This paper explores the employment impact of innovation activity, taking into account both R&D expenditures and embodied technological change (ETC). We use a novel panel dataset 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

Keywords: technology, innovation, R&D, embodied technological change, employment

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* The novel dataset used in this study has been built within 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”. In this work, the access to the anonymized microdata (“Micro_Manu.Istat 2000-2010” dataset) and the whole data management have been carried out exclusively by Laura Barbieri.

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 and 1988) based on 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 and 2014; Frey and Osborne, 2013).

Moreover, technological trends have interlinked with the recent financial and economic crises and with the slow recovery afterwards, often showing a jobless nature. In the background of this scenario, international organizations - including the UNIDO, IDB and the 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 labour-saving innovations creates 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 non-competitive practices, while additional incomes due to technical change are not necessarily invested in labour-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, 2016).

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 paper 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. Firstly, filling a gap in the extant literature, our analysis takes into account both R&D and the "embodied technological change", 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). Secondly, we make use of a unique and novel database where different waves of Italian CIS (Community Innovation Survey) are merged into a longitudinal panel. Thirdly, 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 paper 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 empirical hypotheses; Section 4 provides a description of the dataset and some descriptive statistics; econometric results are discussed in Section 5, while Section 6 briefly concludes.

2. The empirical literature

Whilst theoretical economists have been developing stylized models about the employment impact of process and product innovation, applied economists had to identify

adequate ways to measure process and product innovation and their employment impacts. When considering this issue, a number of critical methodological issues arise.

First of all, innovation is a complex phenomenon not easy to be measured. Among the most used proxies, product and process innovation dummies 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.

Looking at continuous indicators of technological change, the most commonly used proxy 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, while R&D is the most available and commonly used proxy for innovation, it has to be noticed that it is mainly correlated with labour-friendly product innovations; this means that adopting this indicator for innovation implies an "optimistic bias" in terms of assessing the employment impact of innovation. On the other side, most of process innovations are instead implemented through the so-called "embodied technological change" (ETC), introduced through gross investment. This technological input - which is often dominant in economies and sectors where 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 a by labour-saving nature). In this framework, this paper is one of the very few studies able to disentangle ETC; this is indeed an important novelty of this study (see the next section where our empirical strategy is described in detail).

Turning our attention to continuous measures of innovation outputs, two are the most common indicators used by the empirical studies. On the one hand, works based on CIS data make use of the "sales derived from new products", as a continuous measure of product innovation (in contrast with a simple dummy, see above). On the other hand, other studies rely on patents. However, 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).

Together with the choice of a proper indicator of technological change, it is crucial to clearly identify the level of investigation: whether macroeconomic, sectoral or microeconomic. Each level of analysis exhibits *pros* and *cons*.

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 above). Indeed, only the microeconometric empirical analysis can grasp the very nature of firms' innovative activities and throws some light on the actual ways how new products may generate new jobs and labour-saving process innovation may destroy old ones.

However, there are limitations associated to 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. 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 labour-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 ("business stealing" effect).

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).

A third level of complexity concerning the empirical studies of the link between innovation and employment is the time/individual dimension of the observations used in the empirical analyses. Firm-level studies either use cross-sectional data or, more recently, cross-sectional/time-series (longitudinal) data. Indeed, only the latter allow controlling for time-invariant characteristics of the investigated companies, assuring a proper check for endogeneity and using more advanced econometric techniques to be applied to longitudinal data.

In this paper, a microeconometric empirical analysis based on longitudinal data will be proposed (see next sections). Therefore, keeping the aim and nature of this paper and the above-discussed methodological remarks in mind, our attention can be now turned to a detailed survey of previous microeconometric literature.

Indeed, the literature devoted to the microeconometric investigation of the link between technological change and employment has started in the '90s and it is still flourishing[1]. We will deal exclusively on firm-level panel data studies (see the discussion above) and we will group them accordingly to their geographical focus.

Starting from the UK, Van Reenen (1997) 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 emerged. This result turned out to be robust after controlling for fixed effects, dynamics and endogeneity. Consistently, Blanchflower and Burgess (1998) confirmed a positive link between innovation (although roughly

[1] Starting from Berman et al. 1994, a parallel stream of literature has investigated the skill-biased nature of new technologies; this issue is out of the scope of the present study (see also Machin and Van Reenen, 1998; Piva et al., 2005; Acemoglu and Autor, 2011; Bogliacino and Lucchese, 2016)

measured with a dummy) and employment using two different panels of British and Australian establishments.

In France, an interesting panel analysis was conducted by Greenan and Guellec (2000) on 15,186 companies from manufacturing industries over the 1986-1990 period. According to this study, innovating firms created more jobs than non-innovating ones, but the reverse turned out to be true at the sectoral level, where the overall effect was negative and only product innovation revealed to be job-creating. This controversial employment impact of innovation at the firm and sectoral level might be due to the 'business stealing' effect discussed above.

In the case of Italy, even taking the "business stealing" effect fully into account by controlling for lagged firms' employment and current sales, Piva and Vivarelli (2004 and 2005) found evidence in favor of a positive effect of innovation on employment. In particular (applying a GMM-SYS procedure to a panel dataset of 575 manufacturing firms over the period 1992-1997) the authors provided evidence of a positive, although small in magnitude, impact of firm's gross innovative investment on employment. Furthermore, Hall et al. (2008) on a panel of Italian manufacturing firms over the period 1995-2003, found a positive employment contribution of product innovation and no evidence of employment displacement due to process innovation[2].

As far as Germany is concerned, Lachenmaier and Rottmann (2011) - using a very comprehensive dataset of manufacturing firms over the period 1982-2002 - put forward a dynamic employment equation including wages, gross value added, years and industries controls and alternative 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 process rather than product innovation.

[2] Within the 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.

Turning our attention to Spain, Ciriaci et al. (2016) - matching eight waves of the annual Spanish Community Innovation Survey (CIS) - run quantile regressions using a longitudinal dataset of 3.304 Spanish firms over the period 2002–2009. Their results showed that innovative, smaller and younger firms are more likely to experience high and persistent employment growth episodes than non-innovative firms.

Moving outside Europe, Yang and Lin (2008) estimated a dynamic labour demand augmented with innovation, as proposed by Van Reenen (1997). In particular, they run GMM-DIF regressions using a five-year balanced panel including 492 firms listed on the Taiwan Stock Exchange over the period 1999-2003. Interestingly enough, the available data allowed the authors to alternatively include four measures of innovation: R&D, patents, patents addressed to process innovation and patents addressed to product innovation. Their results pointed to a positive and significant employment impact of all the four technological proxies where the entire sample was tested, while process innovations revealed a labour-saving impact when low R&D-intensive industries were singled out.

Benavente and Lauterbach (2008) applied Harrison et al. methodological approach (2005 and 2014; see below) to a sample of 514 Chilean manufacturing firms over the period 1998-2001. Consistently with what found by Harrison et al. (2005 and 2014), their instrumental variable estimates singled out a positive and significant employment impact of the sales due to product innovations, but the coefficient associated to process innovation did not come out significant.

Also based on Harrison et al. (2005 and 2014) is the study by Mejia and Granada (2014), who used data on Colombian firms (both in manufacturing and services) over the period 2007-2011. As common in these bunch of studies based on the Harrison et al. (2014) approach, the continuous variable measuring the sales due to new products turns out to have a positive and significant employment effect; however, in this paper the dummy 'process only' turned out to be not significant. Interestingly enough, when manufacturing data are split into high and low-tech sectors, the labour friendly nature of product innovation loses its significance in the low-tech industries.

As far as the US are concerned, Coad and Rao (2011) focused on high-tech manufacturing industries over the period 1963-2002 and investigated the impact of a

composite innovativeness index (comprising information on both R&D and patents) on employees. The main outcome of their quantile regressions was that innovation and employment were positively linked and innovation had a stronger impact for those firms that revealed the fastest employment growth.

Other more recent studies try to overcome a single-country dimension.

For instance, 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.

Also dealing with European firms, Evangelista and Vezzani (2012), who distinguished between the direct effect of process innovation on employment and its effect through increased sales, found - using CIS-4 data for six European countries - that the substitution effect of process innovation on employment was not statistically significant.

Using firm level data from CIS in four European countries (Germany, France, UK, Spain), the already mentioned work by Harrison et al. (2014) put forward a testable model able to distinguish the relative employment impact of process and product innovation. The authors concluded that process innovation tended to displace employment, while product innovation was fundamentally labour-friendly. However, compensation mechanisms were at work, especially in the service sectors, and revealed to be particularly effective through the increase in the demand for the new products.

More recently, Van Roy et al. (2015) estimated a dynamic and innovation-augmented labour-demand function using a longitudinal dataset - matching different sources - covering almost 20,000 firms from Europe over the period 2003-2012. In this study, technical change is measured by forward-citation weighted patents and reveals its labour-friendly nature, as the outcome of GMM-SYS estimations. However - interestingly enough and consistently with previous 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.

Finally, Dachs et al. (2015) also applied the model developed by Harrison et al. (2005 and 2014) to investigate the employment impact of product innovation (proxied by the sales due to new products), process innovation (dummy) and organizational change (dummy) over the different phases of the business cycle. Using firm-level pooled data from five CIS waves in 26 European countries over the period 1998-2010 (EUROSTAT data) and running IV regressions, they found that product innovations were labour friendly in all the phases of the business cycle, while process innovation and organizational change exhibited a labour-displacing nature during both upturn and downturn periods.

On the whole - although the 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 of technological change and when high-tech sectors (both in manufacturing and services) are considered. A weaker evidence of a labour-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 embodied technological change (ETC), exclusively focusing of the other indicators of innovation: R&D, patents, dummies for product and process innovation, etc. The attempt of what is following is to fill this gap.

3. Methodology and hypotheses to be tested

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

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" (KPF) 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* (mainly delivered by large firms in high-tech sectors) 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 and 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 way how firms introduce more advanced process innovation.

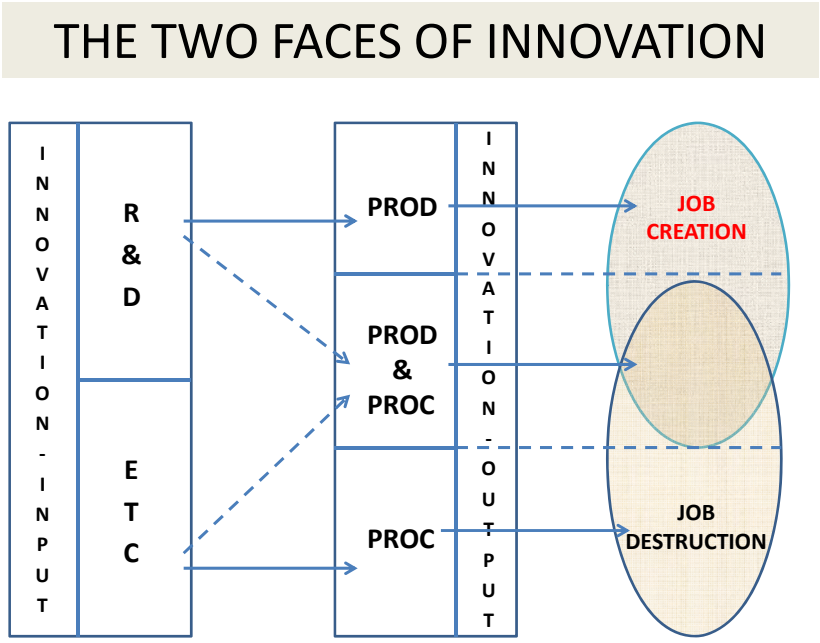
Moreover, sectoral and microeconomic studies show that R&D is crucial in large firms and more advanced sectors, while embodied technological change assumes a dominant role in SMEs and more traditional sectors (see Pavitt, 1984; Acs and Audretsch 1990; Audretsch and Vivarelli, 1996; Brouwer and Kleinknecht,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

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.

Turning our attention to the main issue of this paper 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 labour-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 the emergence of new markets.

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



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 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[3].

In addition, firms' sectoral and size dimensions will be separately investigated, in order 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 reasonable 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, electronics, etc. 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 datasets, the hypotheses above will be tested through a stochastic version of a standard labour demand augmented by including innovation (see, for similar

[3] 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.

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:

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

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

Unfortunately, the Italian CIS database described in the next section does not allow to properly test the specification reported in Eq. (1). In particular, due to an excessive collinearity between value added and capital formation (ρ=0.83) in our dataset, we decided to test a simplified version of eq. (1), dropping the investment variable:

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

4. Data and descriptive statistics

The empirical test of the hypotheses listed above will be developed using a unique and novel longitudinal dataset, based on the merge of different Italian Community Innovation Surveys (CIS), complemented with additional information taken from companies' accounts (see ISTAT and Università Cattolica del Sacro Cuore, 2014[4]).

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

[4] 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".

with more than 10 employees[5]. 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 three 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[6]. 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 possibility 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 size.

Moreover, CIS data - while being extremely detailed with regard to the innovation activities - do not offer economic information which are extremely relevant to our analysis, such as labour costs, sales, investment and value added. In order 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 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).

One of the implications of the matching between the CIS and ASIA database has

[5] In particular, the Italian CIS is a sample survey for firms with 10 to 249 employees and a census survey for firms with more than 250 employees.

[6] The unreliable CIS5 has been excluded, since that particular survey was mainly conducted a long time after the related three-year period, resulting in highly incomplete and mainly interpolated data.

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 need for the matching procedure reduced our workable balanced panel to 288 firms over four time periods, for a total of 1,152 observations.

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 20 firms, ending up with 270 companies (1,080 obs.).

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 five percentiles in terms of innovative intensity (total innovative expenditures over value added) in order to exclude non-reliable outliers, ending up with a final unbalanced panel of 265 firms (892 obs.)

The following Table 1 reports the variables, their definitions and the way they have been measured and deflated.

Table 1: List of variables

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

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

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[7]. 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 small and medium enterprises (SMEs) and large ones.

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

[7] Internal R&D and ETC represent - on average - more than ¾ of the "Total innovative expenditures".

Table 2: Descriptive Statistics (whole sample)

N=892 n=265	**Mean**	**Std.deviation**		**Min**	**Max**
Employment	547.3	overall	648.2	12	4,969
		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 labour 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		
Embodied technological change	10,577	overall	32,859.9	0	462,330
		between	29,640.5		
		within	20,403.8		

Note: monetary variables are expressed in hundreds.

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 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 multi-variate relationships affecting employment dynamics.

Table 3: Correlation matrix

	ln(Employment)	ln(Value added)	ln(Cost of labour per employee)	ln(Total innovative expenditures)	ln(Internal R&D)	ln(ETC)
ln(Employment)	1					
ln(Value added)	0.924	1				
ln(Cost of labour 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

Given the specification (2), we have run fixed-effects (FE) estimates, so controlling for unobservable firm's characteristics[8]. As reported in the following Tables 4 to 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

[8] The Hausman's tests confronting the FE with the random effects (RE) estimations were always in favour of the former (results available from the authors under request). Since our panel is very short (4 periods), this prevents us from testing a dynamic labor demand; in fact, in order to include the lagged dependent variable and therefore using a GMM methodology, one should have at disposal a minimum of 6/7 periods.

firm's innovation efforts (total innovation expenditures, internal R&D and ETC) are reported in the following Table 4. As can be seen, the labour-demand controls (value added and cost of labour) 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).

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 labour-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[9].

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 labour-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 embodied technological change.

[9] R&D and ETC are components of the total innovation expenditures and this prevents from jointly including the three variables in our estimated specification (see also the very high correlation coefficients in Table 3, column 4).

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

	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 labour 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	2.42*	2.20*	2.61*	2.27*
(*p*-value)	(0.066)	(0.088)	(0.052)	(0.081)
R^2 (within)	0.42	0.42	0.42	0.42
No. of observations		*892*		
No. of firms		*265*		

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

In order 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 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 0.7/0.9%; in contrast, in low-tech manufacturing, innovation (in its various aspects) does not reveal any labour-friendly nature.

Finally, Table 6 reports the estimated coefficients separately for the SMEs (firms with less than 250 employees, accordingly to the 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.

Table 5: Econometric results – manufacturing sectors – High-tech and Low-tech. Dependent variable: ln(Employment)

	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 labour 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	2.47*	2.32*	3.17**	2.32*	2.68**	2.48*	2.95**	2.61*
(*p*-value)	(0.066)	(0.080)	(0.027)	(0.080)	(0.049)	(0.063)	(0.035)	(0.053)
R^2 (within)	0.47	0.47	0.46	0.47	0.42	0.42	0.42	0.42
No. of observations	*340*				*552*			
No. 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)

	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 labour 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	1.21	1.19	1.04	1.08	1.88	1.67	2.42*	1.85
(*p*-value)	(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
No. of observations	*315*				*577*			
No. of firms	*99*				*185*			

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

Summing-up, the estimates reported in Tables 4 to 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.

6. Conclusions

In Sections 1 to 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 embodied technological change 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 paper 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 dataset described in Section 4, allow us to draw the following conclusions.

H1: this hypothesis is weakly confirmed by our estimates; on the whole, a generalized and highly significant labour-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 dataset 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 big companies operating in the most advanced sectors.

REFERENCES

Acemoglu, D., Autor, D.H. (2011), 'Skills, tasks and technologies: implications for employment earnings,' in O. Ashenfelter and D. Card (eds), *The Handbook of Labour Economics*. Amsterdam: Elsevier, 1043-1171.

Acs, Z.J., Audretsch, D.B. (1990), *Innovation and Small Firms*, Cambridge (Mass.): MIT Press.

Antonucci, T., Pianta, M. (2002), 'Employment effects of product and process innovation in Europe,' *International Review of Applied Economics*, **16**, 295-307.

Arntz, M., Gregory, T., Zierahn, U. (2016), 'The risk of automation for jobs in OECD countries: A comparative analysis,' *OECD Social, Employment and Migration Working Papers n.189*, Paris.

Audretsch, D. B., Vivarelli, M. (1996), 'Firms size and R&D spillovers: Evidence from Italy,' *Small Business Economics*, **8**, 249-258.

Benavente, J.M., Lauterbach, R. (2008), 'Technological innovation and employment: Complements or substitutes?,' *European Journal of Development Research*, **20**, 318-329.

Berman, E., Bound, J., Griliches, Z. (1994), 'Changes in the demand for skilled labour within US manufacturing industries: Evidence from the annual survey of manufacturing,' *Quarterly Journal of Economics*, **109**, 367-397.

Blanchflower, D., Burgess, S.M. (1998), 'New technology and jobs: Comparative evidence from a two-country study,' *Economics of Innovation and New Technology*, **5**, 109-138.

Bogliacino, F., Lucchese, M. (2016), 'Endogenous skill biased technical change: testing for demand pull effect,' *Industrial and Corporate Change*, **25**, 227-243.

Bogliacino, F., Pianta, M. (2010), 'Innovation and employment. A reinvestigation using revised Pavitt classes,' *Research Policy*, **39**, 799-809.

Bogliacino, F., Vivarelli, M. (2012), 'The job creation effect of R&D expenditures,' *Australian Economic Papers*, **51**, 96-113.

Bogliacino, F., Piva, M., Vivarelli, M. (2012), 'R&D and employment: An application of the LSDVC estimator using European data,' *Economics Letters*, **116**, 56-59.

Brouwer, E., Kleinknecht, A. (1996), 'Firm size, small business presence and sales of innovative products: a micro-econometric analysis,' *Small Business Economics*, **8**, 189-201.

Brynjolfsson, E., McAfee, A. (2011), *Race Against the Machine: How the Digital Revolution is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy*. Lexington, MA: Digital Frontier Press.

Brynjolfsson, E., McAfee, A. (2014), *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. New York: W.W. Norton.

Calvino, F. and Virgillito, M.E. (2016), 'The Innovation-Employment nexus: a critical survey of theory and empirics,' *LEM Papers Series 2016/10*, Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced Studies, Pisa, Italy.

Ciriaci, D., Moncada-Paternò-Castello, P., Voigt, P. (2016), 'Innovation and job creation: A sustainable relation?,' *Eurasian Business Review, forthcoming*.

Clark, J. (1987), A vintage-capital simulation model. In C. Freeman and L. Soete (eds), *Technical Change and Full Employment*. Oxford: Basil Blackwell, 86-98.

Coad, A., Rao, R. (2011), 'The firm-level employment effects of innovations in high-tech US manufacturing industries,' *Journal of Evolutionary Economics*, **21**, 255-283.

Conte, A., Vivarelli, M. (2014), 'Succeeding in Innovation: Key Insights on the Role of R&D and Technological Acquisition Drawn from Company Data,' *Empirical Economics*, **47**, 1317-1340.

Crépon, B., Duguet, E., Mairesse, J. (1998), 'Research, innovation, and productivity: An econometric analysis at firm level,' *Economics of Innovation and New Technology*, **7**, 115-158.

Crespi, F., Ghisetti, C., Quatraro, F. (2015), 'Environmental and innovation policies for the evolution of green technologies: A survey and a test,' *Eurasian Business Review*, **5**, 343-370.

Crespi, G., Tacsir, E. (2012), 'Effects of innovation on employment in Latin Americ', *Inter-American Development Bank Institutions for Development (IFD) Technical Note No.IDB-TN-496*. Inter-American Development Bank, Washington, DC.

Dachs, B., Hud, M., Koehler, C., Peters, B. (2015), 'Employment effects of innovation over the business cycle: Evidence from European countries,' paper presented at the conference: *DRUID15*, Rome, June 15-17, 2015.

Dosi, G. (1982), 'Technological paradigms and technological trajectories', *Research Policy*, **11**, 147-163.

Dosi, G. (1988), 'Source, procedure and microeconomic effects of innovation,' *Journal of Economic Literature*, **26**, 1120-1171.

Edquist, C., Hommen, L., and McKelvey, M. (2001), *Innovation and Employment: Process versus Product Innovation*. Cheltenham: Elgar.

Evangelista, R., Savona, M. (2002), 'The impact of innovation on employment in services: Evidence from Italy,' *International Review of Applied Economics*, **16**, 309-318.

Evangelista, R., Vezzani, A. (2012), 'The impact of technological and organizational innovations on employment in European firms,' *Industrial and Corporate Change*, **21**, 871-899.

Freeman, C., Clark, J., Soete, L. (1982), *Unemployment and Technical Innovation*. London: Pinter.

Freeman, C., Soete, L. (eds), 1987, *Technical Change and Full Employment*. Oxford: Basil Blackwell.

Frey, C.B., Osborne, M.A. (2013), 'The future of employment: how susceptible are jobs to computerisation?,' *Oxford University Working Paper*, September 17, Oxford.

Gagliardi, L., Marin, G., Miriello, C. (2016), 'The greener the better? Job creation effects of environmentally-friendly technological change,' *Industrial and Corporate Change*, **25**, 779-807.

Greenan, N., Guellec, D. (2000), 'Technological innovation and employment reallocation,' *Labour*, **14**, 547-590.

Greenwood, J., Hercowitz, Z., Krusell, P. (1997), 'Long-run implications of investment-specific technological change,' *American Economic Review*, **87**, 342-362.

Griliches, Z. (1979), 'Issues in assessing the contribution of Research and Development to productivity growth,' *Bell Journal of Economics*, **10**, 92-116.

Hall, B.H., Lotti, F., Mairesse, J. (2008), 'Employment, innovation, and productivity: Evidence from Italian microdata,' *Industrial and Corporate Change*, **17**, 813-839.

Hall, B.H., Mairesse, J., Mohnen, P. (2009), *Measuring the returns to R&D*. NBER Working Papers, 15622, Cambridge (Mass.).

Harrison, R., Jaumandreu, J., Mairesse, J., Peters, B. (2005), 'Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries,' *MPRA Paper n. 1245*, Munich.

Harrison, R., Jaumandreu, J., Mairesse, J., Peters, B. (2014), 'Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries,' *International Journal of Industrial Organization*, **35**, 29-43.

Hatzichronoglou, T. (1997), 'Revision of the high-technology sector and product classification,' *OECD Science, Technology and Industry Working Papers No. 1997/02*, Paris.

Hercowitz, Z. (1998), 'The 'embodiment' controversy: A review essay,' *Journal of Monetary Economics*, **41**, 217-224.

Hulten, C.R. (1992), 'Growth accounting when technical change is embodied in capital,' *American Economic Review,* **82**, 964-980.

ISTAT and Università Cattolica del Sacro Cuore (2014). *Innovazione e performance d'impresa in Lombardia e in Italia*. Technical report. Centro Studi Economia Applicata (CSEA), Università Cattolica del Sacro Cuore.

Jorgenson, D.W. (1966), 'The embodiment hypothesis,' *Journal of Political Economy*, **74**, 1-17.

Katsoulacos, Y.S. (1986), *The Employment Effect of Technical Change*. Brighton: Wheatsheaf.

Lachenmaier, S., Rottmann, H. (2011), 'Effects of innovation on employment: A dynamic panel analysis,' *International Journal of Industrial Organization*, **29**, 210-220.

Layard, R., Nickell, S. (1985), 'The causes of British unemployment,' *National Institute Economic Review*, **111**, 62-85.

Machin, S., Van Reenen, J. (1998), 'Technology and changes in skill structure: Evidence from seven OECD countries,' *Quarterly Journal of Economics*, **113**, 1215-1244.

Mairesse, J., Mohnen, P. (2001), *To be or not to be innovative: an exercise in measurement*. NBER Working Papers, 8644, Cambridge (Mass.).

Mejia, J.F., Granada, Y.A. (2014), 'Innovation and its effects on employment composition: Microeconomic evidence from Colombian firms,' *Documentos de trabajo Economía y Finanzas n. 14-20*, CIEF, Universitat EAFIT, Medellín.

Mitra, A., Jha, A. (2015), 'Innovation and employment: A firm level study of Indian industries,' *Eurasian Business Review*, **5**, 45-71.

Mohnen, P. and Hall, B. (2013), 'Innovation and Productivity: An Update,' *Eurasian Business Review*, Springer; Eurasia Business and Economics Society, **3**(1), 47-65.

Mukoyama, T. (2006), 'Rosenberg's "learning by using" and technology diffusion,' *Journal of Economic Behavior & Organization*, **61**, 123-144.

OECD (2016), 'ICT and jobs: Complements or substitutes? The effects of ICT investment on labour market demand by skills and by industry in selected OECD countries,' 2016 Ministerial Meeting on the Digital Economy Technical Report, *OECD Digital Economy Papers n.259*, Paris.

Parisi, M.L., Schiantarelli, F., Sembenelli, A. (2006), 'Productivity, innovation and R&D: Micro evidence for Italy,' *European Economic Review*, **50**, 2037-2061.

Pavitt, K. (1984), 'Patterns of technical change: Towards a taxonomy and a theory,' *Research Policy*, **13**, 343-374.

Pianta, M. (2005), 'Innovation and employment,' in J. Fagerberg, D. Mowery and R.R. Nelson (eds), *Handbook of Innovation*. Oxford: Oxford University Press, 568-598.

Piva, M., Vivarelli, M. (2004), 'Technological change and employment: Some micro evidence from Italy,' *Applied Economics Letters*, **11**, 373-376.

Piva, M., Vivarelli, M. (2005), 'Innovation and employment: Evidence from Italian microdata,' *Journal of Economics*, **86**, 65-83.

Piva, M., Santarelli, E., Vivarelli, M. (2005), 'The skill bias effect of technological and organisational change: Evidence and policy implications,' *Research Policy*, **34**, 141-157.

Sabadash, A. (2013), 'ICT-induced technological progress and employment: a happy marriage or a dangerous liaison? A literature review,' *JRC-IPTS Working Papers JRC76143*, Institute for Prospective and Technological Studies, Joint Research Centre, Sevilla.

Salter, W.E.G. (1960), *Productivity and Technical Change*. Cambridge: Cambridge University Press.

Simonetti, R., Taylor, K., Vivarelli, M. (2000), 'Modelling the employment impact of innovation,' in M. Vivarelli and M. Pianta (eds), *The Employment Impact of Innovation: Evidence and Policy*. London: Routledge, 26-43.

Sinclair, P.J.N. (1981), 'When will technical progress destroy jobs? ,' *Oxford Economic Papers*, **31**, 1-18.

Solow, R.M. (1960), 'Investment and technical progress,' in K.J. Arrow, S. Karlin and P. Suppes (eds), *Mathematical Methods in the Social Sciences*. Stanford: Stanford University Press, 89-104.

UNIDO (2013), *Industrial Development Report 2013. Sustaining Employment Growth: The role of manufacturing and structural change.* United Nations Industrial Development Organization, Vienna.

Van Roy, V., Vertesy, D., Vivarelli, M. (2015), 'Innovation and employment in patenting firms: Empirical evidence from Europe,' *IZA Discussion Papers 9147*, Bonn.

Van Reenen, J. (1997), 'Employment and technological innovation: Evidence from U.K. manufacturing firms,' *Journal of Labor Economics*, **15**, 255-284.

Vivarelli, M. (1995), *The Economics of Technology and Employment: Theory and Empirical Evidence*. Aldershot: Elgar.

Vivarelli, M. (2014), 'Innovation, employment and skills in advanced and developing countries: A survey of economic literature,' *Journal of Economic Issues*, **48**, 123-154.

Vivarelli, M., Evangelista, R., Pianta, M. (1996), 'Innovation and employment: Evidence from Italian manufacturing,' *Research Policy*, **25**, 1013-1026.

Yang, C-H., Lin, C-H. A. (2008), 'Developing employment effects of innovations: Microeconometric evidence from Taiwan,' *Developing Economies*, **46**, 109-134.