THE IMPACT OF PROCESS INNOVATIONS ON FIRM'S PRODUCTIVITY GROWTH: THE CASE OF SPAIN

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Abstract

The main aim of this paper is to investigate about the effect that a measure of the process innovation performance of a firm has on its labour productivity growth. This analysis is mainly consequence of two considerations. The first one derives from a clear differentiation of the role that product and process innovations have on firm's performance. The second one is to assume that the knowledge capital of a firm is mainly composed by its successful research. Along the study, it is demonstrated that process innovation has a positive and significant effect on firm's productivity growth. Moreover, this result is robust under a wide range of alternative specifications and, in any case, our variable behaves much better than R&D intensity. Following previous research, the detected quadratic relationship between vertical product differentiation and process innovation performance leads to the existence of some firms for which there exist a trade-off between quality and productivity.

I.- INTRODUCTION

The study of the impact that technology could have on productivity growth experimented a relevant development when it was observed since the end of the decade of seventies a clear slowdown in this ratio in occidental economies. This worry emerged due to the possible adverse consequences that this fact could have on inflation and competitiveness. The interest of the authors have been essentially focused in trying to discover what the role is of the amount directed to the Research and Development (R&D) of new product and processes on productivity evolution, being the research conducted from distinct stages, mainly at the country and sectorial levels and, to a lesser extend, at the firm level.

To do this, the diverse works have included, in addition to physical capital and labour, a measure of knowledge capital (normally a weighted sum of past R&D) as an input of the productive process and have tested the sign and significance of this variable in the corresponding regression. The results obtained of doing this exercise are not conclusive and differ in an important manner depending, for instance, on the country under study, the characteristics of the sample used (i.e. type of firms that compound it) or the period of analysis, as well as other circumstances such as to consider or not the assumption of constant returns to scale, the existence of externalities, etc.

Our perspective, however, is slightly different. In preceding research (Llorca, 1998a,b) we outlined the convenience of distinguish the distinct impact that process and product innovations have on the profit function of a firm. This is logical if we realise that the effect of a process innovation is to reduce the unit cost of production of the good, implying a productivity improvement, and that of a product innovation is to shift the corresponding demand curve rightward (vertical product differentiation) allowing the firms to charge a higher price-cost margin. Acting in this manner, we have reached to the theoretical and empirical conclusion of the existence, for a wide sample of Spanish manufacturing firms, of a quadratic relationship between an approximated measure of the number of process innovations a firm declares to obtain in a given year and its vertical product differentiation (number of product innovations). That is, we have detected a point, corresponding to a specific degree of vertical product differentiation, beyond which the firm has less incentive for a reduction in its unit cost of production and, therefore, its process innovation performance decreases.

From this point of view we can extract one tentative (at least, partial) explanation for the aforementioned fall in the rate of growth of productivity in modern economies. In this sense, the own evolution in the development of the market mechanism that leads to a great variety and the characteristics of the good the firm sells (the possibility of vertically differentiate it) influences its cost-reduction incentives. The crucial point in order to sustain this conclusion relies in the consideration that the variable we have taken in previous research as a dependent one reflecting the process innovation performance of a firm (Llorca, 1998b) determines, to a greater or lesser extent, its productivity evolution. If this is revealed to be true, we would have been able to give an alternative way to expound the problem.

This is the main contribution of this paper. Basing on a very rich sample of Spanish manufacturing firms yet used in previous research and including in their production function an approximated measure of the number of process innovations obtained by each one in a given year, we test the relevance of this variable both at the cross-section level and at the time dimensional one. Previously, a traditional approach with R&D intensity is conducted in order to make some comparisons.

Although the problems with the measurement of the variables are non negligible along the study (in particular, the identification of implausibly high decreasing returns to scale at the time dimension) the results obtained are satisfactory and robust enough to affirm that the existing trade-off postulated in previous paper between quality and productivity within the firm is a reasonable argument.

The rest of the paper is organised as follows. Section II describes the theoretical considerations. Section III presents the data sources and the variables measurement. Section IV outlines the main results of the cross-section and panel data estimates. Section V concludes.

II.-THEORETICAL BACKGROUND

The point of departure of this type of analysis (see, for instance, Griliches and Mairesse, 1984) is normally the traditional Cobb-Douglas production function extended with a measure of knowledge (or research) capital as an input of the productive process in order to account for the improvement of technology at the firm level. That is.

$$Q_{it} = Ae^{\lambda t} K_{it}^{\alpha} L_{it}^{\beta} R_{it}^{\delta} e^{eit} \qquad (1)$$

where Q_{it} is the output of firm "i" in period "t", A is a constant, λ measures the rate of disembodied technical change, K_{it} and R_{it} are respectively physical and knowledge capital of firm "i" in period "t", L_{it} is labour employed, α, β and δ are the corresponding elasticities of the three defined inputs and e_{it} is the error term.

When the available data are for a long enough period of time, the measure of the knowledge capital is usually achieved by a weighted sum of past (deflated) R&D. If this is the case, the empirical analysis is carried out by a cross-section or panel data regression of equation (1) in its logarithmic version. Unfortunately, the time dimension of our data source is just five years (see next section) and, consequently, it is not possible to construct a reliable variable reflecting research capital.

There is, however, an alternative way of dealing with this problem and is to consider equation (1) in its growth rate form. Therefore, if we take logarithms in equation (1) and we differentiate with respect to time , we obtain:

$$q_{it} = \lambda + \alpha k_{it} + \beta l_{it} + \delta r_{it} + w_{it} \qquad (2)$$

where lower case variables indicate rate of growth.

Being δ the elasticity of knowledge capital with respect to output, we have that $\delta = \frac{\delta Q}{\delta R}\frac{R}{Q}$. If we assume the equality of marginal products across firms ($\frac{\delta Q}{\delta R}$) allowing δ to vary among them, this would lead the rate of growth of productivity to depend on R&D intensity ($\frac{RD}{Q}$). That is:

$$\delta r = \left(\frac{\delta Q}{\delta R}\frac{R}{Q}\right)\left(\frac{\Delta R}{R}\right) = \frac{\delta Q}{\delta R}\frac{\Delta R}{Q} = \rho\frac{\Delta R}{Q} \quad \rho\frac{RD}{Q}$$

where it is assumed no depreciation in R&D ($\Delta R = RD - \eta R$; $\eta = 0$).

Following this procedure, equation (2) is reformulated as follows:

$$q_{it} = \lambda + \alpha k_{it} + \beta l_{it} + \rho \frac{RD}{Q} + w_{it} \qquad (3)$$

where the variable of interest in equation (3) is not a measure of knowledge capital but a measure of R&D intensity.

A second issue to take into account is about the assumption (or not) of constant returns to scale in the Cobb-Douglas production function[1] ($\alpha + \beta = 1$). Introducing this possibility into the regression, the equation to estimate is now in terms of labour productivity and takes the form:

$$(q_{it} - l_{it}) = \lambda + \alpha(k_{it} - l_{it}) + \gamma l_{it} + \rho \frac{RD}{Q} + w_{it} \qquad (4)$$

or simplifying the notation:

$$ql_{it} = \lambda + \alpha kl_{it} + \gamma l_{it} + \rho rd_{it} + w_{it} \qquad (4´)$$

[1] When we define constant returns to scale, there is a controversy about the inclusion in the production function of the parameter affecting the research capital. Following Griliches and Lichtemberg (1984) we have decided not to include it in order to avoid double counting with labour and physical capital inputs,

where $\gamma = \alpha + \beta - 1$ setting it equal to zero when assuming constant returns to scale and leaving free if this is not the case. Equation (4´) will be the basis of a first stage in the analysis performed in section IV. See, for instance, Wakelin (1998), that uses this procedure in a recent study for UK manufacturing firms.

As previously noted, the contribution of this paper relies in considering the analysis before made from a different point of view. In our case, two additional features are in order. The first one is in direct connection with the assumption of Blundell et al. (1993) that, in spite of construct knowledge capital using firm research efforts (R&D), they directly pay attention on effective innovations. The reasoning that supports this substitution is that the process of learning is by doing successfully rather than just the resources directed to R&D. Following this criteria, the increment in knowledge stock is given by:

$$\Delta R = I - \eta R \qquad \Delta R = I \text{ if we continue assuming } \eta = 0 \tag{5}$$

where "I" is the number of innovations achieved by a firm in a given year.

The second novelty is the distinction we make between product and process R&D. As Griliches and Mairesse (1984) recognise, the knowledge capital has to be constructed with the R&D investment on *productivity*, clearly referring to process R&D. However, the authors do not take into account this aspect along their study probably due to data availability[2]. In our case, it is possible, at least in some way, to correct this shortcoming and to construct a variable that approximately measured the process innovation performance of a firm. Therefore, in the construction of knowledge capital we will also consider, in principle, just process innovations. Thus, $\Delta R = pci$, where "pci" is the number of process innovations that a firm obtains in a given year.

Acting in this manner and starting again from equation (2), we have that:

$$\delta r = (\frac{\delta Q}{\delta R}\frac{1}{Q})\Delta R = \lambda pci \qquad (6)$$

assuming now that what is constant across firms is the rate of return of innovations in percentage points.

Substituting, the final expression is of the form:

$$ql_{it} = \lambda + \alpha kl_{it} + \gamma l_{it} + \theta pci + w_{it} \qquad (7)$$

Equation (7) gives the basis for a test of our theory. We expect the parameter θ be positive and significant, not establishing "a priori" any assumption about its relative importance compared with the impact of physical capital. We have also include in some regressions the number of product innovations the firm declares to have each year (pdi) in

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[2] This fact is justified arguing that the price correction of the output variable cannot account for intrasectoral differences in price movements that, from the authors opinion, mostly reflect quality changes. In this sense, the study encompasses not only process but also product innovations. We will turn to this aspect in next pages.

order to validate the assumption we have made about its limited relevance in this type of studies.

III.- DATA AND THE MEASUREMENT OF VARIABLES

The data source is the called *"Encuesta de Estrategias Empresariales"* (Survey of Firm Strategies) conducted by the *"Fundación Empresa Pública"*. This survey provides a vast detailed information that is enough to our study. It encompasses a wide range of aspects of the strategic behaviour of a firm in its respective market that follows from 8 different sections: main activity, products and production process, clients and suppliers, prices and costs, markets, technological activities, foreign trade and accounting data. The sample period for which we have data is five years (1990-94) and the number of firms surveyed exceed 2,000 each year although for reasons of missing observations and outliers this number is considerably reduced for our estimations.

The measure of the different variables we are interested in is as follows:

- The variable reflecting output (Q_{it}) is normally measured by the amount of sales of the firm in the given year. However, we have done a correction in this value because it may not well reflect the real production of a firm if the sales stock variation is high and have important changes year to year. Thus, we have accounted for this fact and our output variable includes not only the sales of the firm but also its stock variation. The inflation correction has been done using the output deflator constructed from the data contained in the National Accounts of Spain (*Contabilidad Nacional de España, CNAE*) with the sectorial level dissagregation described in the left hand side of table 1.

- The physical capital stock (K_{it}) of a firm is represented by its total fixed gross assets. It has been deflated correcting its current rate of growth by the national investment inflation rate collected in the publication *"Boletín Económico del Banco de España"* (Bank of Spain).

- The labour input (L_{it}) is compound by the total number of employees of a firm and the end of the year. Unfortunately, our data availability does not permit us to correct these last two variables for the workers and capital used for research activity, incurring in double counting when we include R&D intensity in the regression probably underestimating its parameter value.

Table 1
Sector classification

Sector (CNAE)	**Price-deflator classification**	**Sector** (CNAE)	**Regression classification**
1 (221,222,223)	Iron and steel industry.	**1** (22)	Extraction of metallic minerals.
2 (224)	Production and preliminary processing of non-ferrous metals.		
3 (242)	Manufacture of cement, lime and plaster.	**2** (24)	Non-metallic mineral products.
4 (246)	Manufacture of glass and glassware.		
5 (241,247)	Manufacture of clay products for constructional purposes.		
6 (243,244,245,249)	Other minerals and non-metallic derivatives.		
7 (251/255)	Chemical products.	**3** (25)	Chemical products.
8 (31)	Manufacture of metal articles.	**4** (31)	Manufacture of metal articles.
9 (32)	Manufacture of agricultural and industrial machinery.	**5** (32)	Manufacture of agricultural and industrial machinery.
10 (33,39)	Manufacture of office machinery.	**6** (33,39)	Manufacture of office machinery.
11 (34,35)	Manufacture of electrical machinery.	**7** (34,35)	Manufacture of electrical machinery.
12 (361,362,363)	Manufacture of automobiles and engines	**8** (36)	Manufacture of automobiles and engines
13 (37,38)	Manufacture of other means of transport.	**9** (37,38)	Manufacture of other means of transport.
14 (413)	Processing and preserving of fruits and vegetables.	**10** (41,42)	Food, drink and tobacco industry.

15 (414)	Manufacture of dairy products.		
16 (411,412,415/23)	Manufacture of other food.		
17 (424/428)	Beverages.		
18 (429)	Tobacco.		
19 (43, 453/56)	Manufacture of textile products, clothing.	**11** (43, 453/56)	Manufacture of textile products, clothing.
20 (441,442,451,452)	Manufacture of leather products and footwear.	**12** (44,451,452)	Manufacture of leather products and footwear.
21 (46)	Manufacture of wooden furniture.	**13** (46,47)	Manufacture of wooden furniture and paper industry.
22 (471,472)	Manufacture of pulp, paper and board.		
23 (473,474,475)	Paper products, printing.		
24 (481,482)	Manufacture of rubber products.	**14** (48)	Manufacture of rubber products.
25 (49)	Other manufacturing industries.	**15** (49)	Other manufacturing industries.

In our estimations we use two different variables measuring the technological input. As before discussed, the first one is R&D intensity (R&D expenses over total sales). For the construction of this variable we have taken the total amount spent by each firm on R&D, that is, we have considered not only internal expenses but also external ones. The second one is the number of process innovations a firm obtains in a year. Although we do not have the exact data for our sample period we have constructed a variable yet used in previous work (Llorca, 1998b) that reasonably approximates the process innovation performance of a firm. The information we have is if the firm has obtained or not a process innovation in a given year and, if this is the case, we know if it consist in a new machine, a new method of production or both. Therefore, our "process innovation" variable *(pci)* will take the value "0" if the firm has not obtained a process innovation, the value "1" when the firm has obtained a new machine or a new method and a value of "2" when it has obtained both, a new machine and a new method.

Finally, in some regressions it has been also included the total number of product innovations achieved y a firm in a year *(pdi)* as a control variable for our theory, existing in relation to this regressor some relevant comments that we outline in the next section.

The sample size used in each regression depends on the availability of data of the corresponding variables for each firm and for the entire period. Nevertheless, we have decided to omit those firms that have experienced a rate of growth of labour productivity or of the capital to labour ratio greater than 100% in a given year. This is because we have considered that these observations could have some kind of problems as might be errors of measurement, the existence of mergers, or some other circumstances that could affect in an important manner our estimates[3].

IV.- RESULTS

As already mentioned, we have firm data of the variables we are interested in during a period of five years: 1990-1994. However, because we are working with rates of growth the sample is reduced to four observations for each firm. This is the typical example of a panel data model. When working with panel data we mainly have three different types of estimators: between-units estimator, within-units estimator and a weighted sum of both. The first one account for the cross-section variation in the sample and is constructed using the firm means. The within-units estimator, also called fixed effects model, pays attention to the time dimension and assumes that each firm has a specific (individual) effect that does not varies

[3] Griliches and Mairesse (1984) demonstrate that mergers of firms have a relevant impact in this type of study.

over time and that is correlated with the corresponding regressors. In order to account for this problem the fixed effects model uses the deviations of the observations from their specific firm means. Alternatively, if the assumption is that the individual effects are randomly distributed across the cross-sectional units we are in a context of a random effects model (GLS estimator) that consider with different weights the two aspects outlined above[4].

We have considered both the time dimension of the data and the cross-sectional one. The great advantage that the first type of estimators has over the second one is that they take into account the unobserved heterogeneity existing among the different units of analysis, which is a good thing in this type of studies. The descriptive statistics for the distinct samples used figure in table 2. The difference that exists in sample size between the cross-section and panel data models is due to a distinct criteria in the application of the decision to eliminate those firms with a variation in labour productivity or in the capital-labour ratio greater than 100% ; in the case of the cross-section regression this restriction is relaxed because it is taken in relation to the average of these rates of growth along the entire period[5].

As it seems logical, the mean value of the different variables is almost identical for the two type of samples studied. However, the standard deviations for the panel data case approximately doubles that of the cross-section one except for the technological variables for which is only slightly higher. This result implies that R&D intensity and the innovation performance of a firm (product or process) are much more stable over time than other

[4] The classical OLS regression can also be performed but in this case assuming the inexistence of individual effects and just an overall constant. In this case, much more weight is directed to the between-units variation.

indicators such as those considered here, probably reflecting that labour is an input with a higher variability than normally is considered.

For the period considered, the mean of the annual rate of growth of labour productivity is about 5% and that of the capital-labour ratio and labour 8% and -2% respectively; a very high values if we compare it, for instance, with the calculations of Wakelin (1998) for a sample (much more small than ours) of UK manufacturing firms corresponding to the period 1988-92 (1.7%, 5% and -1%, respectively). By contrast, the ratio measuring R&D intensity is considerably higher for the UK sample (0.79% versus 1.6%). This probably reveals that in Spain the technological innovation process is conducted in an informal way to a greater extend than in other countries of our economic environment.

Table 2
Descriptive Statistics
(mean and standard deviation)

	Sample (firms)	**ql**	**kl**	**l**	**rd**	**pci**	**pdi**	**corr (kl/l)**	**corr (pci/pdi)**
cross-section	813	0.048	0.082	-	0.0079	0.54	-	-0.44	-
		(0.09)	*(0.13)*	0.020	*(0.019)*	*(0.59)*			
				(0.08)					
	762	0.047	0.080	-	-	0.53	3.66	-0.38	0.05
		(0.08)	*(0.11)*	0.022		*(0.59)*	*(25.2)*		
				(0.08)					
	683	0.046	0.082	-	-	0.49	0.61	-0.38	0.34
		(0.08)	*(0.12)*	0.023		*(0.57)*	*(1.17)*		
				(0.08)					
panel data	778	0.049	0.081	-	0.0079	-	-	-0.51	-

[5] This does not qualitatively affect the conclusions but the fit of the regression (R^2) is reduced considerably in the panel data estimates.

(observations)	*(3112)*	*(0.22)*	*(0.24)*	0.023 *(0.16)*	*(0.022)*				
	655	0.046	0.082	-	0.0072	-	-	-0.52	-
	(2620)	*(0.22)*	*(0.24)*	0.023 *(0.16)*	*(0.022)*				
	815	0.049	0.081	-	-	0.56	-	-0.51	-
	(3260)	*(0.22)*	*(0.24)*	0.022 *(0.16)*		*(0.77)*			
	680	0.046	0.081	-	-	0.49	0.62	-0.51	0.26
	(2720)	*(0.22)*	*(0.24)*	0.023 *(0.16)*		*(0.74)*	(1.56)		

The sectorial evolution that is obscured for this general values is shown in table 3 with the sectorial classification given in the right hand side of table 1. This decomposition have been done for the first sample used in our regressions (813 firms) and also include the mean sectorial values of R&D intensity and our variable measuring the “number of process innovations”. As can be observed, the sectorial variability is quite important. The sector with a higher average annual rate of growth of labour productivity is that of the “automobile industry” followed by “extraction of metallic minerals”, “electrical machinery” and “chemical products”. On the other extreme, we find “metal articles” and “other means of transport”. However, the data I consider have a great interest in this table are derived from four correlations (not showed) that I have calculated of some of the variables listed (each one with 15 observations). The correlation that exists between (the rate of growth of) labour productivity and the capital-labour ratio with respect to R&D intensity by sectors are respectively 0.18 and 0.05, whereas with respect to the “number of process innovations” the values reach to 0.51 and 0.54[6]. Although this is clearly a very rude analysis it is an indicator of what we could find in our regressions.

The parameters estimated of the cross-section regression are showed in table 4. In order to perform this regression we have taken for each firm the average annual rate of growth of each variable except for *pci* and *pdi* that is the arithmetic mean between 1991 and 1994. We have followed the equation specifications given in expressions (4´) and (7). The first three columns of this table do not take into account the parameter λ , which represents disembodied technical change and that reflects those characteristics of the sector that remain constant over time[7] (for instance, technological opportunity or spillover conditions). For the rest of the columns, this sector specific effect is accounted by the inclusion of 15 dummies in the regression (see table 1).

The equation (1) includes the classical R&D intensity variable (*rd*) and does not assumes constant returns to scale. The parameter estimated of the physical capital is in line with that obtained for other countries which are approximately located in the interval (0.2, 0.3). This is the case of Griliches and Mairesse (1984) for USA, Cuneo and Mairesse (1984) for France, Odagiri and Iwata (1988) for Japan and Wakelin (1998) for UK. The assumption of constant returns to scale is clearly rejected, a result also found in other countries but now

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[6] However, there is not a problem of collinearity in the regressions between the capital to labour ratio and the "number of process innovations" because the correlation between these two variables is significatively reduced in our samples.

[7] Firm-specific effects in relation to the level of productivity are removed by the first differencing. However they could remain those related with the *rate of growth* of productivity. It is quite clear that we cannot account for them at this cross-sectional level and we have to postpone the discussion to our panel data estimates.

the effect is stronger than in other cases[8]. The fact of assuming or not constant returns to scale influence some of our estimations in so an important manner that we have decided to present the results considering both alternatives. By its part, the variable we are more interested (*rd*) has a positive and significant impact on productivity growth, showing a higher marginal impact that the observed in other countries. For instance, the parameter estimated of Wakelin (1998) for UK is 0.35, although it is convenient to remember that in this case the average value of this variable is twice that of Spain. Therefore, the marginal impact is greater in Spain but the total (average) effect is higher in the UK.

In column (2) we perform the regression we our alternative measure of the technological input (*pci*). The corresponding parameter estimated is positive and highly significant (much more than R&D intensity) and the importance of the capital to labour ratio is considerably reduced[9]. Even more important, the F-statistics reflecting the joint significance of the regression more than doubles and the same occurs with the adjusted-R^2 . If we put those technological variables together -equation (3)- the estimated coefficient of our preferred technological measure and its significance almost do not suffer any change and that of R&D intensity just vanishes from the model

Table 3
Descriptive Statistics by sectors

[8] The diverse authors have tried to give alternative explanations to this result. Some of them are related with the exclusion of materials in the production function, the omission of labour and capital intensity of utilisation variables, the use of sales instead of value added to measure production, etc. Griliches and Mairesse (1984) also include in this list the simultaneity in the determination of output and employment and propose an alternative estimation. Unfortunately, it is necessary a measure of knowledge capital to perform it.

[9] It is convenient to remember that there is not a problem of collinearity between these two variables. In fact in this sample its correlation coefficient is just 0.11.

Sector (Firms)	**ql**	**kl**	**l**	**pci**	**rd**
1 (23)	0.092	0.093	-0.051	0.65	0.005
2 (58)	0.027	0.085	-0.021	0.375	0.004
3 (61)	0.062	0.082	-0.010	0.61	0.026
4 (77)	0.017	0.059	-0.013	0.49	0.004
5 (43)	0.030	0.079	-0.038	0.61	0.017
6 (6)	0.050	0.048	-0.058	0.54	0.014
7 (75)	0.065	0.079	-0.014	0.68	0.015
8 (39)	0.100	0.120	-0.032	1.06	0.015
9 (23)	0.019	0.100	-0.046	0.87	0.016
10 (132)	0.043	0.074	-0.007	0.49	0.002
11 (88)	0.047	0.084	-0.038	0.45	0.005
12 (25)	0.029	0.041	0.006	0.33	0.003
13 (103)	0.049	0.084	-0.016	0.39	0.003
14 (43)	0.056	0.090	-0.010	0.56	0.004
15 (17)	0.058	0.140	-0.017	0.56	0.004

Equation (4) only differs from equation (1) in the inclusion of the sectorial dummies. It is clear that considering sector-specific effects, the coefficient on R&D intensity turns to be small and far from significant[10]. However, although experimenting a decline, the coefficient on the “number of process innovations” variable remains highly significant -equation (5)- denoting that even accounting for differences among sectors the measure of the process innovation performance of a firm have a relevant impact on its own growth productivity. Moreover, the inclusion of dummies also reduces the parameter affecting the capital to labour ratio. If we assume constant returns to scale -equation (6)- the coefficient affecting our technological variable suffers from a discrete fall but the parameter estimated of the physical capital increases a lot. For an explanation of this phenomenon is enough to see in table (2) the existing correlation between the annual rate of growth of the capital-labour ratio and the rate

[10] Other authors have also obtained this result. This effect is normally attributed to the existence of sector spillovers.

of growth of labour. In any case, the assumption of constant returns to scale increases the relative importance of the physical capital in relation to the knowledge capital.

One of the key points of our contribution relies in the distinction made between product and process innovation. In this sense, the assumption is that, in principle, only process innovations would affect the rate of growth of firm's productivity[11]. Therefore, there would exist an effect of product innovations on productivity only to the extend that they affect process innovations. As mentioned in the introduction, the detected relationship between these two variables (Llorca, 1998a,b) is a quadratic one, that is, there exists a point, called "turning point", beyond which the process innovation performance of a company decreases with the number of product innovations it obtains. Following this reasoning, the foreseeable impact of the number of product innovations on firm's productivity is not so much clear because, in fact, we are not able to know exactly the relative weight of the firms located to the right of their specific turning point, apart for this being really an indirect effect.

[11] As before noted, Griliches and Mairesse (1984) argue that to the extend that the inflation correction does not account for intrasectoral differences in price movements reflecting quality changes, their study encompasses both product and process R&D. For our point of view, this is not necessarily true because the effect of a process innovation could also be a reduction in price and, therefore, compensate the above effect.

Table 4

Cross-section estimates

Ordinary Least Squares corrected for heteroskedasticity

(Dependent variable: average annual rate of growth of labour productivity)

riable s	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
kl	0.21 *(7.22)*	0.14 *(4.50)*	0.14 *(4.44)*	0.09 *(2.97)*	0.08 *(2.64)*	0.19 *(4.16)*	0.058 *(1.79)*	0.12 *(3.48)*	0.06 *(1.82)*	0.13 *(3.49)*
l	-0.29 *(-5.15)*	-0.32 *(-5.49)*	-0.32 *(-5.28)*	-0.33 *(-5.33)*	-0.34 *(-5.50)*	-	-0.25 *(-4.88)*	-	-0.25 *(-4.68)*	-
rd	0.51 *(1.98)*	-	0.033 *(0.13)*	0.032 (*0.13)*	-	-	-	-	-	-
pci	-	0.039 (*9.22)*	0.038 *(8.70)*	-	0.021 *(4.38)*	0.018 *(3.62)*	0.019 *(4.18)*	0.017 (3.52)	0.013 *(2.52)*	0.009 *(1.74)*
pdi	-	-	-	-	-	-	-0.82 E-04 *(-1.42)*	-0.76 E-04 *(-1.30)*	-	-
rpdi	-	-	-	-	-	-	-	-	0.006 *(2.03)*	0.007 *(2.40)*
rms	813	813	813	813	813	813	762	762	683	683
mmie s	no	no	no	yes	yes	yes	yes	yes	yes	yes
-stat	*30.08 (0.00)*	67.02 *(0.00)*	44.64 *(0.00)*	13.71 *(0.00)*	14.91 *(0.00)*	10.03 *(0.00)*	9.75 (0.00)	7.71 (0.00)	8.95 (0.00)	7.03 (0.00)
j-R^2	0.067	0.14	0.14	0.21	0.23	0.15	0.17	0.13	0.17	0.13

Note: T-ratios between brackets except for the F-stat reflecting probability value.

In order to test the impact of this variable in our regressions we have taken the average annual value of the total number of product innovations obtained by a firm in the period considered (*pdi*). In equation (7) we see that this variable has a negative impact on productivity growth although it is non significant. This result probably reveals that the impact of those firms beyond the “turning point” in the sample is sufficiently strong to induce this negative parameter estimated[12]. Curiously, the parameter estimated corresponding to the capital-labour ratio losses its significance at 5% level. However, if we assume constant returns to scale it is significant but with a smaller coefficient than the estimated without the use of this regressor. The coefficient on “*pci*” slightly declines and remains highly significant.

In previous work, when studying the relationship between product and process innovations, we tried some regressions restricting our sample through the elimination of those firms that we considered were exaggerating its product innovation performance. Therefore, we did not consider those firms with more than 10 product innovations "per line of business" in a given year[13]. Doing this, the relationship between these two variables became more narrow. In this case, we have been much more restrictive and we have eliminated those firms with a total number of product innovations that in a given year exceed the value of 10, letting the new variable *rpdi*. As we can see in table (2), acting in this manner increases the correlation between product and "process" innovations to a point that we can starting to think about a problem of collinearity. In fact, presumably the probability that the number of firms beyond the "turning point" in this sample be negligible is quite high.

The result of this experiment is shown in equations (9) and (10). As we can observe, *pdi* has a much greater coefficient than before and is significant. In equation (9), the coefficient on *pci* suffers a decline but remains being significant with a marginal impact that doubles that of product innovations. Things change if we assume constant returns to scale because in this case the coefficient on process innovations losses its significance in favour of the capital-labour ratio[14]. It seems that this last result is quite disappointing, although as we have reasoning not so much strange, but before trying to give any additional explanation we have to confirm it in our panel data estimates.

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[12] In fact, if we also include the square of the *pdi* variable a quadratic relationship appears although the coefficients are non significant.

[13] Note that because now we are working with the productivity growth of the firm we have taken the total number of product innovations as a dependent variable.

[14] This does not occurs if we eliminate only the firms with more than 10 product innovations on average in the given period. However, we have deliberately chosen the most adverse situation.

The problem that appears with panel data estimates of equations (4´) and (7) is that if we perform the regression by a simple OLS, implying that we assume just an overall constant term in the model, or alternatively, we take into account the individual effects (random or fixed) of each cross-sectional unit. Theoretically, the assumption of individual effects implies that firm-specific characteristics that are constant over time influence not the level of productivity but its growth rate[15]. To the extend that, as some authors argue, the ability to innovate persists over time and is firm-specific, this assumption seems quite sensible. In fact, the corresponding test statistic strongly rejects the assumption of considering the same intercept across units. Therefore, our model must be fixed or random effects. The discrimination between these two models is usually derived from the Hausman´s test, in which it is tested the orthogonality of the individuals effects and the regressors. An additional example of the difference that exists of assuming or not constant returns to scale is the fact that when we assume the existence of them the model have to be fixed effects whereas random effects have to be used if this is not the case.

Our panel data estimates are showed in table (4). The first relevant thing to take into account is that at the time level the correlation between the rate of growth of the capital to labour ratio and the rate of growth of labour notably increases and, consequently, in the fixed effects model the coefficient affecting the physical capital is quite small and far from significant[16] whereas in the random effects model a more sensible and significant parameter estimated is found. Now, R&D intensity exercises a negative effect on the rate of growth of

[15] We can assume, for instance, that the parameter of disembodied technical change is firm specific letting it as λ_i .

labour productivity. This result is less strange that it seems at first sight because other authors, depending on the sample and period used, have also obtained a similar result. However, the coefficient of this variable, although negative, is usually non significant. This clearly occurs in our random effects model but not in the fixed effects one in which it is highly significant. From the perspective of our theory, the explanation of this fact is derived from the effect exercised by those firms with a level of vertical product differentiation that is beyond the "turning point". In this case, its effect is not smoothed by the calculation of annual average rates.

Consequently, we have decided for this case to eliminate again those firms with more than 10 product innovations in a given year. The variable representing the R&D intensity in this new sample is called rrd. As it can be observed, in the fixed effects model its coefficient, although it remains negative, is reduced but now is non significant. By contrast, in the random effects model it turns to be positive but non significant.

If we focus on our technological measure, it again appears positive and significant with a marginal effect very similar to that obtained in the cross-section estimates, experimenting an small decline when we assume constant returns to scale because the increment in the relevance of the physical capital. If we include in the regression the "number of product innovations" variable (not presented in the table) its effect is now positive but very small and far from significant, detecting again a quadratic (but non significant) relationship if we also include the square of this variable. As before, we have again decided to eliminate those firms with a

[16] Other authors have also obtained worse results in the within-units estimates. The explanation of this fact has

higher product innovation performance. Contrary to that occurred in the cross-section regression, this variable has completely loss its relevance in the within firms estimations. Including again in the regression our *pci* variable it just suffers from a slightly fall in the corresponding coefficient and its significance. At this point, it is convenient to remember that our theoretical predictions (Llorca, 1998 a,b) made reference to relationships occurred within the firm and, to a lesser extend, across firms because it is necessary to take into account specific firm and market characteristics such us degree of rivalry, technological opportunities, market dimension... that were considered as given. In this regard, the fixed effects model provides the best way to account for the mentioned features.

By its part, the random effects model gives a positive and significant parameter estimated to the *rpdi* variable if it stands in the regression alone reflecting the influence that the between-firms estimates exercises in this estimator. If we also include our *pci* variable the significance of *rpdi* vanishes experimenting the first one a non-drastic decline but continuing to be highly significant.

From the comments above, it appears that the variable we have constructed to approximate the process innovation performance of a firm (pci) has an stable, consistent and permanent effect on the rate of growth of its labour productivity. We have just found an exception in which this variable has loss its significance and it has been for a very special case, much more considering that, by construction, this variable has probably a relevant constraint if we compare it with *pdi* because we really do not have the exact number of process

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yet been outlined in footnote 8.

innovations of a firm and we have not the possibility to compare this measure with the alternative. In any case, when we make a deeper study with panel data the aforementioned shortcoming does not appears as a problem.

To end, we should give an approximation of the relative importance of our technological variable. In fact, this implies to compare the impact of the knowledge capital in relation to the physical capital. Given the assumptions of section II and the special features of our variable this is not an easy task. However, we can use a rudimentary and simple way to provide an approximation of their respective efforts. We can just multiply the corresponding coefficient estimated by the average value of the variable in the sample and we will have the estimated impact of the corresponding regressor. If we divide this number by the average value of the dependent variable in the sample we obtain the percentage of this last term explained by the first one. We will do this for equations (5) and (6) of the cross-section estimations and for equation (3) of the random effects model. We obviate the fixed effects estimation because in this case the physical capital is non significant. The results are showed in table (5).

Table 5

Impact of physical and knowledge capital on labour productivity growth in percentage terms

Variables	**kl**	**pci**
Cross-section		
Equation (5)	13.66%	23.62%
Equation (6)	32.45%	20.25%
Panel data		
Equation (3)	36.36%	18.28%

As noted above, the conclusion essentially depends on the assumption about constant returns to scale but the effect of our preferred technological variable cannot be considered, in any case, as negligible. Much more when the measure of this variable is quite restrictive and its parameter estimated probably is underestimating the real effect.

V.- CONCLUSIONS

With the present paper we have tried to disentangle what the impact is of the number of process innovations a firm declares to obtain in a given year on the rate of growth of its labour productivity. This focus is the consequence of two considerations. On the one hand, a clear differentiation between the role exercised by product and process innovations on firm's performance. On the other hand, to assume that the knowledge capital of a firm is mainly derived from its "successful" innovation process and not just for the amount spent on R&D.

The multiplicity of regressions have demonstrated us that our technological variable has the predicted effect and is significant, showing that this result is robust under a wide range of specifications. This implies not just that, on average, firms are saying the truth but that our predictions based in previous work about the existence of a point beyond which the firm faces a trade-off between quality and productivity is reasonable and sensible.

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