International and domestic R&D spillovers and industrial employment: the case of Spain, 1993 - 2002.

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ABSTRACT

The effect of technology on industrial employment changes depending on whether the technological effort takes place within the own sector or the technological improvements are provided by other sectors or countries. In this paper we estimate international and domestic R&D effects on employment for 28 Spanish manufacturing sectors, using a labour demand function and dynamic panel data techniques.

Technology is proxied using a wide range of variables: sectoral R&D stock; total R&D spillovers; and spillovers from R&D – intensive sectors. These spillovers are calculated combining information from input-output tables and sectoral R&D stocks, for international and domestic terms.

Our results indicate a positive effect from absorbed R&D - intensive spillovers on manufacturing employment, but the most significant effect comes from the spillovers from international R&D intensive sectors.

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KEYWORDS: Labour demand; Technology; R&D spillovers; Dynamic panel data

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1. INTRODUCTION

The effect of technology on industrial employment is shaped by the way the former is obtained. Its impact is different depending on whether the technological effort takes place within the own sector or the technological improvements are provided by other agents. In this last case, we speak of technological spillovers and their study is the purpose of this paper.

The economic literature has not achieved definitive conclusions when studying the link between technology and employment, as it depends on firm strategies, predominant type of innovation, level of aggregation for the study, sector considered, workers' qualification, type of labour market, etc.[1]. Furthermore, the Spanish industry is specialised on traditional sectors where small and medium firms are predominant. This type of firm shows low R&D effort and buys technology, or imports it by means of capital goods, rather than produce it. In this context, it is even more relevant to study the importance of technology impact on employment through different measures: sector R&D expenditure, technology spillovers, and spillovers from R&D – intensive sectors, both in domestic and international terms.

The original contribution of this empirical analysis is the combination of different approaches to the study of technology and employment: a) estimation of a labour demand function using dynamic panel data techniques, and b) use of input – output tables for the calculation of domestic and international R&D spillovers. We follow previous studies by Piva and Vivarelli (2003) and Hubert and Pain (1999) in using labour demand functions, but we further elaborate by calculating spillovers from input-output tables. To our knowledge, there is not previous work on input-output spillovers on employment. On the other hand, the main focus of input – output studies on R&D spillovers, like Terleckyj (1974), Wolff and Nadiri (1993) and Sakurai

[1] See the literature review in Piva and Vivarelli (2003) and Van Reenen (1997).

et al. (1997), is to analyse their effect on productivity and production, rather than employment.

In our study, these spillovers are calculated from each sector R&D stock and an input - output *use table*. In this way, the purchases of intermediate inputs by one sector is used to weight the absorption of technology coming from the remaining sectors. This is what we call vertical spillovers, compared to horizontal ones (interactions among firms within the same sector). Moreover, this methodology allows us to distinguish the effect of spillovers from R&D – intensive sectors, and from domestic and imported inputs.

The aim of this paper is to estimate the effects of (own and absorbed) R&D on employment for 28 manufacturing sectors, for the period 1993-2002. Our results indicate that there is a positive effect of R&D – intensive spillovers on manufacturing sector employment, but the most significant effect comes from the spillovers from international R&D – intensive sectors. The use of these intensive-R&D inputs seems to be complement to employment, rather than labour-saving.

The remainder of this paper is as follows. In sections 2 and 3 we review the relevant literature on labour demand functions and technology spillovers. In section 4 we outline the basic model used and the calculation of R&D spillovers. Section 5 comments on the data and a number of important econometric issues. Section 6 contains the main empirical results and section 7 concludes.

2. TECHNOLOGY AND EMPLOYMENT IN RECENT LITERATURE

Our empirical application combines two established traditions of analysis of the impact of innovation on employment: 1) one based on the estimation of a labour demand function, 2) the use of input-output tables to calculate R&D spillovers. This section discusses the link between employment and technology, while section 3 reviews the literature on spillovers.

In the last years, one of the most important lines of research for the effect of technology on employment is the estimation of labour demand functions. Recent literature shows that the link between technology and employment depends on the level of aggregation for the study, firm or sector – level, and the way to proxy technology: R&D expenditures, R&D stock, economy – wide knowledge stock, process innovations, product innovations, patents and lastly, different measures of spillovers. We will briefly review the main results in recent literature, emphasising sector – level, GMM and spillovers studies.

Griliches (1979) proposed a theoretical framework for the analysis of the **effect of R&D** on productivity that has been widely used in empirical studies. In his theoretical model, the "current state of technical knowledge", measured as the current and past levels of R&D expenditures, was included in the production function. Recent empirical applications of Griliches's model include: Brouwer *et al.* (1993) and Klette and Førre (1998), both interested in the innovation-labour relationship. Brouwer *et al.* uses data for 859 Dutch manufacturing firms for 1983 and 1988, they find no effect of R&D intensity on labour and a significant negative effect for R&D intensity growth. Klette and Førre work with data for 4000 Norwegian manufacturing firms for the period 1982-1992 and finds no significant effect.

Although firms innovative efforts have been traditionally proxied by R&D expenditure this approach does not account for the real impact of innovations, since the whole of the innovative effort will not be transformed into successful innovations, and it does not allow to distinguish between **product** and **process innovations**. Product innovations are expected to increase firm's labour demand. For firms studies, the positive effect is expected to show in either the short-run or, stronger after consumption adapts, in the long-run. However, if the new product is a close substitutive for an existing good, the increase in demand can have its counterpart in a reduction in non-innovative firms demand, so the positive effect of innovation for firms is blurred for industries, where innovators increase labour whereas non-innovators loose it. Even though, the effect would still be positive if the sectoral absolute demand is growing. Process innovation are expected to reduce firm's labour demand, this displacement direct effect shall be caught at the firm level for the short-run. Still this negative effect can be compensated if firms translate innovations to price reduction and this leads to an increase in product demand, through income or substitution effects, with a positive impact on labour that shall be caught at the firm level for a longer run.

Firm level studies have been preferred to assess the microeconomic employment impact of innovation. Smolny (1998) studied the employment-innovation relationship for a panel of 2,405 West German manufacturing firms for the period 1980-1992, his results show a positive and significant impact of firm product innovations on labour but no significant effect of firm process innovations. A similar result was found by Entorf and Pohlmeir (1991) for a dataset of 2,276 German firms at 1984 for a cross-section analysis. Leo and Steiner (1994) found a positive effect from *lagged* product innovations and no effect from process innovations for a panel of 400 Austrian firms for 1990-1992. All the previous papers work with static panels, only Leo and Steiner searches into the time path for the innovative effect.

For sectoral data, Berndt *et al.* (1992) use a proxy to analyse the relationship between high technology equipment and labour demand. They work with US manufacturing data for the period 1968-1986. For a static analysis, they conclude that there is a positive effect of high technology capital on employment intensity, this effect is more clear for skilled labour.

A different line of analysis proposes to study the **dynamics of the relationship.** Piva and Vivarelli (2003) analyse 1992-1997 data for 575 Italian manufacturing firms. They focus on the relationship of innovation (mainly as process) and employment and find a significant and positive relationship. Piva and Vivarelli build a dynamic labour demand function based on a CES production function assuming Hicks neutral technical progress change and unitary scale returns.

Several recent studies analyse the link between technology and employment for the Spanish economy using labour demand functions and dynamic panel data. García *et al.* build a general knowledge measure, based on R&D accumulation, and process and product knowledge measures, based on the general knowledge measure and process and product innovations implementation. They work with data for 1991-1998 for 1,286 Spanish firms and build a model that include functions for production, labour demand, product demand, wages and margins. They find a negative but weak effect of process innovation on employment and a positive effect of knowledge stock on employment. Product innovation is not explicitly included in the labour demand equation because its effect takes place through changes in product demand. Llorca and Gil (2002) estimate the impact of process and product innovations on industrial firms' employment from a labour demand function. They find process innovations have a larger positive effect on employment than product innovations, which they blame on competition through prices, still important in the Spanish industry. Aguirregabirira and Alonso-Borrego (2001) estimate the effect of technology on labour qualification in the Spanish manufacturing sectors in 1986-1991. In this study they distinguish R&D expenditures and technological capital investment, to find that both variables show a positive relationship between innovation and qualified employment. Nevertheless, technological capital investment is more significant to explain the changes in the occupational structure.

The results of the studies on the effect of technology on employment might be different depending on the level of aggregation: firms versus sectors. Sector – level studies, compared to firm – level ones, offer three advantages, identified by Piva and Vivarelli (2003). First, microeconomic empirical evidence cannot be generalized as it does not capture all the sectoral and macroeconomic effects of innovation. Second, firm-level evidence fully captures the direct labour-saving effect of innovation (especially process innovation) at the level of the firm, whilst only partially taking into account all the compensation mechanisms (product innovation, price and income mechanisms, acquisition of capital goods, etc). Third, firm – level studies, especially when they focus on innovative firms, tend to neglect the so-called "business stealing" effect, that is the competitive displacements of laggers and non-innovators.

These two last effects explain why the innovative effect on sectoral labour demand is blurred. It is theoretically possible to expect a positive or negative effect on employment, depending on the firm's characteristics with respect to innovation (type of innovation, innovative, lagger or non-innovative firm). However, at sector level a number of firms with different characteristics are aggregated and, therefore, it is more difficult to predict the result.

Nevertheless, even when estimating the labour demand function at sector level (including consequently innovation by all the firms in that sector), there exists a share of technology we are not including: the inter-industrial effect of innovation (or vertical spillovers). We consider the effect of this absorbed technology on employment as fundamentally different from that of the technology generated internally within a firm or sector. The reason is that, as the majority of firms in the sector acquire the same high technology intermediate goods, the repercussion (positive or negative) on their employment will be the same or similar for all of them. Even small firms, that can hardly undertake any internal technological effort, will have access to this technology.

3. INTERNATIONAL AND DOMESTIC TECHNOLOGY SPILLOVERS

In this section we will be discussing spillovers and recent literature related to them. We will first developed the concept of spillovers. Secondly, we will briefly review studies on employment and aggregated spillovers. We will then focus on ways to consider inter-industry spillovers and the advantages of using input-output tables. Finaly, we will coment on international spillovers.

Firms and industries not only produce technology by means of direct research efforts, but they are also able to capture innovations and productive improvements generated by the remaining firms through copy or imitation and through purchase. Grilliches (1979) distinguish between two types of spillovers, that are nowadays known as rent and knowledge spillovers. *Rent spillovers* refer to profits linked to new products and improvements that are spread by means of economic transactions among different agents. On the other hand, *knowledge spillovers* refer to the transmission of knowledge and they do not need market transactions. Even though entrepreneurs try to code the new knowledge by means of patents or similar instruments, it still retains public good characteristics, which allows spillovers on the rest of the economy. In recent literature, for example Vuori (1997), the distinction between “embodied technology” and “technology spillovers”, defining the second as technology flows from one economic agent to another, which are involuntary from the point of view of their source and which are not based on economic transactions.

Among the studies about employment and aggregated technology spillovers, we focus on Van Reenen (1997) for firm level, and Barrell & Pain (1997), Hubert & Pain (1999), and Mastrostefano and Pianta (2004) for industry level. Van Reenen works with a panel of 598 firms for the period 1976-1982, he analyses the effect of both innovation and spillovers effects from industry innovations. His analysis improves previous studies by controlling for both fixed effects and dynamics. He finds that there is a strong positive association between innovation and employment at the firm level, while he could not find spillovers effects.

Barrell & Pain (1997) and Hubert & Pain (1999, 2001) augment a labour demand function for several manufacturing industries by including different technological variables as own sectoral R&D stock and spillovers measured by other sectors’ R&D stocks, sectoral FDI and imports. When found significant, these variables seem to have a negative effect on employment for Germany and the UK.

Finally, Mastrostefano and Pianta work with data for **11 industrial sectors** and 10 countries for 1994-2001. They focus on the relationship between employment, product innovation and a proxy for the overall diffusion of innovation for sectors, what can be called **horizontal spillovers**. The positive product innovation effect is quite robust, that is not the case for the positive but low significance diffusion effect. The time lags analysis allows the authors to affirm that, in the long run, the negative relationship between wage and job growth 'is less relevant' than the innovation one.

The main advantage of using input – output tables in studying R&D and productivity spillovers is that they allow to weight the technology that a sector transfers to the remaining sectors by the importance of that sector in their input structure. In Grilliches's terms, these would be rent spillovers, but knowledge spillovers are also generated through market transactions, as prices do not completely reflect the higher value to the consumer of improved products and processes. One reason is that output shares indicate technological relatedness that goes beyond just rent spillovers, and they primarily focus on knowledge spillovers of the "idea-creating" kind[2] (Los and Verspagen, 2004). The trouble in distinguishing the impact from rent and knowledge spillovers leads us to speak of **spillovers** in this paper, that we calculate from each sector's R&D stock and the use matrix of coefficients. Some of these spillovers involve economic transactions, but we consider there are still involuntary technology flows.

The contribution of input – output analysis to the study of sectoral spillovers is significant. The main bibliographic reference in this framework is volume 9 number 1 of Economic Systems Research in 1997[3]. Wolff (1997) uses the matrix of technical coefficients and

[2] Recently, Los and Verspagen (2004) classify knowledge spillovers into two subcategories: "imitation-enhancing" and "idea creating". This last subcategory exists because knowledge may evoke new ideas, which can lead to innovations in other applications than where the original knowledge was found.
[3] The methodology to calculate measures of R&D incorporated in an input-output environment is based on seminal work by Terleckyj (1974).

sectoral R&D intensity as technology variable: it is defined as the ratio of R&D expenditures to GDP in constant terms for each sector. In Sakurai *et al*. (1997) the R&D embodiment is calculated using the R&D intensity per gross output of industry and the input-output Leontief inverse matrix. Four types of spillovers were calculated: R&D embodied in purchased domestic and imported intermediate inputs, and R&D embodied in domestic and imported capital goods.

From a different approach, Verspagen (1997) constructs three matrices of knowledge spillovers using information from the US Patent Office and the European Patent Office (EPO); the 650,000 patents from the EPO are classified into claimable and unclaimable knowledge (non-appropriable) and into main and supplementary codes for claimable knowledge. Van Meijl (1997) uses the Yale technology flow matrix based on approximately 200,000 patents for Canada in 1972-89 to measure the effect of knowledge spillovers on productivity growth.

With respect to international R&D spillovers, suveys of recent literature can be found in Cincera & Van Pottelsberghe de la Potterie (2001) and Mohnen (2001). Coe & Helpman (1995) sparked a growing literature on the effect of R&D international spillovers based on trade, but international R&D spillovers might be transmitted through different channels: 1) trade, particularly intermediate inputs, capital goods, etc.; 2) foreign direct investment (FDI); 3) foreign technology payments, e.g. patents; 4) other channels like mobility of scientists, managers, publication or copy of research results, research collaboration, etc. These different channels are reflected in the way the stock of foreign knowledge is calculated, as they determine the variable to proxy that measure and the weights used to average foreign knowledge by countries or by sectors. The most common variable in recent literature is some measure of R&D (expenditures[4], intensity[5] or stock[6]). Basant & Fikkert (1996) use also

[4] As in Sakurai et al (1997) for own sector R&D.

technology purchase payments, and Hubert and Pain (1999) and Blomström & Sjoholm (1999) measure spillovers from FDI or foreign ownership. We will focus on foreign R&D and use trade weights as it has been done by Coe & Helpman (1995), Vuori (1997), Coe, Helpman & Hoffmaister (1997), Sakurai *et al*. (1997), and Hollanders and Ter Weel (2002). Trade weights are not the only option, as Haddad & Harrison (1993), and Hanel (2000) use FDI or foreign ownership by sector, while Verspagen (1997), Hollanders and Ter Weel (2002), Bottazzi & Peri (2003), and Branstetter (2001) use technological proximity in terms of patents. Most of these studies focus on the effect of international R&D spillovers on productivity, rather than employment, which is the aim of our paper.

Nevertheless, all these papers mentioned above analyse the inter-industry spillovers' impact on productivity or production, rather than employment, which is the aim of this research[7]. We are only aware of recent work by Hollanders and Ter Weel (2002), that analyses the influence of technology spillovers on changes in employment skill structure for six OECD countries, estimating a labour demand function à la Machin and Van Reenen (1998). For all countries evidence is found that knowledge spillovers are skill-biased in the sense that they favour high-skilled labour. However, these spillovers come from a matrix built using data from the European Patent Office, which assigns each patented invention to a single technology class, and one or several supplementary technology classes. The main differences between our research and that by Hollanders and Ter Weel are: a) The calculation of spillovers, as we use input – output tables and Hollanders and Ter Weel use a patent matrix; b) We analyse these spillovers' effect on industrial employment, while Hollanders and Ter Weel focus on industrial workers' skills.

[5] As in Sakurai et al (1997), Fors (1997), Frantzen (2000).
[6] As for example in Coe & Helpman (1995), Basant & Fikkert (1996), Bernstein & Mohnen (1998), Bayoumi, Coe & Helpman (1999), Branstetter (2001).
[7] Spanish studies on the topic of technology and spillovers on production or productivity are Lafuente *et al.* (1984), Fluviá (1990), López and Sanaú (1998), and Beneito (2001).

4. LABOUR DEMAND EQUATIONS AND CALCULATION OF R&D SPILLOVERS

Our study on the link between technology on employment involves estimating a dynamic labour demand function from a CES production function, in the style of those estimated by Barrell and Pain (1997), Hubert and Pain (1999), and Piva and Vivarelli (2003)[8]. The starting point is the assumption of firms maximising profits in a perfect competition environment. From there it is possible to obtain the demand function for the labour factor from the first order condition, which states that each factor's marginal product has to equal its real price (that may or may not be adjusted by some kind of mark-up). Applying logarithms, a linear relationship between employment, output, real wage and other factors (as we will see) results.

The formulation by Piva and Vivarelli (2003) starts from a CES function like

$$Y = A\left[(\beta K)^{-\rho} + (\alpha N)^{-\rho}\right]^{-\left(\frac{1}{\rho}\right)} \qquad (1)$$

where Y is output, K is capital stock, N is employment, A is a potential Hicks-neutral technological change, α and β are technical parameters and $0 < \rho < 1$. Solving the first order condition commented above (quantity of labour input that maximises profits), taking logarithms and regrouping, it is possible to obtain an expression like:

$$n = y + \sigma w - (1-\sigma)\ln\alpha \qquad (2)$$

where $\sigma = 1/1-\rho$ is the elasticity of substitution between K and N, small letters denote logarithms, and w is the log of (real) labour cost.

This labour demand function can be augmented by including variables of technical progress, and estimated using panel data:

[8] Several articles combine a neoclassical production function with spillovers calculated from input – output tables or patent matrices, where intersectoral links are fixed. Most of these studies (Van Meijl, 1997; Sakurai et al, 1997; Verspagen, 1997) start from a Cobb-Douglas production function (with several production factors) and analyse the impact of different measures of spillovers, calculated from input – output tables and patent matrices, on total factor productivity (TFP) obtained in the traditional fashion. Our study is similar to those papers as we also start from a neoclassical (CES) production function but it is different as we derived a labour demand function, instead of studing TFP as the above mentioned authors.

$$n_{it} = \alpha_0 y_{it} + \alpha_1 w_{it} + \alpha_2 inno_{it} + (\varepsilon_i + u_{it}) \tag{3}$$

for *i = 1, ..., N* firms or sectors and *t = 1,..., T* years or periods, and where ε are firm – specific (time – invariant) effects and *u* are the usual error term.

When estimating either of those functions (2 and 3), we would calculate a static or long-term relationship between the studied variables. We would however neglect the potential dynamic links between these variables. In terms of time series or static panel data estimations, this involves considering equation (1) as a long-term relation and including it in an error correction model as:

$$\Delta n_t = \alpha + \beta_1 \Delta y_t + \beta_2 \Delta w_t + \beta_3 (n_{t-1} - n^*_{t-1}) + \varepsilon_t \tag{4}$$

where only dynamic elements in output and wages, and not in technology variables, are included.

In the case of panel data, as in the estimation by Piva and Vivarelli (2003) and our research, the equation can be transformed in a dynamic specification as:

$$n_{it} = \alpha_0 n_{it-1} + \alpha_1 y_{it} + \alpha_2 w_{it} + \alpha_3 inno_{it} + \alpha_4 inno_{it-1} + (\varepsilon_i + u_{it}) \tag{5}$$

for *i = 1, ..., N* sectors or firms and *t = 1,..., T* years or periods, where *inno* denotes the different technology variables that may be included in the equation. Furthermore, we will also include lags of all these variables to investigate the dynamic structure of that specification.

From all variables included in the proposed equation, our research focuses in the most appropriate definition of technology variables, under the notation *inno*. Technology impact on employment is determined by the way technology is appropriated. The effect is different depending on whether the technological effort is undertaken by the own firm/sector or if the technological improvements are acquired in the market. This is why our technology proxy will be based on: own sector R&D expenditures, (domestic and international) technology spillovers, and spillovers from R&D – intensive sectors. We will focus an important part of this research to the calculation of the technology spillovers.

In our case, to calculate R&D spillovers we use R&D stocks by sector and the use input – output table, instead of the interindustry symmetrical (commodity by commodity) matrix. The **use table** shows in columns the input structure for the different sectors (including secondary production[9]), as it includes intermediate consumption and remuneration to primary inputs, adding up to the output value. Its main difference with respect to the symmetrical matrix is that the last one includes intersectoral flows, both by columns and by rows, in terms of "pure industries" or "commodities". In this fashion, secondary production for each sector is relocated in its corresponding "pure industry".

The choice of the use table instead of the symmetrical matrix is one of the peculiarities of our calculated spillovers. Our decision is justified, on one hand, by data availability for the period 1993-2002, as we have at our disposal six use tables (1995-2000) but just one symmetrical matrix (1995). The use of those six tables allows us to take into account the technical change linked to changes in the use table coefficients. If we used the symmetrical matrix, we would have to assume that the technological relations reflected in the technical coefficients have not changed for 10 years. Furthermore, another advantage of our approach is that none of the main statistical sources employed in our research, the use table and the *Estadística sobre actividades de I+D*, does not take into account secondary production, and therefore, the statistical error is lower.

To calculate the matrix of R&D spillovers, we start from the **use matrices of coefficients** for domestic inputs *D(40x25)* and imported inputs *M(40x25)*, obtained by dividing each element from the use table by the effective output for each column (sector). The typical element of the

[9] Secondary production refers to the share of the firm's output that cannot be classified in the same category as its main production (which determines its sectoral classification).

domestic matrix, d_{ij}, indicates the amount of domestic input *i* required per euro of output in sector *j*.

Once we have obtained the R&D stock for each sector (as explained in section 5), we calculate the matrix of R&D spillovers [*SpR&D*] multiplying the diagonal matrix of R&D stock [*StR&D(40x40)*] by the use matrix of coefficients: *SpR&D(40x25) = StR&D(40x40) * D(40x25)*. In this case, this matrix of R&D spillovers has 40 rows and 25 columns (sectors)[10]:

$$\begin{bmatrix} StR\&D_1 & 0 & \cdots & 0 \\ 0 & \ddots & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & StR\&D_{40} \end{bmatrix} \begin{bmatrix} d_{1,1} & \cdots & \cdots & d_{1,25} \\ \vdots & \ddots & & \vdots \\ \vdots & & \ddots & \vdots \\ d_{40,1} & \cdots & \cdots & d_{40,25} \end{bmatrix} = \begin{bmatrix} StR\&D_1 * d_{1,1} & \cdots & StR\&D_1 * d_{1,25} \\ \vdots & \ddots & \vdots \\ StR\&D_{40} * d_{40,1} & \cdots & StR\&D_{40} * d_{40,25} \end{bmatrix}$$

The addition of each column of that matrix for year *t* would follow the following expression:

$$SpR\&D_{jt} = \sum_i d_{ijt} StR\&D_{it} \text{ except for } j = i \qquad (6)$$

$SpR\&D_{jt}$ can be defined as the R&D spillovers absorbed by sector *j* through domestic input purchases, and we called them **vertical spillovers**. To avoid double counting of R&D expenditures, in the calculation of R&D spillovers we do not include the value of the main diagonal. If we add up now this matrix by columns, we obtain the R&D transfers by each sector. This way, the technology provided by sector *i* is proportional to its importance in the input structure for sector *j*. In a similar way, using international R&D stocks and the use table of coefficient for imported inputs, we calculate international spillovers.

Not all products and sectors are equally important in terms of technology dissemination. Higher R&D – stock sectors that provide intermediate inputs will transfer more technology.

[10] See tables 3 and 4 in the appendix forthis type of matrix. As we have data from the Encuesta Industrial for 28 manufacturing sectors, we have assumed the spillovers to be the same for those subcategories that were undivided in the input – output classification.

We recognise this fact by constructing a variable, adding up by columns[11], to obtain R&D spillovers from high – technology sectors.

5. DATA AND ESTIMATION ISSUES

In this section we present some of the data used in this paper. The calculation of the different technological variables has been explained in section 4. **Employment** is measured by thousands of worked hours yearly for each sector. **Production** is added value (net sales minus buying of intermediate goods) in € thousands. **Labour cost** is measured by labour related expenditure per worked hour in euros. These data are provided by the *Encuesta Industrial* (INE) and they are deflated for each sector by its industrial price index. We also use **total R&D expenditures** as a measure of internal technological effort for each sector and to construct its **R&D stock**[12].

Most of the statistical sources provide data for flow variables: they measure the increase per year in technology or R&D for a firm or sector. We believe it is important to take into account that the effects from that technology are not restricted to one year, and it is more appropriate to include this variable as a stock (Coe and Helpman, 1995; and Beneito, 2001, also follow this direction).

To obtain this last variable, we deflate the R&D expenditures by GDP prices, and use Griliches formula, $SR\&D_{t=0} = {FR\&D_{t=1}} \big/ {(g+d)}$ (7)

where S denotes stock, F denotes flow, g denotes the average annual logarithmic growth rate of the flow of R&D expenditure in real terms over the available period (since 1986), $t = 0$ refers to the year before the first year for which the R&D expenditure estimates are available,

[11] R&D – intensive sectors according to OECD, corresponding to the 1995 input – output tables classification: Pharmaceutical products; Office machinery and computers; Electronic products; Medical, precision and optical instruments, watches and clocks; Manufacture of aircraft and spacecraft; Telecommunications services; Computer and related services.

[12] Sectoral homogenisation for the data from different sources was required: *Encuesta Industrial*, *Estadística sobre Actividades de I+D,* Input – Output tables, and for international stocks, *ANBERD* and *Bilateral Trade database* (OECD).

and d is the depreciation rate, assumed to be 11%. Again this assumption over the depreciation rate for R&D stock is discussed by different authors. Cameron and Muellbauer (1996) explain that many researchers have chosen a zero rate, while others have argued that if knowledge becomes obsolescent the knowledge capital stock must fall. Some of the articles commented before use very different rates of depreciation: 6% (Coe and Helpman, 1995), 11% (Hubert and Pain, 1999) and 15% (Beneito, 2001; García *et al.*, 2002).

The stock data for the remaining sample years are calculated following the perpetual inventory model: $\left(SR\,\&\,D\right)_{i,t} = \left(1-d\right)\left(SR\,\&\,D\right)_{i,t-1} + \left(FR\,\&\,D\right)_{i,t}$ (8)

This constructed R&D stock is not only used to reflect the accumulated technology in a particular sector but it also will be employed as commented in section 4 to calculate a number of measures of technological spillovers among sectors.

The use input – output tables allow us to include information on how much of the inputs required by one sectors are originated domestically or imported from the rest of the world. These sectoral dimension of our analysis is a fundamental difference with some of the studies mentioned above that follow Coe and Helpman (1995).

First, we calculate R&D stocks for main sectors and a number of countries (Finland, France, Germany, Ireland, Italy, Japan, Netherlands, Sweden, United Kingdom and United States) that concentrate the majority of Spanish imports (75-80%). We use data on R&D expenditures from OECD ANBERD database (in OECD STAN Industrial Structural Analysis), that provides data for main manufacturing and services sectors in millions of current PPP dollars, deflated using national GDP deflators, for the period 1987-2001. In order to calculate sectoral R&D stocks for each country we will use the same method detailed above for Spanish sectoral R&D stocks (following Griliches and the perpetual inventory method). Finally, we convert those sectoral R&D stocks into euros and construct two measures of sectoral R&D

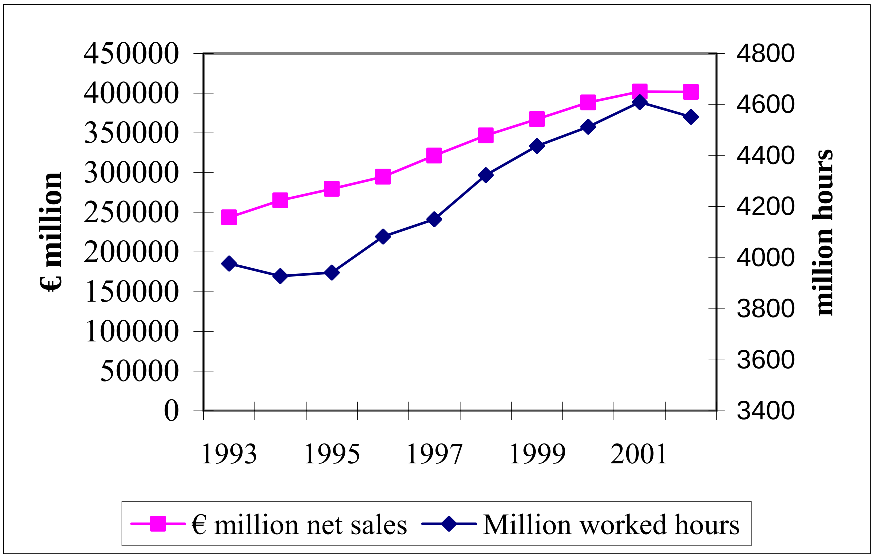
stocks for the total of countries considered to proxy the "world" R&D stock for each sector with respect to Spain: 1) the sum for each sector of the corresponding stocks for the ten countries; 2) an average of those stocks weighted by the relative importance of each country out of the ten in the Spanish imports from each sector. These weights were calculated using data from the Bilateral Trade Database (also from OECD STAN Industrial Structural Analysis).

We then used those stocks to calculate international R&D spillovers, using the imported inputs from the use tables for Spain (1995-2000). Keller (1997) has shown that trade weights to average foreign R&D by country can be misleading, which is why we compare the results for the weighted average and the sum of R&D stocks for the total of countries considered. We do still weight that stock by input purchases in terms of sectors, as this could reflect far better the technology transfer that averaging aggregate countries might be missing.

In this section we will also briefly comment on the behaviour of the main variables included in our regressions. The time period considered (1993-2002) shows the end of a recession (1993-1994), a recovery (1995-2001) and the beginning of a soft slowdown (2002) in Spain. Figure 1 shows how sales and employment reflect that cyclical evolution of the Spanish economy for the manufacturing sectors. It is also interesting to note that both variables have a similar behaviour as we expect employment to be crucially determined by production. Especially in the case of Spain, where the easy terms for dismissal in the case of temporary jobs favours that close link[13].

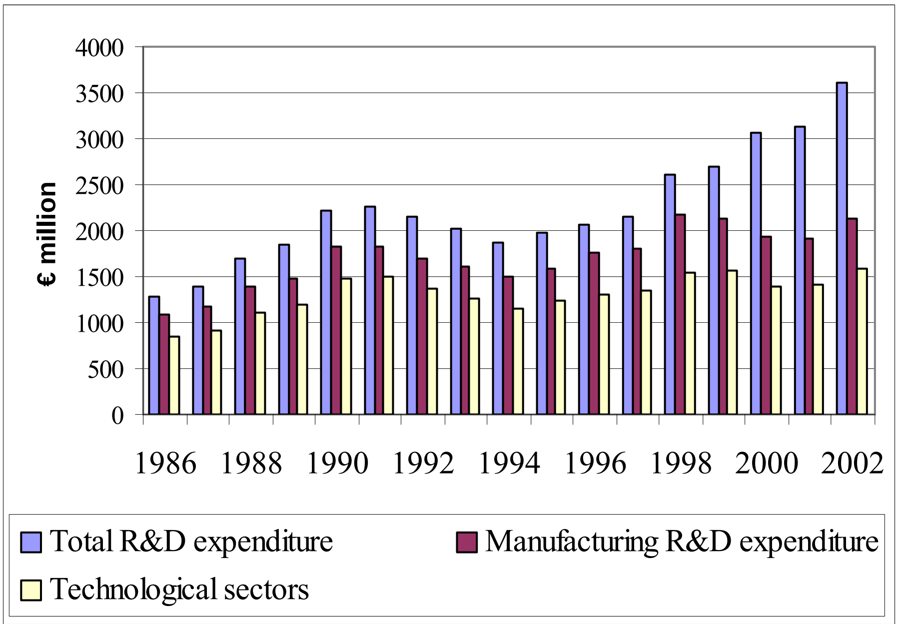
[13] According to Segura (2001), this high share of temporary jobs in Spain (33%, three times higher than EU average), is due to its relative lower cost relative to permanent jobs. This can be explained by. 1) the lower relative wages of temporary workers; 2) the wide range of dismissals legally considered as wrongful; and 3) the higher cost of dismissal compensation for permanent jobs.

Figure 1: Net sales and worked hours for the manufacturing sectors (prices of 2000).



Source: Data from the *Encuesta Industrial*, *Índices de Precios Industriales* and *Contabilidad Nacional* (INE), calculated as explained in this section.

Figure 2: R&D expenditures for the national economy, the manufacturing sectors and the technological manufacturing sectors (prices of 2000).



Source: Data from the *Estadística sobre actividades de I+D* and *Contabilidad Nacional* (INE), calculated as explained in this section.

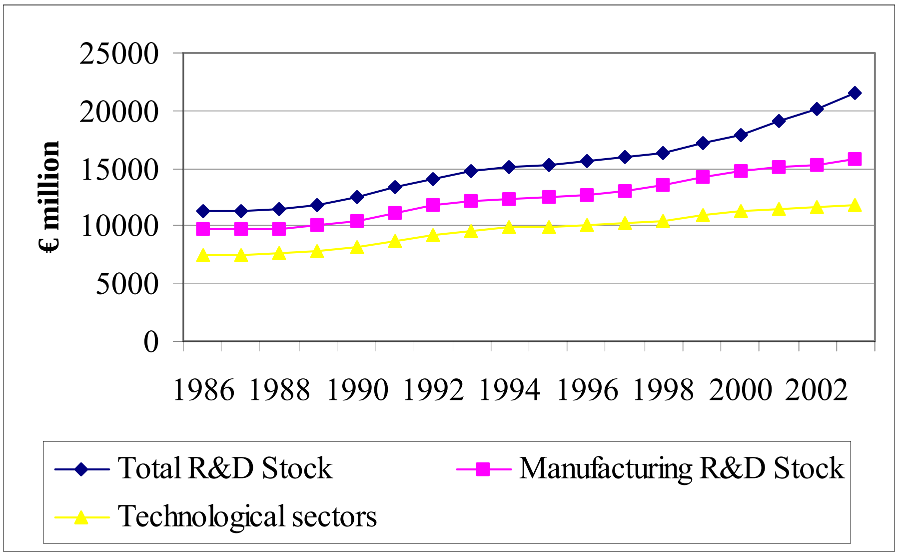
R&D activities are hardly significant in the Spanish economy, as pointed out by Buesa and Molero (1998). The reasons mentioned to explain this situation are: 1) the specialisation in traditional sectors; 2) the firm small average size 3) the lack of innovative tradition; 4) the late openness to external competition. The result of these characteristics is that most of R&D

expenditure is undertaken by the public sector and firms acquire technology in the market through patents or other property rights, or they copy it.

R&D expenditures also seem to reflect the economic cycle, as we can notice in figure 2. Until the last three years of the sample, total R&D expenditures were mainly determined by the evolution of manufacturing, and particularly technological sectors R&D expenditures. In the last years R&D expenditures in the service sectors have taken a more important role, coinciding with the slowdown of production, especially in manufactures, and the development of the ICT.

We also show in figure 3 the calculated measure of R&D stock for the national economy, manufacturing and technological sectors. As expected, with a 11% depreciation rate, these stocks are a softened upward version of the evolution for R&D expenditures. Manufacturing R&D stock follows closely the evolution for technological sectors, while total stock departs slightly from manufacturing as we commented before.

Figure 3: R&D stock calculated for the national economy, the manufacturing sectors and the technological manufacturing sectors (prices of 2000).

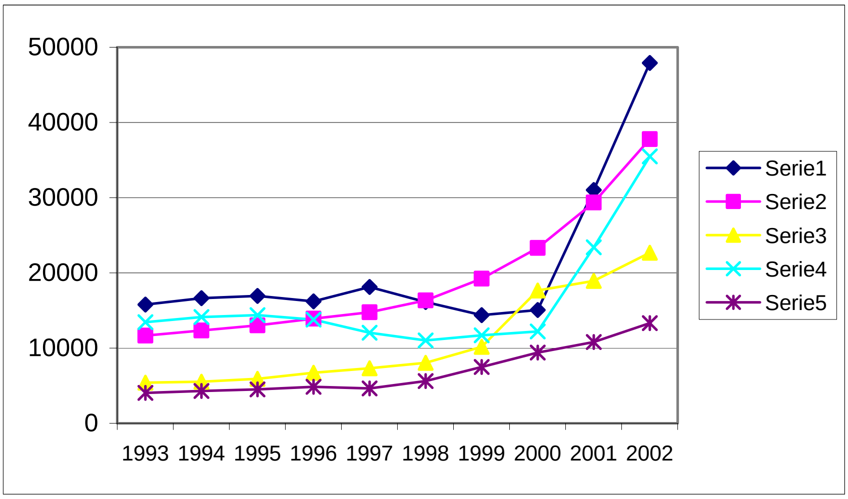


Source: Data from the *Estadística sobre actividades de I+D* and *Contabilidad Nacional* (INE), calculated as explained in this section.

In these years, the absorption of technology through spillovers is growing in all sectors (figures 4 and 5), as a result of the greater intermediate input purchases from technology –

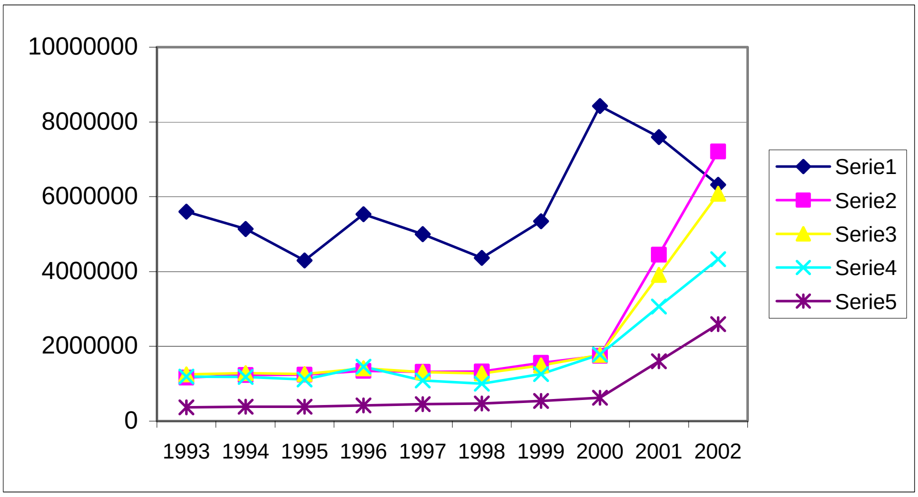
intensive sectors and the growth of the economy – wide R&D stock. Furthermore, despite large differences among sectors, we can underline the following characteristics: a) Those sectors that spend the most in R&D are also those that absorbe indirectly more technology (for example, electronic products, and office machinery and computers) for domestic and international spillovers; b) Nevertheless, some of the traditional industries, in which the Spanish economy is specialised, receive a large amount of domestic (but not international) R&D spillovers (for example, food and beverages, and textile).

Figure 4: Domestic R&D Spillovers for selected sectors, 1993-2002



Note: 1. Medical, precision and optical instruments, watches and clocks; 2. Electrical machinery ; 3. Pharmaceutical products; 4. Furniture; 5. Food and beverages.
Source: Own elaboration from input – output tables and R&D stock.

Figure 5: International R&D Spillovers for selected sectors, 1993-2002



Note: 1. Medical, precision and optical instruments, watches and clocks; 2. Electronic components ; 3. Aircraft, spacecraft and other transport equipment; 4. Telecommunications; 5. Pharmaceutical products.
Source: Own elaboration from input – output tables and R&D stock.

Once we have constructed our variables, we need to consider the most appropriate method of estimation. We have panel data for 28 sectors and 10 years. It is a short panel in terms of observations and it also has an important dynamic component.

The existence of a lagged dependent variable among the regressors generates problems in OLS estimations. Furthermore our model contains endogenous and predetermined variables what points to the use of differences GMM technique (DIF-GMM) as the most suitable one (see, for example, Arellano and Bond, 1991). This is an instrumental variable method that estimates the equation in differences and includes lagged values of the variables as instruments. The order and number of lags included for each variable depends on whether they are considered endogenous, predetermined or exogenous.

Since we work with a short panel and strong autocorrelation is likely in most variables, the difference GMM technique could be affected from a weak instruments problem, leading to biased regressors. For that reason, GMM system technique (SYS-GMM) is expected to be preferred (see Blundell and Bond, 1998). The system GMM estimator combines the standard set of equation in first-differences that uses suitably lagged levels as instruments, with an additional set of equations in levels with suitably lagged first-differences as instruments. The validity of these additional instruments can be tested using standard Sargan test of over-identifying restrictions.

This technique improves the difference GMM by estimating the regression in difference and levels, and using lagged levels as instruments for the differenced equation and lagged differences for the levels equations. The chosen instruments are included in each table.

Validity for this estimation technique depends on the existence of negative first order autocorrelation and the absence of second order autocorrelation. This requisite is tested using m1 and m2 Arellano and Bond tests, as showed in Arellano and Bond (1991). Instrument validity is tested by Sargan tests, reported for each case. We must be cautious about out results: these techniques are optimal for large samples, while in sectoral studies like this one we only have at our disposal a limited number of observations[14].

To apply this econometric technique (and to compare it with other alternative panel data methods), we will use the econometric software PcGive version 10.0, that includes the specific package DPD (dynamic panel data). To control for alterations in the general macroeconomic environment time dummies are included in all regressions.

6. EMPIRICAL ANALYSIS

Our analysis of the technology-employment relationship shows a positive effect of spillovers from R&D – intensive sectors on employment, although only international spillovers are significant. However, the own R&D effort does not have a significant effect. These are the main conclusions achieved in our analysis and have been found in two steps. In the first step, table 1, we compare the parameters obtained from different methods of estimation for our main spillovers measure (spillovers from R&D intensive sectors). In the second step, table 2, we analyse the results for different technological variables using our chosen estimation method, SYS-GMM.

Table 1 investigates the consistency of our regressors and analyses the advantages of our estimation technique, system GMM estimator. Within group and OLS are the usual references for consistency of GMM estimators. Relative to GMM, OLS biases $\hat{\alpha}_0$ (the estimated coefficient for the lagged employment) upwards while within group biases $\hat{\alpha}_0$ downwards[15]. Column (1) and (2) reports the OLS and within group estimations for our base model and expected results are confirmed, with a very high coefficient for lagged labour in the OLS regression, 0.96, and a low coefficient in the within regression, 0.52.

[14] The reduced number of observations renders the 2-step estimations non- reliable, and therefore we show the 1-step estimated coefficients.
[15] See Arellano and Bond, 1998.

<Table 1 (Different methods of estimation) around here>

Column (3) presents the first-differenced GMM, that estimates an equation in differences using instruments in levels, while column (4) shows the system GMM, that improves the first-differenced GMM by estimating the equation both in differences and levels, using instruments in both levels and differences. First-differenced GMM estimators have proved to perform poorly when the instruments available for the first-differenced equation are weak[16], what could be our case since we are working with a short panel. Weak instruments result in a first-differenced GMM regressor that is biased towards the within group one, in our case the first-differenced GMM is even below the within one, so that system-GMM, in column (4) is advisable since it deals with the weak instruments problem. By comparing first-differenced and system GMM estimators we can determine the validity of the extra information provided by the levels equation in the system GMM. Also validity of the instruments is rejected by the Sargan test in column (3), but accepted in column (4).

The assumptions made by the model, based in economic theory and supported by estimation results, are the endogeneity of the output variable, the predetermination of the wages variable and the exogeneity of the spillover variable.

The spillovers proxies considered in table 2 are the following: sectoral R&D; indirect absorbed sectoral R&D (*i*´s sector R&D stock weighted by the technical coefficient inputs of the use matrix incorporated from *i*); external indirect absorbed R&D (R&D stock for any sector but *i* weighted by the technical coefficient inputs incorporated from *j* and aggregated); indirect absorbed R&D coming from any technology intensive sector (but own sector). All these variables (apart from the first one) are calculated both in domestic and foreign terms (using on one hand, domestic inputs and R&D stocks, and on the other, imported inputs and foreign R&D stocks), as explained in section 4.

[16] Arellano and Bover, 1995; Blundell and Bond, 1998.

<Table 2 (Main results for different technological variables) around here>

Results in table 2 show significant coefficients in non-technological variables that are close to previous empirical works on the topic and to theoretical hypothesis. Production is positively related to labour while labour cost has an inverse relationship.

By interpreting our results within the framework of the neoclassical production function they show a capital-labour substitution rate close to 1 and roughly constant returns. Long term coefficients for production and wages are 1,1437 (standard error 0,1054) and –1,2493 (0,1404) relatively.

Table 2 shows that spillovers have a stronger effect on labour than own sectoral technological effort. The weakness of the own sectoral R&D effort proxy could be due to the opposite effects it incorporates. The technological effort performed within the sector has a positive effect on the labour demand for the innovating firm, while the non-innovators loose market share or may even be pushed to close down, with the consequent negative effect on sectoral employment. Followers may imitate innovators' changes with a lagged positive effect on employment that is expected to be smaller than the innovators one. All these different effects may blur the coefficient for the total sectoral R&D proxy leading to ambiguous results.

A similar result has been found in Barrios (2000) and Torres (2002) for the Spanish economy, although they work in a different framework[17]. These papers justify the lack of significance of the R&D expenditure and R&D spillover proxies because of: 1) the different effects on firms with heterogeneous behaviour, and 2) Spanish firms innovative behaviour is based on the introduction of purchased technology in opposition to the introduction of technologies as a result of the firm's own effort.

[17] Barrios focuses on the analysis of technology spillovers for foreign owned firms located in Spain and its relationship to productivity. Torres focuses on the effect of R&D expenditure on wage differentials for skilled and unskilled workers within sectors.

The estimated positive impact of absorbed technology in our results can be explained as more firms can benefit from the technology available in the market, and the negative compensating effects are reduced. We observe in column 3 of table 2 that the international spillovers from R&D – intensive sectors are positive and significant. This result is robust to the use of a measure of this variable as a weighted average of countries (using trade) or as the sum of sectoral R&D stocks for the ten countries considered. The reason for this is that Spanish imports at sector level tend to concentrate on countries with high R&D stock in that sector, especially when considering technology – intensive sectors (in line with what we commented about Keller, 1997, in section 5).

Even more, these spillovers are still significant and its coefficient is not considerably changed when we include two or more technological variables. In particular, in column 6 we include in the regression both domestic and international R&D – intensive spillovers to confirm this conclusion.

The value for the log run coefficient for the proxy for the spillovers from foreign technology - intensive sectors is 0'0182. According to this result an increase of 1% in the absorbed spillover pushes hours worked by 0'02%[18]. These coefficients cannot be directly compared with others in recent literature since we introduce an original framework. Our analysis considers technology spillovers measured through R&D stocks, compared to R&D flows or intensity, and focus on the effect on labour, compared to productivity, production or skill structure. Hubert & Pain (1999) found a negative impact from spillovers measured by total sectoral imports, compared to our positive effect. This difference could be explained by our use of a more refined measure of technology spillovers, as we weight foreign R&D stocks by the imports of inputs. We therefore leave aside final products imports that could compete and

[18] For the spillovers from technology – intensive sectors to increase, we need: 1) an increase in international R&D stock for those sectors; and / or 2) an increase, from all or some sectors, in their share of intermediate imported inputs from this type of sector.

reduce domestic production, and might result in the negative impact on employment found in Hubert & Pain (1999).

Further investigation was undertaken on coefficients robustness. Additional lags for all regressors were included to analyse whether significance and sign were unchanged over time. We must emphasize that as more lags were included the time length of our dataset was reduced, with the consequent implications on regressors significance, so that we shall be cautious in our interpretations.

The successive lags included for all regressors, value added, wage and labour and spillover proxies, behaved differently. Further lags for value added and wages lose significance, faster for wages than for added value. We also notice that the coefficient value grows slightly for value added while the coefficient for wages gets lower. This result is consistent with Mastrostefano and Pianta (2004), what they interpret as in the long run, the historically unquestioned negative relationship between wage and job growth 'is less relevant' and 'the "Schumpeterian" job creating effect of the market impact of innovation is stronger'.

Regarding employment, further lags were non-significant and, when included, they lead to worse statistics and a general loss of significance in all coefficients. For spillovers further lags were also non-significant but they did not affect other coefficients. Spillovers from indirect absorbed sectoral own R&D (from inputs provided by the own sector) and total external indirect absorbed R&D (including all sectors, and not only those intensive in R&D) were not found to be significant, either at domestic or foreign levels.

7. CONCLUDING REMARKS

The research on the effect of technology on the economy based on spillovers is especially interesting for regions or countries like Spain, as its low R&D expenditure and predominance of small and medium firms result in an important share of technology being acquired directly in the market or by means of spillovers, and imports of capital goods.

The Spanish and international literature has focused on the effect of the type of innovation (process or product) or R&D effort on employment or spillovers on productivity, both at firm and sectoral – level. Our study differs since it analyses the technology transfer among sectors (both at domestic and international levels) and its impact on industrial employment. With this aim, we calculate R&D spillovers in the tradition of the input – output methodology, and we use SYS-GMM techniques to estimate these spillovers' impact on employment through a labour demand function.

Our results seem to support the hypothesis that the impact of technology on industrial employment is determined by the source of that technology. Data show a non-significant effect from technological effort performed by the own sector, while the impact from spillovers is positive when technology is generated in R&D – intensive sectors and significant for foreign R&D – intensive sectors.

At sectoral level we aggregate a large number of firms with different characteristics, and therefore the zero impact estimated for the own technological effort and other technological variables might be the net result of positive and negative effects: innovative firms displace their competitors, product and process innovations may have oppositive effects, etc.

The positive effect from R&D – intensive sectors can be explained as sectors purchasing high – R&D – intensity inputs get modernised and increase their employment. This estimated positive impact of externally generated technology is explained because more firms benefit from the technology available in the market. The majority of firms in the sector acquire the same high technology intermediate goods, and therefore the repercussion on their employment is similar for all of them. The greater complementarity of foreign R&D spillovers on domestic employment might be due to a qualitative difference, due to the longer R&D tradition and cutting-edge specialisation of the countries considered.

APPENDIX

<Tables 3 (Domestic R&D spillover matrix, 2000) and 4 (International R&D spillover matrix, 2000) around here>

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Table 1: Different methods of estimation

Estimation	OLS	Within	DIF-GMM	SYS-GMM
Dependent variable: employment L_t				
ln L_{t-1}	0.9570 (38.3)	0.5202 (6.23)	0.4582 (4.11)	0.8121 (11.8)
ln VA_t (Q-CI)	0.0533 (2.03)	0.2794 (10.9)	0.3024 (8.25)	0.2149 (2.78)
ln W_t	-0.0758 (3.11)	-0.1327 (2.52)	-0.1582 (2.43)	-0.2347 (3.13)
ln $FSpillintens_t$	0.0027 (2.20)	-0.0003 (0.155)	-0.00008 (0.049)	0.0034 (2.43)
Sargan test	--	--	0.004	0.117
m (1)	--	--	-3.084 (0.002)	-3.616 (0.000)
m (2)	--	--	-0.5752 (0.565)	-0.1327 (0.894)

Notes:

1. The OLS and within-group estimates are in levels, while the GMM-SYS estimates combine a system of equations in first differences with a system of equations in levels using as instruments respectively the variables in levels and in first differences.
2. Test shown are: *p* values for the null hypothesis of joint validity of the instruments for Sargan test of overidentified restrictions, and autocorrelation tests *m* (1) and *m* (2) (they are tests - with distribution N(0,1) - on the serial correlation of residuals; p values in parentheses). The Sargan-test has a $\chi 2$ distribution under the null hypothesis of validity of the instruments.
3. The GMM-SYS estimates shown are *one-step*, consistent with possible heteroscedasticity and more reliable than the *two-step* ones.
4. Asymptotic standard errors, asymptotically robust to heteroskedasticity, are reported in parentheses.
5. Data for 28 sectors and 10 years.
6. Year dummies are included in all specifications.
7. The equations are estimated using DPD for PcGive
8. The instruments used in (column 3): $\ln L_{i,t-2}$, $\ln L_{i,t-3}$, $\ln L_{i,t-4}$, $\ln(Q-CI)_{i,t-2}$, $\ln(Q-CI)_{i,t-3}$, $\ln(Q-CI)_{i,t-4}$, $\ln W_{i,t-1}$, $\ln W_{i,t}$ and $\ln FSpillintens_{i,t}$.
9. Additional instruments for SYS-GMM (column 4): $\Delta \ln L_{i,t-1}$ and $\Delta \ln(Q-CI)_{i,t-1}$.

Variables:

- L: (log) total worked hours horas in each considered sector, thousands.
- VA (Q-CI): (log) net sales minus intermediate consumption (inputs) (€ thousands).
- W: (log) labour cost per worked hour (€ thousands).
- ln FSpillintens: (log) indirect R&D absorbed from foreign technology – intensive sectors (weighted average).

Table 2: Main results for different technological variables

Estimation	**SYS-GMM**					
Dependent variable: employment Lt						
ln L_{t-1}	0.8019 (12.4)	0.8100 (12.1)	0.8121 (11.8)	0.8120 (9.61)	0.8017 (12.5)	0.8101 (12.5)
ln VA_t (Q-CI)	0.2155 (2.73)	0.2143 (2.91)	0.2149 (2.78)	0.2042 (2.38)	0.2230 (2.15)	0.2168 (3.05)
ln W_t	-0.2541 (3.49)	-0.2407 (3.38)	-0.2347 (3.13)	-0.2189 (2.59)	-0.2506 (3.32)	-0.2391 (3.44)
ln $StR\&D_t$	0.0097 (0.530)				0.0026 (0.142)	
ln $Spillintens_t$		0.0186 (1.11)				0.0082 (0.542)
ln $FSpillintens_t$			0.0034 (2.43)		0.0035 (2.15)	0.0033 (2.43)
ln $FSpillintens2_t$				0.0030 (2.12)		
Sargan test	0.040	0.063	0.117	0.103	0.074	0.110
m (1)	-3.600 (0.000)	-3.604 (0.000)	-3.616 (0.000)	-3.577 (0.000)	-3.617 (0.000)	-3.609 (0.000)
m (2)	0.0167 (0.987)	-0.0492 (0.961)	-0.1327 (0.894)	-0.1464 (0.884)	-0.1471 (0.883)	-0.1474 (0.883)

See notes 2 to 7 in table 1.
New variables:

- ln $StR\&D_t$: (log) sectoral own R&D.
- ln $Spillintens_t$: (log) indirect domestic R&D absorbed from technology – intensive sectors.
- ln $FSpillintens_t$: (log) indirect foreign R&D absorbed from technology – intensive sectors (weighted average).
- ln $FSpillintens2_t$: (log) indirect foreign absorbed R&D from technology – intensive sectors (sum of 10 countries).

The instruments used are the same as in note 9 in table 1.

Table 3: Domestic R&D spillovers matrix, 2000

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1	25949	0	0	0	82173	15388	9358	993	432	9651	14758	0	122	2616	0	0	0	0	0	0	0	0	0	0	167
2	36	422	103	9866	25	0	137	0	0	0	308	0	1184	0	12700	3635	34	0	0	61	0	0	0	0	194
3	3704	7114	3505	10080	590	411	449	712	236	560	1071	227	7302	907	3537	1010	575	596	649	501	373	435	281	331	148
4	72204	0	0	0	90203	0	0	1828	15534	0	2081	0	1761	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	2001	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	136	0	0	0	127	1366	16773	33330	1918	141	269	207	1407	1504	89	8	332	13	0	48	0	0	1212	524	2136
7	43	21	5	19	37	17	9	4226	0	0	30	16	34	28	62	114	103	148	269	87	0	0	57	6	4
8	13	34	0	0	1	0	0	561	10870	24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	108
9	66	201	0	0	86	0	1	0	59	3049	28	29	12	24	152	15	107	54	0	24	16	4	15	53	1999
10	218	37	49	129	2445	3903	787	575	1034	2581	6475	32295	4287	2147	1595	66	514	531	1835	967	94	102	200	258	1525
11	6	10	44	138	44	112	31	16	18	72	139	6065	487	82	102	53	62	62	253	113	91	190	47	46	20
12	3554	0	0	0	110	0	0	0	0	0	0	0	1516	0	0	0	0	0	0	0	0	0	0	0	0
13	20224	51998	2158	8150	10424	1311	29852	12985	13666	23413	47884	20804	88484	32691	28364	52011	25682	13838	27173	35081	6356	6296	25519	17684	23370
14	3691	2832	185	439	8159	385	4837	953	19929	2407	3347	994	10065	67582	3440	2855	5094	2368	16426	11362	8896	815	19411	27425	2066
15	527	1170	131	1044	3661	0	0	0	0	421	0	0	1170	171	26162	2774	1349	577	3267	1018	1115	404	1435	85	1501
16	0	1211	85	438	0	0	0	0	0	198	393	91	162	380	3836	17826	57127	13887	11573	47325	5768	4183	27481	9234	6547
17	7798	9668	1274	4946	4575	2252	2346	1533	1696	6637	5345	1091	7744	3240	8424	58298	27921	36140	5933	16862	3875	1909	12076	11139	5434
18	10021	21256	3451	7409	720	2848	9470	6426	2316	18124	18992	2716	22961	18538	29707	25657	52307	27375	0	8920	3699	5231	15728	31112	9214
19	0	0	0	0	0	0	66	0	0	0	0	0	0	0	0	0	0	0	11257	0	0	0	14	0	0
20	119	510	342	2636	122	0	303	0	0	89	80	0	874	740	1435	1125	2951	48717	24228	68124	52514	56808	9539	10117	1716
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	90	0	6390	4054	56	122	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3674	0	5433	0	956	7491	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	25	0	44	0	3047	43	193	0
24	254	437	98	271	170	0	0	0	0	0	0	0	187	0	6921	0	782	197	0	0	0	0	209166	13520	0
25	1360	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4402	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1051	0
27	0	138	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2767	0

28	2	0	4	23	0	0	0	0	0	0	0	0	0	0	0	43	128	8	193	0	0	0	495	0	3010
29	0	27	0	57	0	0	0	29	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0	0	1389
30	0	0	0	0	0	0	0	0	0	0	101	0	0	0	4	328	0	0	0	0	0	0	0	0	0
31	11294	24350	8255	62666	7370	2112	12290	5089	2726	6842	26628	6663	19297	13584	25963	32917	13756	2774	5119	5771	4826	4116	5964	4159	2703
32	604	977	149	1291	146	349	414	51	89	112	1542	100	487	176	689	655	316	150	123	483	81	230	192	292	200
33	1552	847	118	260	1218	137	983	1142	1597	1830	2549	1275	2035	1403	1065	1666	1569	1120	346	798	377	1635	609	505	2782
34	835	3315	804	170	1628	824	1143	647	341	1909	2268	954	1470	1271	3172	2278	1342	991	519	1052	539	535	492	544	1005
35	1811	7190	2323	8304	5300	2605	5339	10213	2803	4806	9440	17546	10072	5019	5400	8901	6189	9006	18533	6913	4905	8556	2193	4781	5513
36	6	3	2	7	3	2	4	2	1	4	5	3	4	6	4	6	4	5	1	2	4	2	0	2	3
37	11	0	346	701	69	158	86	104	91	0	0	87	290	32	61	493	295	109	2329	154	164	134	160	113	33
38	72	275	846	327	237	1457	337	148	32	36	455	21	2141	922	392	228	209	1380	2363	1559	10015	1330	1610	6985	301
39	6229	44955	24585	49145	48080	56203	38394	36234	24515	30946	48438	30062	66214	26302	73357	47750	50644	45686	96456	69219	64900	48923	11948	29784	35285
40	693	157	352	391	401	513	246	265	184	185	167	859	678	290	266	311	243	213	440	117	467	218	210	287	139
Total	173031	179155	49213	168908	268123	94354	133656	118062	100087	114038	192793	122103	252458	179656	236902	261022	249636	205972	233049	276604	180896	149156	347110	185014	108512
Main Diagonal	**25949**	**422**	**3505**	**62666**	**90203**	**2001**	**16773**	**4226**	**10870**	**3049**	**6475**	**6065**	**90000**	**67582**	**26162**	**17826**	**27921**	**27375**	**11257**	**68124**	**11822**	**3047**	**209166**	**8221**	**4398**
Spillovers	**147082**	**178733**	**45708**	**106242**	**177921**	**92352**	**116883**	**113836**	**89217**	**110988**	**186319**	**116038**	**162457**	**112074**	**210740**	**243196**	**221715**	**178598**	**221792**	**208481**	**169074**	**146109**	**137944**	**176793**	**104113**
Sp R&D	5449	7465	3515	9332	5716	4220	5828	10466	2926	4842	9895	17654	14019	5973	5854	9622	6693	10519	34571	8670	21474	17121	4076	13246	5847

Notes: Year by year R&D spillovers matrices for the period 1993-2002 have been calculated.
Sectors by columns are: 1. Agriculture; 2. Extractive industries; 3. Petroleum industries; 4. Food and beverages; 5. Tobacco; 6. Textile; 7. Clothes and furs; 8. Leather and shoes: 9. Wood and cork; 10. Paper and paperboard; 11. Printed matter and recorded media; 12. Pharmaceutical products; 13. Other chemical products; 14. Rubber and plastic; 15. Non – metallic mineral products; 16. Basic metals; 17. Metallic manufactures; 18. Machinery and equipment; 19. Office machinery and computers; 20. Electrical machinery; 21. Electronic products; 22. Television, radio and communication devices; 23. Metal, precision and optical instruments, watches and clocks; 24. Motor vehicles; 25. Ship building; 26. Aircraft and spacecraft; 27. Other transport equipment; 28. Furniture; 29. Other manufacturing goods; 30. Recycling; 31. Energy and water; 32. Construction; 33. Hotels and trade; 34. Transports and storing; 35. Telecommunications; 36. Financial intermediation services; 37. Computer and related activities; 38. R&D services; 39. Other business activities; 40. Public, social and collective services.
Homogenous products by rows are: 1. Extractive products; 2. Petroleum products; 3. Energy and water; 4. Food and beverages; 5. Tobacco; 6. Textile; 7. Clothes and furs; 8. Leather and shoes; 9. Wood and cork; 10. Paper and paperboard; 11. Printed matters and recorded media; 12. Pharmaceutical products; 13. Rubber and plastic; 14. Non-metallic mineral products; 15. Basic metals; 16. Metallic manufactures; 17. Machinery and equipment; 18. Office machinery and computers; 19. Electrical machinery; 20. Electronic products; 21. Television, radio and communication devices; 22. Motor vehicles; 23. Ships and boats; 24. Furniture; 25. Recycling.

Source: Own elaboration from input – output tables and R&D stock.

Table 4: International R&D spillovers matrix, 2000

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1	1708	0	0	0	11682	20826	3731	267	133	16667	0	0	203	0	0	0	0	0	0	0	0	0	0	0	143
2	0	537	34	5858	0	0	0	0	0	0	18	0	636	0	657	11834	0	26	0	0	0	0	0	0	0
3	17	30	2480	640	6	1	10	6	6	5	11	2	105	9	36	19	6	6	0	4	4	5	2	13	5
4	20	0	0	0	75	0	0	0	47	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	86	49	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
7	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	7	33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
9	0	0	0	0	3	0	0	0	0	376	16	0	0	0	1	0	0	0	0	1	0	2	0	0	29
10	0	0	0	0	3	2	6	4	6	1	757	136	0	1	2	0	0	0	8	2	1	2	0	0	5
11	0	0	0	0	0	0	0	0	0	0	0	14	0	0	0	0	0	0	0	0	0	0	0	0	0
12	201	0	0	0	11	0	0	0	0	0	0	0	135	0	0	0	0	0	0	0	0	0	0	0	0
13	377	0	47	3	40	0	1859	30	13	66	63	186	3031	3965	80	83	111	26	0	5	0	5	48	133	20
14	2	1	0	0	7	0	0	0	5	0	7	0	8	99	0	0	0	32	6	81	45	17	100	24	43
15	0	0	0	0	5	0	0	0	0	0	0	0	2	2	3	6	0	0	0	4	0	9	6	10	2
16	0	6	0	2	0	0	0	0	0	1	2	0	1	3	5	245	229	101	33	118	34	38	62	155	93
17	2	7	1	6	6	2	2	0	0	11	5	1	2	3	5	22	36	27	29	8	7	7	10	14	25
18	14	324	32	109	12	74	139	96	50	193	313	32	244	236	323	379	480	731	0	89	71	90	170	447	131
19	1	0	1	1	0	0	7	0	0	0	0	0	0	0	0	0	0	0	4559	0	0	0	6	5	0
20	2	25	4	212	4	0	15	0	0	9	8	0	25	22	44	128	87	1012	1860	3448	1535	1414	401	309	45
21	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	447	0	12704	8428	62	313	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1198	0	964	0	69	101	0
23	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	3	0	917	12	48	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8783	475	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
26	17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9674	0
27	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	31	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20
29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6

30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	30	259	29	322	67	0	404	209	121	271	122	78	315	130	192	198	46	29	0	52	0	0	38	0	44
32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	79	0	0	0	68	0	127	108	126	39	115	45	14	118	78	109	81	91	0	144	220	93	0	113	79
34	97	0	23	5	58	11	3	39	18	7	6	6	130	9	7	8	9	38	102	16	22	27	89	8	15
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
36	0	0	2	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	0
37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
38	0	0	0	242	0	0	0	0	0	0	0	0	629	0	0	0	0	0	0	0	1747	0	367	1405	0
39	1381	1165	365	2313	10558	56962	9547	8400	14818	1340	1651	21513	44320	6868	7282	2432	2962	12656	33620	7320	2959	4828	21203	6120	17094
40	0	0	0	0	0	0	0	0	0	0	0	1095	0	0	0	0	0	0	0	0	0	0	0	0	7
Total	3949	2357	3018	9715	22604	77895	15934	9219	15376	18987	3094	23110	49806	11465	8714	15463	4049	14780	41860	11293	20313	15880	31429	19400	17807
Main Diagonal	**1708**	**537**	**2480**	**322**	**75**	**16**	**86**	**2**	**33**	**376**	**757**	**14**	**3166**	**99**	**3**	**245**	**36**	**731**	**4559**	**3448**	**13668**	**917**	**8783**	**9706**	**26**
Spillovers	**2241**	**1820**	**538**	**9394**	**22529**	**77879**	**15848**	**9216**	**15343**	**18611**	**2337**	**23096**	**46640**	**11366**	**8711**	**15218**	**4013**	**14049**	**37300**	**7845**	**6645**	**14963**	**22646**	**9694**	**17781**
Sp R&D	220	0	1	245	11	0	7	0	0	0	0	0	629	0	0	0	0	4	447	3	1747	8428	447	1772	6

Notes: Year by year R&D spillovers matrices for the period 1993-2002 have been calculated.
Sectors by columns are: 1. Agriculture; 2. Extractive industries; 3. Petroleum industries; 4. Food and beverages; 5. Tobacco; 6. Textile; 7. Clothes and furs; 8. Leather and shoes: 9. Wood and cork; 10. Paper and paperboard; 11. Printed matter and recorded media; 12. Pharmaceutical products; 13. Other chemical products; 14. Rubber and plastic; 15. Non – metallic mineral products; 16. Basic metals; 17. Metallic manufactures; 18. Machinery and equipment; 19. Office machinery and computers; 20. Electrical machinery; 21. Electronic products; 22. Television, radio and communication devices; 23. Metal, precision and optical instruments, watches and clocks; 24. Motor vehicles; 25. Ship building; 26. Aircraft and spacecraft; 27. Other transport equipment; 28. Furniture; 29. Other manufacturing goods; 30. Recycling; 31. Energy and water; 32. Construction; 33. Hotels and trade; 34. Transports and storing; 35. Telecommunications; 36. Financial intermediation services; 37. Computer and related activities; 38. R&D services; 39. Other business activities; 40. Public, social and collective services.
Homogenous products by rows are: 1. Extractive products; 2. Petroleum products; 3. Energy and water; 4. Food and beverages; 5. Tobacco; 6. Textile; 7. Clothes and furs; 8. Leather and shoes; 9. Wood and cork; 10. Paper and paperboard; 11. Printed matters and recorded media; 12. Pharmaceutical products; 13. Rubber and plastic; 14. Non-metallic mineral products; 15. Basic metals; 16. Metallic manufactures; 17. Machinery and equipment; 18. Office machinery and computers; 19. Electrical machinery; 20. Electronic products; 21. Television, radio and communication devices; 22. Motor vehicles; 23. Ships and boats; 24. Furniture; 25. Recycling.
For agriculture and services sectors we use domestic R&D stocks rather than international R&D stocks because of lack of data. The impact from this must be reduced, as imports of services are rather small.

Source: Own elaboration from input – output tables and R&D stock.