

***IPTS WORKING PAPER on  
CORPORATE R&D AND INNOVATION - No. 10/2011***

**Job Creation Effects of R&D Expenditures:  
Are High-tech Sectors the Key?**

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## **Abstract**

In this paper we assess the job creation effect of R&D expenditures, using a unique longitudinal database of 677 European companies over the period 1990-2008. We estimate a dynamic labour demand specification using a Least Squares Dummy Variable Corrected (LSDVC) technique.

The labour-friendly nature of R&D emerges from the empirical analysis on the overall sample. However, this positive significant effect corresponds to the high-tech sector and services, while the effect is not significant for traditional manufacturing. The results support the policy agenda of promoting structural change in European economies.

**JEL Classification:** O33

**Keywords:** innovation, employment, manufacturing, services, LSDVC

# 1 Introduction

Assessment of the possible effects of technological change on employment<sup>1</sup> is an old and controversial issue. Indeed, over the last three decades the diffusion of a 'new economy' based on ICT technologies has led to re-emergence of the classical debate on the possible adverse effects of innovation on employment. In a nutshell, that debate was characterised by two opposing views. On the one hand, fear of technological unemployment as a *direct* consequence of labour-saving innovation was the source of social and political concern<sup>2</sup>. On the other, economic theory pointed to the existence of *indirect* effects which could counterbalance the reduction in employment, due to process innovation entailed by use of new machinery. Indeed, in the first half of the 19th century, classical economists put forward a theory that Marx later called the 'compensation theory' (see Marx, 1961, vol. 1, chap. 13, and 1969, chap. 18). This theory relies on different market compensation mechanisms which are triggered by technological change itself and which can counterbalance the initial labour-saving impact of process innovation (for an extensive analysis, see also Vivarelli, 1995, chaps. 2 and 3; Petit, 1995; Vivarelli and Pianta, 2000, chap. 2; Spiezia and Vivarelli, 2002; Pianta, 2005).

Within this framework, the aim of the research presented in this paper is to test empirically the possible job creation effect of business R&D expenditures at the firm level.<sup>3</sup> Our study contributes to the empirical microeconomic literature addressing the link between technology and employment in a number of ways. Firstly, it is the initial attempt at assessing the impact of R&D expenditures on employment in a European context; since increasing R&D is one of the main targets of European economic policy,<sup>4</sup> assessing the possible impact of such a policy on employment is of paramount importance to European policy design. Secondly, our

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<sup>1</sup> This paper will focus exclusively on the quantitative employment impact of innovation; for an introduction to the literature on the qualitative effect of technological change on the demand for skills see Berman, Bound and Griliches (1994); Laursen and Foss (2003); Vivarelli (2004); Piva, Santarelli and Vivarelli (2005).

<sup>2</sup> For instance, the response of English workers to the first industrial revolution was to destroy machines under the charismatic leadership of Ned Ludd in the industrial areas and of Captain Swing in the countryside (see Hobsbawm, 1968; Hobsbawm and Rudé, 1969).

<sup>3</sup> It is important to note that the technological indicator used in this study (R&D) is a better proxy for product than for process innovation. Indeed, while process innovation is mainly incorporated in the new vintages of fixed capital, R&D is mainly devoted to the promotion of prototypes, the introduction of entirely new products, or the radical differentiation of existing products (see Rosenberg, 1976; Nelson and Winter, 1982; Dosi, 1988). Recent microeconomic studies — using data from the European Community Innovation Surveys (CIS) — have confirmed empirically how R&D expenditures are closely linked with product innovation, while innovative investment (especially in new machinery and equipment) turns out to be related to process innovation (see Conte and Vivarelli, 2005; Parisi, Schiantarelli and Sembenelli, 2006).

<sup>4</sup> See the Lisbon-Barcelona target, aiming to move the European R&D/GDP ratio up to 3%, (2% of which from private companies' R&D expenditures), recently re-proposed as the 'Innovation Union' flagship strategy (see European Commission 2002 and 2010).

microeconometric investigation is based on a unique large and international panel dataset (see Section 3), able to overcome the limitations of previous empirical studies which were mainly based on cross-section analyses, small longitudinal samples or single country data (see next section). Thirdly, our proxy for technology is a measurable and continuous variable, while most previous studies have relied on either indirect proxies for technological change or dummy variables (such as the occurrence of product and process innovation). Fourthly, our dataset allows us to disentangle the impact of R&D on employment on a sectoral level, including the possibility of focusing on high-tech manufacturing sectors and service sectors (to our knowledge, very few previous microeconometric studies have been able to undertake sectoral comparisons; see next section).

The rest of the paper is organised as follows: Section 2 gives an overview of the empirical literature on the relationship between technological change and employment at the firm level, and also points out some specific methodological issues; Section 3 presents the dataset; Sections 4 and 5 describe our econometric strategy and discuss the results; Section 6 briefly illustrates conclusions and policy implications.

## **2 Previous microeconomic empirical literature**

As we said above, in order to discuss the labour market effect of innovation we need to be mindful of both direct labour-saving impact and compensation mechanisms.

Compensation mechanisms include both price and income effects. With regard to the former, process innovation leads to a decrease in the unit costs of production, which in a competitive market translates to decreasing prices; in turn, decreasing prices stimulate new demand for products and therefore additional production and employment.<sup>5</sup> As for the latter, in a world where competitive convergence is not instantaneous, we observe that during the lag between the decrease in costs due to process innovation and the consequent fall in prices, extra profits and/or extra wages may be accumulated by innovative entrepreneurs and their employees. On the one

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<sup>5</sup> This mechanism was singled out at the very beginning of the history of economic thought (see Say, 1964) and has been re-proposed more recently (see Neary, 1981; Hall and Heffernan, 1985; Dobbs, Hill and Waterson, 1987; Smolny, 1998).

hand, additional profits may be invested, resulting in the creation of new jobs.<sup>6</sup> On the other, additional wages may translate to higher consumption; in turn, this increase in demand leads to an increase in employment which may compensate initial job losses due to process innovation<sup>7</sup>.

Obviously, both the price and income compensation mechanisms may be more or less effective depending on: 1) the degree of market competition (monopolistic rigidities can hinder the decrease in prices due to process innovation); 2) demand elasticity; 3) 'animal spirits' and agents' expectations, which may delay the translation of additional profits and wages into 'effective demand' (for a critique of the compensation theory, see Pasinetti, 1981; Freeman and Soete, 1987; Appelbaum and Schettkat, 1995; Vivarelli, 1995; Pianta, 2005). Moreover, technological change cannot be reduced to *process* innovation alone, since *product* innovation may imply the birth of entirely new economic branches in which additional jobs can be created<sup>8</sup>. Indeed, the labour-intensive impact of product innovation was underlined by classical economists (Say, 1964) and even the most severe critic of the compensation theory signalled the positive employment benefits which can arise from this kind of technological change (Marx, 1961, vol. I, p. 445). In the current debate, various scholars (Freeman, Clark and Soete, 1982; Katsoulacos, 1986; Freeman and Soete, 1987 and 1994; Vivarelli and Pianta, 2000; Edquist, Hommen and McKelvey, 2001; Bogliacino and Pianta, 2010) agree that product innovations have a positive impact on employment, since they open the way to the development of entirely new goods or to the radical differentiation of mature goods (although some negative effects can also be present due to product obsolescence).

Previous literature devoted to the investigation of the link between technology and employment at the firm level is relatively recent. For instance, Entorf and Pohlmeier (1990) found that product innovation, measured using a dummy, had a positive impact on employment in a cross-section of 2276 West German firms in 1984. The positive impact of product innovation on employment in West German manufacturing was confirmed by Smolny (1998), using a panel of 2405 firms for the period 1980–1992. Furthermore, using the 1984 British Workplace Industrial Relations Survey, both Machin and Wadhwani (1991) and Blanchflower, Millward and Oswald (1991) found a negative raw correlation between ICT adoption and employment; however, once controlled for workplace characteristics and fixed effects, this correlation turned out to be positive.

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<sup>6</sup> Originally put forward by Ricardo (1951), this argument has also been used by neo-classical thinkers such as Marshall (1961) and later developed into dynamic models by Sylos Labini (1969), Hicks (1973) and Stoneman (1983, pp. 177-81).

<sup>7</sup> See Pasinetti (1981) and Boyer (1988).



In contrast with the previous studies, Brouwer, Kleinknecht and Reijnen (1993), using a cross-section of 859 Dutch manufacturing firms, discovered an aggregate negative relationship between aggregate R&D expenditures and employment (while the opposite was observed when only product innovation was considered). By the same token, Zimmermann (1991), using microdata from 16 German industries, concluded that technological change was one of the determining factors in the decrease in employment in Germany during the 1980s. Although the impact on employment of innovation is not the main object of the study by Doms, Dunne and Troske (1997), the authors found that advanced manufacturing technologies, measured by a set of dummy variables, implied higher employment growth in US manufacturing plants over the period 1987–1991. More controversial results come from Klette and Førre (1998). The authors' database comprised 4333 Norwegian manufacturing plants over the period 1982–1992; in contrast with most of the other studies, they did not find any clear-cut positive relationship between net job creation and the R&D intensity of the examined plants.

Most recent studies have taken full advantage of newly-available longitudinal datasets and have applied more sophisticated panel data econometric methodologies. For example, Van Reenen (1997) matched the London Stock Exchange database of manufacturing firms with the SPRU innovation database and obtained a panel of 598 firms over the period 1976–1982. Running GMM-DIF estimates, the author found a positive impact of innovation on employment, and this result turned out to be robust after controlling for fixed effects, dynamics and endogeneity. Similarly, 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 proved to be robust after controlling for sectoral fixed effects, size of firm and union density.

An interesting panel analysis was conducted by Greenan and Guellec (2000), using microdata from 15 186 French manufacturing firms over the 1986–1990 period. According to this study, innovating firms, defined according to the outcomes of an innovation survey, create more jobs than non-innovating ones, but the reverse is true at the sectoral level, where the overall effect is negative and only product innovation creates jobs. Interestingly enough, innovation having opposite effects on employment at the firm and sectoral levels may be due to the 'business stealing effect' discussed below (Section 4). However, even when taking the business stealing effect into account, Piva and Vivarelli (2004 and 2005) found evidence suggesting that innovation

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<sup>8</sup> Indeed, new products (for instance cars) also displace old products (for instance carriages); generally speaking, however, the 'welfare effect' (increasing demand) far exceeds the substitution effect (see Freeman, Clark and Soete, 1982; Katsoulacos, 1984).

had a positive effect on employment at the firm level. In particular, by applying a GMM-SYS methodology to a longitudinal dataset of 575 Italian manufacturing firms over the period 1992–1997, the authors provide evidence of a significant, although small in magnitude, positive link between a firm's gross innovative investment and employment.

Using firm-level data (obtained from the third wave of the Community Innovation Survey, CIS) from four European countries (Germany, France, UK, Spain), Harrison, Jaumandreu, Mairesse and Peters (2008) put forward a testable model based on Peters (2004) which was able to distinguish the relative effects on employment of process and product innovation (discrete variables). The authors conclude that process innovation tends to displace employment, while product innovation is basically labour-friendly. However, compensation mechanisms (see Section 1) are at work, and they are particularly effective in the service sectors due to the increase in demand for the new products. Hall, Lotti and Mairesse (2008) applied a similar model to a panel of Italian manufacturing firms over the period 1995–2003 and found that product innovation had a positive effect on employment, with no evidence of employment displacement due to process innovation.

More recently, Lachenmaier and Rottmann (2011) put forward a dynamic employment equation including wages, gross value added, year and industry controls, and alternative proxies (dummies) for 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 — show that different innovation measures have a significantly positive impact on employment. Partially in contrast with previous contributions, the authors found that process innovation had a higher positive impact than did product innovation.<sup>9</sup>

In previous literature, empirical analysis has very rarely been carried out according to sector. One of the exceptions is the contribution by Greenhalgh, Longland and Bosworth (2001), which develops fixed effects estimates based on a panel of UK firms over the period 1987–1994. Concurring with most of the other studies discussed here, the authors found that R&D expenditures had a positive, albeit modest, effect on employment. However, once they had analysed the data according to firms' sectors, the positive impact of R&D on employment turned out to be limited solely to the high-tech sectors. In contrast, once they had grouped the sectors as high-tech and non high-tech, Lachenmaier and Rottmann (2011) did not find any significant sectoral heterogeneity in the effects that innovation has on employment.

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<sup>9</sup> However, this result may 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 corresponding to patent applications, they found a highly positive and significant employment effect.



As already mentioned, Harrison, Jaumandreu, Mairesse and Peters (2008) distinguished manufacturing from service firms and pointed out the effectiveness of compensation mechanisms and the labour-friendly nature of product innovation. One of the novelties of this paper is its grouping of sectors, both in terms of manufacturing vs services and of high-tech vs non high-tech. Lastly, in a very recent study, Coad and Rao (2011) limit their focus to US high-tech manufacturing industries over the period 1963–2002 and investigate the impact of a composite innovativeness index (comprising information on both R&D and patents) on employment. The main outcome of their quantile regressions is that innovation and employment are positively linked and that innovation has a stronger impact on those firms experiencing the fastest growth in employment.

On the whole, although previous microeconomic evidence is not fully conclusive about the possible impact of innovation on employment, more recent panel investigations tend to support a positive link, especially when R&D and/or product innovation are adopted as proxies for technological change and when the focus is on high-tech sectors.

### **3 The Dataset**

The original microdata strings used in this study were provided by the JRC–IPTS (Joint Research Centre – Institute for Prospective Technological Studies) of the European Commission. The information includes only publicly-traded companies and is extracted from a variety of sources, including companies' annual reports, the Securities and Exchange Commission (SEC) 10-K and 10-Q reports, daily news services and direct company contact.<sup>10</sup> More specifically, this work is limited to a study of EU firms over a period of 19 years (1990–2008). The longitudinal database contains the following information:

- Company identification: name and address, industry sector (Global Industry Classification Standard (GICS), which can be translated to the standard SIC classification);
- Fundamental financial data, including income statements, cash flows, taxes, dividends and earnings, pension funds, property assets, ownership data, etc.
- Fundamental economic data, including the crucial information for this study, namely: sales, capital formation, R&D expenditures, employment and the cost of labour.

Data are filed in current national currencies.

Given the crucial role assumed by the R&D variable in this study, it is worthwhile to discuss in

detail what is meant by the R&D figure. This item represents all costs incurred during the year relating to the development of new products and services. It is important to note that this amount only represents company's contribution and excludes amortisation and depreciation of previous investments, therefore providing a genuine flow of current additional in-house R&D expenditures. In particular this definition excludes customer or government-sponsored R&D expenditures; engineering expenses such as routine ongoing engineering efforts to define, enrich or improve the qualities and characteristics of existing products; inventory royalties; and market research and testing. Therefore, our impact variable can be considered a better proxy for product rather than process innovation. In fact, while we cannot deny that a portion of the registered R&D expenditures may be devoted to complementary process innovation, the adopted definition of R&D renders the expected correlation between such expenditures and product innovation much more straightforward.<sup>11</sup>

It is important to note that the number of years available for each company depends on the company's history; more specifically, a firm enters the database when it first publishes a public financial statement and is dropped in the event of bankruptcy, exiting from the relevant market or due to M&A. In addition, not all of the information from the same firm may be available for the entire 20-year period covered by the statistical sources. Thus, the longitudinal database is unbalanced by nature.

Once we had acquired the rough original IPTS data, we proceeded to construct a consistent longitudinal database that would be adequate for running panel estimations intended to test the relationship between R&D and employment. For the sake of simplicity, we will describe the complex procedure adopted step by step below.

#### First step: data extraction

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

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<sup>10</sup> The original source was the Standard & Poor's Compustat database.

<sup>11</sup> Unfortunately, our data source does not permit to split the R&D costs into the two components specifically devoted to product and process innovation. However, recent microeconomic studies — using data from the European Community Innovation Surveys (CIS) — have confirmed empirically how R&D expenditures are mainly and significantly linked to product innovation. At the same time, other innovative expenditures, such as those in new machinery and equipment, turn out to be mainly related to process innovation, especially within the “supplier dominated” traditional manufacturing sectors (see Conte and Vivarelli, 2005; Parisi, *et al.* 2006). By the same token, Cincera (2005) shows that R&D expenditures are intended for product innovation in 77% of all cases (*ibidem*, Table 2, p. 9).

- We selected only those companies with R&D > 0 in at least one year in the available time-span;
- We selected only those companies located in the EU 27 countries;
- We extracted information concerning R&D, sales, capital formation, R&D expenditures, employment and cost of labour. More specifically, the list of the available information for each firm included in the obtained workable dataset appears below:
  - country of incorporation (location of the headquarters);
  - industry code at 2008;
  - R&D expenses (as defined in the previous sub-section);
  - capital expenditures;
  - sales;
  - employees;
  - cost of labour (defined as staff expenses<sup>12</sup>).
- We expressed all data values in the current national currency in millions (for instance, countries which currently use the euro have values in euros for the entire study period).
- We excluded a minority of unreliable data such as negative sales.

#### Second step: deflation of current nominal values

Nominal values were translated into constant price values through GDP deflators (source: IMF) centred on the year 2000. For a tiny minority of firms reporting in currencies different from the national currency (*i.e.* 41 British, 9 Dutch, 4 Irish, 2 Luxembourg, 1 German and 1 Swedish firms reporting in US dollars; 7 British, 2 Danish and 1 Estonian firms reporting in euros), we opted to deflate the nominal values through the national GDP deflator as well.

#### Third step: values in PPP dollars

Once we had obtained constant 2000 price values, all figures were converted into US dollars

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<sup>12</sup> This item represents all direct remunerations to the firm's employees.

using the PPP exchange rate at year 2000 (source: OECD).<sup>13</sup> Nine companies from 4 countries (Lithuania, Latvia, Malta and Romania) were excluded, due to the unavailability of PPP exchange rates from the OECD. The 10 companies reporting in euros but located in non-euro countries (Denmark, Estonia and the UK) were excluded as well<sup>14</sup>, while the 58 European companies reporting in US dollars were kept as such.

#### Fourth step: the final format of the panel data

The obtained unbalanced database comprises 804 companies (for a total of 4244 observations), 2 codes (country and sector) and 5 variables (see the bullet list above) over a period of 19 years (1990–2008).

Since one of our research objectives is to distinguish between manufacturing and service firms, and between high-tech and medium/low-tech sectors<sup>15</sup> within manufacturing, we then added a third code to label the following sectors as high-tech.<sup>16</sup>

SIC 283: Drugs (ISIC Rev.3, 2423: Pharmaceuticals);

SIC 357: Computer and office equipment (ISIC Rev.3, 30: Office, accounting and computing machinery);

SIC 36 (excluding 366): Electronic and other electrical equipment and components, except computer equipment (ISIC Rev.3, 31: Electrical machinery and apparatus);

SIC 366: Communication equipment (ISIC Rev.3, 32: Radio, TV and communications equipment);

SIC 372-376: Aircraft and spacecraft (ISIC Rev.3, 353: Aircraft and spacecraft);

SIC 38: Measuring, analysing and controlling instruments (ISIC Rev. 3, 33: Medical, precision and optical instruments)

However, as discussed in the next section, our econometric exercise is based on a standard

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<sup>13</sup> This procedure is consistent with that suggested by the Frascati Manual (OECD, 2002) in order to adjust R&D expenditures correctly for differences in price levels over time (*i.e.* intertemporal differences requiring deflation) and between countries (*i.e.* interspatial differences requiring a PPP equivalent). In particular “...the Manual recommends the use of the implicit gross domestic product (GDP) deflator and GDP-PPP (purchasing power parity for GDP), which provide an approximate measure of the average real “opportunity cost” of carrying out the R&D (*ibidem*, p. 217). PPP dollars were chosen, since the US dollar is commonly considered the reference currency for global transactions, such as those carried out by the firms we researched.

<sup>14</sup> Given the very small number of firms involved, we decided not to make the arbitrary choice of using either the national or the euro PPA converter.

<sup>15</sup> In this respect, and using the same dataset, Ortega-Argilés, Piva, Potters and Vivarelli (2010) found significant sectoral differences in the R&D–productivity relationship.

<sup>16</sup> We took the standard OECD classification (see Hatzichronoglou, 1997) and extended it to include the entire electrical and electronic sector 36 (considered as a medium-high tech sector by the OECD). We opted for this

dynamic specification of the demand for labour. Given the unbalanced nature of our longitudinal database, the inclusion of the lagged dependent variable in the estimated specification involved both a reduction in the number of firms (retaining only those firms with at least two consecutive employment datasets) and a further decrease in the number of observations (initial and isolated data). Therefore, in order to estimate the proposed dynamic specification, we ended up with 677 companies for a total of 3049 observations. Table 1 below reports the distribution of the firms we retained by their home countries.<sup>17</sup>

The database covers the largest R&D spenders. As can be deduced from European R&D Scoreboard, expenditure on R&D is extremely concentrated, with the top 1000 groups accounting for about 80% of world expenditure and with approximately 300 groups accounting for about 60% of business R&D worldwide. All of those groups are included in our database.

**Table 1: Sample composition**

COUNTRY	FIRMS	OBS.
AUT	19	35
BEL	20	49
CZE	1	3
DEU	134	472
DNK	25	143
ESP	3	5
EST	2	3
FIN	52	142
FRA	46	211
GRC	16	32
HUN	2	7
IRL	10	63
ITA	5	10
LUX	3	5
NLD	27	119
SVN	1	2
SWE	69	388
UK	242	1360
<b>EU</b>	<b>677</b>	<b>3049</b>

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extension considering that we are comparing only the high-tech sectors with all of the others and that we need an adequate number of observations in the sub-group of high-tech sectors.

<sup>17</sup> Bearing in mind that all of the included firms are quoted, countries such as the UK where stock exchange quotation is more common tend to be over-represented.

## **4 Identification Strategy**

This section focuses on illustrating the adopted microeconomic strategy, while the following section discusses the results in detail. We will start with some methodological notes.

As briefly discussed in Section 1, economic theory cannot provide a clear-cut answer to the question of the effect of technological change on employment; attention should therefore be turned to empirical analysis. However, this is not an easy task. Firstly, the microeconomic specification of the employment equation has to take into account the sticky and path-dependent nature of a firm's demand for labour (due to institutional factors such as labour protection and high adjustment costs in hiring and firing) and the possible negative impact of wage dynamics. These considerations call for a dynamic (autoregressive) specification of a firm's employment dynamics and for the inclusion of a variable measuring the cost of labour as perceived by the firm under study (see the specification introduced below).

Secondly, the investigation of the relationship between technological change and employment at the firm level may involve both a 'pessimistic' and an 'optimistic' bias which must be noted. Starting with the former, it is important to recall that microeconomic analyses fully capture the direct labour-saving effect of innovation at the firm level, while only partially taking into account all of the compensation mechanisms briefly discussed in Section 1 (in fact, price and income effects operate within the innovating firm but they also leak out in favour of other firms and sectors). This 'pessimistic' bias makes it more likely that a negative employment impact of innovation will be found, especially when a firm is characterised by prevalent process innovation. In this paper, the adopted measure of technological change (R&D) minimises the likelihood of this particular bias, since — as discussed above — R&D expenditures are more closely linked to product than to process innovation.

Thirdly, when dealing only with samples of innovative firms (as is the case in this study), microeconomic studies should take into account the so-called 'business stealing' effect, that is, the competitive displacement of laggards and non-innovators. In fact, once the empirical analysis is developed at the level of the single firm, innovative firms tend to be characterised by better employment performance since they gain market share because of innovation. Indeed, even when innovation is intrinsically labour-saving, simple microcorrelations generally show a positive link between technology and employment, since they do not take into account the important effect on rivals, which are crowded out by the innovative firms. In contrast with the pessimistic bias, the optimistic bias makes it more likely that a positive impact of innovation on employment will be found. This result may be reversed at the sectoral and aggregate levels. In



this respect, the empirical specification should include a demand variable (such as sales) capable of screening for the business stealing effect (see below).

Bearing these methodological caveats in mind, we now turn our attention to the adopted specification used to investigate the link between R&D and employment at the firm level.

Consider a perfectly competitive firm maximising its profits under a Constant Elasticity of Substitution (CES) function of the type:

$$(1) \quad Y = A[(\alpha L)^\rho + (\beta K)^\rho]^{1/\rho}$$

where  $Y$  is the output,  $L$  (Labour) and  $K$  (capital) the inputs,  $A$  is a potential Hicks-neutral technological change, and  $\alpha$  and  $\beta$  are the parameters measuring the reaction of labour and capital to a technological shock and  $0 < \rho < 1$ .

If  $W$  represents the cost of labour and  $P$  is the output price, profit maximisation leads to the following labour demand (in logarithm form):

$$(2) \quad \ln(L) = \ln(Y) - \sigma \ln(W/P) + (\sigma - 1) \ln(\alpha)$$

where  $\sigma = 1/(1-\rho)$  is the elasticity of substitution between capital and labour.

The stochastic version of labour demand (2) augmented by including innovation (see Van Reenen, 1997, for a similar approach) for a panel of firms ( $i$ ) over time ( $t$ ) is:

$$(3) \quad l_{i,t} = \beta_1 y_{i,t} + \beta_2 w_{i,t} + \beta_3 r_{i,t} + \beta_4 g_{i,t} + (\varepsilon_i + v_{i,t}) \quad i = 1, \dots, N \quad t = 1, \dots, T$$

where lower-case letters indicate natural logarithms,  $l$  is labour,  $y$  is output (proxied by sales),  $w$  represents real wages (deflated with prices),  $r$  &  $d$  stands for R&D expenditures,  $g$  for gross investments,  $\varepsilon$  is the idiosyncratic individual and time-invariant firm's fixed effect and  $v$  is the usual error term.<sup>18</sup>

While specification (3) is static, a dynamic one would be more appropriate for studying the relationship between labour and innovation (see above):

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<sup>18</sup> Under the assumption that the disturbances are independent across firms.

$$(4) \quad l_{i,t} = \alpha l_{i,t-1} + \beta_1 y_{i,t} + \beta_2 w_{i,t} + \beta_3 r \& d_{i,t} + \beta_4 g i_{i,t} + (\varepsilon_i + v_{i,t})$$

It is well known that this dynamic specification gives rise to some problems. First of all, the lagged dependent variable  $l_{i,t-1}$  is — by construction — correlated with the individual fixed effect  $\varepsilon_i$  transforming the Ordinary Least Squares (OLS) into a biased and inconsistent estimator. On a more general level, the OLS estimates do not take into account the unobservable individual effects (in our case a firm's specific characteristics such as managerial capabilities) which may affect both the dependent variable and the regressors. A first available solution for this problem is to compute the within-group estimate based on the inclusion of the fixed effects in the estimation procedure (fixed effect estimator). A second solution, employed to wipe out the fixed effects, is to switch to the first difference.<sup>19</sup>

$$(5) \quad \Delta l_{i,t} = \alpha \Delta l_{i,t-1} + \beta_1 \Delta y_{i,t} + \beta_2 \Delta w_{i,t} + \beta_3 \Delta r \& d_{i,t} + \beta_4 \Delta g i_{i,t} + \Delta v_{i,t}$$

A common problem with this kind of dynamic specification concerns the endogeneity of the lagged dependent variable, *i.e.* the correlation between  $\Delta l_{i,t-1}$  and the error term  $\Delta v_{i,t}$ .<sup>20</sup> To solve this problem and obtain consistent estimates, it is necessary to rely on instrumental variable techniques (Arellano, 1989; Arellano and Bond, 1991; Arellano and Bover, 1995; Ahn and Schmidt, 1995; Blundell and Bond, 1998).<sup>21</sup> In particular, Arellano and Bond (1991) introduced the GMM-DIF estimator (first-differenced GMM) as a suitable tool for dealing with the endogeneity of the lagged dependent variable.<sup>22</sup> Blundell and Bond (1998) improved the DIF-estimator by developing the GMM-SYS estimator, which is more appropriate in the case of high persistency of the dependent variable (*i.e.*  $\alpha$  approaching 1).

However, recent econometric literature has revealed that both of these GMM-estimators perform poorly when the panel is characterised by a low number of individuals ( $n$ ). This is our case, since we start with a relatively small number of firms (677) and drop to a very small  $n$ -value when dealing with service sectors (178) and high-tech manufacturing sectors (152).

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<sup>19</sup> The first difference (following Anderson and Hsiao, 1981) may be more reliable than the within-group estimator, especially when the available panel is limited in its time dimension (see also Van Reenen, 1997, and Baltagi, 2001). A well-known problem when first differencing equation (4) is that if variables are highly persistent, then taking the F.D. of these variables brings them close to zero; in addition to generating measurement errors, this tends to bias the estimates towards zero. However, the flow formulation for R&D and investment guarantees that this is not a problem in our sample.

<sup>20</sup> The dependence of  $\Delta v_{i,t}$  on  $v_{i,t-1}$  implies that OLS estimates of  $\alpha$  in the first-differenced model are inconsistent.

<sup>21</sup> Under the assumption of no serial correlation of the error term in levels, it is possible to use values in level of the dependent variable lagged two periods or more back as instruments. This implies that the number of instruments grows with the time dimension. The instruments in level permit the use of all the available moment conditions (see Arellano and Bond, 1991; Ahn and Schmidt, 1995). In our case, for instruments to be valid, the following two conditions must be respected:  $E(\Delta l_{i,t-1} l_{i,t-s}) \neq 0$ , if  $s \geq 2$  and  $E(l_{i,t-2} \Delta v_{i,t}) = 0$ .

Therefore, we have used the recently proposed Least Squares Dummy Variable Corrected (LSDVC) estimator. This method was proposed by Kiviet (1995), Judson and Owen (1999), Bun and Kiviet (2001 and 2003) as being a suitable panel data technique in the case of small samples in which GMM cannot be applied efficiently. This procedure is initialised by a dynamic panel estimate (in our case the GMM-SYS one, given the high persistency of our dependent variable), and then relies on a recursive correction of the bias of the fixed effects estimator.

Bruno (2005a and 2005b) extended the LSDVC methodology to unbalanced panels, such as the one used in this study. The author tested the behaviour of unbalanced small samples (also making robustness checks according to the different sizes of the samples, various time-spans and alternative unbalanced designs) through Monte Carlo experiments. These experiments have highlighted the fact that the LSDVC estimator should be preferred to the original LSDV estimator and widely-used GMM estimators when the number of individuals is small and the degree of unbalancedness is severe<sup>23</sup> (Bruno, 2005a).

In accordance with Bun and Kiviet (2001), who demonstrated that the estimated asymptotic standard errors may prove to be poor approximations in small samples, the statistical significance of the LSDVC coefficients was tested using bootstrapped standard errors (50 iterations; see also Bruno, 2005a).

## 5 Results

As discussed in Section 3, the following estimates are based on a subsample of 677 European firms, for a total of 3049 observations. Table 2 below reports the descriptive statistics of the variables (prior to log-transformation) relevant to the regression analysis.

**Table 2: Descriptive statistics (677 firms, 3049 observations)**

VARIABLES	MEAN	STANDARD DEVIATION	
Employment	20.648	Overall	52.121
		Between	44.883
		Within	9.158
Sales	6002.89	Overall	20 587.41
		Between	14 510.41
		Within	7946.49

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<sup>22</sup> Interestingly enough, the demand for labour was put forward by Arellano and Bond (1991) as the typical example of a dynamic specification for which the GMM-DIF appears particularly suitable.

<sup>23</sup> Two conditions which are verified in our dataset. The pattern of the database can be seen in Table 1.

Wages	107.57	Overall	1063.13
		Between	341.84
		Within	918.97
R&D expenditures	190.96	Overall	663.05
		Between	440.74
		Within	187.24
Gross Investments	460.87	Overall	1977.46
		Between	1416.50
		Within	812.03

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Note: employment and wages are expressed in thousands; other values are in millions of PPP US dollars.

As detailed in the previous section, we ran regressions of the dynamic labour demand specification (5) using three different methodologies:

- Pooled Ordinary Least Squared (POLS) estimates with heteroskedasticity-robust standard errors, controlling for time, country and sectoral dummies. Although very preliminary, POLS estimates give an approximate idea of the results. However, it is important to bear in mind that POLS estimates do not control for unobserved individual effects or for the endogeneity of the lagged dependent variable (resulting in overestimation of the corresponding coefficient).

- Fixed Effects (FE) estimates, checked for time dummies. Much more reliable than POLS, these estimates control for individual unobservables but are still affected by the endogeneity of the lagged dependent variable (resulting in underestimation of the corresponding coefficient). Using this methodology, individual specific country and sectoral dummies are dropped and absorbed by the individual fixed effect.

- Least Squares Dummy Variable Corrected (LSDVC) estimates, checked for time dummies. This is the most reliable and complete methodology, controlling for both individual effects and the endogeneity of the lagged dependent variable.

Table 3 reports the results from the POLS, FE and LSDVC estimates. As can be seen, the sticky and path-dependent nature of labour demand is well-confirmed by the large and highly significant coefficient of the lagged dependent variable (ranging from 0.629 to 0.796).

Turning our attention to the standard determinants of labour demand, it is worth noting that sales, gross investment and wages all exhibit the expected signs and very significant coefficients (not surprisingly, the largest impact is attributable to output dynamics). Where our main variable of interest (R&D) is concerned, the aggregate outcomes seem to suggest a positive and significant relationship between R&D expenditures and employment, with a coefficient that is always significant for at least the 90% level of confidence (95% in the most

reliable LSDVC estimate), and showing a magnitude ranging from 0.018 to 0.033. In general terms, this evidence supports R&D expenditures playing a labour-friendly role. However, the estimated elasticity turns out to be rather low: if a company doubles its R&D expenditures, the expected increase in its employment is about 2–3%.

The overall Wald tests on the joint significance of the inserted dummies are always 99% significant, confirming the need to take into account time, country and sectoral fixed effects where possible.

**Table 3: Econometric results - whole sample**  
**Dependent variable: log(Employment)**

	(1) POLS	(2) Fixed Effects	(3) LSDVC
Log (Employment-1)	0.796*** (0.016)	0.629*** (0.098)	0.691*** (0.015)
Log (Sales)	0.121*** (0.016)	0.242*** (0.063)	0.212*** (0.015)
Log(R&D expenditures)	0.018*** (0.004)	0.033* (0.018)	0.023** (0.010)
Log(Gross investments)	0.044*** (0.007)	0.063*** (0.011)	0.064*** (0.008)
Log(Wages)	-0.068*** (0.009)	-0.066*** (0.021)	-0.060*** (0.006)
Constant	-0.400*** (0.090)	-1.138*** (0.360)	
Wald time-dummies ( <i>P</i> -value)	4.75*** (0.000)	2.87*** (0.000)	48.94*** (0.000)
Wald country-dummies ( <i>P</i> -value)	4.15*** (0.000)		
Wald sectoral-dummies ( <i>P</i> -value)	5.18*** (0.000)		
	R <sup>2</sup> 0.99	R <sup>2</sup> (within) 0.82	
<i>No. of observations</i>		3049	
<i>No. of firms</i>		677	

Note:

- Standard errors in parentheses, robust standard errors in POLS estimates;
- \* significance at 10%, \*\* 5%, \*\*\* 1%.

On the following pages, Tables 4, 5, 6, and 7 show the results of testing specification (5) using different sectoral groups, namely manufacturing vs service firms and high-tech manufacturing sectors vs other manufacturing sectors.



**Table 4: Econometric results – manufacturing sectors**

**Dependent variable: log(Employment)**

	(1) POLS	(2) Fixed Effects	(3) LSDVC
Log (Employment $_{t-1}$ )	0.829*** (0.016)	0.707*** (0.094)	0.772*** (0.016)
Log (Sales)	0.102*** (0.016)	0.208*** (0.058)	0.179*** (0.020)
Log(R&D expenditures)	0.010** (0.005)	0.032* (0.018)	0.025* (0.013)
Log(Gross investments)	0.041*** (0.006)	0.054*** (0.011)	0.054*** (0.009)
Log(Wages)	-0.063*** (0.010)	-0.064*** (0.021)	-0.055*** (0.008)
Constant	-0.330*** (0.104)	-0.991*** (0.332)	
Wald time-dummies ( <i>P</i> -value)	2.52*** (0.000)	2.07*** (0.008)	39.08*** (0.001)
Wald country-dummies ( <i>P</i> -value)	4.03*** (0.000)		
Wald sectoral-dummies ( <i>P</i> -value)	4.71*** (0.000)		
	R <sup>2</sup> 0.99	R <sup>2</sup> (within) 0.82	

*No. of observations*

2331

*No. of firms*

499

Note:

- Standard errors in parentheses, robust standard errors in POLS estimates;
- \* significance at 10%, \*\* 5%, \*\*\* 1%.

**Table 5: Econometric results – service sectors**

**Dependent variable: log(Employment)**

	(1) POLS	(2) Fixed Effects	(3) LSDVC
Log (Employment-1)	0.692*** (0.033)	0.364*** (0.043)	0.425*** (0.027)
Log (Sales)	0.194*** (0.033)	0.392*** (0.040)	0.362*** (0.030)
Log(R&D expenditures)	0.046*** (0.010)	0.068*** (0.027)	0.056** (0.022)
Log(Gross investments)	0.047*** (0.015)	0.076*** (0.021)	0.075*** (0.015)
Log(Wages)	-0.072*** (0.017)	-0.049*** (0.018)	-0.049*** (0.014)
Constant	-0.658*** (0.176)	-2.015*** (0.207)	
Wald time-dummies ( <i>P</i> -value)	3.40*** (0.000)	1.99** (0.015)	24.51* (0.079)
Wald country-dummies ( <i>P</i> -value)	3.67*** (0.000)		
Wald sectoral-dummies ( <i>P</i> -value)	5.07*** (0.000)		
	R <sup>2</sup> 0.99	R <sup>2</sup> (within) 0.84	

*No. of observations*

718

*No. of firms*

178

Note:

- Standard errors in parentheses, robust standard errors in POLS estimates;
- \* significance at 10%, \*\* 5%, \*\*\* 1%.

**Table 6: Econometric results – high-tech manufacturing sectors**

**Dependent variable: log(Employment)**

	(1) POLS	(2) Fixed Effects	(3) LSDVC
Log (Employment-1)	0.777*** (0.026)	0.465*** (0.047)	0.544*** (0.032)
Log (Sales)	0.115*** (0.025)	0.320*** (0.035)	0.278*** (0.035)
Log(R&D expenditures)	0.018** (0.008)	0.059*** (0.015)	0.049*** (0.015)
Log(Gross investments)	0.057*** (0.011)	0.050*** (0.011)	0.050*** (0.017)
Log(Wages)	-0.069*** (0.021)	-0.040* (0.025)	-0.033** (0.015)
Constant	-0.421*** (0.128)	-1.591*** (0.245)	
Wald time-dummies ( <i>P</i> -value)	1.74** (0.035)	2.04** (0.013)	15.57 (0.483)
Wald country-dummies ( <i>P</i> -value)	2.27*** (0.005)		
Wald sectoral-dummies ( <i>P</i> -value)	3.69*** (0.005)		
	R <sup>2</sup> 0.99	R <sup>2</sup> (within) 0.80	

*No. of observations*

685

*No. of firms*

152

Note:

- Standard errors in parentheses, robust standard errors in POLS estimates;

- \* significance at 10%, \*\* 5%, \*\*\* 1%.

**Table 7: Econometric results – non high-tech manufacturing**

**Dependent variable: log(Employment)**

	(1) POLS	(2) Fixed Effects	(3) LSDVC
Log (Employment-1)	0.851*** (0.019)	0.769*** (0.086)	0.867*** (0.033)
Log (Sales)	0.105*** (0.020)	0.209*** (0.056)	0.170*** (0.031)
Log(R&D expenditures)	0.003 (0.006)	0.037 (0.022)	0.021 (0.018)
Log(Gross investments)	0.028*** (0.007)	0.051*** (0.015)	0.039** (0.019)
Log(Wages)	-0.059*** (0.012)	-0.063*** (0.020)	-0.060*** (0.008)
Constant	-0.372*** (0.132)	-1.077*** (0.301)	
Wald time-dummies (P-value)	2.45*** (0.001)	2.30*** (0.003)	43.35*** (0.000)
Wald country-dummies (P-value)	4.27*** (0.000)		
Wald sectoral-dummies (P-value)	4.30*** (0.000)		
	R <sup>2</sup> 0.99	R <sup>2</sup> (within) 0.84	

*No. of observations*

*1,646*

*No. of firms*

*347*

Note:

- Standard errors in parentheses, robust standard errors in POLS estimates;

- \* significance at 10%, \*\* 5%, \*\*\* 1%.

As can be seen, the econometric results concerning the lagged dependent variable, the three standard regressors of the demand for labour (sales, investment, wages) and the diagnostic tests are consistent across all tables. Therefore, our comments will focus solely on the R&D coefficient and on possible departures from what is shown in Table 3.

The overall positive employment impact of R&D expenditures is weakly confirmed in the case of manufacturing firms (in the LSDVC estimate, the coefficient exhibits a magnitude of 0.025

at the 90% level of statistical significance), while it is more consistently confirmed in the case of services (0.056 at the 95% level of significance).

Once we divide manufacturing into high-tech vs other sectors (see Section 3, step 4), it is interesting to note that the labour-friendly nature of R&D investment re-emerges as highly significant in the case of the high-tech sectors (0.049 at 99%), while it is revealed as not significant — although still positive — in the non-high-tech sectors. This evidence supports the view that the positive impact of R&D expenditures on employment is detectable in the services and in the high-tech manufacturing sectors, but not relevant in the more traditional manufacturing sectors. Taking into account the theoretical framework and the previous literature discussed in Sections 1 and 2, a possible interpretation of these results is that services and high-tech manufacturing are characterised by a dominant role played by product innovation and by more effective ‘compensation mechanisms’ fostered by increasing demand (see also Harrison, Jaumandreu, Mairesse and Peters, 2008), while more traditional manufacturing sectors are instead characterised by a prevalence of process innovation and decreasing demand, at least in relative terms.

The value of this elasticity is in line with previous studies at the industry level (for instance Bogliacino and Vivarelli, 2010) and slightly lower than previous estimates at firm level (e.g. van Reenen, 1997, but we should be mindful of the European dimension since the cited study addressed the UK only).

## **6 Conclusions & implications for policy**

In general terms, the main finding of this study is unequivocal: the labour-friendly nature of companies’ R&D investments is clearly shown to be statistically significant, although not very large in terms of relative magnitude.

This outcome provides further support to the Europe 2020 policy target aiming to increase the European R&D/GDP ratio, and is reassuring with regard to the possible employment consequences of increasing R&D investment across the different countries of the EU. Indeed, the evidence provided supports the view that R&D expenditures are beneficial not only to European productivity and competitiveness, but also to European job creation capacity.

However, this policy implication should be qualified in two important respects. Firstly, in this study we have focused our attention on one indicator of innovation, that is, R&D expenditures.

While strictly related to labour-friendly product innovation, this indicator imperfectly captures the alternative mode of technological change, *i.e.* (possibly) labour-saving process innovation (see Sections 1 and 2). This means that embodied technological change and process innovation, with their possible adverse impacts on employment, are underestimated in this study.

Secondly, what emerges clearly from the empirical analysis is that the positive and significant effect on employment of R&D expenditures is not equally detectable across the different economic sectors. More specifically, it is evident for services and high-tech manufacturing, but absent for the more traditional manufacturing sectors. This means that we should not expect a positive impact on employment from increasing R&D in most industrial sectors. This is something that should be borne in mind by European innovation policy makers considering employment as one of their main targets.

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***IPTS WORKING PAPER on CORPORATE R&D AND INNOVATION - No. 10/2011***

Title: Job Creation Effects of R&D Expenditures: Are High-Tech Sectors the Key?

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## **Abstract**

In this paper we assess the job creation effect of R&D expenditures, using a unique longitudinal database of 677 European companies over the period 1990–2008. We estimate a dynamic labour demand specification using a Least Squares Dummy Variable Corrected technique.

The labour-friendly nature of R&D emerges from the empirical analysis on the overall sample. However, this positive significant effect corresponds to the high-tech sector and services, while the effect is not significant for traditional manufacturing. The results support the policy agenda of promoting structural change in European economies.

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