

The innovation returns to internal and external R&D experience*

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Abstract

This paper analyses the role of learning in firms' innovation success distinguishing between learning arising from the internal organization of R&D activities and learning from externally contracting these activities. We use a representative sample of Spanish manufacturing firms for the period 1990-2006, and within an innovation production function approach, we estimate count data models to investigate the influence of firms' internal R&D experience as compared to experience from externally contracted R&D in the achievement of product innovations. Our results show that learning is important when firms organize R&D activities internally. However, experience from externally contracted R&D activities does not seem to influence the number of product innovations, if not accompanied by internal R&D activities.

Keywords: innovation, accumulation of knowledge, internal R&D experience, external R&D experience, count data models.

JEL classification: O30, O34, C23, C10.

Resumen

Este trabajo analiza el papel del aprendizaje en la obtención de innovaciones de las empresas, distinguiendo entre el aprendizaje que surge de la organización interna de las actividades de I+D y el aprendizaje asociado a la contratación externa de estas actividades. Utilizando una muestra representativa de empresas manufactureras españolas durante el período 1990-2006, y dentro del enfoque de la función de producción de innovaciones, estimamos modelos de datos count para investigar el efecto de la experiencia interna y externa en I+D en la obtención de innovaciones de producto. Nuestros resultados muestran que el aprendizaje es importante cuando las empresas organizan las actividades de I+D internamente. Sin embargo, la experiencia que se obtiene de las actividades contratadas externamente no parece influir en el número de innovaciones de producto, si no va acompañada de actividades internas de I+D.

Palabras clave: innovación, acumulación de conocimiento, experiencia interna en I+D, experiencia externa en I+D, modelos de datos de recuento.

Clasificación JEL: O30, O34, C23, C10.

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1. Introduction

Despite widespread acknowledgement of the importance of persistence in conducting R&D activities for the achievement of innovation outcomes, the empirical literature has devoted little attention to the role of experience in the process of innovation.

In this paper we follow Beneito *et al.* (2011, 2014) and argue that R&D learning, defined as the accumulation of knowledge and measured as past experience in carrying out R&D activities, is an important driver in the achievement of innovation results, and that its effect is not properly measured by R&D capital stock¹. However, in this paper we extend our analysis by considering that knowledge accumulation and learning derived from engagement in internal R&D activities, is of a different nature as compared to learning from externally contracted R&D². In particular, our working hypothesis is that internal R&D experience is more relevant in the achievement of product innovations than the experience obtained from externally contracted R&D activities³.

According to Mowery (1983), conducting in-house R&D activities is usually related to complex research projects requiring knowledge of a highly specialized, idiosyncratic variety, specific to a firm, or knowledge involving a high degree of coordination within the firm. On the other hand, conducting extramural R&D activities entails research projects that require more generic knowledge, applicable to a relatively wide range of industries and firms, and dealing with isolated or separable aspects of a firm's operations. Consequently, one may expect innovation outcomes to be more related to the learning process and accumulation of knowledge associated with conducting in-house R&D activities, as compared to extramural engagement in these activities.

The aim of this paper is to investigate whether firms' R&D effectiveness, i.e., the rate at which R&D investments yield innovation output, depends both upon firms' accumulated in-house and externally contracted R&D experience, respectively. In particular, we test the hypothesis that internal R&D experience is more important for

¹ The usual approach in the literature to capture the concept of knowledge capital and its cumulateness nature has been the "knowledge capital" model of GRILICHES (1979). This model considers that, in the line of the "perpetual inventory method" used for physical capital, knowledge capital is accumulated from period to period at a linear and constant rate proportional to R&D investments, subject to a constant depreciation rate.

² The complexity of the process of innovation and the heterogeneous nature of R&D activities has been extensively analysed in the literature. Within the approach of the evolutionary theory of technological innovation, the multiplicity of R&D activities performed by firms has been described by the concepts of technological trajectories (PAVITT, 1984) or technological regimes (NELSON and WINTER, 1982).

³ Thorough all the paper we will indistinctly use the terms *internal*, *in-house* and *internally organised* R&D as synonymous expressions for R&D activities undertaken within the firm, and we will indistinctly use *external*, *extramural* and *externally contracted* R&D as synonymous expressions to refer to those R&D activities contracted out with third parties (firms or research institutions). Thus, we do not take into account other external R&D activities that the firm may carry out, such as collaborative R&D activities with other firms or institutions.

the achievement of firms' product innovations than external R&D experience. Both internal and external R&D experience are measured as the number of years that a firm has been engaged in these activities, respectively⁴.

For this purpose, we use a representative sample of Spanish manufacturing firms for the period 1990-2006. The dataset is drawn from the *Encuesta sobre Estrategias Empresariales* (ESEE, henceforth), a survey carried out annually since 1990 providing detailed information at firm level. Within the framework of an innovation production function and using count data models, we estimate the influence of firms' accumulated internal and external R&D experience on their R&D innovative effectiveness, measured as the number of product innovations. In order to do this, and following Beneito *et al.* (2011, 2014), we treat R&D experience as a moderator variable for the impact of R&D capital on firms' innovation output, but distinguishing between internal and external R&D experience.

The main contribution of this paper to the existing empirical literature is that, to the best of our knowledge, this is the first attempt to empirically address the different role of experience associated with internal and external R&D on the achievement of firms' product innovations. Both West and Iansity (2003) and Beneito *et al.* (2011, 2014) consider R&D experience as a key driver of innovation outcomes. However, they do not distinguish between learning arising from in-house or external engagement in R&D activities, and in this paper we attempt to fill this gap.

The rest of the paper is organised as follows. Section 2 briefly describes our theoretical framework and related literature. Section 3 presents the data. Section 4 discusses the empirical model and econometric procedure, and section 5 presents the estimation results. Finally, section 6 concludes.

2. Theoretical framework and related literature

The importance of knowledge accumulation in explaining innovation has been developed by the approach of evolutionary theory (Nelson and Winter, 1982). The argument is based on the idea that experience allows the accumulation of knowledge, which is associated with dynamic increasing returns in the form of learning-by-doing and learning-to-learn effects. This stream of literature considers that innovations are the result of a process of accumulation of firms' specific competencies (Rosenberg, 1976). In particular, by investing in R&D projects, firms develop abilities in the form of knowledge, both scientific and informal know-how that may be used to develop further innovations at consecutive times. According to this view, firms benefit from

⁴ We use the number of product innovations as our measure of innovation outcomes achieved by firms. The ESEE also provides information on whether or not the firm introduces process innovations in a given period but not on the number of process innovations. Hence, we cannot use the number of process innovations as a measure of innovation outcomes, since this information is not available in the ESEE. Finally, the ESEE provides information on the number of patents registered by firms. However, using patents as an indicator of innovation outcomes is subject to criticism (see, *e.g.* GRILLICHES, 1990).

dynamic increasing returns in the form of learning-by-doing, learning-to-learn or scope economies in the production of innovations (Cohen and Levinthal, 1989)⁵.

The accumulation of knowledge firms obtain from experience in conducting R&D activities is likely to affect positively the achievement of innovation outcomes, as stressed by Nelson (1982):

“Strong knowledge means ability to guide R&D effectively. Stronger knowledge enables a larger expected advance to be achieved from a given R&D outlay: alternatively, strong knowledge reduces the expected cost of any R&D achievement. Strong knowledge enhances efficiency both by enabling R&D to proceed on a generally better set of candidate projects, and by enabling the set worked upon to reflect more accurately particular demands and needs.”

Regarding the sources of knowledge, the same author points out the following:

“Knowledge is not only won through specialized knowledge-seeking activities; knowledge is also won as by-product of searching for new technologies. Knowledge of correlates and of effective testing techniques grows through experience. One learns about efficacious R&D strategies through one’s successes and failures. What succeeded and fails last time gives clues as to what to try next, etc. The applied R&D system itself generates new knowledge as well as new techniques.”

In order to understand the process of knowledge accumulation, it is useful to characterize R&D activities as iterated cycles of problem-solving, in which organizations select a problem, device a set of potential solutions, and test and choose the optimal option (Newell and Simon, 1972). These cycles of problem-solving build up experience in relevant fields and raise the firms’ stock of knowledge (Nelson, 1982; Dosi and Marengo, 1993). As firms accumulate experience and relevant knowledge, the effectiveness of their research and selection processes improves. Experience in previous research projects turns out to be important in at least three categories of knowledge (West and Iansiti, 2003): (i) choosing which problems are more important to solve; (ii) achieving a better understanding of the search process and tools; and (iii) searching for information about the most likely potential solutions. These sources of knowledge can be considered as different forms of firms’ learning⁶.

⁵ For a review of this literature, see DOSI and MARENGO (2007) and references therein.

⁶ The literature of organizational learning also emphasizes the key role of experience in improving organizational performance. According to this literature, the production process creates knowledge about the organization of production that enhances the firm’s future productivity. The accumulation of this knowledge, or learning, is associated mainly with new technologies or new plants, and gives rise to what is called as organizational capital. This organizational capital, or experience, is usually measured as accumulated output (see, e.g. BAHK and GORT, 1993, and JOVANOVIĆ and NYARKO, 1995, and references therein).

The theory of “absorptive capacity” by Cohen and Levinthal (1989) may also be used for the foundation of the role of experience in R&D activities. They suggest that R&D “not only generates new information, but also enhances the firm’s ability to assimilate and exploit existing information” (Cohen and Levinthal, 1989)⁷. By investing in R&D and, therefore, by accumulating R&D experience, firms develop their ability to identify, assimilate and exploit externally available knowledge, that is, what these authors call “learning” or “absorptive” capacity. This absorptive capacity represents a sort of learning that differs from learning-by-doing: while learning-by-doing refers to the mechanism by which firms become more efficient as they accumulate experience in doing what they are already doing, absorptive capacity allow firms to assimilate outside knowledge in doing new things. Therefore, the accumulation of knowledge from experience in R&D allows firms to develop their absorptive capacity and, thus, it is likely to affect positively the achievement of innovation outcomes.

Regarding related empirical literature, there is a wide body of empirical literature that has focused on the analysis of the relationship between firms’ R&D inputs (measured as R&D capital stock, R&D expenditures, or as the ratio of R&D expenditures to sales or revenues) and innovative output (measured, e.g., in terms of patents or productivity). The relationship between innovation, R&D and patents has been surveyed by Griliches (1990), who reports a robust R&D-patents relationship at firm level⁸. Another strand of the literature has been devoted to the analysis of innovation persistence *per se*, both in the achievement of innovations (see, e.g., Geroski *et al.*, 1997; Malerba *et al.*, 1997; Cefis, 2003) and in the engagement in R&D activities (Máñez *et al.*, 2009; Peters, 2007).

More recently, with the availability of *Community Innovation Surveys* (CIS) data, a number of empirical works have further analysed the innovative performance of firms by relating innovation inputs to innovation outputs. Some of these works are Klomp and van Leeuwen (2001) for the Netherlands, Smith and Sandven (2001) for Norway, Löf and Heshmati (2001) for Sweden, or Mairesse and Mohnen (2005) and Kremp and Mairesse (2004) for France. However, these empirical studies do not explicitly take into account the possibility that the effectiveness of the R&D innovation inputs changes as firms accumulate experience in conducting their R&D activities.

In particular, there is a lack of empirical evidence explicitly analysing the role of firms’ experience in R&D activities as a key driver of their innovative success. To the best of our knowledge, only West and Iansiti (2003) and Beneito *et al.* (2011, 2014) consider the role of experience in R&D as a key driver of R&D performance. The work

⁷ See COHEN and LEVINTHAL (1990) for a discussion of the cognitive structures underlying learning.

⁸ Among the most well known works are those of SCHMOOKLER (1966, ch. 2), SCHERER (1965), BOUND *et al.* (1984), HAUSMAN *et al.* (1984), HALL *et al.* (1986), PAKES and GRILICHES (1984), SCHERER (1983), ACS and AUDRETSCH (1989), HENDERSON and COCKBURN (1993), BRANSTETTER (1996) and CRÉPON *et al.* (1998).

of West and Iansiti (2003), in the context of the evolutionary theory of organizational competencies, provides evidence for the US semiconductor industry. These authors point out that experience accumulation and experimentation are two organizational tools that generate flows of new knowledge, which through the learning process, significantly affect firms' performance. However, their empirical analysis is limited to a reduced number of research projects in one particular industry, and their measure of experience is rather limited: they use a *dummy* variable indicating if at least one of the project members involved in technology selection decisions has experience in the organization of research.

In some of our previous research on this topic (see Beneito *et al.*, 2011, 2014), we have already provided evidence that R&D experience matters in the achievement of innovation results. However, we did not distinguish between experience from internally organised R&D activities and from external or contracted out R&D as different sources of learning. This is precisely the aim of this paper: to analyse how these two different ways of conducting R&D may have potentially different roles in the achievement of innovations.

There are theoretical arguments suggesting that internal and external R&D may exhibit different innovation outcomes (Mowery, 1983). On the one hand, the requirements needed to develop complex research projects, involving highly specialized, idiosyncratic knowledge, are more likely to be met when R&D activities are internally organised. On the other hand, extramural R&D activities are, in general, conceived to match the generalised needs of potential customers, so that the research of this kind tends to be more standardised and focused on routinized and relatively simple research tasks. In spite of this, firms may recourse to external R&D when they lack financial resources, or their size is insufficient to face the sunk costs associated with opening and maintaining their own R&D lab. Consequently, one may expect the learning process and accumulation of knowledge associated with conducting in-house R&D activities, to be more fruitful in terms of innovations, as compared to extramural engagement in these activities.

3. The data: R&D experience, R&D strategy and product innovation

The data used in this paper are drawn from the ESEE for the period 1990-2006. This is an annual survey that is representative of Spanish manufacturing firms classified by industrial sectors and size categories⁹. It provides exhaustive information

⁹ The sampling procedure of the ESEE is the following. Firms with less than 10 employees were excluded from the survey. Firms with 10 to 200 employees were randomly sampled, holding around 5% of the population in 1990. All firms with more than 200 employees were requested to participate, obtaining a participation rate equal to around 70% in 1990. Important efforts have been made to minimise attrition and to annually incorporate new firms with the same sampling criteria as in the base year, so that the sample of firms remains representative of the Spanish manufacturing sector over time.

at the firm level including information on innovation activities¹⁰. Regarding product innovations, the particular question in the ESEE is as follows: *“Indicate if during year t the firm obtained product innovations (either completely new products or with so important modifications that they are perceived as different from the previous ones). If yes, indicate its number”*.

In this section, we present some descriptive statistics that are calculated for firms that declare to conduct R&D activities at least one year in the sample, and that report information both on the product innovation question and on all variables involved in estimation. Applying these criteria we end up with a sample of 12,598 observations, corresponding to an unbalanced panel of 1,853 firms.

Table 1 lists and describes the variables involved in estimation. Regarding the inputs in the innovative process, the ESEE provides information not only on firms' R&D expenditures, but also on whether R&D activities are internally organized within the firm or are externally contracted. The ESEE also reports information that, following Beneito (2003, 2006), may be considered as informal innovation-related activities, which may also affect the achievement of innovation results. These informal activities include services of scientific and technical information, works oriented to normalization and quality control, efforts to assimilate imported technologies, marketing studies, design, and other activities¹¹.

With respect to our measure of innovation output, firms obtain product innovations in 32.52% of the sample observations. Therefore, we need to take into account the presence of a high number of zero counts in product innovations in the econometric analysis in section 4¹². Out of these observations, 81.60% correspond to firms conducting R&D activities and, within this percentage, 92.49% are observations corresponding to firms that carry out internal R&D activities (either jointly with externally contracted R&D activities or not), and the remaining 7.51% of the observations correspond to firms engaged only in externally contracted R&D activities. Regarding the 67.48% sample observations where firms do not introduce any product innovation, 47.59% of these observations correspond to firms conducting R&D activities. Of these, 82.97% of the observations correspond to firms engaged in internal R&D activities (again either jointly with externally contracted R&D activities or not), and the remaining 17.03% correspond to firms reporting only externally contracted R&D activities. Regarding informal innovation-related activities, for the observations in which firms introduce product innovations, in 86.99% of the cases they carry out at least one of the informal innovation-related activities, whereas this percentage is 70.51% for observations in which firms do not introduce product innovations¹³.

¹⁰ See <http://www.fundacionsepi.es/esee/en/epresentacion.asp>.

¹¹ The information in the ESEE about these informal activities is collected on a 4-years basis.

¹² Regarding firms, instead of firms' observations, in our sample 67.38% of firms introduce at least one product innovation along the sample period.

¹³ More in detail, for observations in which firms introduce product innovations, in 43.54% of the cases there are involved services of scientific and technical information, in 66.93% works oriented to normaliza-

TABLE 1
VARIABLES DEFINITION

Product innovations	Number of product innovations introduced by the firm during the year
<i>R</i> : R&D-capital	<p>The knowledge capital derived from the firm's R&D investment follows the historical or perpetual inventory method:</p> $R_{it} = (1 - \delta)R_{it-1} + I_{it-1}$ <p>where δ is the rate of depreciation, R is the R&D-capital stock and I are real R&D expenditures (current R&D has been deflated using industrial prices for the whole manufacturing industry). To calculate the R&D-capital according to the equation above we need an initial value for I to start the recursion. We use for that purpose the information about the number of years the firm has been investing in R&D activities. By backwards induction, the sequence of past R&D expenditures can be imputed till the first year of R&D activities, when the initial R&D-capital stock is equal to zero. The R&D-capital is defined for a depreciation rate of 15 percent and a pre-sample growth rate of real R&D investment equal to the mean growth rate for the firms which conduct R&D activities and are observed during the sample period, that is $g = 4.5\%$.</p>
<i>E</i> : R&D experience	Number of years the firm has been engaged in R&D activities in the past.
<i>IE</i> : Internal R&D experience	Number of years the firm has been engaged in internal R&D activities in the past.
<i>EE</i> : External R&D experience	Number of years the firm has been engaged in externally contracted R&D activities in the past.
Hired personnel in "t" with R&D experience	Dummy variable taking value 1 if the firm has recruited (during current year) personnel with experience in corporate R&D. Information on this variable is only available from 1998 onwards.
Scientific/technical services	Dummy variable taking value 1 if the firm has undertaken services of scientific and technical information, and 0 otherwise.
Quality control	Dummy variable taking value 1 if the firm has undertaken works of normalisation and quality control, and 0 otherwise.
Imported technology	Dummy variable taking value 1 if the firm has undertaken efforts to assimilate imported technologies, and 0 otherwise.
Marketing	Dummy variable taking value 1 if the firm has undertaken marketing studies orientated to the commercialisation of new products, and 0 otherwise.
Design	Dummy variable taking value 1 if the firm has undertaken design activities, and 0 otherwise.
Other	Dummy variable taking value 1 if the firm has undertaken other informal innovation-related activities, and 0 otherwise.
Age	Age of the firm.
Age squared	Age of the firm to the square.
Size1	Dummy variable that equals 1 if the number of employees of the firm is above 10 and below or equal to 20, and 0 if otherwise.
Size2	Dummy variable that equals 1 if the number of employees of the firm is above 20 and below or equal to 50, and 0 if otherwise.

TABLE 1 (continued)
VARIABLES DEFINITION

Size3	Dummy variable that equals 1 if the number of employees of the firm is above 50 and below or equal to 100, and 0 if otherwise.
Size4	Dummy variable that equals 1 if the number of employees of the firm is above 100 and below or equal to 200, and 0 if otherwise.
Size5	Dummy variable that equals 1 if the number of employees of the firm is above 200 and below or equal to 500, and 0 if otherwise.
Size6	Dummy variable that equals 1 if the number of employees of the firm is above 500, and 0 if otherwise.
Industry dummies	Industry dummies accounting for 20 industrial sectors of the NACE-93 classification.
Time dummies	Time dummies accounting for the 17 years in our sample period.
Exclusive external R&D strategy	Dummy variable that equals 1 for those firms which base their R&D strategy uniquely on externally contracted R&D.

We turn now into the analysis of the number of accumulated years of R&D experience by R&D strategy (either internal or external). In order to distinguish between internal and external R&D experience we establish a typology of firms according to the type of R&D activities they mainly carry out. We construct two *dummy* variables taking the value one when the firm is engaged *mainly* in in-house R&D activities (and zero otherwise), and when the firm carries out *mainly* contracted R&D activities (and zero otherwise), respectively. For this purpose we summed up, on the one hand, the number of years in which a firm conducts mainly internal R&D activities, considering as such those years with only internal R&D spending, and also those years with a higher percentage of internal R&D spending as compared to external R&D spending. On the other hand, we summed up the number of years in which a firm conducts mainly external R&D, considering as such those years with only external R&D, and those years with a higher percentage of external R&D spending as compared to internal R&D spending. According to these criteria, a firm is classified into the first group (firms with “*mainly an internal R&D strategy*”) if the number of years doing mainly internal R&D activities is greater than the number of years doing mainly external R&D activities. The firm is classified into the second group (firms with “*mainly an external R&D strategy*”) if the case is the other way around. According to this classification, approximately 73% of firms in our sample

zation and quality control, in 30.73% efforts to assimilate imported technologies, in 42.79% marketing studies, in 58.53% design, and in 3.39% other activities. For observations in which firms do not introduce product innovations these percentages are as follows: in 26.29% of the cases are involved services of scientific and technical information, in 52.65% works oriented to normalization and quality control, in 20.72% efforts to assimilate imported technologies, in 23.75% marketing studies, in 33.88% design, and in 2.11% other activities.

are following mainly an internal R&D strategy, and the remaining 27% are following mainly an external one. In Table 2 we report the distribution of frequencies for the number of firms in our sample according to the total number of accumulated years of R&D experience, separately for each group of firms. Regarding firms following mainly an internal R&D strategy, 90% of them accumulate less than 13 years of R&D experience. As for firms pursuing mainly an external R&D strategy, 90% of them accumulate less than 9 years of R&D experience.

Finally, Table 3 reports the annual average number of product innovations introduced by firms depending upon their accumulated R&D experience and their R&D strategy. For the whole sample period, firms with an internal R&D strategy obtain an annual average of approximately 5 product innovations, whereas firms with an external R&D strategy obtain an annual average of 2 product innovations.

TABLE 2
DISTRIBUTION OF THE TOTAL NUMBER OF ACCUMULATED YEARS
OF R&D EXPERIENCE BY R&D STRATEGY

Total number of years of R&D experience	Percentage of firms by total number of years of R&D experience		Accumulated percentage of firms by total number of years of R&D experience	
	Firms with mainly an internal R&D strategy	Firms with mainly an external R&D strategy	Firms with mainly an internal R&D strategy	Firms with mainly an external R&D strategy
1	30.58	42.86	30.58	42.86
2	11.95	17.58	42.53	60.44
3	10.26	8.79	52.79	69.23
4	7.17	5.22	59.96	74.45
5	5.78	4.14	65.74	78.57
6	5.38	3.30	71.12	81.87
7	6.27	4.40	77.39	86.26
8	2.69	2.20	80.08	88.46
9	3.09	2.75	83.17	91.21
10	2.79	1.37	85.96	92.58
11	2.09	1.37	88.05	93.96
12	1.39	0.82	89.44	94.78
13	2.19	1.37	91.63	96.15
14	0.70	0.55	92.33	96.70
15	1.10	1.10	93.43	97.80
16	1.79	0.55	95.22	98.35
17	4.78	1.65	100	100

In addition, Table 3 shows the annual averages of the number of product innovations that firms achieve when they are in their 1st to 3rd year of R&D experience, in their 4th to 6th year of R&D experience, and so on. Considering the 90% of the R&D experience distributions given in Table 2, we see in Table 3 that the average number of product innovations that firms achieve annually rise with R&D experience. For the group of firms with an internal (external) R&D strategy this average number ranges from 4.06 (1.95) in the first three years of R&D experience to 9.16 (5.62) in the interval of 10-12 (7-9) years of R&D experience. Therefore, for this 90% of the distributions, the average number of product innovations is larger for firms with an internal R&D strategy than for firms with an external one.

TABLE 3
R&D EXPERIENCE BY R&D STRATEGY, AND PRODUCT INNOVATION RESULTS

Intervals of R&D experience (years)	Annual average number of product innovations for firms with mainly an internal R&D strategy	Annual average number of product innovations for firms with mainly an external R&D strategy
1-3 years	4.06	1.95
4-6 years	5.17	2.73
7-9 years	6.54	5.62
10-12 years	9.16	10.43
13-17 years	4.01	2.62
Total	4.60	2.35

4. Empirical model and econometric procedure

Our empirical approach is based on the concept of an *innovation production function*:

$$N_{it} = f(x_{it}, \beta) \quad [1]$$

where i refers to the firm and t to the time period, N_{it} stands for the number of product innovations, and x_{it} represents the vector of innovation inputs in the equation. Usual components of x_{it} are R&D inputs, quite often measured by R&D capital. Following Beneito *et al.* (2011, 2014), our innovation production function will differ from the standard one in that the effectiveness of R&D capital is specified as a function of the R&D experience of the firm. In particular, the parameter vector β may be decomposed as

$$\beta = [\beta_1(E_{it}), \beta_2] \quad [2]$$

where β_1 is the parameter measuring the “*innovative effectiveness*” of the R&D input, E_{it} stands for firms’ R&D experience, and β_2 stands for other inputs’ parameters. Therefore, the effect of R&D in the achievement of product innovations depends on R&D experience, measured as the number of years the firm has been engaged in R&D activities. In particular, we assume that expression [1] takes the form

$$N_{it} = A(t)R_{it}^{\beta_1(E_{it})}\exp(z_{it}\beta_2) \quad [3]$$

where R_{it} is knowledge or R&D capital (derived from the flow of real R&D investments)¹⁴, E_{it} is the firm’s R&D experience, and z_{it} stands for a vector of other inputs and control variables. Expression [3] includes a direct proportionate relationship between the R&D capital and innovation *counts* and a multiplicative set of variables hypothesized to shift the distribution of expected innovation results.

The econometric approach to estimate equation [3] is conditioned by the *count* (non-negative integers) nature of our dependent variable, N_{it} , the number of product innovations introduced by the firm during period t . It will also incorporate the fact that in any given year many firms may not introduce product innovations, so that we may have a high number of zero *counts* in our sample. We consider that our *count* data may be subject to a problem of excess of zeros because the mechanism explaining which firms are potential (product) innovators may be different of that explaining the positive number of product innovations. Although in estimation we select those firms conducting R&D activities at least one year of the sample period, it may be the case that in a given year either the firm is not carrying out R&D, or its innovation efforts are not aimed at introducing product innovations. In such cases, we will observe a zero *count* because this firm is not a potential product innovator, which differs from those zero *counts* of firms that search for product innovations but have not been successful in a given year.

In order to deal with the presence of zero counts and the likely different nature of the zeros and the positive values of our dependent variable, we use the *Zero Inflated model*¹⁵. This model gives more weight to the probability that the *count* variable equals zero and it considers an underlying mechanism to distinguish between what could be named “non-innovators” and “potential innovators”, with probability $q(w_{it}\gamma)$ and

¹⁴ For a discussion on the use and construction of the R&D capital, see, for example, HALL and MAIRESSE (1995). Details about how we construct this measure are given in Table 1.

¹⁵ A standard empirical approach in the literature is to assume that the Poisson distribution is a reasonable description for count data. However, one restriction of the Poisson model is that the variance of N_{it} equals its mean. As CAMERON and TRIVEDI (1998) noted, the Poisson regression fails if there is unobserved heterogeneity in the data, which leads to overdispersion. In this case, the Negative Binomial model is more appropriate, and it is possible to test one specification against the other by testing the significance of the overdispersion parameter, that is, testing the invalidity of the “variance equal to the mean” assumption of the Poisson model. In addition, although the Negative Binomial model allows for overdispersion, it has been noted by GURMU (1997) that it provides poor fit if there are excess of zeros in the data. Thus, the *zero inflated* model seems a more suitable model to our case. The *zero inflated* model may be estimated for the Poisson and the NB distribution, ZIP and ZINB models, respectively. In estimation, we test all these distributional alternatives.

$1 - q(w_{it}, \gamma)$, respectively, where w_{it} represents the vector of variables to be used for estimating these probabilities. We estimate the Zero Inflated model for the Negative Binomial distribution (ZINB model) and, in estimation, we use the *Vuong statistic* (Vuong, 1989) to test the non-nested ZINB model against its NB counterpart¹⁶.

The probability function for the ZINB model is defined as:

$$P_{it}^{ZINB}(n_{it}/x_{it}) = 1(n_{it} = 0)q_{it} + (1 - q_{it})P_{it}^{NB}(n_{it}/x_{it}) \quad [4]$$

where $1(n_{it} = 0)$ stands for an indicator function that takes value of one when the condition within the parenthesis holds, and zero otherwise; and $P_{it}^{NB}(n_{it}/x_{it})$ stands for the standard NB model¹⁷. The ZINB model jointly estimates two equations: one of them is a binomial probit or logit model to estimate the probability (q_{it}) of a zero against a positive value for the *count* variable, and the other equation estimates the probability of the observed *count* according to [4].

As our baseline Model, we start estimating equation [3] for the case where R&D experience in a given year t is measured as the sum of the number of past years the firm has been conducting R&D activities, without specifying if these R&D activities are internal or external (we refer to this case as Model I in our table of estimation results). As stated above, the specification given by equation [3] means that the impact of R&D capital on the rate of achievement of product innovations is assumed to be a function of the R&D experience of the firm. As this function may be non-linear, in order to allow for a non-linear relationship we assume the following quadratic form:

$$\beta_1(E_{it}) = \alpha_0 + \alpha_1 E_{it} + \alpha_2 E_{it}^2 \quad [5]$$

Formally, from equation [3] β_1 is defined as the percentage change in the number of product innovations generated by a one per cent change in R&D capital. Thus, this elasticity represents the effectiveness of R&D capital, moderated by R&D experience, in obtaining product innovations. Note that α_0 would be the standard elasticity parameter if R&D experience would not matter for R&D success. In addition, α_1 captures the impact of firms' R&D experience on R&D effectiveness, and α_2 is the change in the impact of firms' R&D experience on R&D effectiveness. If the estimate of α_1 is significantly positive and the one of α_2 is significantly negative, then the relationship between R&D effectiveness and firms' R&D experience approximates to an inverted-U shape. However, if the estimate of α_1 is significantly different from zero but the estimate of α_2 is non-significant, then firms' R&D effectiveness is a monotonically increasing or decreasing function of firms' R&D experience.

¹⁶ The null hypothesis in the Vuong test is that the two models being considered are equally close to the true specification. Rejection of the null hypothesis leads to the acceptance of the zero inflated version of the model.

¹⁷ See CAMERON and TRIVEDI (1998) for details about the likelihood function of a Zero Inflated count data model.

In order to distinguish between internal and external R&D experience as potential and differentiated sources of accumulation of knowledge and learning, and so affecting differently to the R&D capital effectiveness, we consider in estimation three approaches. These three approaches may be regarded as three different methods of capturing and distinguishing between the learning associated with these two types of engagement in R&D activities. In the first approach, we make the hypothesis that internal engagement in R&D activities is a condition *sine qua non* to accumulate knowledge and learning, whereas external R&D activities in isolation do not necessarily create such learning effects. To test this hypothesis, we have split the total number of years of R&D experience into two measures: on the one hand, we consider the number of years of in-house engagement in R&D activities, no matter whether or not the firm carries out also external R&D activities; on the other hand, we have summed up the number of years the firm only contracts R&D activities, but does not carry out internal R&D. We call IE_{it} and EE_{it} to our measures of internal and external R&D experience, respectively, and then specify the R&D capital elasticity as:

$$\beta_1(E_{it}) = \alpha_0 + \alpha_1 E_{it} + \alpha_2 E_{it}^2 = \alpha_0 + \alpha_1^I IE_{it} + \alpha_2^I IE_{it}^2 + \alpha_1^E EE_{it} + \alpha_2^E EE_{it}^2 \quad [6]$$

We refer to this case as Model II in our table of estimation results.

In a second approach, we consider that the contribution of internal and external R&D activities to total R&D experience depends on the relative effort devoted to each of these alternatives, measured as the percentage of total R&D expenditure accounted for by each of them. As an example, if a firm allocates in a given year fifty per cent of its total R&D investment to internal R&D activity and fifty per cent to external R&D, we could say that, in that year, the total R&D experience of that firm is fifty per cent internal R&D experience, and fifty per cent external R&D experience. Total R&D experience of a firm i in a given year t is computed as a weighted sum as follows:

$$E_{it} = \sum_{\tau=1}^t (d_{it}^I \cdot \rho_{it}^I + d_{it}^E \cdot \rho_{it}^E) = \sum_{\tau=1}^t d_{it}^I \cdot \rho_{it}^I + \sum_{\tau=1}^t d_{it}^E \cdot \rho_{it}^E = IE_{it} + EE_{it} \quad [7]$$

where d_{it}^I and d_{it}^E are *dummy* indicators taking value 1 if the firm undertakes internal and external R&D activities, respectively, in year τ , and where ρ_{it}^I and ρ_{it}^E are the shares of total R&D expenditures devoted to internal and external R&D activities, respectively. To test statistically different effects, we allow the coefficients α_1 and α_2 in [5] to vary for internal and external R&D experience and, then, [5] takes the form:

$$\begin{aligned} \beta_1(E_{it}) &= \alpha_0 + \alpha_1 E_{it} + \alpha_2 E_{it}^2 = \\ &= \alpha_0 + \alpha_1 (IE_{it} + EE_{it}) + \alpha_2 (IE_{it} + EE_{it})^2 = \\ &= \alpha_0 + \alpha_1^I IE_{it} + \alpha_1^E EE_{it} + \alpha_2^I IE_{it}^2 + \alpha_2^E EE_{it}^2 + \alpha^{I\&E} IE_{it} \cdot EE_{it} \end{aligned} \quad [8]$$

We refer to this case as Model III in our table of estimation results.

Finally, we follow a third approach for measuring internal and external R&D experience. In this case, we classify firms into two groups according to what we consider to be “*mainly an internal R&D strategy*” or “*mainly an external R&D strategy*”, as explained in Section 3. We multiply total R&D years of experience by a *dummy* indicator that identifies firms in one or another group. The specification for our R&D-capital elasticity, expression [5], becomes in this case:

$$\beta_1(E_{it}) = \alpha_0 + (\alpha_1^I E_{it} \cdot d_{it} + \alpha_2^I E_{it}^2 \cdot d_{it}) + (\alpha_1^E E_{it} \cdot d_{iE} + \alpha_2^E E_{it}^2 \cdot d_{iE}) \quad [9]$$

where d_{it} and d_{iE} equal one if firm i has been classified into the first or the second group, respectively, as defined above. Note that, in this case, estimated coefficients should be interpreted as the effect of total R&D experience for firms which have mainly internal R&D experience as compared to the effect of total R&D experience for firms which have mainly external R&D experience. We refer to this case as Model IV in our table of results.

Additionally, from 1998 onwards, the ESEE includes information about firms' recruitment of R&D workforce. In particular, the questionnaire of the ESEE asks firms to respond “*whether or not the firm has recruited (during current year) personnel with experience in corporate R&D*”. Thus, we construct a *dummy* variable capturing this information and introduce this variable into the estimation of Model II¹⁸. The inclusion of this *dummy* variable leads us to discard more than half of the sample observations since it is available only since 1998, but we find interesting to include it in the estimation because it captures the idea we want to test in this paper: that internal experience, in this case embodied in hired R&D personnel, contributes noticeably to firms innovation success. We refer to this case as Model V in the table of estimation results.

Taking into account the different specifications given to $\beta_1(E_{it})$ in each of the models presented above, and taking logs in (3), our estimating function takes the form:

$$\log N_{it} = \log A(t) + \beta_1(E_{it}) \cdot \log R_{it} + z_{it} \beta_2 \quad [10]$$

where $\beta_1(E_{it})$ has to be replaced by expressions [5], [6], [8] or [9], depending on the particular model we are estimating in each case. As an example, for the particular case of our baseline Model, substituting expression [5] into [3] gives

$$N_{it} = A(t) R_{it}^{(\alpha_0 + \alpha_1 E_{it} + \alpha_2 E_{it}^2)} \exp(z_{it} \beta_2) \quad [11]$$

and, taking logs,

$$\begin{aligned} \log N_{it} &= \log A(t) + (\alpha_0 + \alpha_1 E_{it} + \alpha_2 E_{it}^2) \log R_{it} + z_{it} \beta_2 = \\ &= \log A(t) + \alpha_0 \log R_{it} + \alpha_1 E_{it} \log R_{it} + \alpha_2 E_{it}^2 \log R_{it} + z_{it} \beta_2 \end{aligned} \quad [12]$$

¹⁸ We include this *dummy* variable only in Model II, but conclusions hold irrespective of the model we consider.

Control variables in z_{it} include informal innovation-related activities carried out by firms, firm size *dummies*, firm age and its square, industry *dummies* accounting for 20 industrial sectors of the NACE-93 classification, and time *dummies* approximating $\log A(t)$. The “zero inflate equation” (which aims at estimating the probability of being a “non-innovator”, and which is used to weight the probability of zeros in the data as showed in [4]), includes all the variables that enter z_{it} , as well as a variable that accounts for those firms that follow an R&D strategy based completely on external activities. This variable has been proved to be a good predictor for zero product innovations in exploratory work.

5. Estimation results

The econometric results from estimation of Models I to V are reported in Table 4¹⁹. In all cases, the parameter capturing overdispersion in the data, ϕ , is statistically significant, indicating the rejection of the Poisson against the NB distribution. In addition, the Vuong statistic leads to reject the NB model in favour of the ZINB model. These tests are reported at the bottom of Table 4.

The first column in Table 4 reports the results corresponding to our baseline model (Model I), where a measure of total R&D experience is included without distinguishing between internal and external R&D activities. The second, third and fourth columns of Table 4 display the results for our Models II, III and IV described above, respectively, and finally, the fifth column shows Model V, corresponding to the case in which Model II also includes the *dummy* variable of “*hired personnel in t with corporate R&D experience*”. The top half of each column displays the estimation results for our innovation production function and the bottom half of each column presents the results for the zero inflate equation.

In all regressions the innovation function equation includes (the log of) our R&D-capital variable and its interactions with R&D experience and with squared R&D experience (see [12]). Depending on the way used to differentiate between internal and external R&D experience, that is, depending on whether we look at Model II, Model III or Model IV, the log of R&D capital multiplies expressions [6], [8] or [9], respectively. For the sake of simplicity, in Table 4 we use the notation α_1^I , α_2^I , α_1^E and α_2^E for the whole set of estimations, taking into account that the interaction terms of the log of R&D capital both with internal and external R&D experience take different forms in each Model.

If we look at the first column in Table 4, a first result is that both the coefficient α_0 corresponding to the log of R&D capital, and the coefficient α_1 corresponding to the interaction of the log of R&D capital with R&D experience, exhibit positive

¹⁹ Although we only present the results corresponding to the ZINB model, that is, the zero inflated negative binomial model, we have tested also other distributional alternatives, as described in Section 4. Results from these alternative estimations are available from the authors on request.

TABLE 4
ESTIMATES OF THE INNOVATION PRODUCTION FUNCTION FOR PRODUCT
INNOVATIONS (ZERO INFLATED NEGATIVE BINOMIAL MODEL)

	Model I	Model II	Model III	Model IV	Model V
α_0	0.048*** (0.001)	0.047*** (0.001)	0.049*** (0.001)	0.053*** (0.003)	0.044 (0.171)
α_1	0.011*** (0.000)				
α_2	-0.001*** (0.001)				
α_1^I		0.013*** (0.000)	0.012*** (0.000)	0.011*** (0.001)	0.007* (0.063)
α_2^I		-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.001)	-0.000** (0.037)
α_1^E		-0.005 (0.395)	-0.008 (0.277)	-0.004 (0.418)	-0.008 (0.131)
α_2^E		-0.000 (0.834)	0.000 (0.975)	0.000 (0.354)	0.001 (0.161)
$\alpha^I \cdot \alpha^E$			0.001 (0.531)		
Hired personnel in "t" with R&D experience					0.833*** (0.001)
Scient./Tech. Services	0.153 (0.180)	0.157 (0.165)	0.158 (0.165)	0.195 (0.101)	0.221 (0.215)
Quality control	-0.558*** (0.000)	-0.562*** (0.000)	-0.563*** (0.000)	-0.558*** (0.000)	-0.583*** (0.001)
Imported technology	-0.094 (0.453)	-0.097 (0.435)	-0.099 (0.428)	-0.071 (0.579)	-0.015 (0.943)
Marketing	0.223* (0.077)	0.221* (0.078)	0.222* (0.076)	0.277** (0.027)	0.054 (0.722)
Design	0.410*** (0.001)	0.404*** (0.001)	0.404*** (0.001)	0.483*** (0.000)	0.580*** (0.001)
Other	-0.294 (0.137)	-0.319 (0.113)	-0.316 (0.117)	-0.362* (0.092)	-0.993** (0.023)
Age	0.000 (0.958)	-0.000 (0.969)	-0.000 (0.970)	-0.001 (0.920)	0.008 (0.388)
Age squared	0.000 (0.848)	0.000 (0.883)	0.000 (0.886)	0.000 (0.771)	-0.000 (0.335)
Size2	-0.001 (0.995)	-0.008 (0.965)	-0.007 (0.970)	-0.054 (0.786)	0.073 (0.785)

NOTA: *P*-values calculated from robust standard errors in parentheses. * Significant at 10%; ** Significant at 5%; *** Significant at 1%. All estimations include 16 time *dummies* and 19 industry *dummies*.

TABLE 4 (continued)
ESTIMATES OF THE INNOVATION PRODUCTION FUNCTION FOR PRODUCT
INNOVATIONS (ZERO INFLATED NEGATIVE BINOMIAL MODEL)

	Model I	Model II	Model III	Model IV	Model V
Size3	0.049 (0.852)	0.065 (0.802)	0.071 (0.785)	-0.043 (0.864)	-0.197 (0.583)
Size4	0.340 (0.188)	0.329 (0.198)	0.327 (0.200)	0.319 (0.234)	0.146 (0.688)
Size5	0.108 (0.642)	0.101 (0.661)	0.103 (0.654)	0.086 (0.724)	0.251 (0.514)
Size6	0.232 (0.365)	0.238 (0.349)	0.236 (0.355)	0.181 (0.504)	0.274 (0.539)
Constant	-0.136 (0.695)	-0.116 (0.736)	-0.127 (0.712)	-0.345 (0.360)	-0.288 (0.601)
Zero inflate equation					
Exclusive external R&D strategy	0.805*** (0.000)	0.746*** (0.000)	0.740*** (0.000)	0.803*** (0.000)	0.877*** (0.000)
Scient./Tech. Services	-0.416*** (0.001)	-0.425*** (0.001)	-0.425*** (0.001)	-0.345** (0.011)	-0.360 (0.254)
Quality control	-0.336*** (0.003)	-0.348*** (0.003)	-0.350*** (0.003)	-0.330*** (0.009)	-0.390* (0.064)
Imported technology	-0.215 (0.154)	-0.239 (0.126)	-0.240 (0.125)	-0.254 (0.136)	-0.294 (0.479)
Marketing	-0.508*** (0.001)	-0.519*** (0.001)	-0.520*** (0.001)	-0.457*** (0.005)	-0.751*** (0.003)
Design	-0.565*** (0.000)	-0.559*** (0.000)	-0.559*** (0.000)	-0.564*** (0.000)	-0.601** (0.013)
Other	-0.643** (0.050)	-0.659* (0.051)	-0.660* (0.051)	-0.599 (0.133)	-1.007 (0.515)
Age	0.015** (0.016)	0.015** (0.017)	0.015** (0.018)	0.014** (0.034)	0.019 (0.115)
Age squared	-0.000** (0.016)	-0.000** (0.016)	-0.000** (0.016)	-0.000** (0.015)	-0.000 (0.284)
Size2	-0.265* (0.085)	-0.272* (0.078)	-0.272* (0.078)	-0.335* (0.053)	-0.546** (0.024)
Size3	-0.443* (0.066)	-0.443* (0.066)	-0.440* (0.068)	-0.598** (0.039)	-0.787** (0.032)
Size4	-0.249 (0.234)	-0.257 (0.228)	-0.258 (0.228)	-0.298 (0.190)	-0.863** (0.027)

NOTA: *P*-values calculated from robust standard errors in parentheses. * Significant at 10%; ** Significant at 5%; *** Significant at 1%. All estimations include 16 time *dummies* and 19 industry *dummies*.

TABLE 4 (continued)
ESTIMATES OF THE INNOVATION PRODUCTION FUNCTION FOR PRODUCT INNOVATIONS (ZERO INFLATED NEGATIVE BINOMIAL MODEL)

	Model I	Model II	Model III	Model IV	Model V
Size5	-0.197 (0.310)	-0.195 (0.320)	-0.195 (0.321)	-0.292 (0.179)	-0.706* (0.090)
Size6	-0.196 (0.459)	-0.186 (0.492)	-0.188 (0.490)	-0.259 (0.407)	-0.737 (0.221)
Constant	-0.395 (0.349)	-0.388 (0.365)	-0.387 (0.366)	-0.483 (0.278)	-0.302 (0.638)
N. Observations.	12598	12598	12598	11229	5157
Log. pseudo-likelihood	-18609.94	-18595.87	-18595.54	-17036.29	-7429.07
$H_0: \phi = 0$ (test overdispersion)	9.4e+04 ($P = 0.000$)	9.4e+04 ($P = 0.000$)	9.4e+04 ($P = 0.000$)	8.7e+04 ($P = 0.000$)	3.2e+04 ($P = 0.000$)
Vuong test of ZINB vs. standard NB	13.82 ($P=0.000$)	13.28 ($P = 0.000$)	13.20 ($P = 0.000$)	12.37 ($P = 0.000$)	9.25 ($P = 0.000$)

NOTA: P -values calculated from robust standard errors in parentheses. * Significant at 10%; ** Significant at 5%; *** Significant at 1%. All estimations include 16 time *dummies* and 19 industry *dummies*.

signs, while the estimated sign of the coefficient α_2 (corresponding to the interaction with squared R&D experience) is negative. This finding confirms some results from our previous research (Beneito *et al.*, 2011, 2014), and suggests that the relationship between R&D capital effectiveness (here expressed in elasticity form) and R&D experience is of an inverted U-type. This means that the effectiveness of R&D capital rises with R&D experience but at a decreasing rate. If we take the (statistically significant) results in this first column, the corresponding R&D-elasticity would be of a magnitude of $\beta_1(E_{it}) = 0.048 + 0.011 \cdot E_{it} - 0.001 \cdot E_{it}^2$. This means that for a value of 4 years undertaking R&D activities (corresponding approximately to the mean of the sample distribution), the value of the R&D-capital elasticity would be of 0.076, which is around 30% larger than the elasticity of a firm that has been undertaking R&D for only one year. Our estimated elasticity reaches its maximum value, approximately, on the 6th year of R&D experience, and decreases for further years of R&D experience. However, more than 70% of our sample distribution lies below a maximum value of 6 years of experience.

Columns II to V show the main results of this paper. The first and main conclusion from these estimations is that experience from in-house engagement in R&D activities seems to be a key driver in the achievement of product innovations. In Models II to IV the two coefficients corresponding to the interaction of R&D capital with internal R&D experience and its square, α_1^I and α_2^I , respectively, are statistically significant and of the same estimated signs as in our baseline model, where total R&D experience

was considered. However, the coefficients corresponding to the interaction terms of R&D capital with external R&D experience, α_1^E and α_2^E , do not render statistical significance. According to the definition of variables in Model II, we could say that only the number of years the firm has been conducting internal R&D activities is important in explaining R&D capital effectiveness, whereas the number of years of engagement in external R&D, if not accompanied by internal R&D activities, does not seem to help firms to make their R&D capital more productive in terms of product innovations. In Model III, where the internal and external components of total R&D experience are, respectively, the sum of the number of years doing internal and external R&D activities, multiplied by the shares of total R&D allocated to each of them in each year, results indicate that when firms intensify their strategy of internal R&D they also obtain a higher R&D capital elasticity. As for Model IV, we could reach a similar conclusion to the extent that the effectiveness of the R&D capital of firms with “*mainly an internal R&D strategy*” is affected by their R&D experience, while firms with “*mainly an external R&D strategy*” do not seem to get any return from the number of years of engagement in R&D.

The last column of Table 4 displays the results for Model V, which corresponds to Model II including the *dummy* variable, available only since 1998, that accounts for firms that *have recruited personnel with experience in corporate R&D during the current year*. This variable has a positive and highly significant effect on the achievement of product innovations, a result that reinforces the two main conclusions of our paper: first, that R&D experience is an important source of knowledge that matters to explain innovation results and, second, that it is the internal engagement in R&D activities what allows exploitation of the effects of learning through experience. Nonetheless, in this case the coefficient α_0 corresponding to the log of R&D capital is not significant. One of the possible reasons is that the number of sample observations is reduced considerably due to the lack of information before 1998 on the variable *Hired personnel in t with R&D experience*. Other possible explanation could be that the effect of R&D capital on the achievement of product innovations is captured by the variable *Hired personnel in t with R&D experience*, not included in the previous estimated Models.

Other complementary results in Table 4 are those related to informal innovation-related activities. In the estimation of the innovation production function offered in the top half of Table 4, we observe that both marketing and design activities contribute positively to the achievement of product innovations, whereas quality control activities exhibit a negative and significant sign.

We now turn to comment briefly the results of our zero-inflate equation, reported at the bottom half of Table 4. Recall that in this equation we estimate the probability of observing zeros, so that a positive sign of a parameter estimate means a higher probability of a zero, and a negative sign means a higher probability of observing a positive number of product innovations. A first result is that the *dummy* variable accounting for those firms that base their R&D strategy exclusively on external R&D helps significantly to predict the event of no product innovations. As for informal

innovation-related activities, almost all of them are negatively and significantly correlated with the event of a zero product innovation, reinforcing the hypothesis that these activities correlate positively with the innovative performance of firms. The only exception is imported technology that, although negative, it is not statistically significant. Furthermore, age explains, at a decreasing rate, the probability of zeros, indicating that younger firms are more product innovators than older ones. Finally, firm size intervals indicate that firms with 20 to 100 employees have a lower probability of a zero outcome.

6. Conclusions

In this paper we have tested two hypotheses related to firms' innovation activities using a representative sample of Spanish manufacturing firms for the period 1990-2006. The first hypothesis is that, due to knowledge cumulativeness, the effect of R&D-capital stock in the achievement of product innovations depends on R&D experience, defined as the period of time during which firms conduct R&D activities. Our second hypothesis is that the rate at which R&D investments yield product innovations depends on the type of R&D activities, distinguishing between firms' internal R&D experience and externalized or contracted out R&D. For testing both hypotheses we have estimated, within the framework of a knowledge production function and using *count* data models, the influence of firms' accumulated R&D experience on their R&D innovative outcomes, measured as the number of product innovations.

The results of our empirical analysis indicate that, after controlling for R&D-capital stock and other firms' individual heterogeneity factors, the number of product innovations introduced by firms rises with internal R&D experience, that is, with the accumulation of technical skills and knowledge that emerges as firms invest in in-house R&D over time. However, the experience that firms accumulate in conducting only external R&D does not seem to affect the number of product innovations introduced. This result is probably due to the nature of research related to extramural R&D activities, usually of a generic character and not specifically related to the development of new products, which usually requires firms' specific and complex knowledge, arising from a dynamic, cumulative process of internal R&D activities. Finally, and in addition to past R&D experience, some informal innovation-related activities have also been found to be important determinants in the achievement of product innovations.

Our results contribute to a better understanding of the role of the cumulative process of learning in the effectiveness of R&D investments. These findings may suggest the direction of potential policy measures to be implemented in order to stimulate the production of R&D knowledge. In particular, given that internal R&D experience positively affects the achievement of product innovations, our results indicate the convenience of implementing policy measures aimed at inducing firms

to engage in internal R&D activities. Our results are also interesting from a strategic management point of view. If in-house R&D experience is more convenient for the achievement of product innovations, this knowledge may be considered as a firm's strategic asset (in a similar way as plants, equipment or brand names), in order to maximize the returns from the investment in innovation.

Finally, with regards to future lines of research, it would be interesting to investigate the nature of the interactions between internal and external R&D, using an empirical approach that allows the joint analysis of these two firms' decisions. In particular, we would like to address the key question of whether these two types of R&D investments are bound together by a relationship of complementarity or substitutability, and how this relationship influences the achievement of innovation outcomes.

References

- [1] ACS, Z.J. and AUDRETSCH, D.B. (1989). «Patents as a measure of innovative activity». *Kyklos*, 42(2), 171-80.
- [2] BAHK, B. H. and GORT, M. (1993). «Decomposing learning-by-doing in new plants». *Journal of Political Economy*, 101, 561-583.
- [3] BENEITO, P. (2003). «Choosing among alternative technological strategies: an empirical analysis of formal sources of innovation». *Research Policy*, 32, 693-713.
- [4] BENEITO, P. (2006). «The innovative performance of in-house and contracted R&D in terms of patents and utility models». *Research Policy*, 35, 502-517.
- [5] BENEITO, P., ROCHINA BARRACHINA, M.E. and SANCHIS, A. (2011). «La experiencia en I+D como factor determinante de la innovación». *Papeles de Economía Española*, 127, 89-104.
- [6] BENEITO, P., ROCHINA-BARRACHINA, M.E. and SANCHIS, A. (2014). «Learning through experience in Research and Development: an empirical analysis with Spanish firms», *Technological Forecasting & Social Change*, 88, 290-305.
- [7] BOUND, J., CUMMINS, C., GRILICHES, Z., HALL, B.H. and JAFFE, A. (1984). «Who does R&D and who patents?», in Z. Griliches (ed.), *R&D, Patents and Productivity*, Cambridge, University of Chicago Press, 21-54.
- [8] BRANSTETTER, L. (1996). «Are knowledge spillovers international or intranational in scope? Microeconomic evidence from the U.S. and Japan», *NBER Working Paper Series*, No. 5800.
- [9] CAMERON, A.C. and TRIVEDI, P.K. (1998). *Regression Analysis for Count Data*, Cambridge: Cambridge University Press.
- [10] CEFIS, E. (2003). «Is there persistence in innovative activities?». *International Journal of Industrial Organization*, 21, 489-515.
- [11] COHEN, W.M. and LEVINTHAL, D.A. (1989). «Innovation and learning: the two faces of R&D». *The Economic Journal*, 99, 569-596.
- [12] COHEN, W.M. and LEVINTHAL, D.A. (1990). «Absorptive capacity: a new perspective on learning and innovation». *Administrative Science Quarterly*, 35, 128-152.
- [13] CRÉPON, B., DUGUET, E. and MAIRESSE, J. (1998). «Research, innovation and productivity: an econometric analysis at the firm level». *NBER Working Paper Series* 6696.

- [14] DOSI, G. and MARENGO, L. (1993). «Some elements of an evolutionary theory of organizational competences», in R. W. England (ed.), *Evolutionary Concepts in Contemporary Economics*, University of Michigan Press, Ann Arbor.
- [15] DOSI, G. and MARENGO, L. (2007). «On the evolutionary and behavioural theories of organizations: a tentative roadmap», *Organization Science*, 18, 491-502.
- [16] GEROSKI, P.A., VAN REENEN, J. and WALTERS, C.F. (1997). «How persistently do firms innovate?». *Research Policy*, 26, 33-48.
- [17] GRILICHES, Z. (1979). «Issues in assessing the contribution of R&D to productivity growth». *Bell Journal of Economics*, 10, 92-116.
- [18] GRILICHES, Z. (1990). «Patent statistics as economic indicators: a survey». *Journal of Economic Literature*, 28, 1661-1707.
- [19] GURMU, S. (1997). «Semi-parametric estimation of hurdle regression models with an application to medic aid utilizations». *Journal of Applied Econometrics*, 12: 225-242.
- [20] HALL, B.H., GRILICHES, Z. and HAUSMAN, J. (1986). «Patents and R&D: is there a lag?». *International Economic Review* 27(2), 265-283.
- [21] HALL, B.H. and MAIRESSE, J. (1995). «Exploring the relationship between R&D and productivity in French manufacturing firms». *Journal of Econometrics*, 65, 263-293.
- [22] HAUSMAN, J., HALL, B.H. and GRILICHES, Z. (1984). «Econometric models for count data with and application to the patents-R&D relationship». *Econometrica*, 52(4), 354-383.
- [23] HENDERSON, R. and COCKBURN, I. (1993). «Scale, scope and spillovers: the determinants of research productivity in the pharmaceutical industry». *NBER Working Paper Series* 4466.
- [24] JOVANOVIĆ, B. and NYARKO, Y. (1995). «A Bayesian learning model fitted to a variety of empirical learning curves». *Brookings Papers on Economic Activity*, 247-299.
- [25] KLOMP, L. and VAN LEEUWEN, G. (2001). «Linking innovation and firm performance». *International Journal of the Economics of Business*, 8(3), 343-364.
- [26] KREMP, E. and MAIRESSE, J. (2004). «Knowledge management, innovation and productivity: a firm level exploration based on French manufacturing CIS3 data». *NEBR Working Paper* 10237, Cambridge, MA.
- [27] LÖÖF, H. and HESHMATI, A. (2001). «Knowledge capital and performance heterogeneity: a firm level innovation study». *International Journal of Production Economics*, 0, 1-25.
- [28] 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.
- [29] MALERBA, F., ORSENIGO, L. and PERETTO, P. (1997). «Persistence of innovative activities', sectoral patterns of innovation and international technological specialization». *International Journal of Industrial Organization*, 15, 801-826.
- [30] MÁÑEZ, J.A., ROCHINA-BARRACHINA, M., SANCHIS-LLOPIS, A. and SANCHIS-LLOPIS, J.A. (2009). «The role of sunk cost in the decision to invest in R&D». *Journal of Industrial Economics*, 57(4), 712-735.
- [31] MOWERY, D.C. (1983). «The relationship between intrafirm and contractual forms of industrial research in American manufacturing, 1900-1940». *Explorations in Economic History*, 20, 351-374.

- [32] NELSON, R.R. (1982). «The role of knowledge in R&D efficiency». *Quarterly Journal of Economics*, 97, 453-470.
- [33] NELSON, R. and WINTER, S. (1982). *An Evolutionary Theory of Economic Change*, Cambridge, Harvard University Press.
- [34] NEWELL, A. and SIMON, H.A. (1972). *Human Problem Solving*, Prentice Hall, Englewood Cliffs, NJ.
- [35] PAKES, A. and GRILICHES, Z. (1984). «Patents and R&D at the firm level: a first look», in Z. Griliches (ed.), *R&D, Patents and Productivity*, Cambridge: University of Chicago Press, 55-72.
- [36] PAVITT, K. (1984). «Sectoral patterns of technological change: towards a taxonomy and a theory». *Research Policy*, 13, 343-373.
- [37] PETERS, B. (2007). «Persistence in innovation: stylised facts and panel data evidence». *Journal of Technological Transfer*, forthcoming.
- [38] ROSENBERG, N. (1976). *Perspectives on Technology*, Cambridge University Press, Cambridge.
- [39] SMITH, K. and SANDVEN, T. (2001). «Innovation and economic performance at the enterprise level». *Innovation and Enterprise Creation: Statistics and Indicators*, European Commission, Luxembourg, 106-116.
- [40] SCHERER, F. M. (1965). «Corporate inventive output, profits and growth». *Journal of Political Economy*, 73 (3), 240-297.
- [41] SCHERER, F. M. (1983). «The propensity to patent». *International Journal of Industrial Organization*, 1, 107-28.
- [42] SCHMOOKLER, J. (1966). *Invention and Economic Growth*, Cambridge: Harvard University Press.
- [43] VUONG, Q. (1989). «Likelihood ratio tests for model selection and nonnested hypotheses». *Econometrica*, 57, 307-333.
- [44] WEST, J. and IANSITI, M. (2003). «Experience, experimentation, and the accumulation of knowledge: the evolution of R&D in the semiconductor industry». *Research Policy*, 32, 809-825.