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Beyond R&D: The role of embodied technological change in affecting employment

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BEYOND R&D: THE ROLE OF EMBODIED TECHNOLOGICAL CHANGE IN AFFECTING EMPLOYMENT

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ABSTRACT

In this work, we test the employment impact of distinct types of innovative investments using a representative sample of Spanish manufacturing firms over the period 2002-2013.
Our GMM-SYS estimates generate various results, which are partially in contrast with the extant literature. Indeed, estimations carried out on the entire sample do not provide statistically significant evidence of the expected labor-friendly nature of innovation. More in detail, neither R&D nor investment in innovative machineries and equipment (the so-called embodied technological change, ETC) turn out to have any significant employment effect. However, the job-creation impact of R&D expenditures becomes highly significant when the focus is limited to the high-tech firms. On the other hand - and interestingly - ETC exhibits its labor-saving nature when SMEs are singled out.

Key words: Innovation; R&D; Embodied Technological Change; Employment; GMM-SYS

JEL codes: O33

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1. Introduction

The fear that robots - and technology in general - can steal human jobs is somehow archaic and interconnected with the history of capitalism. In 1821 David Ricardo admitted that this concern by the working class was understandable (Ricardo, 1951, vol. 1, p. 392); almost two centuries later IBM's Watson Explorer has started to displace white-collar workers in service firms[1] and some forecasting institutes are convinced that almost 50% of jobs might be performed by robots by 2035 (Nomura Research Institute, 2015).

Indeed, in the past decades, the pervasive diffusion of a new paradigm based on ICT and automation (see Freeman and Soete, 1994; Rifkin, 1995) has led to a dramatic adjustment of the employment structure - both in quantitative (employment levels) and qualitative terms (the so-called "skill-biased technological change", see Berman et al. 1994; Autor et al., 1998; Machin and Van Reenen, 1998; Morrison and Siegel, 2001) - in all the industrialized economies and, with some delay, in the emerging and developing ones.

More recently, the arrival of 3D printing, self-driving cars (Tesla, Apple, Google), agricultural manufacturing and domestic robots has raised again a widespread interest in the possibility of a massive 'technological unemployment'.

Moreover, not only agricultural and manufacturing employment appears at risk, but employees in services - including cognitive skills - are no longer safe: see for instance how the already mentioned IBM Watson artificial intelligence may displace the majority of legal advices and insurance/banking tasks; how Uber software is fully crowding out taxi companies; how the Airbnb internet platform is becoming the biggest provider of "hotel services" in the world; how "big data" software can displace jobs in consultancy and marketing services.

In addition, the evolution of labor demand, linked to the needs brought about by the new technologies, has destroyed 'routine' jobs, while creating opportunities in professional categories and skills which turn out to be novel and significantly different from previous ones (see Autor et al., 2006; Goos et al., 2014).

Finally, these recent trends have interlinked with the financial and economic crises and with the slow recovery afterwards, often showing a jobless nature. Taking into account these scenarios, Brynjolfsson and McAfee (2011 and 2014) think that the root of the current employment problems

1 See The Guardian, January 5th, 2017.

is not the Great Recession, but rather a “great restructuring”, characterized by a massive growth in computers’ processing speed and diffusion, having a dramatic impact on jobs and skills. Consistently, Frey and Osborne (2013) - using a Gaussian process classifier applied to data from the US Department of Labor - predict that 47% of the occupational categories are at high risk of being substituted by automated devices, including service/white-collar/cognitive jobs in accountancy, logistics, legal and financial services, trade and retail and so on so forth.

However, the relationship between technology and employment is not so straightforward and the economic theory may be of some help in investigating the issue more deeply.

Firstly, technological change is two-fold: on the one hand, process innovation - mainly incorporated in new machineries and robots (the so-called “embodied technological change”, ETC) - is mainly labor-saving, since by definition it means to produce the same amount of output with a lesser extent of labor; on the other hand, product innovation - that can be seen as the ultimate outcome of R&D investments - display a dominant job-creation nature through the development of new goods or even the emergence of brand-new markets (see, for instance, the automobile at the beginning of the XX century or the personal computer in the last decades of the same century; on the labor-friendly nature of product innovation, see Freeman et al., 1982; Freeman and Soete, 1987; Katsoulacos, 1986; Vivarelli, 1995; Edquist et al., 2001).

Secondly, the economic analysis has always pointed out the existence of price and income effects which can compensate for the reduction in employment due to process innovation. Indeed, technological change is introduced because it allows a reduction in costs and an increase in profitability, if this reduction in costs is translated - at least partially - in decreasing prices, an increase in demand, production and employment can occur. On the other hand, if the price/cost elasticity is less than one (for instance because of imperfect competition), the productivity gains due to process innovation are appropriated by profits and wages, which in turn may lead to increasing investment and/or increasing consumption, also implying more production and more employment (on the role of the so called “compensation mechanisms” and the possible hindrances to their efficacy, see Vivarelli, 1995; Pianta, 2005; Vivarelli, 2014).

However, the ultimate employment impact of innovation depends on crucial parameters such as the relative roles of process and product innovation, the degree of competition, the demand elasticity, the rate of substitution between capital and labor, the investment and consumption rates in turns based on expectations and so on, so forth.

Therefore, economic models do not provide a clear-cut answer in terms of the final employment impact of technological change; indeed, attention should be turned to the empirical analysis. This paper is precisely a microeconometric attempt to empirically test the possible labor-saving impact of technological change on the one hand and the scope for job creation on the other hand.

The main novelties of this contribution are the following.

1) In the innovation studies, the most commonly used proxy for technology is R&D expenditures. While this is a precise indicator and it is often available on an annual basis directly from companies' accounts, with regard to the aim of this work, its main limitation lies in being mainly correlated with labor-friendly product innovations.[2] This means that adopting this kind of proxy for innovation implies an "optimistic bias" in terms of assessing the employment impact of innovation. Indeed, as discussed above, most of labor-saving process innovations are implemented through the ETC, introduced through gross investment. Unfortunately, data on this technological input - which is often the dominant one in economies where low-tech sectors and SMEs are prevalent[3] - are generally either not available or indistinguishable from gross investment. An asset of this paper is the availability of data directly and precisely measuring ETC. Indeed, to our knowledge, this paper is the first one filling a gap in the extant literature (see the next section), since our analysis takes into account both R&D and ETC, with the latter regularly neglected by previous studies.
2) Secondly, we make use of a unique longitudinal database long enough (12 years) to implements lags, endogeneity controls and alternative instrumentations (see Sections 3 and 4 and the Appendix).
3) Thirdly, together with aggregate estimates, we will be able to disentangle our microeconometric evidence according to sectoral belonging and firm's size allowing on the one hand to propose a deeper understanding of the peculiarities of the relationship between technological change and employment and, on the other hand, to put forward more articulated policy implications (see Section 5)

The rest of the paper is organized as follows: the next section provides an updated survey of the

2 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.

3 A plethora of 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 and more traditional sectors (see Pavitt, 1984; Acs and Audretsch 1990; Audretsch and Vivarelli, 1996; Brouwer and Kleinknecht, 1996; Conte and Vivarelli, 2014).

previous microeconometric evidence; Section 3 introduces the econometric setting, describes the data and provides some descriptive statistics; Section 4 discusses the results; Section 5 briefly concludes.

2. Previous microeconometric evidence

Starting from the main contributions fully taking the advantage of longitudinal datasets, Van Reenen (1997), matching the London Stock Exchange database with the SPRU innovation database, obtained a panel of 598 manufacturing firms over the period 1976–1982. Running dynamic panel estimates, the author found a positive employment impact of innovation and this result turned out to be robust after controlling for fixed effects, dynamics and endogeneity.

By the same token, Blanchflower and Burgess (1998) confirmed a positive link between innovation (roughly measured with a dummy) and employment using two different panels of British and Australian establishments. Their results showed to be robust after controlling for sectoral fixed effects, size of firm and union density.

Considering the sectoral-level dimension in addition to the firm-level one, an interesting analysis was conducted by Greenan and Guellec (2000). They used microdata from 15,186 French manufacturing firms over the 1986–1990 period, showing that innovating firms created more jobs than non-innovating ones, but the reverse was true at the sectoral level, where the overall effect was negative. Interestingly enough, the conflicting employment impact of innovation at the firm and sectoral level may be due to the “business stealing effect”. Nevertheless, even when controlling for the “business stealing effect”, Piva and Vivarelli (2004 and 2005) provided evidence in favour of a positive effect of innovation on employment at the firm level. In particular - applying a GMM-SYS methodology to a panel of 575 Italian manufacturing firms over the period 1992–1997 - the authors provided evidence of the existence of a significant positive link between firm’s gross innovative investment and employment.

When disentangling the different types of innovation, product (more labor-friendly) and process innovations (less labor-friendly), results turn out to be more differentiated.

Lachenmaier and Rottmann (2011) 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 – based on a very comprehensive dataset of German manufacturing firms over the period 1982-2002 – showed a general positive impact of innovation measures on employment. Partially in contrast with expectations, the authors found out a higher positive impact of process rather than product innovation.[4]

Extending the perspective and considering multi-country studies, Harrison et al. (2005 and 2014) put forward a testable model able to distinguish the relative employment impact of process and product innovation (discrete variables) in four European countries (Germany, France, UK, Spain). The authors concluded that process innovation tended to displace employment, while product innovation was basically labor friendly. However, compensation mechanisms (see Section 1) were at work and, in the service sectors, were particularly effective through the increase in the demand for the new products. Along the same line, Hall et al. (2008) applied a similar model to a panel of Italian manufacturing firms over the period 1995-2003 and found a positive employment contribution of product innovation, while no evidence of employment displacement due to process innovation was found. Moreover, Evangelista and Vezzani (2012), dealing with European firms and distinguishing 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.

Turning to the analysis of the relationship between innovation and employment considering potential differences among different sectors, previous literature has very rarely split the empirical analysis according to sectoral belonging. Yang and Lin (2008) - for the Taiwanese case - estimated a dynamic labor demand augmented with innovation. They run GMM-DIF regressions using a panel including 492 firms listed on the Taiwan Stock Exchange over the period 1999-2003. Interestingly enough, the available data allowed the authors to include four measures of innovation: R&D, patents, patents addressed to process innovation and patents addressed to product innovation. Their results pointed to a significantly positive employment impact of all the four technological proxies where the entire sample was tested, while process innovations revealed a labor-saving impact when low R&D-intensive industries were singled out.

Moreover, Coad and Rao (2011), focusing on US high-tech manufacturing industries over the period 1963-2002, investigated the impact of a composite innovativeness index (comprising information on both R&D and patents) on employment. The main result of their quantile regressions was that innovation and employment are positively linked. Moreover, innovation has a stronger

4 However, this result can be due to the discrete nature of the adopted measure of process and product innovation (dummy variables). Interestingly enough, once the authors restrict their attention to (important) product innovation which went along with patent applications, they found out a highly positive and significant employment effect.

impact in those firms that reveal the fastest employment growth.

Finally, Bogliacino et al. (2012) – using a database including 677 European manufacturing and service firms over the period 1990-2008 – found that a positive and significant employment impact of R&D expenditures was evident in services and high-tech manufacturing but not in the more traditional manufacturing sectors.

On the whole - although the microeconometric evidence is not conclusive about the possible employment impact of innovation - the 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 (manufacturing and services) are considered. A feebler evidence of a labor-saving impact of process innovation is also detected in some studies, especially when low-tech manufacturing is exploited.

3. Econometric setting and data

3.1 Empirical specification

Consistently with the literature surveyed in the previous section and following the most recent approaches adopted in testing the employment impact of innovation using longitudinal firm-level datasets, we investigate the link between technology and employment through a stochastic version of a standard labor demand, augmented by including innovation (see, for similar approaches: Van Reenen, 1997; Lachenmaier and Rottmann, 2011; Bogliacino et al., 2012).

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

$$l_{i,t}=\beta_1 y_{i,t}+\beta_2 w_{i,t}+\beta_3 gi_{i,t}+\beta_4 LagInno_i+\left(\varepsilon_i+v_{i,t}\right) \qquad i = 1, .., n;\ t = 1, .., T \qquad (1)$$

where small letters denote natural logarithms, *l* is labor, *y* output, *w* labor cost, *gi* is gross investments, *LagInnov* denotes our innovation proxies (properly lagged in order to take into account a delay in the employment impact of innovation), *ε* is the idiosyncratic individual and time-invariant firm's fixed effect and *v* the usual error term.

In order to take into account viscosity in the labor demand (as common in the literature, see Arellano and Bond, 1991; Van Reenen, 1997), we move from the static expression to the following proper dynamic specification (2):

$$l_{i,t}=\alpha l_{i,t-1}+\beta_1 y_{i,t}+\beta_2 w_{i,t}+\beta_3 gi_{i,t}+\beta_4 LagInno_i+\left(\varepsilon_i+v_{i,t}\right) \qquad i = 1, .., n;\ t = 1, .., T \qquad (2)$$

As far as the econometric methodology is concerned, given the very high AR(1) correlation of our dependent variable (equal to 0.98) and the dominant role of the between variability (standard deviation equal to 1,092 employees) *vs* the within variability (standard deviation equal to 146 employees) in our dataset, we opted for a GMM-SYS methodology (see Blundell and Bond, 1998).[5]

3.2 Data

The empirical test provided in this study will be conducted using firm-level data from the Survey on Business Strategies (*Encuesta Sobre Estrategias Empresariales, ESEE*) which has been conducted yearly since 1990 by the SEPI foundation, on behalf of the Spanish Ministry of Industry. This annual survey gathers extensive information on around 2,000 manufacturing companies operating in Spain and employing at least ten workers; given its longitudinal structure and its reliability, this source has been extensively used by previous empirical research (see, among others, González et al., 2005; Triguero and Córcoles, 2013; Garcia Quevedo et al., 2014), albeit no former study has been specifically addressed to investigate the employment impact of innovation.

The sampling procedure ensures representativeness for each two-digit NACE-CLIO[6] manufacturing sector, following both exhaustive and random sampling criteria. In particular, in the first year of the survey all Spanish manufacturing firms employing more than 200 workers were required to take part (715 in 1990) and a sample of firms employing between 10 and 200 workers were selected by stratified sampling (across 20 manufacturing sectors and four company's size intervals), with a random start (1,473 firms in 1990). To ensure a proper level of representativeness

5 GMM-SYS requires T is, at least, equals to 3.

6 NACE is the usual industrial classification of economic activities within the European Union while CLIO is the nomenclature used by the Spanish input–output tables. The Spanish Accounting Economic System (Spanish National Statistics Institute: http://www.ine.es/) officially recognizes both classifications

over time, all newly created companies with more than 200 employees (rate of response around 60%) together with a random sample of firms with fewer than 200 workers and more than 10 (rate of response around 4%) have been incorporated in the survey every year.

In this study we used data for the period 2002-2013 and selected our working database from an initial theoretical sample of 63,648 firm-year cells. Firstly, we checked for missing values for the variables relevant to our empirical analysis (loosing 49,047 cells, mainly due to missing values in innovative indicators). Secondly, we discarded all firms involved in M&A (loosing 1,084 firm-year observations). Thirdly, we excluded all those non-innovative firms that during the observed time period have never invested in R&D and in innovative machinery and equipment (in other words, we retained those firms that have invested in R&D at least once in their life and have invested in ETC at least once in their life). Finally, given the target to estimate a dynamic equation (see above and FN 5), we retained only firms for which three consecutive lags of the dependent variable (employment) were available.

Table 1 shows the composition of the final dataset following the data cleaning described above.[7] As can be seen, almost 43% of the 561 firms included in the final sample are observed for less than six years; the remaining 57% are observed for at least 6 years and about 16% of the firms in the sample are observed for all the investigated period.

Table 1: Panel composition

Time obs.	Nº of firms	%	% Cum.
3	111	19.79	19.79
4	66	11.76	31.55
5	64	11.41	42.96
6	56	9.98	52.94
7	39	6.95	59.89
8	41	7.31	67.20
9	70	12.48	79.68
10	11	1.96	81.64
11	12	2.14	83.78
12	91	16.22	100
Total	561	100	

According to the previous discussion (see Section 3.1) our dependent variable is represented by the natural logarithm of the number of employees within the firm, while the explanatory variables

7 Obviously enough, the multi-step procedure adopted to build this unbalanced panel has implied a certain degree of selection bias in favor of the largest and most innovative firms; this should be taken into account in interpreting our results.

used in the econometric specification have been selected on the basis of a standard labor demand function augmented for taking into account innovation (eq. 2).

Given the available information in our dataset, we computed output as the natural logarithm of firm's value added; labor cost was measured as the natural logarithm of gross wage per employee and gross investment was measured as the natural logarithm of investment in tangible capital goods.

Moreover, in order to assess the impact of R&D and ETC on labor demand (see Section 1), we considered two key impact variables: namely, 1) the total amount of firm's expenditures in both internal and external R&D; and 2) the firm's expenditures to acquire machinery or equipment specifically bought for introducing new or significantly improved products and/or processes.

Value added, fixed capital investment, wages and the two indicators of innovation activity were deflated using industry-specific deflators.[8]

Table 2 presents a detailed description of the variables used in the empirical analysis, while Table 3 provides the related descriptive statistics.

Table 2: The variables: acronyms and definitions

Dependent Variable	
ln(Employment)	Log of employees
Explanatory variables	
ln(Value added)	Log of value added
ln(Cost of labor per employee)	Log of gross wage per employee
ln(Investment in physical capital)	Log of investment in physical capital (purchases of information processing equipment, technical facilities, machinery and tools, rolling stock and furniture, office equipment and other tangible fixed assets)
ln(R&D)	Log of internal and external expenditures in R&D
ln(ETC)	Log of expenditures in innovative machinery and equipment

8 Specifically, information provided in current prices in the ESEE database were converted into constant prices by using sectoral GDP deflators (source: INE-Spanish National Statistics Institute) centered on the year 2010.

Table 3: Descriptive statistics

	Mean	St Dev.	Min	Max
ln(Value added)	9.72	1.77	3.09	16.36
ln(Investment in physical capital)	6.23	2.39	0	12.95
ln(Cost of labor per employee)	3.60	0.35	1.88	5.16
ln(Employment)	5.20	1.25	1.79	9.58
ln(R&D)	5.40	2.34	0	13.13
ln(ETC)	2.95	3.29	0	12.66

4. Results

As clarified in Section 3.1, in the following tables our attention will be focused on the GMM-SYS estimated coefficients, although POLS and FE estimates are also reported for completeness.[9]

According to the outcomes of the Wald tests for the joint significance of the included dummies, all the POLS and GMM-SYS estimates have been obtained including time and sectoral (two-digit) dummies. As far as the diagnostic tests are concerned, LM tests in the GMM-SYS specifications require a two-lag structure of the instruments in Table 4, while a three-lag structure turns out to be necessary in Tables 5 and 6. Finally, the Hansen test never rejects the hypothesis of a correct instrumentation and this is very reassuring.[10]

As can be seen in the following Tables 4 to 6, the dependent variable - as expected and common in an employment equation - reveals to be strongly auto-correlated with a highly significant coefficient of about 0.9. Moreover, the controls (value added, cost of labor and investment in tangibles and time and sectoral dummies – where appropriate) always turn out with the expected signs and with a 99% level of statistical significance, with the only exception of the investment variable that - although always positive - is not significant in most of the GMM-SYS estimates.

9 Notice that in the following tables the GMM-SYS estimated coefficients for the lagged dependent variable always turn out within the upper bound given by the corresponding POLS estimated coefficients and the lower bound given by the FE estimated coefficients; these outcomes strongly support the chosen methodology (see Bond, 2002).

10 Moreover, a battery of differenced Hansen tests has been run to test the alternative ways to instrument the various variables (available upon request). In the preferred specification, the lagged dependent variable and the investment variable have been considered endogenous. In addition, in the Appendix, a summary table (Table A1) with a lower number of instruments to test for robustness for severely reducing the instrument count (instruments including lags from two to four when AR(2) is not rejected and from three to four when AR(2) is rejected) is reported, as suggested by Roodman (2009). As can be seen, results from Tables 4 to 6 are confirmed.

Turning our attention to the two variables of interest (R&D and ETC), the former has been lagged two years while the latter one year[11]; this structure of lags takes into account that innovation may need some time to have an impact on employment and that this delay is likely to be shorter for ETC - that is directly embodied in new machineries - while longer for R&D expenditures which may take time in generating an innovation output. This dynamic structure reduces the overall number of firms and observations available to - respectively - 517 and 2,404.

Another advantage of having a disposal a long-enough longitudinal structure is the possibility to include both R&D and ETC in the same specification and jointly test their possible impacts on employment.[12]

As obvious in Table 4, neither R&D nor ETC seems to have any significant employment impact, at least when the entire sample of firms is taken into account.

However, when we split (according to the OECD classification, see Hatzichronoglou, 1997) into high and low-tech manufacturing (Table 5), a positive and very significant (99%) employment impact of R&D clearly emerges, although limited to the high-tech firms. While in the low-tech firms the impact of both R&D and ETC is negligible and not significant, in the high-tech companies an increase of 100% in the R&D expenditures implies an increase in the employment level of 1.7%.[13]

Once we turn our attention to the size dimension[14], no significant impacts emerge with regard to the large firms, while the ETC exhibits a significant labor-saving nature within the smaller companies: an increase of 100% in the ETC expenditures might cause a potential decrease of the employment level of 0.6%.[15]

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11 The correlation coefficient between Value added and Investment in physical capital turned out to be as high as 0.78. To mitigate possible multicollinearity issues, we decided to lag the Investment variable, as well (the correlation coefficient dropping to 0.35).

12 Moreover, the different lag structure of the two variables minimizes their possible contemporaneous interaction.

13 Control variables have the expected signs both in high-tech and low-tech firms. No relevant differences emerge in the magnitude of coefficients, with the exception of the cost of labor which affects employment more in high-tech companies than in low-tech ones (-0.284 vs. -0.236). This may suggest that more qualified and expensive workers are employed in the high-tech sectors.

14 The chosen size threshold is 200 employees, very close to the size median of our sample (199) and allowing a good balance between the two estimates (1,233 observations *vs* 1,171).

15 As in the previous estimates, control variables have the expected signs both in large and small firms. However, employment in small firms reveals to be positively and significantly affected by capital formation and more sensitive to the cost of labor.

Table 4: Dependent variable: ln(Employment); whole sample (2,404 observations)

	(1) **POLS**	(2) **FE**	(3) **GMM-SYS**
ln(Employment)$_{t-1}$	0.927***	0.651***	0.902***
	(0.007)	(0.036)	(0.034)
ln(Value added)	0.065***	0.072***	0.081***
	(0.007)	(0.010)	(0.024)
ln(Cost of labor per employee)	-0.189***	-0.422***	-0.236***
	(0.020)	(0.044)	(0.022)
ln(Investment in physical capital)$_{t-1}$	0.009***	0.009***	0.008
	(0.002)	(0.002)	(0.006)
ln(ETC)$_{t-1}$	-0.001	-0.001	-0.002
	(0.001)	(0.001)	(0.001)
ln(R&D)$_{t-2}$	0.002	0.002	0.004
	(0.001)	(0.002)	(0.003)
Time-dummies	Yes	Yes	Yes
Sectoral-dummies	Yes	No	Yes
Constant	0.265***	2.485***	0.386***
	(0.049)	(0.247)	(0.089)
Wald test time-dummies (p-value)	20.27*** (0.000)	17.10*** (0.000)	10.13*** (0.000)
Wald test sectoral-dummies (p-value)	4.39*** (0.000)	-	4.07*** (0.000)
R^2	0.99		
R^2 (within)		0.66	
AR(1) (p-value)			0.000***
AR(2) (p-value)			0.449
Hansen test $\chi^2(96)$ (p-value) (129 instruments)			0.653

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

Table 5: Dependent variable: ln(Employment);
High-tech (684 observations) and Low-tech firms (1,720 observations)

	HIGH-TECH FIRMS			LOW-TECH FIRMS		
	(1) POLS	**(2) FE**	**(3) GMM-SYS**	**(1) POLS**	**(2) FE**	**(3) GMM-SYS**
ln(Employment) $_{t-1}$	0.925***	0.725***	0.878***	0.923***	0.590***	0.908***
	(0.015)	(0.048)	(0.029)	(0.007)	(0.047)	(0.033)
ln(Value added)	0.055***	0.045***	0.084***	0.072***	0.092***	0.087***
	(0.016)	(0.017)	(0.021)	(0.059)	(0.012)	(0.022)
ln(Cost of labor per employee)	-0.232***	-0.418***	-0.284***	-0.180***	-0.423***	-0.236***
	(0.057)	(0.078)	(0.061)	(0.018)	(0.054)	(0.030)
ln(Investment in physical capital) $_{t-1}$	0.012***	0.009**	0.007	0.008***	0.009***	0.001
	(0.003)	(0.004)	(0.009)	(0.002)	(0.002)	(0.002)
ln(ETC) $_{t-1}$	-0.001	0.001	-0.002	-0.001	-0.001	0.001
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
ln(R&D) $_{t-2}$	0.009***	0.002	0.017***	0.004	0.002	0.001
	(0.003)	(0.004)	(0.006)	(0.001)	(0.002)	(0.002)
Constant	0.519***	2.466***	0.695***	0.322***	2.564***	0.317***
	(0.127)	(0.258)	(0.174)	(0.049)	(0.332)	(0.109)
Wald test time-dummies (p-value)	5.73*** (0.000)	6.13*** (0.000)	3.17** (0.027)	17.30*** (0.000)	12.83*** (0.000)	4.92*** (0.000)
Wald test sectoral-dummies (p-value)	5.34*** (0.001)	-	3.17** (0.027)	3.48*** (0.000)	-	73.71*** (0.000)
R^2 (POLS) / R^2 within (FE)	0.99	0.63		0.99	0.68	
AR(1) (p-value)			0.000***			0.001***
AR(2) (p-value)			0.050**			0.063*
AR(3) (p-value)			0.377			0.251
Hansen test (p-value)			0.495 $\chi^2(77)$ (97 instruments)			0.336 $\chi^2(77)$ (111 instruments)

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

Table 6: Dependent variable: ln(Employment);
Large (1,233 observations) and Small firms (1,171 observations)

	LARGE FIRMS			**SMALLFIRMS**		
	(1) POLS	**(2) FE**	**(3) GMM-SYS**	**(1) POLS**	**(2) FE**	**(3) GMM-SYS**
ln(Employment) $_{t-1}$	0.919***	0.850***	0.893***	0.898***	0.590***	0.871***
	(0.011)	(0.015)	(0.053)	(0.011)	(0.048)	(0.045)
ln(Value added)	0.058***	0.066***	0.068**	0.075***	0.075***	0.080***
	(0.009)	(0.011)	(0.028)	(0.012)	(0.016)	(0.025)
ln(Cost of labor per employee)	-0.139***	-0.166***	-0.202***	-0.224***	-0.426***	-0.266***
	(0.017)	(0.022)	(0.032)	(0.032)	(0.065)	(0.039)
ln(Investment in physical capital) $_{t-1}$	0.007***	0.007***	0.014	0.010***	0.010***	0.023***
	(0.002)	(0.002)	(0.009)	(0.002)	(0.003)	(0.007)
ln(ETC) $_{t-1}$	-0.0001	-0.0003	-0.002	-0.002	0.001	-0.006**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
ln(R&D) $_{t-2}$	0.001	0.003	0.001	0.001	0.002	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.262***	2.466***	0.479***	0.513***	2.484***	0.558***
	(0.059)	(0.258)	(0.115)	(0.077)	(0.188)	(0.113)
Wald test time-dummies (p-value)	16.04*** (0.000)	117.73*** (0.000)	14.37*** (0.000)	7.23*** (0.000)	4.82*** (0.000)	2.82*** (0.005)
Wald test sectoral-dummies (p-value)	3.53*** (0.000)	-	3.14** (0.000)	3.32*** (0.000)	-	2.48*** (0.000)
R^2 (POLS) / R^2 within (FE)	0.98	0.58		0.99	0.61	
AR(1) (p-value)			0.000***			0.000***
AR(2) (p-value)			0.019**			0.888
AR(3) (p-value)			0.156			-
Hansen test (p-value)			0.687 $\chi^2(77)$ (110 instruments)			0.190 $\chi^2(77)$ (129 instruments)

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

On the whole, our estimates seem to suggest an employment-neutral impact of innovation when run on the aggregate: although showing the expected signs (positive for R&D linked to product innovation and negative for ETC linked to process innovation), both our key impact variables do not turn out to be significant in Table 4. Yet, when the estimates are split into high- and low-tech sectors the job-creation role of R&D emerges, albeit limited to the technologically advanced firms (Table 5). Finally, from the estimates based on the size differentiation, a significant labor-saving effect of ETC emerges with regard to the SMEs.

5. Conclusions and policy implications

As discussed in Section 1, the relationship between innovation and employment is far from being a simple one: indeed, technological change generates a direct impact and many indirect effects.

At a first glance, process innovation implies a labor-saving effect, while product innovation is generally labor friendly. However, together with their labor-saving impact, process innovations involve decreasing prices and increasing incomes and these in turn boost an increase in demand and production that can compensate the initial job losses. On the other hand, the job creating effect of product innovation may be more or less effective, as well: indeed, the introduction of new products and the generation of new industries have to be compared with the displacement of mature products. Of course, the scenario appears even more complicated when these direct and indirect impacts occur within a period of structural crisis as the current one.

On the whole, the economic theory does not have a clear-cut answer about the likely employment effects of innovation and attention should be turned to the empirical analysis: this paper has provided some microeconometric evidence on the issue.

As far as the previous empirical literature is concerned, the examined econometric evidence is not fully conclusive; however, most of recent studies provide evidence of a positive relationship between technological change and jobs. In particular, the job-creation effect is more obvious when R&D and/or product innovation are adopted as proxies of innovation and when high-tech sectors (both in manufacturing and services) are considered. However, a common limitation of previous studies is the lack of a proper measure of ETC, which is indeed the main culprit of a possible labor-saving impact of technological change. Indeed - as far as we know - this study is the first attempt to fill this crucial gap in the extant literature, since our analysis takes into account both R&D (mainly linked to the labor-friendly product innovation) and ETC (mainly linked to the labor-saving process innovation). Therefore, our microeconometric tests have been based on different estimations of a standard dynamic labor demand augmented by the inclusion of firm’s R&D expenditures and firm’s expenditures to acquire innovative machinery or equipment. Our results can be summarized as follows.

- Partially in contrast with the previous literature, a generalized labor-friendly nature of R&D expenditures is not detectable in the present study. In more detail, neither R&D nor ETC (although exhibiting the expected signs) appears to have any significant employment impact, at least when the entire sample of firms is taken into account.
- However, the job-creation impact of R&D expenditures (after being assessed as not significant with regard to the entire sample) becomes highly significant when the focus is limited to the high-tech firms.
- On the other hand, ETC clearly exhibits its labor-saving nature when SMEs are singled out.

One has to be extremely cautious in proposing possible policy suggestions based on econometric results that are obviously affected by the particular data used and their intrinsic limitations. However, these outcomes suggest the following implications.

In general terms, the first conclusion of this study is unequivocal: the labor-friendly nature of companies' R&D investments is not a general regularity as it is statistically significant for high-tech manufacturing, but not at all for the more traditional sectors. This is something that should be borne in mind by policy makers considering employment as one of their main targets: if the policy purpose is to maximize the employment impact of innovation, R&D incentives should be concentrated in the high-tech industries.

Turning our attention to the alternative mode of technological change - *i.e.* the possibly labor-saving impact of ETC involving process innovation - its possible adverse impact on employment emerges as a likely outcome when SMEs are focused on. In terms of policy implications, this means that non-R&D-based innovation in SMEs may imply an adverse effect in terms of employment and some targeted policies become necessary. For instance, adequate training and re-training policies might be designed, taking into account the specific needs of the SMEs.

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APPENDIX

Table A1: Dependent variable: ln(Employment)

	(1) GMM-SYS WHOLE	(2) GMM-SYS HT	(3) GMM-SYS LT	(4) GMM-SYS LARGE	(5) GMM-SYS SMALL
ln(Employment)$_{t-1}$	0.904***	0.833***	0.898***	0.888***	0.896***
	(0.033)	(0.050)	(0.037)	(0.047)	(0.050)
ln(Value added)	0.077***	0.099***	0.087***	0.081***	0.059**
	(0.024)	(0.034)	(0.023)	(0.025)	(0.025)
ln(Cost of labor per employee)	-0.218***	-0.259***	-0.240***	-0.201***	-0.244***
	(0.022)	(0.058)	(0.028)	(0.041)	(0.029)
ln(Investment in physical capital)$_{t-1}$	0.008	0.012	0.009	0.004	0.024*
	(0.007)	(0.011)	(0.015)	(0.006)	(0.012)
ln(ETC)$_{t-1}$	-0.001	-0.002	-0.001	-0.001	-0.006*
	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)
ln(R&D)$_{t-2}$	0.003	0.019**	0.002	0.001	0.001
	(0.002)	(0.008)	(0.002)	(0.002)	(0.002)
Time-dummies	Yes	Yes	Yes	Yes	Yes
Sectoral-dummies	Yes	Yes	Yes	Yes	Yes
Constant	0.349***	0.742***	0.334***	0.414***	0.576***
	(0.097)	(0.160)	(0.113)	(0.101)	(0.093)
Wald test time-dummies (p-value)	83.30*** (0.000)	46.85*** (0.000)	3.98*** (0.000)	59.63*** (0.000)	2.18** (0.029)
Wald test sectoral-dummies (p-value)	66.19*** (0.000)	170.50*** (0.000)	63.13*** (0.000)	67.34*** (0.000)	2.98*** (0.000)
AR(1) (p-value)	0.000***	0.000***	0.001***	0.000***	0.000***
AR(2) (p-value)	0.410	0.063*	0.059*	0.040**	0.665
AR(3) (p-value)	-	0.443	0.256	0.148	-
Hansen test (p-value)	$\chi^2(57)$ 0.404 90 inst.	$\chi^2(38)$ 0.418 58 inst.	$\chi^2(38)$ 0.755 72 inst.	$\chi^2(56)$ 0.852 89 inst.	$\chi^2(38)$ 0.758 90 inst.
No. of observations	2,404	684	1,720	1,233	1,171
No. of firms	517	137	387	263	300

Notes:
- Robust standard errors in parentheses;
- * significance at 10%, ** 5%, *** 1%;
- instruments include lags from 2 to 4 when AR(2) is not rejected and from 3 to 4 when AR(2) is rejected - see Roodman (2009).