# Does history matter for the relationship between R&D, Innovation and Productivity?

Elena Huergo and Lourdes Moreno

*GRIPICO - Universidad Complutense de Madrid*

(January 2010)

***Abstract***

This paper analyzes the relationship between R&D expenditures, innovation and productivity growth, taking into account the possibility of persistence in the firms' behaviour. We study this relationship for a sample of Spanish manufacturing firms between 1990 and 2005 estimating a model with four equations: the participation in technological activities, the R&D intensity, the generation of innovations and the impact of these technological outputs on total factor productivity growth. Our results reflect the existence of true state dependence both in the decision of R&D investment and in the production of innovations. The omission of this persistence leads to an overestimation of the current impact of innovations on productivity growth. However, the presence of persistence in technological inputs and outputs entails that current R&D activities have long–run effects on firm's productivity.

**Keywords*:*** CDM model, productivity growth, persistence in R&D and innovation.

**J.E.L. Classification:** D24, L6, O3

**Corresponding author:**

Lourdes Moreno
Departamento de Fundamentos de Análisis Económico I
Facultad de Ciencias Económicas y Empresariales. UCM
Campus de Somosaguas. 28223 – Spain

Email: lmoreno@ccee.ucm.es
Phone: +34 91 3942408 Fax: + 34 91 3942561

## 1. Introduction

The analysis of productivity growth and its determinants is a classic topic in Industrial Economics. There is a large number of papers that study this question from a empirical point of view, pointing out the performance of technological activities as an essential source of firms' growth. Following the method proposed by Griliches (1979), some authors include a stock of knowledge capital as an additional input in the firm's production function. Recently, the idea that the growth of firms is more related to the results of technological activities than to the inputs used in them has generated some studies that analyze directly the impact of technological outputs (process and/or product innovations, patents…) on the firms' productivity. Specifically, Crepon, Duguet y Mairesse (1998) developed a multi-equational model (hereafter CDM model) that explains productivity growth by technological outputs and the later by technological effort. Since this seminal paper, many researchers have applied the same methodology to different European countries using basically cross-sectional data from the Community Innovation Surveys (CIS Data)[1].

However, only a few studies have used panel data to perform the analysis, mainly due to information availability, and therefore there is little evidence about these decisions that takes into account the dynamics in firm's behaviour. Some exceptions are the papers by Cefis and Orsenigo (2001), Cefis (2003), Raymond et al. (2006), Mañez-Castillejo et al. (2009) and Peters (2009) that analyse empirically the persistence of R&D activities or technological outputs with different methodologies and results.

In this line, the objective and the main contribution of the present paper is to consider the existence of persistence both in the R&D investment decision and in the achievement of innovations when estimating the recursive model that reflects the relationship between R&D, innovations and productivity. With this aim, we adapt the CDM model to analyse this relationship for a panel of Spanish manufacturing firms between 1990 and 2005. Our econometric results suggest the existence of true state dependence both in the decision of R&D investment and in the production of innovations. The omission of this persistence in the

---

[1] See, for example, Mairesse and Mohnen (2002, 2005) and Mohnen *et al*. (2006) using French CIS1 and CIS3 data, Parisi *et al*. (2006) for Italian manufacturing firms, Lööf and Heshmati (2006) using Swedish manufacturing data, Van Leeuwen and Klomp (2006) and Van Leeuven et al. (2009) for Dutch manufacturing firms, and Griffith et al. (2006) using firm-level data from the internationally harmonized CIS3 for France, Germany, Spain and the UK. Two examples for Non-European countries are Benavente (2006) for Chile and Jefferson et al. (2006) about China.

analysis leads to an overestimation of the current impact of innovations on productivity growth. However, the existence true state dependence in technological inputs and outputs entails that current innovation activities have long–run effects on firm's productivity. This is especially important when analyzing the relevance of technological policy as an instrument to induce productivity increases.

Following this introduction, next section presents the theoretical framework and the empirical multi-equational model. Section 3 describes the database and the variables included in the specification. The results of the estimation of the model are presented in section 4 and, finally, section 5 summarizes the main conclusions.

## 2. Theoretical framework and empirical model

As we explain in the introduction, the model to be estimated is an adaptation of the CDM model, which reflects the sequence of firm's decision. The first equation describes the firm's decision to engage or not in technological activities. The second one refers to the intensity of technological inputs (measured basically by the intensity of the R&D expenditure). The third equation deals with the generation of innovations departing from both internal and external technological inputs and, finally, the fourth equation shows the impact of these innovations on productivity growth, measured by the Solow residual.

Unlike the CDM model that circumscribes the analysis to innovative firms, in this paper we also take into account those firms that do not declare R&D expenditures. Following the approach of Griffith et al. (2006), we consider that to some extent all firms do some innovative effort. However, below certain threshold the firm is not capable to pick up explicit information about this effort and will not report on it. Thus, we estimate a selection model for the observed R&D intensity.

Additionally, instead of considering a static framework, we model the firm's decision to engage in R&D activities and the equation for the generation of innovations taking into account the possible persistence in these stages. As Heckman (1981) points out, there are two explanations for persistent behaviour: the true state dependence and the spurious dependence.

The first one implies a real causal effect: the probability of investing in *t*-1 increases the probability of investing in *t*. There are some theoretical explanations for this real true dependence in the case of innovation activities (Peters, 2009): the sunk cost associated with the performance of R&D activities, the “success breeds success” hypothesis and the existence of dynamic increasing returns. Alternatively, some firm characteristics can affect positively the decision to engage in R&D activities or the generation of innovations and, if they are correlated over time, could also create spurious relation between current and future status (spurious dependence). Some of them can be observables, as size, and it is possible to control them in the empirical analysis. However, there are other characteristics, as managerial ability, technological opportunities or risk attitudes that are unobservable. If these characteristics are persistent over time and they are not properly treated in the estimation, they can generate a spurious state dependence in R&D activities.

According to these theoretical explanations for real state dependence, it is not clear whether persistence is more related to technological inputs or outputs. Under the sunk cost hypothesis, R&D decisions are modeled in a long-term horizon, given that sunk costs could represent not only a barrier to entry for new firms, but also a barrier to exit for incumbent firms that have not recover their investments. In this case, an input measure would be desirable. However, the “success breeds success” and the “learning by doing” hypotheses are more associated with technological results. Additionally, if we assume that innovation outputs are basically determined by innovation inputs, input persistence should be translated partially into output persistence.

The empirical evidence about this question is mixed. Mañez et al. (2009) study the persistence in the firm R&D status, i.e., in the decision to engage in R&D activities, while Peters (2009) analyses whether firms innovate persistently, defining an innovator as a firm which exhibits positive innovation expenditure in a given year. In contrast to these studies, Duguet and Monjon (2004) and Raymond et al. (2009) examine the persistence in innovation outputs, although, as they use CIS data, their indicators whether a firm has introduced an innovation are related to a 3–year period, which could induce an artificial persistence due to overlapping time periods and double counting (Peters, 2009). However, Raymond et al. (2006) find that there is not true persistence for process and product innovations, while past shares of innovative sales affect current innovative sales.

Our paper differs from the previous ones in the sense that we analyze the persistence in both input and output R&D activities in a recursive model[2]. Nevertheless, we do not consider the dynamics of the R&D intensity (R&D expenditures over employment), but only in the decision to engage in R&D activities.

In particular, our empirical model is as follows. The first equation describes the R&D effort of firm *i* in year *t* in terms of the latent variable $id_{it}^{*}$:

$$id_{it}^{*} = z_{it}^{'}\beta + e_{it} \qquad [1]$$

, where $z_{it}$ is a vector of determinants of the innovation effort. We consider that we can measure the R&D effort $id_{it}^{*}$ by the intensity of the R&D expenditure $id_{it}$ only if the firm makes and reports that expenditures. To represent this decision to perform and report R&D expenditures, we assume the following selection equation:

$$r_{it} = \begin{cases} 1 \quad \text{si} \quad r_{it}^{*} = \gamma \cdot r_{it-1} + x_{it}{'}\beta + \mu_i + \varepsilon_{it} > 0 \\ 0 \quad \text{si} \quad r_{it}^{*} = \gamma \cdot r_{it-1} + x_{it}{'}\beta + \mu_i + \varepsilon_{it} \leq 0 \end{cases} \qquad [2]$$

, where $r_{it}$ is a binary variable that takes value 0 when the firm invests in (and reports) R&D, and 1 otherwise. If the latent variable $r_{it}^{*}$ is bigger than a constant threshold (than can be zero), we then observe that the firm engages in (and reports) R&D activities. In this equation, $r_{it-1}$ captures the previous innovation experience (true state dependence), $x_{it}$ is a vector of observable explanatory variables (time-variant and time-invariant variables which can differ from those that explain the R&D effort) and the permanent unobserved heterogeneity is captured by $\mu_i$. Finally, $\varepsilon_{it}$ is an idiosyncratic error (that refers to other time-variant unobservable determinants).

For estimation of this dynamic equation, we have to solve two theoretical and empirical problems: how to treat the unobservable heterogeneity ($\mu_i$) and the treatment of initial conditions ($r_{i0}$). With respect to the first problem, a fixed effects (FE) or a random effects (RE) model can be used to model $\mu_i$. However the problem with the FE model is that there is

[2] With the aim to jointly analyze the dynamics of trade and innovation, Esteve and Rodríguez (2009) present estimations for R&D performance, product and process innovations as “alternative" measures of the innovation status. Their results indicate the existence of true state dependence in both export and innovation.

not a transformation to eliminate de unobserved effects in non-linear models. For this reason, we use a random effects model. The second problem arises because the first observation of each firm (initial condition) is affected by the same generation process and for this reason is endogenous. There are three different ways to solve this problem. The first one is to assume that the initial condition is a non-random constant and therefore is uncorrelated with the unobservable heterogeneity. However this assumption is very unrealistic. The second solution considers that $r_{i0}$ is random and tries to estimate the joint density for $r_{i0}$ and for all $r_{it}$ conditioned to the strictly exogenous variables. Although Heckman (1981) proposes a method to approximate the conditional distribution, this function can be only founded in some special cases. The third solution also assumes that $r_{i0}$ is random, but in this case a distribution of $\mu_i$ conditional on $r_{i0}$ and $x_{it}$ is specified. This method was suggested by Wooldridge (2005) who develops an estimator for dynamic nonlinear RE models where it is necessary to model the unobservable heterogeneity[3].

We follow this last methodology. Specifically, we assume that this unobserved individual heterogeneity depends on the initial conditions and the strictly exogenous variables:

$$\mu_i = \alpha_1 + \alpha_2 \cdot r_{i0} + \overline{x}_i{}' \alpha_3 + a_i \qquad [3]$$

, where $\overline{x}_i$ is the time-average of $x_{it}$ and where $r_{i0}$ is the initial value. The assumptions about $a_i$ are $a_i \cong i.i.d.\, N(0,\sigma_a^2)$ and $a_i \perp (r_{i0}, \overline{x}_i)$. In this context, $\rho_a$ is $\frac{\sigma_a^2}{1+\sigma_a^2}$ and shows the percentage of total variance explained by the unobserved heterogeneity.

In the original estimator proposed by Wooldridge (2005), instead of the average of the exogenous variables, he uses all the time observations of the variables. However, he shows that time-averages can be used to reduce the number of explanatory variables.

Therefore, under this parameterization, the probability of being a firm which engages in (and reports) R&D activities is:

$$r_{it} = \begin{cases} 1 & \text{si} \quad r_{it}^* = \gamma \cdot r_{it-1} + x_{it}{}'\beta + \alpha_1 + \alpha_2 \cdot r_{i0} + \overline{x}_i{}'\alpha_3 + a_i + \varepsilon_{it} > 0 \\ 0 & \text{si} \quad r_{it}^* = \gamma \cdot r_{it-1} + x_{it}{}'\beta + \alpha_1 + \alpha_2 \cdot r_{i0} + \overline{x}_i{}'\alpha_3 + a_i + \varepsilon_{it} \le 0 \end{cases} \qquad [2']$$

[3] This method was proposed by Chamberlin (1980) for a linear AR(1) model without covariates.

Conditional on the performance (and reporting) of R&D activities, we can observe the quantity of resources allocated to this purpose, that is,

$$id_{it} = \begin{cases} id^*_{it} = z'_{it}\beta + e_{it} & \text{si} \quad r_{it} = 1 \\ 0 & \text{si} \quad r_{it} = 0 \end{cases} \qquad [4]$$

Therefore, to capture the true impact of R&D intensity on the knowledge production, we estimate a selection model for the observed intensity and to use the predicted value as a proxy of the innovation effort in the production function of knowledge or innovations. However, to our knowledge, there is not an accepted econometric procedure that integrates in a selection model the intensity equation [4] and the Wooldridge's (2005) approach to estimate a dynamic RE model for equation [2'].

For this reason, we start with the estimation of a Heckman model where a static pooled model for the first decision is considered. That is, we implicitly assume that there is not state dependence ($\gamma = 0$) and where the unobservable individual heterogeneity is not parameterized. Secondly, we consider a dynamic pooled Probit for the decision whether to engage or not in R&D activities, where the individual heterogeneity is parameterized as in Wooldridge (2005). In both cases, we assume that the error terms $e_i$ and $\varepsilon_i$ follow a bivariate normal distribution with mean equal to 0, variances $\sigma^2_\varepsilon = 1$ and $\sigma^2_e$, and correlation coefficient $\rho_{e\varepsilon}$ (Rho). Finally, as a robustness check, we compare the results for the selection equation in the second case with the estimation of a dynamic RE Probit model where individual heterogeneity is parameterized following Wooldridge (2005).

The third equation of the model corresponds to the estimation of the new knowledge production function, $g_i$, generated from firms' technological effort. This new knowledge is measured, alternatively, by the achievement of product and process innovations. Given that the investment intensity is a public good inside the firm, it can be used to produce different outputs without depletion. Therefore, we can model $g_{it}$ as a vector of technological outputs:

$$g_{it} = \gamma \cdot g_{it-1} + \lambda \cdot id^*_{it} + y_{it}'\delta + \zeta_i + u_{it} \qquad [5]$$

, where the latent investment intensity $id_{it}^{*}$ appears as an explanatory variable joint with the vector $y_{it}$, that includes other determinants of the knowledge production (time-variant and time-invariant variables). We also add in the specification the dependent variable lagged one period, $g_{it-1}$, to reflect whether the firm has previously generated new knowledge capturing the innovation output experience.

As in the equation [3], following Wooldridge (2005) we model the unobserved heterogeneity $\zeta_i$ as dependent on the initial conditions and the average of the explanatory variables:

$$\zeta_i = \pi_1 + \pi_2 \cdot g_{i0} + \bar{y}_i{}' \pi_3 + \upsilon_i \qquad [6]$$

We assume that $\nu_i \cong i.i.d.\ N(0, \sigma_\nu^2)$ and $\upsilon_i \perp (g_{i0}, \bar{y}_i)$. In this context, $\rho_\upsilon$ is $\dfrac{\sigma_\upsilon^2}{1+\sigma_\upsilon^2}$ and shows the percentage of total variance explained by the unobserved heterogeneity. Therefore, the new knowledge production function can be expressed as:

$$g_{it} = \gamma \cdot g_{it-1} + \lambda \cdot id_{it}^{*} + y_{it}{}'\delta + \pi_1 + \pi_2 \cdot g_{i0} + \bar{y}_i{}'\pi_3 + \upsilon_i + u_{it} \qquad [5']$$

Given that our meausers of new knowledg generation are binary variables for process or product innovation, the last equation will be estimated by a dynamic RE Probit model.

Finally, firms produce goods using the following production function (in growth rates):

$$y_{it} = a(g_{it}) + \varepsilon_{y,l} l_{it} + \varepsilon_{y,k} k_{it} + \varepsilon_{y,m} m_{it} + v_{it} \qquad [7]$$

where *y, l, k* y *m* stand respectively for the logarithmic differences in production and in the quantities of labor, physical capital and intermediated inputs, $\varepsilon_{y,l}$, $\varepsilon_{y,k}$ y $\varepsilon_{y,m}$ are the output elasticities with respect to the above inputs, and *a* is the productivity growth, which in part will be determined by the technological output *g*.

Rearranging terms it is possible to explain the last expression as a total factor productivity equation:

$$\theta_{it} = y_{it} - (s_l l_{it} + s_k k_{it} + s_m m_{it}) = \pi_\varpi \varpi_{it} + \pi_g g_{it} + v_{it} \qquad [8]$$

, where $\theta_{it}$ is the well-known Solow residual and $\varpi_{it}$ is a vector that includes the variables reflecting the non-fulfillment of the assumptions associated with this kind of models (constant returns to scale, perfect competition), joint with other control variables.

To summarize, our model consists of equations [2], [4], [5] and [8]. Following the CDM methodology, we assume a recursive model where feedback from productivity growth to technological effort is not allowed, and therefore we apply a three stages estimation procedure.

## 3. Data and variables definition

Estimations are carried out with an unbalanced panel of Spanish manufacturing firms for the period 1990-2005. The variables are obtained from the *Encuesta Sobre Estrategias Empresariales* (ESEE), a survey that is sponsored by the Spanish Ministry of Industry and carried out by the Fundación SEPI[4]. The sampling scheme of this survey is conducted for each manufacturing NACE class (two-digit) level. Companies employing between 10 and 200 employees are chosen by a random sampling scheme and the rate of participation is around 4%. For firms employing more than 200 employees, the rate of participation is about 60%. The sample considered is about 2000 manufacturing firms that have ten or more employees each year.

Table 1 shows the main characteristics of the database distinguishing between small and medium-sized firms (SME) (with less than 200 workers) and large firms (more than 200 employees). For analysing the dynamics of R&D activities it is required that the firms answer consecutively. In this sense, only those firms that have at least eight consecutive observations, that is the average period of our sample, have been taken into account. As can be seen in Table 1, in our unbalanced panel the average number of consecutive years by firm is around 12. We could restrict the analysis to the balanced panel, but due to attrition in this case we loose two thirds of the observations.

[4] See a more detailed description of the database in http://www.funep.es/esee/en/einfo_que_es.asp

**Table 1**
Characteristics of the sample

| | Firms with at least eight consecutive observations | | |
|---|---|---|---|
| | SME | Large Firms | All Firms |
| No. of observations | 8052 | 4251 | 12303 |
| No. of firms | 709 | 363 | 1072 |
| Average no. of consecutive observations by firm | 12.0 | 12.3 | 12.1 |

Although the ESEE is not specifically designed to analyze technological activities, it includes a relevant set of indexes about this subject and has information not only for firms engaged in technological activities but also for firms without R&D expenditures. In fact, for the analysis we have 12,303 observations and 7,548 of them correspond to firms that do not perform formal R&D. This is especially suitable in this case, given that we assume that all firms do some innovative effort, although not all reflect this effort in their answer to the survey. That's why we estimate the model for the whole sample, and not only for firms with positive R&D expenditures. As a measure of the R&D investment intensity we use the total R&D expenditure by employee (in logs), assuming that a firm decides to performance technological activities if its expenditures are positive.

Table 2 presents the transition probabilities whether to engage or not in R&D activities over the period 1990-2005. Notice that the status in *t*-1 is positively correlated with status in *t*. Almost 90% of firms which perform R&D activities in one year persist in the following year. Additionally, more than 93% of non-performer firms in *t*-1 are also non-performers in *t*, while 7.3% engaged in R&D activities. This implies that the probability of undertaking R&D in *t* is 82 percentage points higher for performers than for non-performers in *t*-1[5]..

Following theoretical models (Arvanitics y Hollenstein, 1994, Klepper, 1996…) the variables to be included in the participation and the intensity equations relate basically to the technological environment, demand and market conditions, appropriability of the benefits derived for technological investments[6], financial restrictions and size (to capture the existence of economies of scale in R&D).

[5] When the balanced panel is considered, the transition probabilities of the R&D status are almost the same.
[6] See in Cohen and Levin (1989) a discussion about the effect of technological opportunities, appropriability conditions and market evolution on R&D activities.

**Table 2**
Transition probabilities of the R&D status

| | | *Performer in t* | |
|---|---|---|---|
| | *Performer in t-1* | Yes | No |
| SME | Yes | 83.2 | 16.8 |
| | No | 5.0 | 95.1 |
| Large Firms | Yes | 92.7 | 7.3 |
| | No | 15.5 | 84.5 |
| All Firms | Yes | 89.1 | 11.0 |
| | No | 6.9 | 93.2 |

In this line, given the available information in the database, to capture environmental and demand conditions we have introduced as explanatory variables one indicator of the firm's export character and a variable reflecting whether the market evolution perceived by the firm each year has been expansive or recessive respect to the previous year.

Following Schumpeterian tradition, we include a qualitative measure of the number of firm's rivals to capture the degree of market competition.[7] A negative impact of this variable on the participation decision would be coherent with the hypothesis that the more competitive the market, less capacity of firms to appropriate the benefits of their investments, and therefore less incentives to do these investments. To indicate appropriability conditions we have also used the proportion of engineers and graduate employees inside the firm. We can think that those firms with more qualified personnel are more capable to assimilate new knowledge, whether it is developed internally or externally.

With respect to financial restrictions, we use a categorical variable that shows if the firm has obtained public support during the year. The evidence about the impact of financial restrictions on investment effort is mixed. Hall et al. (1999) obtain that during the period 1978-1989 the R&D in the high-tech American sector was sensitive to the cash flow, while the results are not so clear in the case of France and Japan. Bond, Harhoff and Van Reenen (1999) find that the cash flow affects more to the decision to perform R&D that to the levels of expenditure. Previous works for Spanish economy point out that, irrespective of firms size, the investment effort since 2000 has been superior in firms that achieved public support than

[7] The concentration ratio CR4 is also available in the database, but with a very low response.

in those who apply for it without success, and greater in the later than in firms that didn't search for it.

Joint to the above variables, the model also includes indicators to capture differences in the firms' investment behavior in terms of the time of permanence in the market. International evidence suggests that entrants use to be among the more innovative and that the growth rate post entry depends on their innovative behavior, being the survival probability tied to the existence of technological opportunities.[8] Therefore we introduce as explanatory variables the firm's age and two dummies reflecting whether the firm has been an entrant or an exiting firm during the period. The set of mobility indicators is fulfilled with two event dummies for mergers and scissions.

Finally we include as control variables in both equations sets of time, size, and industry dummies, and two factors related to firms' organizational aspects: the belonging to a society and the degree of services subcontracting.

As for the knowledge production function, the ESEE provides qualitative information about the achievement of process and product innovations. In particular, a product innovation is assumed to have occurred when the firm answers in the affirmative to the following request: "Please indicate if during the year 199x your firm has obtained product innovations (completely new products or products with such important modifications which made them different from the old ones). In a similar way, a process innovation is assumed to have occurred when the firm answers positively to the following request: "Please indicate if during the year 199x your firm introduced some significant modification in the production process (process innovation). If the answer is yes, please indicate the way: a) introduction of new machines; b) introduction of new methods of organization; c) both."

Table 3 shows the transition probabilities for the generation of product or process innovations during the sample period. In both cases, the status in *t*-1 is positively correlated with status in *t*, although the persistence seems to be slightly higher for product innovations. Almost 70% of firms which innovate in one year persist in innovating in the following year, while more than

[8] See, for example, Audretsch (1995) and, for Spanish industry, Huergo and Jaumandreu (2004).

82% of non-innovative firms in *t*-1 are also non-innovators in *t*. This confirms the interest for taking persistence into account when analyzing the generation of new knowledge.

**Table 3**
Transition probabilities of the innovator status

| | | *Innovator in t* | | | |
|---|---|---|---|---|---|
| | | Process Innovator | | Product Innovator | |
| | *Innovator in t-1* | Yes | No | Yes | No |
| Small and medium firms | Yes | 60.3 | 39.7 | 65.9 | 34.1 |
| | No | 14.8 | 85.2 | 8.5 | 91.5 |
| Large Firms | Yes | 75.6 | 24.4 | 73.7 | 26.3 |
| | No | 23.7 | 76.3 | 15.9 | 84.1 |
| All Firms | Yes | 67.6 | 32.4 | 69.7 | 30.3 |
| | No | 17.2 | 82.8 | 10.7 | 89.3 |

With respect to the explanatory variables in the knowledge production function, in the case of process innovations, given that these can be obtained by buying new machines, joint to investment effort we include physical capital intensity (in logs). In addition, irrespective of the type of innovation, the set of variables also comprise specific industry characteristics. Notice that, along with internal inputs, it is also necessary to take into account other elements that do not depend completely on the firms' decision but can affect their generation of innovations. In particular, the incentives to allocate resources can change dependent on demand price elasticity. In markets where the product supplied by the firm is highly standardized, product innovations are a better mechanism to reduce competitive pressure. In the estimations, we use a binary variable reflecting the degree of product homogeneity as a "naive" proxy of demand price elasticity. This index takes the value one if the product sold by the firm is highly standardized. The specification also includes industry dummies to capture the possibility of technological spillovers and different life cycles and technological regimes (Klepper, 1996, and Utterback, 1994).

In what refers to productivity growth, as dependent variable in equation [8], the available information allows us to compute a cost-based Solow residual in terms of a Tornqvist index[9]. In this equation, together with the control variables (mobility, time, size and industry dummies) we introduce the change in the capacity utilization to pick up the impact in the

[9] In the ESEE, firms report the price changes on their output and inputs, which makes possible the construction of Paasche-type firm individual indices to deflate output and intermediate consumption real changes.

degree of inputs use in presence of quasi-fixed factors. In addition, we include the weighted input variation to capture the potential bias by the non-fulfillment of the constant returns to scale assumption[10].

Table 4 shows the descriptive statistics of the main variables in our model. Except the degree of services subcontracting[11], all of them can vary across firms and time. Note that for almost all explanatory variables to be used in the selection equation the variation across firms ("*between*" variation) is bigger than the time variation ("*within*"). See, for example, the age, the degree of services subcontracting, the engineers and graduates proportion and the number of competitors. For this reason, we are going to treat them as time constant in the equation [2'].

**Table 4**
Descriptive Statistics

| | *Mean* | *Standard deviation* | | | *Min* | *Max* |
|---|---|---|---|---|---|---|
| | | *Overall* | *Between* | *Within* | | |
| Age | 24.781 | 12.297 | 12.077 | 3.038 | 1 | 40 |
| Belonging to a group | 1.324 | 0.468 | 0.427 | 0.197 | 1 | 2 |
| Capacity utilization variation (%) | 0.077 | 15.739 | 2.591 | 15.539 | -230.259 | 289.037 |
| Demand evolution | 2.113 | 0.689 | 0.367 | 0.588 | 1 | 3 |
| Degree of product homogeneity | 0.636 | 0.481 | 0.429 | 0.226 | 0 | 1 |
| Degree of services subcontracting | 47.013 | 11.215 | 11.345 | 0.000 | 0 | 93.4 |
| Engineers and graduates proportion | 4.165 | 6.512 | 6.308 | 2.244 | 0 | 78.9 |
| Exporter in t-1 | 0.640 | 0.480 | 0.425 | 0.227 | 0 | 1 |
| Export intensity in t-1 (in logs.) | 6.226 | 4.861 | 4.473 | 1.933 | 0 | 13.637 |
| Physical capital intensity (in logs.) | 9.746 | 0.948 | 0.885 | 0.367 | 7.118 | 12.644 |
| Process innovation | 0.352 | 0.478 | 0.295 | 0.377 | 0 | 1 |
| Product innovation | 0.266 | 0.442 | 0.300 | 0.325 | 0 | 1 |
| Public support in t-1 | 0.100 | 0.300 | 0.217 | 0.205 | 0 | 1 |
| Number of competitors | 1.787 | 1.113 | 0.884 | 0.692 | 1 | 4 |
| R&D intensity | 2.683 | 3.509 | 3.059 | 1.720 | 0 | 11.142 |
| R&D performer | 0.387 | 0.487 | 0.414 | 0.255 | 0 | 1 |
| Size (number of employees) | 216.2 | 463.5 | 463.5 | 103.9 | 3 | 9043 |
| Total factor productivity growth (%) | 0.810 | 14.435 | 2.907 | 14.154 | -208.197 | 170.461 |
| Weighted inputs variation (%) | 2.873 | 21.327 | 6.355 | 20.427 | -161.171 | 310.349 |

Notes: The period used is 1991-2005. For lagged variables the reference period is 1990-2004.

[10] See in the Appendix a more detailed explanation of the variables definition.
[11] In the survey, firms only answer the question referred to this information every four years.

## 4. Econometric results

In this section we present the results of the estimation of the model depicted in section 2. As equations [2], [4], [5] and [8] point out, we assume a recursive model where feedback from productivity growth to technological effort is not allowed. Taking this into account, we apply a three stages estimation procedure.

In the first stage, the decision to engage in R&D activities is jointly estimated with the R&D intensity (equations [2] and [4]) using the Generalized Tobit model. We investigate the possibility of persistence in the selection equation but we do not consider any dynamics in the R&D effort. In particular, we use the Wooldridge's (2005) approach to parameterize the unobserved individual heterogeneity.

In the second stage, we estimate the knowledge production function [5] introducing the predicted value of the R&D intensity as explanatory variable. As we indicate in section 2, the technological effort can be used to obtain new products and/or processes. Therefore, we consider both types of innovations as technological outputs. Additionally, we study whether the probability of obtaining a process or product innovation is positively affected by the previous success in the generation of innovations. Given the binary character of our innovation indexes, we estimate this equation as dynamic RE Probit models. As in the first stage, Wooldridge's approach is used to parameterize the unobserved individual heterogeneity.

Finally, in the last stage the productivity growth equation [8] is estimated taking into account the potential endogeneity of the technological factor in the production function.

*The R&D investment intensity*

Table 5 shows the results of the estimation associated with equations [2] and [4] explained in section 2. We start with the estimation of a pooled and static RE Probit model assuming implicitly not state dependence in the selection equation ($\gamma = 0$). In columns (1) and (4), we present the results of the Generalized Tobit model where the participation and the intensity equations are estimated consistently by maximum likelihood. .

Secondly, in column (2) we investigate the persistence of the decision whether to engage or not in R&D activities by estimating this equation as a dynamic RE Probit model (equation [2']), following the Wooldridge's approach to take into account the unobservable individual heterogeneity. Finally, given that we confirm the existence of true state dependence in the selection equation, a Generalized Tobit model is estimated parameterizing the individual unobserved heterogeneity in terms of the initial conditions and the exogenous variables (columns (3) and (5)) as in the dynamic RE Probit model.

The three first columns exhibit the marginal effects of the Probit model for the participation decision, while the coefficients showed in columns 4 and 5 correspond to the R&D intensity for the static and dynamic pooled model, respectively. Notice that the correlation term rho ($\rho_{e\varepsilon}$) is significant in both estimations, pointing out the necessity of estimating a selection model for the observed intensity.

We tried almost the same set of explanatory variables for both equations ($x_{it} = z_{it}$), but finally we have included in the specification only those variables that result statistically significant in each equation. There are four variables, the engineers and graduates proportion, the firms' age, the degree of services subcontracting and the number of competitors, which present a very small within variation. For these reason, we consider them as time-constant specific variables in the estimation for the participation equation. This implies that these variables can not be included in the parameterization of the individual effects[12].

Additionally, the dynamic RE Probit model require the strict exogeneity of the explanatory variables. Although it is possible to assume that most variables are exogenous, the indicators for being an exporter and for the achievement of public support are introduced with a lag in the decision equation to control for endogeneity.

[12] Due to the high collinearity between them and their time-averages, when we introduce the last ones in the parameterization of the individual heterogeneity, all are not significant.

**Table 5**
The R&D intensity

| | Propensity to engage in R&D (0/1) | | | R&D Intensity | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *Estimation method* | *Pooled Probit* | *Dynamic RE Probit* | *Dynamic Pooled Probit* | *Generalized Tobit (selection from (1))* | *Generalized Tobit (selection from (2))* |
| R&D performer in t-1 | | 0.586*** | 0.638*** | | |
| | | (0.016) | (0.012) | | |
| Exporter in t-1 | 0.196*** | 0.039 | 0.032 | | |
| | (0.012) | (0.029) | (0.028) | | |
| Export intensity in t-1 | | | | 0.031*** | 0.016*** |
| | | | | (0.006) | (0.006) |
| Public support in t-1 | 0.534*** | -0.022 | -0.066** | 0.685*** | 0.624*** |
| | (0.018) | (0.032) | (0.029) | (0.048) | (0.050) |
| Demand evolution | 0.048*** | 0.040*** | 0.037*** | 0.067*** | 0.083*** |
| | (0.008) | (0.012) | (0.011) | (0.028) | (0.028) |
| Engineers and graduates | 0.012*** | 0.004*** | 0.004*** | 0.050*** | 0.047*** |
| proportion | (0.001) | (0.002) | (0.001) | (0.003) | (0.003) |
| Degree of services | 0.001*** | 0.000 | 0.000 | | |
| subcontracting | (0.000) | (0.001) | (0.001) | | |
| Number of competitors | -0.046*** | -0.018 | -0.016* | | |
| | (0.007) | (0.011) | (0.009) | | |
| Age | 0.002*** | 0.001 | 0.001 | -0.004*** | -0.007*** |
| | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) |
| Belonging to a group | | | | 0.061 | 0.016 |
| | | | | (0.042) | (0.041) |
| *Initial conditions* | | | | | |
| M_Exporter in t-1 | | 0.067* | 0.063* | | |
| | | (0.039) | (0.035) | | |
| M_Public support in t-1 | | 0.618*** | 0.617*** | | |
| | | (0.075) | (0.063) | | |
| M_Demand evolution | | 0.037 | 0.032 | | |
| | | (0.028) | (0.023) | | |
| R&D performer in 0 | | 0.390*** | 0.317*** | | |
| | | (0.023) | (0.015) | | |
| Rho | | | | 0.104*** | -0.203*** |
| | | | | (0.044) | (0.031) |
| Wald test – Industry dummies | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 |
| Wald test – Time dummies | 0.059 | 0.000 | 0.000 | 0.000 | 0.000 |
| Wald test – Size dummies | 0.000 | 0.000 | 0.000 | | |
| $\rho_a$ | | 0.119 (0.025) | | | |
| lnL | -5155.8 | -2773.8 | -2789.5 | -13069.2 | -10684.1 |
| Observed Probability | 38.6 | 38.6 | 38.6 | | |
| Predicted Probability | 38.6 | 38.4 | 38.6 | | |
| Correct predictions | 79.9 | 91.5 | 91.6 | | |
| Correct predictions: 1 / 0 | 82.0/ 78.7 | 91.1 / 91.7 | 90.7 / 92.2 | | |
| No. observations | 12303 | 12303 | 12303 | 4755 | 4755 |

Notes: Marginal effects (standards errors in brackets) are showed. ***, ** and * indicate significance on a 1%, 5% and 10% level, respectively. All regressions include a constant and 19 industry and 14 time dummies. Regressions (1) to (3) also include 5 size dummies. To avoid multicolinearity, the dummy variables corresponding to year 1991, industry 1 and size up to 20 employees are excluded. The estimates also include four dummies to capture firm's mobility (merger, scission, entry and exit). Rho is the correlation coefficient, $\rho_{e\varepsilon}$, and $\rho_a$ is the percentage of total variance explained by the unobserved heterogeneity.

With respect to the decision to engage in (and report) R&D activities, the estimation in column (2) confirms that it is relevant to consider the existence of persistence. Even after controlling for individual unobserved heterogeneity, the previous behavior as R&D performer has a positive effect on the probability of engaging in R&D activities at present. That is, conditional on other firm's characteristics, a firm which performs R&D in *t*-1 has almost a 60 percentage points higher probability of making R&D activities in the next period.

The initial conditions are also significant, which suggests the existence of a high correlation between the initial value and the unobserved heterogeneity. In particular, the achievement of public support or being an exporter in the previous period have a positive impact on the probability of innovating. Additionally, the coefficient of correlation $\rho_a$ at the bottom of column (2) indicates that the unobserved heterogeneity explains 12% of the total variance of the dependent variable[13].

Comparing the first and the second columns, the results show that, when the persistence in the decision to perform R&D activities is taken into account, some explanatory variables which are strongly significant in the pooled Probit estimation loose their effect. For example, the number of rivals that exhibits a negative coefficient in column (1) - which is coherent with the Schumpeterian hypothesis - is non significant in column (2). The same result occurs with the degree of services subcontracting and the firms' age. All of them are variables with a small time variation and their effect is probably captured by the lagged dependent variable.

However, there are some explanatory variables which still are significant and increase the probability of carrying out R&D expenditures. Specifically, the proportion of engineers and graduates (as a proxy of skilled employees) confirms the relevance to have qualified workers inside the firm to more easily assimilate new knowledge. In addition, firms which operate in markets with an expansive demand present a higher probability of engaging in R&D activities.

[13] When estimating the equation through a Static RE Probit model, unobserved heterogeneity is relatively more important: almost the 75% of the variance is explained by it.

As can be seen at the bottom of Table 5, the Wald tests confirm that the control variables are jointly significant. From the coefficients of the size dummies[14], a positive relationship between firm's size and the decision of carrying out R&D is established. This is consistent with the hypothesis that large firms are more capable to exploit economies of scale or scope in technological activities, but also with the idea that these firms have advantages to appropriate the results of them and to obtain external funding.

Due to the fact that estimation in column (2) confirms the existence of true state dependence in the innovation activity and that we are interested on the prediction of the R&D intensity for the second step of the CMD model, we proceed to estimate a Generalized Tobit model with dynamic in the participation equation. Again we parameterize the unobservable heterogeneity following Wooldridge (2005). The results in column (3) are quite similar to the ones in column (2), although the coefficient of the lagged dependent variable is slightly bigger and the number of competitors as proxy of market competition is now significant as in the pooled Probit.

As can be seen in columns (4) and (5), once the firm has decided to invest, the proportion of engineers and graduates, the achievement of public support in the previous period, and the export intensity stimulate the intensity of R&D investment, while the firm's age has the opposite effect. These results are in accordance with Hall et al. (2009) and Griffith et al. (2006). However, unlike this last paper, we find that the demand evolution not only has a positive effect on the participation decision but also on the R&D intensity. Additionally, belonging to a group of companies does not affect the amount of R&D expenditures.

*The knowledge production function*

The second stage of the model corresponds to the estimation of the new knowledge production function (equation [5]) generated from the firm's technological efforts. In Table 6 we show the results of this estimation, using the predicted value of R&D intensity (obtained from the estimations in columns (3) and (5) in Table 5) as an explanatory variable. Notice that the R&D intensity equation can be interpreted as an instrumental variables equation, in which innovation effort is presumably endogenous to the innovation production function – that is,

[14] The coefficients are available from the authors upon request.

there can exist unobservable (to the econometrician) firm characteristics that make firms to invest more in R&D and, at the same time, make them more productive in the use of this effort. This could generate spurious correlation and upward bias in the coefficients of the knowledge generation equation.

Both for product and process innovation equations, the estimations in columns (2) and (4) confirm also in this case the existence of true state dependence. Conditional on other firm's characteristics, a firm which innovates in *t*-1 has around 35 percentage points more of probability of innovating in the next period.

As we expected, the predicted investment intensity has a significant positive impact on the generation of process and product innovations, even when we consider the dynamics in the generation of innovations. Nevertheless, its impact is smaller when persistence is taking into account. The quantitative effect of this variable is quite similar for process and product innovations. Physical capital intensity is also positively related to the achievement of process innovation, which is coherent with the fact that part of these innovations are attained through the purchase of new machinery. The degree of product homogeneity, used as a proxy of demand price elasticity, presents the correct sign according to theoretical predictions, positive for product innovations and negative for process innovations. However, when dynamic is considered in the generation of process innovation, the variable looses its significance.

The Wald tests show that, when persistence is taken into account, there are not significant differences between the probabilities to obtain process innovations among industries. The size dummies reflect again the advantages of large firms to innovate, and the time dummies denote an increase in the achievement of both types of innovations until 2003, but stagnation during the last two years of the period.

*The Total Factor Productivity growth*

Finally, in Table 7 we present the results of estimating the productivity equation [8]. All estimates are carried out considering the information as a pool. To control for unobserved heterogeneity, we also made complementary estimations taking into account the panel structure of the data. However, the test for the null hypothesis that all fixed effects are equal to zero can not be rejected, as it is showed at the bottom of the table.

## Table 6

The knowledge production function

| | Process innovation | | Product innovation | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Estimation method* | *Static RE Probit* | *Dynamic RE Probit* | *Static RE Probit* | *Dynamic RE Probit* |
| R&D intensity[a] | 0.098*** | 0.047*** | 0.110*** | 0.055*** |
| | (0.017) | (0.016) | (0.016) | (0.013) |
| Process Innovation in t-1 | | 0.350*** | | |
| | | (0.012) | | |
| Product Innovation in t-1 | | | | 0.371*** |
| | | | | (0.014) |
| Physical capital intensity | 0.110*** | 0.077*** | | |
| | (0.011) | (0.015) | | |
| Demand evolution | 0.050*** | 0.043*** | 0.009 | 0.008 |
| | (0.008) | (0.008) | (0.006) | (0.007) |
| Degree of product | -0.034** | -0.018 | 0.040*** | 0.042** |
| homogeneity | (0.017) | (0.013) | (0.013) | (0.011) |
| *Initial conditions* | | | | |
| M_Physical capital intensity | | -0.031* | | |
| | | (0.017) | | |
| M_Demand evolution | | 0.061*** | | 0.050*** |
| | | (0.021) | | (0.018) |
| Process Innovation in 0 | | 0.241*** | | |
| | | (0.015) | | |
| Product Innovation in 0 | | | | 0.293*** |
| | | | | (0.018) |
| Wald test – Industry dummies | 0.006 | 0.439 | 0.000 | 0.007 |
| Wald test – Time dummies | 0.000 | 0.000 | 0.000 | 0.000 |
| Wald test – Size dummies | 0.000 | 0.000 | 0.000 | 0.000 |
| $\rho_v$ | 0.412 | 0.122 | 0.538 | 0.155 |
| | (0.017) | (0.015) | (0.018) | (0.018) |
| lnL | -6392.9 | -5825.7 | -5196.1 | -4536.5 |
| Observed Probability | 35.2 | 35.2 | 26.6 | 26.6 |
| Predicted Probability | 31.6 | 34.2 | 19.6 | 25.1 |
| Correct predictions | 66.5 | 76.5 | 70.6 | 81.4 |
| Correct predictions: 1 / 0 | 57.0 / 71.6 | 74.7 / 77.5 | 48.1 / 78.7 | 79.0 / 82.2 |
| Number of observations | 12303 | 12303 | 12303 | 12303 |

[a] - The prediction of the R&D intensity is obtained from estimations (3) and (5) in Table 5.

Notes:

Marginal effects (standards errors in brackets) are showed. ***, ** and * indicate significance on a 1%, 5% and 10% level respectively. All regressions include a constant and 19 industry and 5 size and 14 time dummies. To avoid multicolinearity, the dummy variables corresponding to year 1991, industry 1 and size up to 20 employees are excluded. The estimates also include four dummies to capture firm's mobility (merger, scission, entry and exit). $\rho_v$ is the percentage of total variance explained by the unobserved heterogeneity.

Instead of observed technological outputs, we include in the specification the predicted values for the generation of innovations obtained from the estimations in Table 6. The results show that the omission of the persistence in the analysis of the generation of knowledge leads to an overestimation of the impact of innovations on productivity growth. Specifically, when the predictions from the static RE Probit model are considered (columns (1) and (3) in Table 7), the impact of innovations on the PTF growth is clearly significant, and the quantitative effect is quite similar for both types of innovation. However, when the persistence of innovations is taken into account -columns (2) and (4)- the effect of process innovations on productivity growth is reduced more than fifty percent and the effect of product innovations disappears. Firms which obtain process innovations during the period, show a TFP growth almost three points bigger than non-innovators. In this sense, it seems relevant to consider the true state dependence in the generation of knowledge if we want to capture the real effect of technological outputs on growth.

These results are confirmed when we jointly introduce the predictions for process and product innovations as explanatory variables, as can be seen in column (5) of Table 7. Unlike most previous empirical papers, that obtain a significant effect of product innovations on the growth of labor productivity, the PTF growth is only affected by process innovations. In that respect, our findings show that the choice of the productivity measure is relevant to properly study the effect of knowledge generation on growth.

The rest of variables included in the estimations try to control for the non-fulfillment of the assumptions associated with the Solow residual models (constant returns to scale, instantaneous adjustment of the inputs) and the firm's mobility (entry, exit, merger, scission) during the period. In this sense, the capacity utilization variation is positively related to growth and the negative sign of the weighted inputs variation supports the existence of decreasing returns to scale. In addition, all the mobility dummies show the expected signs but only merger and scission are statistically significant. They have a similar quantitative impact on productivity growth, positive (negative) for mergers (scissions). Although, the signs of the dummies for entrants and exiters support the predictions of industry dynamic models, the coefficients are non-significant. Notice that this result can be affected by the fact that we have restricted the sample to firms with more than 7 consecutive observations and therefore we are not capturing all the entries and exits during the period in a suitable way.

**Table 7**
Total Factor Productivity Growth

| | Total Factor Productivity Growth | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *Estimation method* | *IV regression* | *IV regression* | *IV regression* | *IV regression* | *IV regression*[c] |
| Process innovation[a] | 7.251*** | 2.663*** | | | 2.825*** |
| | (1.275) | (0.573) | | | (0.605) |
| Product innovation[b] | | | 6.686*** | 0.380 | -0.460 |
| | | | (1.842) | (0.526) | (0.556) |
| Weighted inputs variation | -0.196*** | -0.195*** | -0.194*** | -0.193*** | -0.195** |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) |
| Capacity utilization variation | 0.082*** | 0.082*** | 0.082*** | 0.082*** | 0.082*** |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) |
| Merger | 5.462*** | 5.921*** | 5.854*** | 6.081*** | 5.922*** |
| | (1.151) | (1.146) | (1.148) | (1.147) | (1.146) |
| Scission | -7.559*** | -7.373*** | -7.296*** | -7.356*** | -7.379*** |
| | (1.657) | (1.657) | (1.658) | (1.659) | (1.658) |
| Entry | 0.242 | 0.407 | 0.517 | 0.479 | 0.394 |
| | (0.359) | (0.357) | (0.357) | (0.358) | (0.358) |
| Exit | -0.384 | -0.706 | -0.150 | -0.839 | -0.745 |
| | (0.574) | (0.569) | (0.602) | (0.570) | (0.571) |
| Wald test – Industry dummies | 0.188 | 0.069 | 0.001 | 0.012 | 0.080 |
| Wald test – Time dummies | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Wald test – Size dummies | 0.002 | 0.236 | 0.030 | 0.378 | 0.276 |
| Fixed effects test: F(1071,11212) | 0.53 | 0.52 | 0.54 | 0.53 | 0.51 |
| Number of observations | 12303 | 12303 | 12303 | 12303 | 12303 |

[a] - Predictions used in columns (1) and (2) are obtained from estimations (1) and (2) in Table 6, respectively.
[b] - Predictions used in columns (3) and (4) are obtained from estimations (3) and (4) in Table 6, respectively.
[c] – Prediction of process/product innovation used in column (5) are obtained from estimations (2)/(4) in Table 6.
Note: All estimates include a constant, 19 industry dummies and 14 time dummies. To avoid multicolinearity, the dummy variables corresponding to year 1991 and industry 1 are excluded. Standards errors (in brackets) are showed. ***, ** and * indicate significance on a 1%, 5% and 10% level respectively. The estimates also include four dummies to capture firm's mobility (merger, scission, entry and exit).

## 5. Conclusions

Since middle nineties, productivity in Spanish manufacturing industry has experienced a strong deceleration. This phenomenon, shared with the majority of EU members, keeps European countries away from American firms that have been able to use the new telecommunication and information technologies to improve the efficiency in sectors not directly related to them.

With the objective of clarifying the relationship between technological activities and productivity growth, many researchers have empirically tested, with data from different European countries, the recursive CDM model that explains productivity growth by technological outputs and the later by R&D effort. In this line, we estimate an adaptation of the CDM model for a panel of Spanish manufacturing firms during the period 1990-2005. Our main contribution consists of the consideration of persistence both in the R&D investment decision and in the achievement of innovations when estimating the model that reflects the relationship between R&D, innovations and productivity.

The results reflect that the R&D investment status and the production of innovations in one period strongly influence these variables in the next period. The omission of this persistence leads to an overestimation of the effect of the current impact of innovations on productivity growth. Additionally, our paper shows that the choice of the productivity measure is relevant to study the effect of knowledge generation on growth. Specifically, unlike most empirical previous evidence that finds a positive effect of product innovation on labor productivity growth, in our analysis only firms who obtain process innovations increase their TFP growth.

These empirical regularities hide important differences in firms’ behavior according to their size. Large firms present advantages to exploit economies of scope and scale in the R&D activities. However, they have more difficulties to improve their productivity.

Furthermore, the paper points out that the evolution of markets plays a relevant role not only for the probability of engaging in R&D expenditures but also for the effectiveness in obtaining process innovations. Both of them rise when firms perceive their market as expansive.

The estimations also point out the relevance of technological policy as an instrument to increase productivity. In particular, the public funding seems to stimulate R&D investment intensity and the improvements on workers’ level of education increase both the probability of carrying out R&D activities and the technological effort. In that respect, public support and private R&D investment seem to be complementary rather than substitute activities. In addition, the evidence of persistence in R&D inputs and innovation outputs suggests that the effects of technological policy can persist also in the long term.

**References:**


Audretsch, D. (1995): *Innovation and Industry Evolution*, MIT Press.

Arvanitis, S. and Hollenstein, H. (1994), "Demand and supply factors in explaining the innovative activity of Swiss manufacturing firms", *Economics of Innovation and New Technology 3*, 15-30.

Benavente J.M. (2006), 'The role of research and innovation in promoting productivity in Chile', *Economics of Innovation and New Technology*, 15(4/5), 301-315.

Bond, S., Harhoff, D. y Van Reenen, J. (1999), "Investment, R&D and Financial Constraints in Britain and Germany", Institute for Fiscal Studies Working Paper W99/05.

Cefis, E. (2003), "Is there Persistence in Innovative Activities?", *International Journal of Industrial Organization* 21, 489–515.

Cefis, E. and Orsenigo, L. (2001), "The Persistence of Innovative Activities. A Cross–Countries and Cross–Sectors Comparative Analysis", *Research Policy* 30(7), 1139–1158.

Chamberlain, G. (1980), "Analysis of Covariance with Qualitative Data", *Review of Economic Studies* 47, 225-238.

Cohen, W.M. and Levin R.C. (1989), "Empirical Studies of Innovation and Market Structure", in R. Schmalensee and R. Willig (eds.): *Handbook of Industrial Organization, vol.* 11, North-Holland, Amsterdam.

Crepon, B., Duguet, E. and Mairesse, J.(1998), "Research, innovation and productivity: an econometric analysis at the firm level", *Economics of Innovation and New Technology 7*, 115-158.

Duguet, E. and Monjon S. (2004), "Is innovation persistent at the firm Level. An econometric examination comparing the propensity score and regression methods", *Cahiers de la Maison des Sciences Economiques* v04075, Université Panthéon-Sorbonne.

Esteve, S. and Rodríguez D. (2009), "The dynamics of trade and innovation", Documento de trabajo 467, Fundación de las Cajas de Ahorros, Madrid.

Griffith, R., Huergo, E., Mairesse, J. and Peters, B. (2006): "Innovation and productivity across four European countries", *Oxford Review of Economic Policy* 22(4), 483-498.

Griliches, Z. (1979): "Issues in assessing the contribution of R&D to productivity growth", *Bell Journal of Economics* 10, 92-116.

Hall, B., Lotti, F. and Mairesse, J. (2009): "Innovation and productivity in SMEs. Empirical evidence for Italy", *Small Business Economics* 33, 13-33.

Hall, B.H., Mairesee, J., Branstetter, L. and Crepon, B. (1999), "Does cash flow cause investment and R&D: An exploration using panel data for French, Japanese and United States scientific firms", in D. Audretsch and A.R. Thurik (eds.), *Innovation, Industry Evolution and Employment*, Cambridge University Press.

Heckman, J.J. (1981): "Statistical models for discrete panel data", in: C. Manski and D. McFadden (Eds.), *Structural analysis of discrete data with econometric applications* (pp. 114-178), Cambridge, MA.

Huergo, E. and Jaumandreu, J. (2004), "How does probability of process innovation change with firm age?", *Small Business Economics* 22, 193-207.

Jefferson, G., Huamao, B., Xiaojing, G. and Xiaoyun Y. (2006), “R&D Performance in Chinese Industry”, *Economics of Innovation and New Technology*, 15(4/5), 345-366.

Klepper, S. (1996), “Entry, exit, and innovation over the product life-cycle”, *American Economic Review* 86, 562-583.

Lööf, H. and Heshmati, A. (2006), ”Knowledge capital and heterogeneity in firm performance. A sensitivity analysis”, *Economics of Innovation and New Technology*, 15(4/5), 317-344.

Mairesse, J. and Mohnen, P. (2002), “Accounting for Innovation and Measuring Innovativeness: An Illustrative Framework and an Application”, *American Economic Review*, 92 (2), 226-230.

Mairesse, J. and Mohnen, P. (2005), “The Importance of R&D for Innovation: A Reassessment Using French Survey Data”, *The Journal of Technology Transfer*, 30(1–2), 183–197.

Mañez-Castillejo, J. A., Rochina-Barrachina, M. E., Sanchis-Llopis, A. and Sanchis-Llopis, J. (2009): “The role of sunk costs in the decision to invest in R&D”, *Journal of Industrial Economics*, forthcoming.

Mohnen, P., Mairesse, J. and Dagenais, M. (2006), “Innovativity: A Comparison across Seven European Countries”, *Economics of Innovation and New Technology*, 15(4/5), 391-413.

Parisi, M., Schiantarelli, F. and Sembenelli, A. (2006), “Productivity, Innovation and R&D: Micro Evidence for Italy”, *European Economic Review*, 50(8), 2037-61.

Peters, B. (2009): “Persistence of innovation: stylised facts and panel data evidence”, *Journal of Technology Transfer* 34(2), 226-243.

Raymond, W., Mohnen, P., Palm, F., and Schim van der Loeff, S. (2006): “Persistence of innovation in Dutch manufacturing: Is it spurious?”, CESifo Working Paper No. 1681.

Utterback, J. (1994), *Mastering the Dynamics of Innovation*, Boston, MA: Harvard Business School Press.

Van Leeuwen, G. and Klomp, L. (2006), “On the Contribution of Innovation to Multi-Factor Productivity Growth”, *Economics of Innovation and New Technology*, 15(4/5), 367-390.

Van Leeuwen, G., Mohnen, P., Polder, M., & Raymond, W. (2009), “Productivity effects of innovation modes”, CBS Discussion paper 09033, Statistics Netherlands.

Wooldridge, J. (2005): “Simple Solutions to the Initial Conditions Problem in Dynamic Nonlinear Panel Data Models with Unobserved Heterogeneity”, *Journal of Applied Econometrics* 20(1), 39–54.

**Appendix:** ***Variable definitions***

*Belonging to a group:* Dummy variable which takes the value 1 if the firm belongs to a group of companies.

*Capacity utilization variation:* Variation in the percentage of utilization of installed capacity reported by the firm.

*Capital intensity*: Ratio of capital stock in equipment goods to employees.

*Capital stock of equipment goods:* Net stock of capital for equipment goods in real terms. It is calculated by using the perpetual inventory formula: $K_t = (1-d)K_{t-1}(P_t / P_{t-1}) + I_t$, where $P$ is the price index for equipment, $d$ is the depreciation rate, and $I$ is the investment in equipment.

*Degree of product homogeneity:* Dummy variable which takes the value 1 if the product supplied by the firm is highly standardized.

*Degree of services subcontracting:* Variable which indicates the degree of the subcontracted services by the firm no related with its productive activity as legal and fiscal advice, audit, administration, personal selection and training, computer programming, installing of software package, courier service, machinery hire, security, cleaning and packing and labeling.

*Effective hours of work:* Normal hours plus overtime hours minus lost hours.

*Demand evolution:* Each firm identifies the behavior of market demand in its main market during the year with respect to previous years according to three different categories: recession, stability and expansion. A value of 1, 2 and 3 is assigned respectively to each category.

*Export intensity:* Ratio of exports over total employment.

*Exporter:* Dummy variable which takes the value 1 if the firm has exported during the year.

*Firm's age:* Difference between the current year and the constituent year reported by the firm. We have assigned 40 to firms older than forty years old.

*Foreign capital participation*: Percentage of foreign capital in the social capital of the firm.

*Number of competitors:* Discrete variable which takes values 1, 2, 3 and 4 when the number of competitors reported by the firm is up to 10, from 11 to 25, more than 25, and atomized market, respectively.

*Process Innovation:* Dummy variable which takes the value one if the firm has obtained a process innovation during the year.

*Product Innovation:* Dummy variable which takes the value one if the firm has obtained a product innovation during the year.

*Proportion of engineers and graduates:* Ratio of engineers and graduates over total employment.

*Public support:* Dummy variable which takes the value 1 if the firm has obtained public funding during the year.

*R&D expenditures per employee:* Ratio of total expenditures in R&D (including technology imports) over total employment.

*Total factor productivity (Solow residual)*: It is calculated using the Tornqvist index: $TFP = y - s_L l - s_K k - s_M m$, where the real output and the inputs are in logarithmic differences and the weights *s* in t are the cost shares of each input in the year *t*. Intermediate consumption variation (*m*) includes raw materials, services purchases and energy and fuel cost. Output and intermediate consumption real changes are deflated using Paasche-type firm individual indices, constructed starting from the price changes on output and inputs reported by firms. Labor input variations (*l*) are the changes in total effective hours of work. The user cost of capital is calculated as the long-run debt interest rate paid by the firm plus equipment good depreciation minus the rate of change of a capital goods price index.