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R&D PRODUCTIVITY AND SPILLOVERS AT THE FIRM LEVEL: EVIDENCE FROM SPANISH PANEL DATA

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This article offers some evidence on the productivity effects of both own R&D capital and spillovers using a panel of Spanish manufacturing firms for the period 1990-96. Spillover variables are defined combining information regarding the firm's product industry with its type of technological orientation. The results suggest that both the sources and the beneficiaries of the spillover effects are found in the group of firms that may be defined as users of advanced technologies, whereas non-significant effects are observed for those less technology-oriented ones. Moreover, the spillover effects also differ depending on the intensity of R&D investment, firms in the intermediate positions being the ones which experience the largest productivity gains from others' R&D results.

Key words: R&D, spillovers, productivity, panel data.

(*JEL* O30, L60, C23)

1. Introduction

Productivity and its growth are typically discussed in the context of a Cobb-Douglas production function that relates various inputs with a final output. The list of inputs necessarily includes the usual factors of production, that is, physical capital and labour. Nevertheless, economists have also identified R&D spending as an important determinant of productivity growth. The R&D Capital Stock Model, Griliches (1979), asserts that the stock of a firm's technical knowledge or knowledge capital is itself a factor of production. This article

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is in the line of research initiated by this author and analyses both, the effect of own R&D capital and the influence of other's R&D capital, or spillover, using firm level panel data from the *Encuesta sobre Estrategias Empresariales (ESEE)*, for the period 1990-1996.

The pioneering work of Griliches has been followed more recently by Cuneo and Mairesse (1984), Sassenou (1988), Lichtenberg and Siegel (1989) and Hall and Mairesse (1995, 1996), to mention some of the most well-known contributions to the field.[1]

In the case of Spain, there also exist some works that have previously estimated the output elasticity of R&D. Lafuente, Salas and Yagüe (1986) estimated the own R&D elasticity using a time series of aggregate data for the period 1966-1981. Fluviá (1990), Grandón and Rodríguez Romero (1991), and Rodríguez Romero (1993), using panel data from a survey of large Spanish firms (*Encuesta de Grandes Empresas Españolas* of the Ministry of Industry and Energy) for the period 1975-1981, offer additional evidence on R&D productivity. More recently, Gumbau (1996) investigates the productivity effects of research using a cross section for 1993 of firm level data from the ESEE, and López-Pueyo and Sanaú (1998) using panel data of thirteen industrial sectors for the years 1986-1992, estimate both the own R&D elasticities and spillover elasticities. Finally, García *et al.* (1998) using an unbalanced panel from the ESEE (1990-1995) estimate a production function in a more general framework, their main goal being the estimation of the direct elasticity of employment with respect to innovation.

There now exist a growing literature about the way of measuring spillovers and the analysis of their effects. In the framework of productivity analysis, spillovers may be considered as another input of the knowledge production process of a firm, industry or country. Griliches (1992), reviews the basic model of R&D spillovers and comments on the empirical evidence for their existence and magnitude. Other, more recent surveys may be found in Nadiri (1993), and Mairesse (1995). The pioneering work of Jaffe (1986) deserves special mention. The author uses patent data to classify the firms in technology-based categories. After that, the correlation existing between the "research vectors" of the firms, are used as weights in the calculus of the pool of knowledge that surrounds a firm.[2]

[1] Mairesse and Sassenou (1991) survey econometric studies that investigate the relationship between own R&D and productivity using data at the firm level.

[2] The same idea is more recently found in Adams and Jaffe (1996) for the US,

Regrettably, most researchers do not have access to such information. One of the more usual practices in these cases is simply to sum others' R&D in the same industrial sector. Nevertheless, some authors have pointed out that it may not be possible to model the effect of spillovers irrespectively of the type of industry. In this line, Bernstein and Nadiri (1988) select five high-technology industries to identify both the sources and beneficiaries of each industry spillovers, and Kettle (1994), using an indicator of a firm's technical sophistication, concludes that only the advanced firms benefit from R&D spillovers, while the effect is negative for most of the others. Also Mamuneas (1999) focuses his attention on six high-tech industries in the US manufacturing sector, obtaining positive spillover effects of publicly financed R&D capital.

In the case of Spain, the attempts to model and estimate spillovers are still quite scarce. Fluviá (1990), using firm level data, defines the potential spillover pool of a firm as the sum of others' R&D capital in the same technological neighbourhood. Gumbau (1996) defines spillovers both as the sum of others' R&D expenditures and as the sum of others' innovation results in the same industrial sector. López and Sanaú (1998) introduce different spillover variables (those from other manufacturing sectors, non-manufacturing sectors and from the public sector) and analyse the effects of different types of own knowledge capital according to their financial source, the type of expenditure or the type of research (applied versus basic research, and research versus technological development).

The value added of the study presented in this article is twofold. Firstly, the study offers some evidence on the effects of R&D capital on the productivity of Spanish manufacturing firms using a newly available dataset for the period 1990-1996 (*Encuesta sobre Estrategias Empresariales*, ESEE). Thus, the study updates the existing evidence on R&D productivity by using a much wider dataset. Secondly, the article focuses also on the study of the spillover effects of R&D investment. Spillover variables are defined by taking different groups of firms as potential sources of knowledge creation. In particular, the kind of technology the firms base their production processes on, is taken as an indicator of their techological sophistication. Experimentation with different subsamples of firms, selected according to such criterion, allow us to discern not only which are the relevant originators of R&D spillovers,

Branstetter (1996) with data for the US and Japan, and Harhoff (1997) for the German case.

but also what kind of firms are most benefited by the social returns of the research efforts.

I begin by outlining the production function framework. Then I describe the dataset, the choice of sample and the definition of variables. After that, I present the basic set of results and to end, some comments and conclusions.

2. Empirical framework: the Cobb-Douglas production function

I assume that the production function for manufacturing firms can be described by a Cobb-Douglas function with three 'conventional' factors and with a degree of relative efficiency that depends both on the stock of the firm's knowledge capital and on the stock of other's R&D efforts, which can be written as

$$Y_{it} = Ae^{\lambda t} K_{it}^{\gamma} S_{it}^{\phi} M_{it}^{\alpha} C_{it}^{\beta} L_{it}^{\delta} u^{\varepsilon_{it}} \qquad [1]$$

where Y is a measure of output, M stands for raw materials, L is a measure of labour (as hours worked), C is physical capital (usually plant and equipment), K is the knowledge capital of the firm and S is the stock of others' knowledge capital, or spillover[3]; A is a constant and λ is the rate of disembodied technical change (the time trend λt is usually replaced by time dummies in the estimation); α, β, δ, γ and ϕ are the parameters of interest; the subscripts i and t denote the firm and the period (year) respectively. ε is the random error term for the equation, reflecting the effect of unknown factors, differences in technologies across firms and other disturbances. This error term may be decomposed as

$$\varepsilon_{it} = \mu_i + \xi_{it} \qquad [2]$$

where μ_i stands for the firm (permanent) specific effect that accounts for the possible heterogeneity across firms, for example, in their technologies, whereas ξ_{it} reflects temporary effects with finite moments, and in particular

$$E(\xi_{it}) = E(\xi_{it}\xi_{js}) = 0 \text{ for } t \neq s \text{ and } i \neq j \qquad [3]$$

[3] It is also frequent to choose value added as a measure of output, thus not including raw materials in the production function. Nevertheless, in this work the production function will be basically estimated as described by [1], since it seems that the use of value added instead of sales and materials, renders some biased results, as Delgado *et al.* (1999) have pointed out using the same data source as the one I will use in this article.

I will use in estimation the logarithmic first differenced version of [1] to remove all time-constant unobservable heterogeneity (μ_i). This allows us to write the production relationship to be estimated as

$$y_{it} = a + \lambda t + \gamma k_{it} + \phi s_{it} + \alpha m_{it} + \beta c_{it} + \delta l_{it} + \Delta \xi_{it} \qquad [4]$$

where lower-case letters are the growth rates of their upper-case counterparts.

3. Data and variables

3.1 The data

The data source I have used in this study is the "Survey of Industrial Strategic Behaviour" (*Encuesta sobre Estrategias Empresariales*, (ESEE)), carried out by the "Public Enterprise Foundation" (*Fundación Empresa Pública*) and the Spanish Ministry of Industry and Energy from 1990 to 1994, and by the former from 1994 onwards. The data set used in this work covers the period 1990-1996. The ESEE is an unbalanced panel sample with two groups of firms with different representativenes: those firms with more than 200 employees and those with 200 or less employees. From this sample I have selected firstly, those firms that have been for at least four years in the sample, and then, those firms that report R&D expenditures for at least during four consecutive years, having as a result, a final sample of 501 firms. The assumption made is that only these latter firms may be considered to undertake R&D activities in a permanent and meaningful way. The goal is also to have at least four years to be able to construct the R&D capital variable.[4]

Table 1 displays the sectorial breakdown of the selected sample: the first and second columns display the composition of the sample before firms with positive R&D expenditures are selected; the third and forth columns refer to the final panel selected, whereas columns five and six show the sectorial breakdown of observations with research spending and the percentages over the initial panel. This table also shows the mean ratio of real R&D expenditures to sales, or R&D intensity, for each sector.[5]

[4] The possible selectivity bias caused by this sample selection has been investigated using Heckman's two step estimation for correction of sample selection bias. This exploratory work rendered no statistical evidence of such kind of bias.

[5] This breakdown corresponds to the NACE-CLIO R-44 classification. It is also the same used in MINER (1992, 1993, 1994 and 1995).

TABLE 1
Industrial sector breakdown

	Number of observations (%) after selecting firms with 4 or more years in the survey N=9,648		Number of obs. (%) after selecting firms with 4 or more years of R&D expenditures N=2,980		Number of obs. with R&D>0 and percentages over columns (1) and (2) N=2,820		mean R&D/sales ratio (%) N=2,820	
	(1) L>200	(2) L≤200	(3) L>200	(4) L≤200	(5) L>200	(6) L≤200	(7) L>200	(8) L≤200
1. Metals	140 (4.21)	78 (1.23)	104 (4.91)	11 (1.27)	100 (71 42)	9 (11.53)	0.76	1.17
2. Non-Metallic Minerals	238 (7.15)	428 (6.77)	111 (5.25)	34 (3.94)	105 (44.11)	31 (7.24)	1.60	0.99
3. Chemical Products	383 (11.50)	291 (4.61)	345 (16 30)	100 (11.57)	343 (89.55)	98 (33.67)	3.47	3.13
4. Metallic Products	214 (6.43)	755 (11 95)	126 (5.95)	82 (9.49)	123 (57.47)	74 (9.80)	1.54	1.76
5. Machinery for Agriculture and Industry	161 (4.84)	381 (6 03)	108 (5.10)	109 (12.62)	106 (65.83)	103 (27.03)	3.08	3.01
6. Machinery for offices, Data processing, etc	67 (2.01)	37 (0.59)	40 (1.89)	7 (0.81)	38 (56.71)	6 (16.21)	2.10	1.68
7. Electrical Material & Accessories	407 (12.23)	515 (8.15)	318 (15.03)	18 (621.53)	313 (76.90)	174 (33.78)	3.27	3.30
8. Motors & Autos	272 (8.17)	129 (2.04)	220 (10.40)	43 (4.98)	215 (79.04)	41 (31.78)	2.48	2.66
9. Other transport material	95 (2.85)	106 (1.68)	56 (2.65)	6 (0.69)	54 (56.84)	6 (5.66)	5.05	1.62
10. Meat & by-products	110 (3 30)	184 (2.91)	61 (2.88)	2 (0.23)	57 (51.81)	2 (1.08)	0.42	0.50
11. Food & Tobacco	334 (10.03)	732 (11 58)	194 (9.17)	33 (3.82)	175 (52.39)	32 (4.37)	1.11	1.27
12. Beverages	145 (4.36)	110 (1.74)	56 (2.65)	18 (2 08)	55 (37.93)	15 (13.63)	0.59	1.37
13. Textiles & Clothing	272 (8.17)	747 (11.82)	123 (5.81)	86 (9 95)	107 (39.33)	76 (10.17)	1.37	2.83
14. Leather & Footwear	34 (1.02)	268 (4.24)	23 (1.09)	35 (4.05)	21 (61.76)	29 (10.82)	0.99	2.80
15. Wood & Wood furniture	49 (1.47)	540 (8.55)	27 (1.28)	6 (0.69)	25 (51.02)	6 (1.11)	0.23	0.59
16. Paper & by-products	229 (6.88)	494 (7.82)	87 (4.11)	44 (5.09)	77 (33.62)	39 (7.89)	0.96	2.42
17. Plastic & Rubber	137 (4.12)	345 (5.46)	89 (4.21)	39 (4.51)	89 (64.96)	31 (8.98)	1.95	1.14
18. Other manufactures	42 (1.26)	179 (2.83)	28 (1.32)	23 (2.66)	27 (64.28)	18 (10.05)	1.65	1.39
Total Manufacturing	3,329	6,319	2,116	864	2,030	790	2.25	2.54

Firms with more than 200 employees, represent about 71 percent of the selected sample, and about 96 percent of these observations show positive R&D spending (2,030 over 2,116 observations). Furthermore, small firms account for 29 percent of the sample, with about 91 percent of the observations showing positive R&D spending. Columns five and six show the sectors where observations with R&D expenditures concentrate. Firstly, it has to be stressed that large firms account for 72 percent of observations with positive R&D spending (2,030 over 2,820), although large firms were just 35 percent of the initial sample (3,329 over 9,648). This implies that the percentage of large firms that perform R&D activities (2,030 over 3,329, that is, about 61 percent) is much greater than that corresponding to the smaller firms. In fact, only about a 12.5 percent of the observations corresponding to small firms that were present in the initial sample, remain after selecting those that spend in R&D at least during four consecutive years (790 over 6,319).

The sectors of chemical products, motors & autos, electrical material, metals and machinery for agriculture & industry, show the highest percentages of observations with positive R&D both in the group of large firms and, except for the sector of metals, in the group of small firms. Moreover, three of these five sectors (chemical, machinery and electrical materials) make (alongside large firms in the sector of other transport material), the greatest research efforts, according to the real R&D to sales ratio.

3.2 The variables: R&D capital and spillovers

The appendix at the end defines the whole set of used variables. However, some further comments regarding the R&D capital measure and the spillover variables are necessary for clarification.

The R&D capital variable

The R&D or knowledge capital stock is computed using the well-known perpetual inventory method (see the appendix). However, this is just an input measure of the innovative activity carried out by firms whereas it is broadly accepted that innovation results are those which can affect the firm's production results rather than innovation inputs. To take account for this fact, I follow García *et al.* (1998) who define the operative knowledge capital stock, K^*, for each year t as

$$K_t^* = K_t d_t + K_{t-1}^*(1 - d_t) \qquad [5]$$

where K is the R&D stock calculated according to the perpetual inventory method and where d_t is defined as an indicator variable equal to one if the firm has achieved process innovations and 0 if otherwise. The assumption made is that the R&D stock of the firm can only affect its productivity if the firm has achieved this kind of innovation results during the period under analyasis.[6]

The spillover variables: the technological sophistication of firms

Following the suggestions of Griliches (1992), spillovers are understood as ideas borrowed by research teams of firm/industry i from the research results from firm/industry j. I define here spillovers combining information regarding the firm's product field with the type of technological orientation of the firm. In particular, the ESEE provides information to classify the firms as mainly users of advanced technologies (numeric control machines; computer-aided-design (CAD); computer-aided-manufacturing (CAM), and robotics) or those who do not. From now onwards, AT and NAT will denote those firms that use advanced technologies and those that do not use advanced technologies, respectively.

To identify the relevant channels of influence of others' R&D results, I have defined several measures of spillovers as follows:

SP_{50AT}: sum of others' R&D capital in the same 50-sector classification that use advanced technologies;[7]

SP_{50NAT}: sum of others' R&D capital in the same 50-sector classification that do not use advanced technologies;

SP_{18AT}: sum of others' R&D capital in the same 18-sector classification that use advanced technologies, minus the R&D capital of those in the 50-sector classification that are also included in the 18-sector one;

SP_{18NAT}: sum of others' R&D capital in the same 18-sector classification that do not use advanced technologies, minus the R&D capital of those in the 50-sector classification that are also included in the 18-sector one.

All the above defined measures of the spillover pool are conditional on

[6]I would like to acknowledge the comments of an anonimous referee with regard to this definition of the R&D capital.

[7]The CNAE 3-digit classification has been grouped into 50 sectors as in Huergo (1994).

having achieved innovation results during the current or past years. The assumption is made that if no results exist, no results are susceptible to spill over. Thus, those firms without research results are not included in the calculus of the spillover variable. Therefore, as general formulation, we can write the spillover pool for each firm i as follows

$$S_{it} = \sum_{\substack{j=1 \\ j \neq i}}^{J} K_{jt} \times I_{jt} \qquad [6]$$

where J refers to the category defined for each particular case described above, and where I_{jt} is an indicator variable equal to one if the j firm has achieved innovation results during the current or past years, and 0 if otherwise.

I will first introduce the spillover measures in the estimation using all firms in the sample. Subsequently, definitions SP_{50AT} to SP_{18NAT} will be used selecting, first, all firms, then only AT firms and, finally, only NAT firms. This way of proceeding will give an idea as to how the possibility of drawing from others' research results depends on the commonality in their technologic orientations. In Griliches' (1992) words, pp. S29: *"To measure them (spillovers)..., one has to assume ..., that one can detect the path of the spillovers in the sands of the data"*. This is what the goal of the used approach is focused on: to allow the data to inform us about how proximity should be defined in order to identify which others' research efforts have to be summed up into the proper measure of spillovers.

4. Results

Table 2 presents the obtained results for the whole sample. I first estimate the relationship presented in [4] by Ordinary Least Squares (OLS). These results are presented in column (1). However, it is widely accepted that the estimation of production functions are very often affected by biases due both to simultaneity and to measurement errors in the inputs. In particular, the *variable* inputs (materials and labour) are likely to be simultaneously determined with output whereas the *constant* inputs are more likely to be affected by measurement errors. As we are already aware, the existence of these sources of bias affects the first differences estimates to a greater extent than the cross-sectional estimates. Thus, column (2) presents the results for the first differenced version using instrumental variables with GMM techniques (Arellano and Bond, (1991)). The Sargan test of overidentifying restrictions has been used here to test the validity of the used instruments. According to this, the hypothesis of valid instruments is not rejected at conventional levels of significance.

TABLE 2
Cobb-Douglas production function
Dependent variable: Δ log Sales (total sample)

	(1) First differences	(2) First diff. + IV
Log M	0.557**	0.507**
	(0.014)	(0.021)
Log Lab	0.280**	0.343**
	(0.021)	(0.028)
Log C	0.038**	0.047**
	(0.018)	(0.025)
Log CU	0.104**	0.124**
	(0.025)	(0.056)
Log K	0.036**	0.033**
	(0.003)	(0.009)
log SP_{18AT}	0.007**	0.012**
	(0.003)	(0.006)
log SP_{50AT}	0.001	0.1e-03
	(0.001)	(0.005)
log SP_{18NAT}	-0.002	0.009
	(0.003)	(0.008)
log SP_{50NAT}	-0.2e-03	-0.003
	(0.001)	(0.003)
dumK	0.004	0.010
	(0.021)	(0.038)
		$S_{(d\,f=112)}$ = 112.24 P-value= 0.475
Adj. R^2:	0.378	0.396
Period:	1991-1996	1992-96
N. of firms:	501	501
Obs:	2,479	2,054

Notes· Heteroskedasticity-robust standard errors in parentheses. (* significant at α=10%, ** significant at α=5%). K is constructed assuming δ=15% and g=4% All regressions include time dummy variables for the respective survey years. Also they contain sectorial dummies and other control variables as described in the main text.

Instruments: two period lagged levels of the log of raw materials and hours, and the corresponding flows for the capital variables (flow of investment in physical capital, flow of R&D expenditures and spillovers computed from R&D flows).

$S_{(d\,f)}$: Sargan test of overidentifying conditions (degrees of freedom= number of overidentifying conditions)

Tables 5 and 6 give a synoptic account of the existing evidence on own R&D elasticities. Of course, much care has to be exercised when comparing different authors' results, not just because of the different data sources or countries but also because slight modifications in the specifications may cause appreciable changes in the obtained elasticities. The majority of the estimates presented in Table 5 have been obtained from the estimation of production functions with value added as dependent variable (or sales without including materials in the specification). This increases the difficulty of the comparison with my results. Within the framework of the work presented here, the estimation of the production function with value added as dependent variable lead to an R&D capital elasticity equal to 0.070 for instrumented first differences.[8]

The time-series estimates for other countries offer R&D elasticities that range from some negative and even statistically significant coefficients (-0.138 for France in the period 1985 to 1989 (Hall and Mairesse (1996)), to values around 0.16 for the US case (Griliches and Mairesse (1984)).[9] Many of these time-series estimates are no statistically significant. In the case of Spain, Fluviá (1990) obtains values that range from about 0.120 to 0.180, and Grandón and Rodríguez Romero (1991) obtain similar results for the period 1979-1981 in within groups. García *et al.*'s (1998) results also display significative and quite high values for the R&D capital elasticity using sales as dependent variable, (0.092), whereas Rodríguez Romero (1993) finds an R&D elasticity of about 0.047. My results here are, then, an intermediate case if they are compared with other countries' estimates, although they are somewhat lower to the majority of previously obtained results for the Spanish case: as already mentioned, the obtained elasticity for R&D

[8] It is well known that the estimation of the production function with value added as the measure of output and, correspondingly, excluding raw materials from the right hand side of the production function, renders higher values for the inputs elasticities. This is the reason why I mention the achieved results with value added: to make possible the comparison with previous results that use such a measure of output. However, the use of sales with raw materials among the inputs, is preferred to that alternative, and so, it has been the choice made in this article. Although not reported here, the estimates for the case of value added as dependent variable, are available from the author upon request.

[9] Both first differences and within-group estimates, (that is, those performed on the deviations of the variables from their individual firm means), are referred in the literature of panel data as time-series estimates, as opposed to cross-sectional estimates, which refer to the regressions carried out on the variables in levels for a given year, or on the individual firm means of variables over several years.

is about 0.070 and statistically significant in first differences when value added is used as the measure of output in the production function.

TABLE 3
Cobb-Douglas production function
Dependent variable: Δ log Sales
(subsamples of firms of advanced and non-advanced production processes)

	Advanced technology		Non-advanced technology	
	(1) First differences	(2) First diff. + IV	(1) First differences	(2) First diff. + IV
Log M	0.421**	0.451**	0.456**	0.588**
	(0.028)	(0.031)	(0.022)	(0.029)
Log Lab	0.279**	0.419**	0.212**	0.252**
	(0.018)	(0.040)	(0.030)	(0.041)
Log C	0.053**	0.068**	0.046*	0.059**
	(0.026)	(0.035)	(0.024)	(0.030)
Log CU	0.142**	0.079*	0.048	0.029
	(0.033)	(0.041)	(0.038)	(0.036)
Log K	0.033**	0.035**	0.034**	0.048**
	(0.004)	(0.005)	(0.006)	(0.009)
$log\ SP_{18AT}$	0.016**	0.017**	0.005	0.011
	(0.005)	(0.004)	(0.004)	(0.009)
$log\ SP_{50AT}$	0.2e-03	0.002	0.003	0.007
	(0.002)	(0.002)	(0.002)	(0.009)
$log\ SP_{18NAT}$	-0.002	-0.001	-0.8e-03	0.8e-04
	(0.003)	(0.002)	(0.005)	(0.007)
$log\ SP_{50NAT}$	-0.4e-03	0.002	-0.002	-0.002
	(0.002)	(0.001)	(0.003)	(0.008)
dumK	0.020	0.047	0.003	0.012
	(0.029)	(0.035)	(0.030)	(0.055)
		$S_{(d\ f=112)}$ =109.32 P-value= 0.554		$S_{(d\ f=112)}$ =109.10 P-value=0.559
Adj. R^2:	0.379	0.397	0.340	0.356
Period:	1991-96	1992-96	1991-96	1992-96
N. of firms:	305	305	196	196
Obs.:	1489	1236	990	818

Notes. Heteroskedasticity-robust standard errors in parentheses. (* significant at α=10%; ** significant at α=5%). K is constructed assuming δ=15% and g=4% All regressions include time dummy variables for the respective survey years. Also they contain sectorial dummies and other control variables as described in the main text

Instruments: two period lagged levels of the log of raw materials and hours, and the corresponding flows for the capital variables (flow of investment in physical capital, flow of R&D expenditures and spillovers computed from R&D flows).
$S_{(d\ f)}$: Sargan test of overidentifying conditions (degrees of freedom= number of overidentifying conditions)

Focusing now the attention on the spillover effects, we observe that the only definition of the spillover that renders a significative estimated coefficient is SP_{18AT}. The estimated coefficient is slightly higher when instrumenting with GMM methods.

TABLE 4
Cobb-Douglas production function
Dependent variable: Δ log Sales
(First differences + IV with GMM)

	High R&D intensity	Medium R&D intensity	Low R&D intensity
Log M	0.356**	0.416**	0.498*
	(0.055)	(0.024)	(0.040)
Log Lab	0.403**	0.367**	0.267**
	(0.035)	(0.039)	(0.059)
Log C	0.057**	0.073**	0.049**
	(0.016)	(0.031)	(0.044)
Log CU	0.097*	0.152**	0.174**
	(0.053)	(0.046)	(0.068)
Log K	0.031**	0.038**	0.032**
	(0.009)	(0.006)	(0.006)
log SP_{18AT}	-0.011	0.019**	0.009
	(0.024)	(0.007)	(0.007)
dumK	0.064	0.010	0.038
	(0.106)	(0.036)	(0.036)
$S_{(d.f.=112)}$	105.10	109.20	118.51
P-value	0.664	0.557	0.318
Adj. R^2:	0.372	0.421	0.432
Period:	1992-96	1992-96	1992-96
N. of firms:	73	148	84
Obs.:	292	590	354

Notes: Heteroskedasticity-robust standard errors in parentheses. (* significant at α=10%; ** significant at α=5%) K is constructed assuming δ=15% and g=4% All regressions include time dummy variables for the respective survey years. Also they contain sectorial dummies and other control variables as described in the main text.

Instruments: two period lagged levels of the log of raw materials, hours and the corresponding flows for the capital variables (flow of investment in physical capital, flow of R&D expenditures and spillovers computed from R&D flows).

$S_{(d.f.)}$. Sargan test of overidentifying conditions (degrees of freedom= number of overidentifying conditions)

TABLE 5
Other countries studies on R&D producivity. Firm level data
R&D capital as measure of knowledge capital. Elasticity estimates

Author	Sample	Totals	Time-series	
Minasian	US 17 firms	0.26**	Within	0.08
(1969)	chemicals 1948-57	(0.03)		(0.007)
	US 883 firms	0.07**	-	-
Griliches	1963 cross-section	(0.01)		
(1980)	US 883 firms	-	Average	0.08*
	1957-65		growth rate	(0.01)
Schankerman	US 110 firms	0.16**	-	-
(1981)	1963 cross-section	(0.04)		
	US (1966-1977)	0.05**		0.16**
Griliches and	133 firms	(0.01)	Within	(0.02)
Mairesse	US (1966-1977)	0.18**	estimate	0.09**
(1984)	77 firms	(0.01)		(0.02)
	Scientific sector			
	France (1972-1977)	0.20**		0.11**
Cuneo and	182 firms	(0.01)	Within	(0.04)
Mairesse	France (1972-1977)	0.21**	estimate	0.05
(1984)	98 firms	(0.01)		(0.04)
	Scientific sector			
	France 296 firms	0.10**	-	-
Mairesse and	Scientific sectors	(0.02)		
Cuneo	(1974 and 1979)			
(1985)	France 390 firms	-	Long	0.02
	(1974 and 1979)		diferences	(0.10)
	US 491 firms	0.11**	-	-
	1972 cross section	(0.02)		
Griliches	US 491 firms	0.09**	-	-
(1986)	1977 cross section	(0.02)		
	US 652 firms	-	Average	0.12**
	1966-77		growth rate	(0.02)
	Japan (1976)	0.16**	-	—
	394 firms	(0.03)		
	Japan (1976)	0.08**	-	-
	112 firms	(0.03)		
	Scient. sector			
Sassenou			Within	-0.01
(1988)	Japan		estimate	(0.01)
	394 firms	-	Annual	0.02
	1973-1981		growth rate	(0.02)
			Average	0.04
			growth rate	(0.04)
			Within	0.0069**
Hall and Mairesse	France	0.25**		(0.035)
(1995)	197 firms	(0.008)	First	0.051
	1980-1987		differences	(0.070)

(continued...)

TABLE 5 *(continued)*
Other countries studies on R&D producivity. Firm level data
R&D capital as measure of knowledge capital. Elasticity estimates

Author	Sample	Totals	Time-series	
	France 441 firms 1981-85 balanced panel	0.103** (0.009)	First differences	-0.063 (0.041)
	France 381 firms 1985-89 balanced panel	0.078** (0.011)	First differences	-0.138** (0.044)
Hall and Mairesse (1996)	US 535 firms 1981-85 balanced panel	0.035** (0.007)	First differences	0.033 (0.061)
	US 442 firms 1985-89 balanced panel	0.041** (0.008)	First differences	-0.039 (0.048)

Looking more closely at the spillover effects, an interesting result is found when the sample is split into the subsamples of advanced-technology users, and those which are less technology-orientated ones. Table 3 shows that, first, only the R&D efforts of AT firms have a relevant effect on others' productivity, and, second, only AT firms are able to benefit from their technological neighbourhood. A similar result is presented in Kettle (1994) who found that only the advanced firms (as defined by an indicator of the firm's technical sophistication) benefit from spillover R&D, while the effect is negative for most of the others.

It may seem at first sight somewhat intriguing that the spillover variables for the narrower definition (SP_{50AT}) perform worse than for the wider ones (SP_{18AT}). One possible explanation may lie in the recognised existence of two opposite effects behind any spillover measure: the technological externality and the competitive effects of others' R&D. From this point of view, one might hypothesise that AT firms are able to draw knowledge from a broad range of firms, whereas those that are closest in their product space (and also with advanced-technology orientation) are mainly its competitors. In this latter case, the "competitive" effect of the pool may be cancelling out the positive (externality) effect. Jaffe (1986) uses the same argument to explain some of the negative signs obtained for the spillover elasticity.

To inquire to which extent the spillover effects may differ depending on the intensity of R&D investment, I present in Table 4 some results for different subsamples of AT firms, according with their R&D intensity. I consider high-R&D intensive firms those that exhibit, over the whole period, a mean R&D to sales ratio in the 75 percentile (a ratio by about 2.3 percent). Medium intensive firms refer to cases between the 50 and the 25 percentiles, (ratios from 2.3 percent to 0.5 percent), and low intensive cases are those in the 25 percentile (R&D to sales ratios below 0.5 percent).

TABLE 6
Previous studies on R&D productivity for the Spanish case

Author	Data	Estimation method	Results
Lafuente *et al.* (1985)	1966-1981 Time series of macro data	OLS	0.11**-0.16**
Fluviá (1990)	1973-1981 unbalanced panel (500 firms in 1973; 1,344 firms in 1981)	Totals	0.12**-0.18**
		First differences	0.20**-0.18**
Grandón and Rdguez. Romero (1991)	1973-1981 balanced panel 53 firms	Totals	0.008
		Within	0.040
	1975-1978 balanced panel	Totals	0.01
		Within	-0.001
	1979-81 balanced panel	Totals	0.001
		Within	0.15**
Rodríguez Romero (1993)	1979-81 59 firms balanced panel	Orthogonal deviations GMM	0.047**
Gumbau (1996)	1993 cross-section	OLS	-0.43e-03** 0.25e-03[a]
López and Sanaú (1998)	13 industrial sectors 1986-92	Between estimation	0.093**-0.125**
García *et al.* (1998)	1990-1995 1,200 firms unbalanced panel	First differences (Two step-IV)	0.092**

[a] Theses results correspond to the elasticity of R&D expenditures lagged up to three years

The results do not seem to support the idea that the highest-R&D intensive firms are the "winners" in the race for appropriating others' research results. Neither the group of less intensive firms are the most benefited by the spillover pool. On the contrary, firms in the intermediate quartiles seem to experience the largest productivity gains from spillovers. The obtained results suggest in their combination an interesting conclusion: both the origin and the destination of spillovers are found in the group of AT users, but once in this group, the spillover effects do not linearly increase with the R&D intensity of the recipient firms. Given the results obtained, low R&D-intensive firms seem to be incapable of drawing from others' knowledge, but, at the opposite extreme, the most R&D intensive firms reveal themselves more as generators of technical knowledge than as recipients of spillover gains.

This result may come to reconcile previous apparently contradictory findings of no evidence in favour of greater spillovers for high R&D intensive firms (Fluviá (1990), for example), and those that obtain spillover effects rising with R&D to sales ratios (Harhoff (1997), for example). We would draw the first conclusion from the results presented in this work if we were to compare the results obtained here for medium intensive firms with those obtained for high intensive firms. Nevertheless, we would point out that R&D intensity enhances the possibilities to benefit from the spillover pool if the attention is focused on the comparison of the medium intensive firms' results with the results obtained for the lowest R&D intensive ones.

The above commented results may also be in line with the "absorptive capacity hypothesis", that is, the idea that own research efforts enable firms to utilise the existing spillover knowledge, Cohen and Levinthal (1989). Given the results obtained, we might claim that it is necessary to go beyond a threshold in order to be able to capture and benefit from others' results, but that, once a certain level has been achieved, subsequent increments in the own R&D investment do not necessarily enhance the possibilities to profit from others' R&D results. Some previous results (Jaffe (1986), Harhoff (1997)) only found positive significant effects of spillovers to the extent that this variable was combined with the own level of knowledge capital.

5. Conclusions

The empirical exercise performed in this article has offered some evidence on the effect of R&D activity on productivity for Spanish manufacturing firms for the period 1990-1996. The work is framed in the line of research initiated by Griliches, that have given rise to a considerable number of applications or case studies. The main goal of the study developed here has been to look deeper into the comprehension of how spillovers have to be defined and implemented in estimation.

The basic results from the analysis of spillover effects reflect that they are only relevant, not just from, but also for, users of advanced technologies (AT firms), and that the spillover pools calculated as aggregation over the broadest industrial classification performs better than their narrower counterparts. These results are especially important to address the study of spillover effects. They may be revealing how trying to determine the effects of the diffusion of knowledge among too broad and heterogeneous groups of firms, may be pure illusion, since it is impossible to disentangle the positive externality effect and the negative competition effect. Instead, the main conclusion emerging from the obtained results is that, in the absence of properly detailed data to acutely calculate weights to account for technological proximity, the best option might be to study the spillover effects for narrowly defined groups of firms, allowing the data to inform us about the relevant originators and, also very importantly, about the main receivers of the productivity gains derived from the stocks of knowledge accumulated in their neighbourhoods.

Once the analysis has been focussed on the group of AT oriented firms, the data does not support the notion of greater spillovers for the most high-intensive firms. Instead, it seems that the highest-intensive firms are more the creators than the receivers of knowledge. Other studies have obtained opposite results, but it is important to bear in mind the distinction made here between firms that are users of advanced technologies and high-R&D intensive firms (within the group of AT firms). To the extent that AT firms are also, in general, the most R&D intensive firms, other previous studies might be mixing both concepts when determining that spillovers rise with R&D intensity. The distinction made here has lead us to observe that, at least, this direct relationship is not linear, allowing to more acutely determine the final receivers of the social gains of the R&D activity. Future studies for other countries will hopefully add some evidence on this field which will then encourage the debate further.

Apendix. Definition of variables

A1.1 Output variable

I use as the output variable the real production of goods and services. It is defined as the sum of sales and the variation of inventories (I call this variable Sales through out this article), and it has been deflated using yearly output deflators at the two-digit level. These deflators are the Industrial Price Indexes (IPI) published by the National Institute of Statistics of Spain (INE).

A1.2 Raw materials

Nominal raw materials (M) are calculated as the sum of purchases and external services minus the variation of purchase inventories. These have been deflated by the IPI for these type of goods.

A1.3 Physical capital

The physical capital stock variable (C) has been constructed following the method used by Martín and Suárez (1997). It is defined as the value of equipment net of depreciation and adjusted for inflation using the deflator for equipment of the INE.

A1.4 Capacity utilization

The ESEE also provides information about the extent to which physical capital has been used during the period. In particular, the percentage of capacity utilisation (CU) is reported in the data and it has been used to control for short term adjustments to business cycle fluctuations by the firm.

A1.5 Labour: number of hours worked

Finally, using the available information, the labour variable (L) is defined as effective total hours worked. It has been computed as the number of workers, times the (mean) normal hours plus overtime and minus lost hours.

A point that deserves special mention when defining the variables for this kind of study is the convenience of adjusting the variables for double counting: research labour and capital are double-counted, once in the labour and capital measures and again in the research expenditure input. This problem commonly yields estimates for the R&D capital elasticity that are below its actual values. The correction should be applied both to the physical capital and to the labour variables. Regrettably, the information contained in the ESEE does not allow us to adjust the physical capital variable. Nevertheless, as Hall and Mairesse (1995, 1996) report, the most important adjustment seems to be that corresponding to the labour variable.

The number of workers in R&D activities within the firm have to be subtracted from the total number of employees or, if using hours worked, the number of hours worked in research activities have to be subtracted from the total hours worked. The ESEE reports the number of employees working in R&D activities, so that I have been able to adjust the labour variable on the assumption that the percentage of research workers over the total number of workers, approximates to the percentage of hours devoted to research activities. That is

$$\frac{\text{number of workers in R\&D activities}}{\text{total number of workers}} \text{total hours} = \text{hours worked in R\&D}$$

A1.6 R&D capital

The R&D capital variable has been constructed using the historical or perpetual inventory method, which specifies the capital for each period as the sum of the capital of the previous period minus the depreciated capital and plus the investment of the previous period:

$$K_{it} = (1-\delta)K_{it-1} + R_{it-1} \qquad \text{[A1]}$$

where δ is the rate of depreciation, K is the R&D capital stock and R are real R&D expenditures (defined here in a broad sense: nominal R&D expenditure plus technology imports payments and deflated by a total manufacturing price deflator).

To estimate the R&D capital according to equation [A1] we need an initial value for K (say, in $t = 1$), to start the recursion. By backwards induction, the sequence of past R&D expenditures can be imputed till the year of establishment of the firm, when the initial R&D capital stock is, of course, equal to zero. Using then [A1] the stock of R&D capital at the end of the first year can be measured as

$$K_1 = \frac{R_1}{(1+g)} \frac{1-\mu^{\tau}}{(1-\mu)} \qquad \text{[A2]}$$

where $\mu = (1-g)(1-\delta)$ and τ is the number of years since the firm was established.

Following the assumptions which have been most frequently used before in this kind of study, I have defined the R&D capital for a depreciation rate of 15 percent and a presample growth rate of real R&D investment equal to the mean growth rate for the firms which perform R&D activities and are observed during the sample period, that is $g = 4\%$.

Then the operative knowledge capital stock, K^*, for each year t is defined as

$$K_t^* = K_t d_t + K_{t-1}^*(1-d_t) \qquad \text{[A3]}$$

where K is the R&D stock calculated according with the perpetual inventory method and where d_t is defined as an indicator variable equal to one if the firm has achieved process innovations and 0 if otherwise. According with [A3] the operative R&D capital stock for year t is all the accumulated stock, (defined by [A1]), if the firm achieves process innovations in that year, whereas for a firm which does not achieve innovations in year t, the operative stock is that already accumulated in the last year the firm achieved innovation results.

For those firms which assess not having achieved innovations in the first year of the panel (1990), two cases are considered: first, for those which achieve process innovations in other years of the panel, it is assumed that the stock in the first year is that corresponding to the previous year (that is, the value of K_{t-1} calculated according with [A1]). The assumption made in this case is that in this period, $t-1$, all the previous accumulated R&D capital became operative; second, for those which report no innovations in any year of the panel (48 firms in the used sample), it is assumed that the initial "operative" stock is zero. The assumption made in this case is that these firms have orientated their R&D efforts towards other kind of innovations, and then, their 'operative' R&D capital is zero all through the observed period.

A.1.7 Dummy variables

All the estimations include time dummies which try to approximate the time trend λt present in the production function. There are also industry dummies (which correspond to the eighteen industrial sectors described in Table 1), a size dummy equal to one if the firm has more than 200 employees and 0 if otherwise, and four dummies to account for acquisition and merger of firms, scission, entry and exit.

In the dataset some observations for the R&D capital are equal to zero. I have used the standard fix for this problem by setting the log of this variable equal to zero in that case and introducing a dummy variable ($dumK$) that takes the value of one for those cases where the R&D capital is zero, and zero otherwise (see, for example, Kettle (1996)). The coefficient of this dummy variable has then to be interpreted as the log of the average amount of knowledge acquisition (other than in the form of formal R&D) for these cases.

TABLE A1.1
Descriptive statistics on the basic variables

All firms	Mean	Std.dev.	Min	Max
N. Obs.	2980			
log sales	15.973	1.626	10.674	21.129
log materials	14.540	1.621	9.267	19.620
log value added	14.634	1.548	9.180	20.045
log physical capital	13.746	1.902	6.525	19.591
log capacity utilization	4.373	0.205	2.302	4.605
log hours worked	13.135	1.278	7.482	17.646
log knowledge capital	11.541	2.412	1.609	20.043
log spillover pool (SP_{50AT})	14.789	2.044	7.242	20.349
log spillover pool (SP_{50NAT})	13.464	2.219	5.908	17.384
log spillover pool (SP_{18AT})	16.441	2.028	8.496	20.378
log spillover pool (SP_{18NAT})	14.519	2.065	5.908	17.931
Firms with L>200				
N. Obs.	2116			
log sales	16.695	1.135	13.686	21.159
log materials	15.225	1.192	10.652	19.620
log value added	15.313	1.073	10.760	20.045
log physical capital	14.519	1.374	9.231	19.591
log capacity utilization	4.388	0.189	2.302	4.605
log hours worked	13.746	0.819	12.266	17.646
log knowledge capital	9.854	1.975	2.394	16.476
log spillover pool (SP_{50AT})	14.914	2.051	7.996	20.349
log spillover pool (SP_{50NAT})	13.503	2.247	5.908	17.384
log spillover pool (SP_{18AT})	16.460	2.018	8.496	20.378
log spillover pool (SP_{18NAT})	14.580	2.078	5.908	17.931
Firms with L<=200				
N. Obs.	864			
log sales	14.206	1.252	10.674	18.260
log materials	12.868	1.282	9.267	17.425
log value added	12.945	1.198	9.180	17.605
log physical capital	11.853	1.676	6.525	15.563
log capacity utilization	4.337	0.237	2.302	4.605
log hours worked	11.638	0.903	7.482	12.825
log knowledge capital	12.488	2.098	1.609	20.043
log spillover pool (SP_{50AT})	14.470	1.994	7.242	18.406
log spillover pool (SP_{50NAT})	13.361	2.141	7.791	17.384
log spillover pool (SP_{18AT})	16.394	2.054	8.496	20.349
log spillover pool (SP_{18NAT})	14.382	2.029	8.591	17.931

Descriptives on the research variables (knowledge capital and number of R&D workers) are calculated from those observations with positive values.

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Resumen

Este trabajo analiza empíricamente los efectos en la productividad de los propios esfuerzos en I+D realizados por las empresas así como la existencia de externalidades tecnológicas derivadas de dichos esfuerzos. Las variables utilizadas para aproximar tales externalidades se definen teniendo en cuenta no únicamente el sector industrial en que operan las empresas sino también el grado de sofisticación tecnológica de las mismas. Los resultados obtenidos sugieren que las empresas de tecnologías avanzadas son tanto el origen como las destinatarias de los efectos difusión aludidos, mientras que no se observan resultados significativos para aquéllas con procesos productivos menos avanzados tecnológicamente. El impacto de las externalidades depende además del esfuerzo tecnológico realizado por las empresas receptoras, siendo las empresas con ratios I+D/ventas en los quartiles intermedios las que experimentan las mayores ganancias en productividad.

Palabras clave: I+D, externalidades tecnológicas, productividad, datos de panel.

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