Economics of Innovation and New Technology
Vol. 20, No. 8, November 2011, 727–748

Productivity and R&D sources: evidence for Catalan firms

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(*Received 4 November 2009; final version received 30 September 2010*)

This paper draws on a sample of innovative Catalan firms to identify how two main sources of innovation – internal R&D and external R&D acquisition – affect productivity in the manufacturing and service industries. The sample comprises 1612 innovative firms from the fourth European Community Innovation Survey (CIS-4) during the period 2002–2004. We compare empirical results when applying the usual OLS and quantile regression techniques controlling with a non-parametric sample selection. Our results indicate the different patterns that are attributable to the two sources of innovation as we move up from lower to higher conditional quantiles. First, the marginal effect of internal R&D on productivity decreased as we moved up to higher productivity levels. Second, the marginal effect of external R&D acquisition increased as we moved up to higher productivity levels. Finally, empirical results show significant complementarities between internal and external R&D, which are higher for knowledge-intensive service sectors.

Keywords: innovation sources; productivity; quantile regression; sample selection

JEL Classification: O300; C100; O140

1. Introduction

The effect of innovative activity on growth and productivity at the firm level has received much attention in recent years (see Hall, Mairesse, and Mohnen 2010 for their survey). This can be explained in part by the increased availability of micro-level data from innovation surveys conducted in the EU. These surveys have enabled a growing number of studies into the links between R&D, innovation and productivity to be undertaken. In general, these empirical studies have found a direct link between R&D and innovation, on the one hand, and productivity, on the other hand, both in terms of levels and rates. But empirical evidence gathered at the firm level underlines the high degree of heterogeneity in the efficiency and productivity levels of firms within the same industry (Bartelsman and Doms 2000; Baldwin and Gu 2006; Haltiwanger, Lane, and Spletzer 2007). Moreover, regarding the productivity differentials between firms, evidence shows that productivity level dispersion is extensive and persistent over space and time.[1]

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ISSN 1043-8599 print/ISSN 1476-8364 online

http://dx.doi.org/10.1080/10438599.2010.529318
http://www.tandfonline.com

The reasons underpinning these productivity differentials are diverse. Productivity levels reflect factors such as investment in equipment, R&D activities, use of new technologies and the skill of the workforce (Caselli 1999). In addition, Bresnahan, Brynjolfsson, and Hitt (2002) argue that practices related to the use of information technologies and organizational changes in a firm's structure have complementary effects on productivity. Furthermore, these authors claim that a synergy, or complementarity, exists between such innovations and the percentage of skilled workers in the firm.[2] The joint analysis between technology, skilled workers and a firm's characteristics (market share, export activities, innovation performance, etc.) can also shed light on the complementarity between internal and external sources of knowledge generation.

The aim of this paper is to analyse the effects of internal and external R&D on the productivity levels of manufacturing and service firms in Catalonia. In general, recent literature on the impact of R&D sources does not distinguish according to firm productivity. In order to tackle this, we use quantile regression techniques to analyse R&D returns on labour productivity across the entire productivity distribution function. Hence, we focus on the marginal effects of internal and external sources of R&D on labour productivity across the overall distribution. Furthermore, our results also shed light on complementarities between both R&D across the firm productivity distribution.

Since Cohen and Levinthal's (1989) contribution, R&D investments have adopted a dual dimension. When a firm invests in internal R&D, it stimulates its own innovation and also develops its absorptive capacity. According to this approach, there is a clear temporal synchronization between internal and external R&D. First, a firm invests in internal R&D activity and increases its ability to capture external knowledge. Second, a firm invests in external R&D and captures the knowledge developed outside of the firm (Fabrizio 2009).

This positive relationship between both sources of R&D suggests that these activities are complementary, that is, the marginal returns on one activity increase as the intensity of the other activity increases (Cassiman and Veugelers 2006). There is evidence to indicate that internal R&D activities have both direct and indirect effects on a firm's productivity: a direct effect in that these activities increase innovation and an indirect effect in that they increase a firm's ability to absorb external R&D (Cohen and Levinthal 1989). The hypothesis we seek to test is the following: internal and external R&D investments play a complementary role in those firms that invest in both sources, and that these firms obtain larger returns than other innovative firms that only invest in internal or external R&D sources.

By partially adopting the analytical framework described by Crépon, Duguet, and Mairesse (1998), we can establish a sequence that ranges from a firm's R&D activities to how these activities affect its productivity. Thus, in line with Lokshin, Belderbos, and Carree (2008), we aim to analyse the direct link between R&D activities and firm productivity. Despite the considerable heterogeneity associated with firm innovation, the literature still tends to use the regression methodology based on standard OLS. However, the usual assumption of normally distributed error terms is not warranted here as the distribution of innovation expenditure is highly skewed, yet despite this potential bias, few empirical studies have dealt with the problem. In this framework, therefore, conditional regression techniques constitute a suitable instrument for examining non-normally distributed error terms. Our results confirm our hypothesis: those firms with low productivity levels show higher sensibility to internal R&D investment, while firms with high productivity levels obtain higher returns on external R&D investment.

This paper makes three contributions to the analysis of the link between internal and external R&D and the productivity of the firm. First, we observe the effects of the two main sources of innovation – internal and external R&D investment – on the productivity of manufacturing and service industries. This is because very few studies have linked innovation sources and productivity at the firm level in both these sectors (Miles 2005), despite the increasing weight of the service sector in innovation activities and the overall economy. Second, we analyse the complementarity between both sources of innovation across the firm productivity distribution. Third, we use quantile regression to observe the effects of internal and external R&D across different productivity levels. This paper compares OLS and quantile regression parameters controlling for sample selection and provides a rich view of R&D–productivity relationships.

The remainder of this paper is organized as follows. Section 2 reviews the literature that discusses the relationship between internal and external R&D. Section 3 presents the data set and describes the variables used in our analysis. Section 4 outlines the econometric methodology. Section 5 sets out our empirical results, and Section 6 highlights our main conclusions.

2. The complementarity of internal and external R&D

Complementarity between a firm's activities appears when the carrying out of one activity increases both the firm's propensity to adopt other activities and the marginal returns on its other activities. Such complementarities are an important part of a firm's strategy since they are crucial for its survival. First, they prevent imitation by rivals since the success of innovation depends on the internal strategies of the other firms (Dierickx and Cool 1989). Second, complementary assets raise the value of a firm's technological innovations (Teece 1986). Third, they allow the firm to reap the benefits of innovative activities. This section discusses the literature that has analysed the complementarities between internal and external R&D.

Internal R&D activities performed by firms affect their capacity to generate and assimilate knowledge in a variety of ways. Typically the literature distinguishes two 'faces' of internal R&D. The first is the direct effect of R&D in promoting innovation. Over the last decade, the empirical literature has paid increasing attention to the effects of R&D on the innovative performance of firms (Griliches 1995; Crépon, Duguet, and Mairesse 1998; Mairesse and Mohnen 2005; Hall and Mairesse 2006; Mohnen, Mairesse, and Dagenais 2006). In general, their results show that the probability of a firm becoming innovative increases with internal R&D input.

The other face of internal R&D is that it can indirectly increase the impact of R&D spillovers and facilitate the imitation of cutting-edge innovation in a particular technological or scientific field. This aspect of the role of internal R&D is related to the interaction between the internal capacity to generate knowledge and the absorptive capacity to capture external knowledge generated by others. This second face of internal R&D originates from the tacit dimension of knowledge and can be perceived in different ways, including technology transfer flows, R&D spillovers, and the capacity of the firm to imitate the innovation generated by others.

The significance of the indirect effects of R&D has been stressed in a number of studies. For example, Arrow (1962) stresses the role of tacit knowledge in the generation of technological innovation and the relevance of learning-by-doing in adaptation to new technologies. Similarly, Teece (1986) shows that innovative firms have a vector of complementary assets which determine their capacity for appropriating returns on innovation. At the same time, firms may invest in appropriation instruments to reduce outgoing spillovers (Arrow 1962). In general, appropriation instruments fall within two categories: legal and strategic. The former includes patents, trademarks, and copyrights, while strategic instruments include investments in complementary assets, secrecy and lead time, and the relative complexity of products and services (Mansfield 1986). However, the effectiveness of appropriation barriers varies across industries, so when the effects are low and the cost is high the firm's incentives to invest in R&D and innovation fall.[3]

However, Griliches's (1979) seminal paper proposes two different concepts of *spillovers* that are often misunderstood in the economic literature. The first refers to pecuniary *spillovers*, which are related to the intermediate inputs that a firm acquires at a lower price if it takes into account the quality of inputs. However, these are not real *spillovers*, but a reflection of the difficulties inherent in accurately valuating technological improvements, which themselves result from the traditional problems in measuring the variables. The second concept refers to authentic technological *spillovers* and is related to the set of technical knowledge that a firm's researchers obtain during their research. This concept therefore considers the technological research to be the result of two main factors (Nordhaus 1962): on the one hand, there is the low cost of the knowledge compared with their generation; and, on the other hand, there are the problems of appropriability associated with the lack of measures for protecting the new technological knowledge.

Adopting an alternative analytical approach, Cohen and Levinthal (1989) introduced the term 'absorptive capacity' in describing the dual role of R&D in a firm's ability to both produce new information and learn from existing information. The notion of 'absorptive capacity' highlights the importance of the R&D undertaken by a firm and the complementarities between internal and external R&D sources (Veugelers 1997). Arora and Gambardella (1994) and Cassiman and Veugelers (2000) propose two dimensions to this absorptive capacity. The first one is related to the firm's ability to scan the market and to evaluate external information, and the second one is related to the firm's ability to use information and to absorb the technology acquired. Additionally, Cassiman and Veugelers (2002) distinguish between incoming spillovers related to a firm's absorptive capacity, which affect the innovation rate of the firms, and appropriability, which affects the ability of the firm to reduce outgoing spillovers and to appropriate the returns from innovation.

In fact, recently Zahra and George (2003) have suggested, first, that absorptive capacity is a multidimensional construct that impinges at different times on different capabilities and routines, and, second, by pointing out the existence of two types of absorptive capacity: potential and realized. More recently, Fosfuri and Tribó (2008) studied a sample of 2464 innovative Spanish firms and found evidence that for R&D cooperation, external knowledge acquisition and experience with knowledge searching are key antecedents of a firm's potential absorptive capacity (PAC). Finally, those authors found that PAC is a source of competitive advantage in innovation, which helps to reduce the distance between potential and realized capacity.

Empirical evidence describing the two faces of R&D (that is, the direct effect of inducing innovation and the indirect effect of facilitating absorptive capacity) presents several stylized facts at the sectoral and firm level. At the sectoral level, Griffith, Redding, and Van Reenen (2003) offer a single model that integrates the theoretical literature on Schumpeterian endogenous growth and the empirical literature on R&D and productivity. Their model identifies three sources of productivity growth: R&D-induced innovation, technology transfer, and R&D-based absorptive capacity. Using industry level data for a panel of OECD countries these authors find evidence that R&D raises the rate at which technology is transferred from frontier to non-frontier countries. With a similar panel of 12 OECD countries, Griffith, Redding, and Van Reenen (2004) report how human capital and R&D increase the absorptive capacity to adopt efficient technologies in countries that lie far behind the technological frontier. Finally, for nine industries in 12 OECD members, Kneller and Stevens

(2006) find that the differences in absorptive capacity explain cross-country differences in productivity levels.[4]

Furthermore, there is also evidence about the benefits of external R&D on the adoption of internal R&D. Bönte (2003) points out that increasing the external R&D share positively affects productivity because it leads to specialization and/or knowledge spillovers, but up to a limit. Furthermore, the combination between internal and external R&D increases the complexity of the innovation and protects a firm from its competitors. His results show that external R&D has a positive effect on productivity. Finally, Bönte (2003) claims that the literature does not identify differences between the impact of internal R&D and external R&D on firms' growth or productivity. In that sense, we analyse the effect of internal and external R&D on productivity at the sectoral level.

In short, the empirical evidence indicates that a firm's innovation activities are related to its ability to absorb external information, knowledge, and technologies. In this sense, a recent trend in the analysis of innovative performance at the firm level involves observing whether internal and external R&D are complementary or not. When firms carry out internal and external R&D activities simultaneously, it can be assumed that the marginal return on one activity increases as the intensity of the other activity increases. In this case internal and external R&D activities are complementary (Cassiman and Veugelers 2006).

The importance is that the return on internal and external R&D may be different depending on the productivity level. Beneito (2006) points out that previous models neglect the different returns on R&D sources. She shows that internal R&D activities in isolation may succeed in terms of incremental and radical innovations but that external R&D does not create radical innovations, unless it is combined with internal capabilities. Here, we aim to analyse the complementarity between internal and external R&D investment and the differences across the firm productivity distribution.

Furthermore, there is no evidence regarding the differences in the level of complementarity of R&D sources between high and low productive firms. Hence, we are interested in measuring the marginal effects of internal and external R&D when a firm's labour productivity levels vary and whether there are any differences at the sectoral level.

3. Data and summary statistics

The data used in this study were provided by a sample of Catalan firms who responded to the fourth version of the Community Innovation Survey (CIS-4). The CIS is the main statistical instrument used by the EU to analyse the returns of public policy and thus determine the innovation process at the firm level. The CIS has been carried out every 4 years since 1992. CIS-4 collected firm innovation data during the period 2002–2004 (Table 1).

Catalonia is an interesting case to study for various reasons. First, Catalan firms are much more committed to R&D activities than those from other Spanish regions. Second, although the urban system is dominated by the Barcelona metropolitan area, there is also a network of medium-sized cities with considerable economic and social vitality. Third, the region's industrial tradition is based on medium and low technological manufacturing industries and is undergoing increasing specialization in services.[5] Fourth, in Catalonia, knowledge-intensive services (KISs) play an important role in spreading knowledge and in firm innovation projects.

Our database contains CIS questionnaires completed by 3267 Catalan firms, of which 1612 invest in R&D. Among the firms that invest in R&D, 750 operate in high-tech manufacturing industries, 557 in low-tech manufacturing industries, and 305 in KIS. This industrial classification based on technology and knowledge intensity in manufacturing and service industries follows OECD criteria.

The CIS survey provides exhaustive information about innovation expenditure. The questionnaire asked firms to: 'Please estimate the amount of expenditure for each of the following four innovation activities in 2004 only' (p. 5, question 5.2 of the CIS-4 survey), with the following options: internal R&D; acquisition of R&D; acquisition of machinery, equipment and software; acquisition of external knowledge; training; all forms of design; and marketing expenditure. In this way, the CIS survey allows us to study a firm's R&D strategies as it provides information about its R&D decision process.

Table 1 shows a descriptive distribution of the innovation expenditure in the CIS sample of Catalan firms in the year 2004. Internal R&D projects are carried out by 1503 firms, accounting for 54.1% of the total innovation expenditure of our sample. A small group of 679 firms acquires external R&D, accounting for 21.7% of total innovation expenditure. Furthermore, the two main innovation sources related to internal and external R&D account for three of every four euros that Catalan firms spend on their innovation projects. The remaining sources of innovation register more moderate amounts.[6]

As in other economies, R&D and innovation in Catalonia also differ across industries and firms. Our database shows that the 1% of firms that made the largest investments in innovation concentrated 48.6% of the total, while 5% of firms made 70.1% of the total investment. This skewed distribution of innovation expenditure at the firm level can be explained by a variety of factors. First, R&D and innovation activities are uncertain and risky and the returns for success are extremely variable. Second, few firms have the required financial capacity to engage in innovation projects, which usually need to be carried out over long periods of time. And third, not all firms can effectively protect their innovations in the market and enjoy returns on their innovations.

This heterogeneity can be observed when comparing new firms and incumbents. In general, R&D investment and labour productivity differ between firms. On the one hand, new firms invest more in R&D per employee but their productivity is lower and they are

Table 1. Sources of firm innovation (2004).

	All firms	High-tech industries	Low-tech industries	KISs
Number of firms	3267	1130	1443	694
Number of firms with R&D activities	1612	750	557	305
Firms with internal R&D activities	1503	713	504	286
Firms with external R&D activities	679	325	218	136
Innovation expenditure per firm (1)	882.9	1489.9	260.4	1189.0
R&D expenditure per firm (1)	669.4	1157.7	148.3	957.9
Other innovation sources (1)	213.5	332.2	112.1	231.1
Innovation expenditures by sources				
Internal R&D	(54.1)	(47.3)	(50.6)	(69.5)
External R&D	(21.7)	(30.4)	(6.3)	(11.0)
Machinery and software	(15.4)	(17.6)	(25.5)	(6.3)
External knowledge	(1.2)	(0.9)	(0.7)	(2.2)
Training	(0.7)	(0.4)	(0.6)	(1.4)
All forms of design	(2.2)	(2.1)	(4.4)	(1.5)
Marketing expenditures	(4.6)	(1.3)	(11.7)	(8.0)

Source: Catalan Innovation Survey.
Note: (1) average firm amounts in thousands of euros, percentage in parentheses.

Table 2. Productivity and innovation expenditures.

	New firms	Incumbents firms	Firms with less than 100 workers	Firms with more than 100 workers
Productivity (sales by workers)	90,147	155,858	135,089	200,572
Innovation expenditure by employees	35,882	5590	7076	4506
R&D internal by employees	24,316	3640	4740	2694
R&D external by employees	7660	657	787	922
Size (workers)	32	172	34	492

Source: Catalan Innovation Survey.
Note: Amounts in euros.

smaller than incumbent firms. On the other hand, small firms present larger internal R&D and innovation investment per worker than larger firms. However, small firms invest less in external R&D and obtain lower productivity per employee (Table 2).

When firms engage in R&D activities, they first have to take two important decisions. First, they must choose how to implement R&D projects internally and externally. Second, they have to decide how much to invest in their R&D projects. Although a considerable body of empirical research has focused on this second question (Geroski 1990; Griliches 1995; Crépon, Duguet, and Mairesse 1998; Mairesse and Mohnen 2005), the evidence suggests that the first question is also important and that responses can differ markedly between industries and firms (Love and Roper 2002). During the process of establishing a firm's innovation strategies, the choice as to whether a firm should undertake internal R&D (*make)* or whether it should invest in external R&D (*buy*) is crucial.

Figure 1 presents the log distribution of internal and external R&D investment per worker for firms in our sample. We observe that there is a heterogeneous pattern in the R&D investment per employee, regardless of the R&D source. However, the mode for external R&D investment is lower than the mode for internal R&D investment. Furthermore, the distribution of internal R&D is much more concentrated than for the external R&D.

But what happens if we plot simultaneously both variables? Figure 2 plots the simultaneous expenditure on internal and external R&D per worker (in logs) for innovating firms.

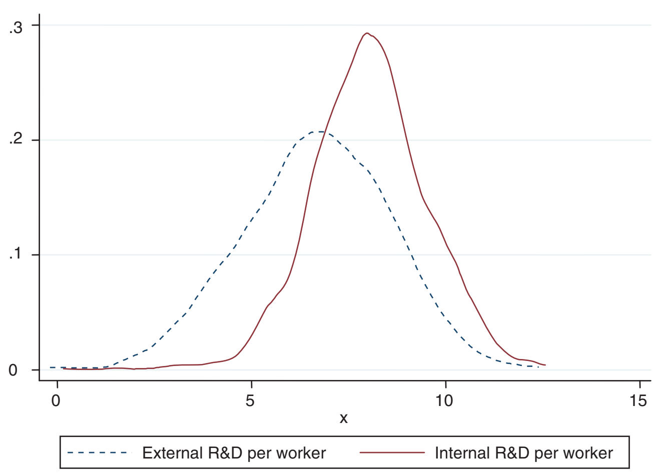

Figure 1. Kernel density of internal and external R&D investment per worker (in log terms).
Source: Authors.

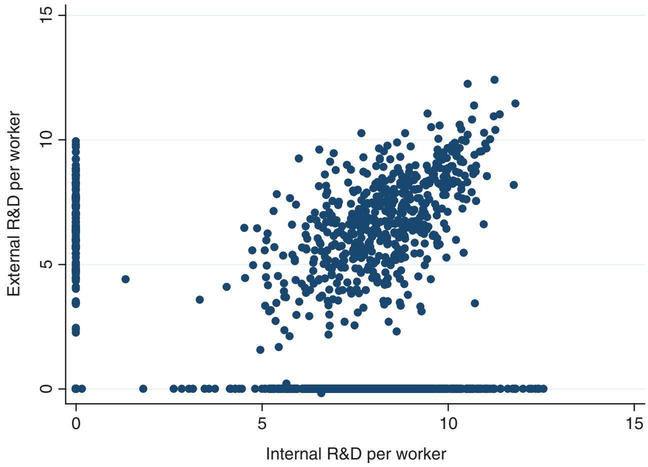

Figure 2. Plot of internal and external R&D investment per worker (in log terms).
Source: Authors.

First of all, three different strategies appear: (i) firms that only invest in external R&D (those in the *y*-axis), (ii) firms that only invest in internal R&D (those in the *x*-axis), (iii) and finally those investing in both sources. Second, firms that invest simultaneously in both R&D sources simultaneously show a positive relationship between internal and external R&D expenses. In other words, those firms that invest more in internal R&D will also invest more in external R&D.

Table 3 shows the frequency with which firms adopted each R&D innovation strategy. Our results show how innovation strategies differ between the three sectoral groups. Firms that operate in high-tech manufacturing industries are more likely to undertake

Table 3. Internal and external R&D firm strategies.

	Firms	R&D strategy (%)	Product new to the firm (%)	Product new to the market (%)
High-tech manufacturing industries				
Make and buy	288	25.5	14.5	11.7
Make only	425	37.6	15.6	7.8
Buy only	37	3.2	7.4	3.5
No make and buy	380	33.6	5.7	0.9
Total	1130	100.0	11.7	6.3
Low-tech manufacturing industries				
Make and buy	165	11.4	14.5	5.2
Make only	339	23.4	11.6	7.3
Buy only	53	3.6	8.6	7.1
No make and buy	886	61.4	5.3	1.0
Total	1443	100.0	7.9	3.2
Knowledge-intensive services				
Make and buy	117	16.8	14.4	20.4
Make only	169	24.3	13.9	16.0
Buy only	19	2.7	16.3	0.26
No make and buy	389	56.0	3.5	1.9
Total	694	100.0	8.2	8.4

Source: Catalan Innovation Survey.

R&D (37.6%), while a high percentage of these firms carry out both internal and external R&D (25.5%). However, the percentage of firms with internal R&D or internal and external R&D falls in low-tech manufacturing industries and in the service industries.

Furthermore, firms that only buy external R&D are scarce, around 3% over the whole sample, although when we only consider firms investing in R&D the percentage increases (up to 4.9% in high-tech manufacturing industries, 9.5% in low-tech manufacturing industries, and 6.2% in KISs). The scarcity of firms investing only in external R&D reflects the importance to a firm of engaging in earlier internal R&D activities so it can develop its absorptive capacity and capture the returns of external R&D. In addition, internal R&D has a positive effect on output innovation measured as a firm's share of new products, both when it produces a moderate innovation – new to the firm – and when it produces substantial innovative output – new to the market.[7]

However, the relationship between internal and external R&D is complex, because it is affected by both individual and sectoral dimensions. Before analysing the extent of the impact of R&D sources on productivity, we focus on whether there is a significant difference in return between adopting a *buy only*, *make only*, or a *buy and make* strategy. In order to determine this, we analyse the complementarities between internal and external R&D using the theory of supermodularity. We assume a firm can perform two activities: internal R&D, A_1, and external R&D, A_2. A firm can adopt two binary decisions in relation to each activity; these being $A_i = 1$ when a firm performs the activity and $A_i = 0$ otherwise. The function $\Pi(A_1, A_2)$ is supermodular and A_1 and A_2 are complementary only if,

$$\Pi(1,1) - \Pi(0,1) \geq \Pi(1,0) - \Pi(0,0).$$

In other words, the complementarity test measures how productivity is affected when a firm adds an activity to one that it is already carrying out and compares this to a situation where a firm adopts an activity in isolation. Thus, supermodularity leads to a formalization of synergies and system effects. The complementary test was estimated following Mohnen and Röller (2005), Cassiman and Veugelers (2006), and Belderbos, Carree, and Lokshin (2006). First, we regressed firm productivity on dummies that identify combinations of innovation activities, these being: firms that only have their own R&D activities (*make only*); firms that only have external R&D sources (*buy only*); and firms that combine their own R&D activities with external R&D sources (*make and buy*). Second, we make the same estimation depending on the sectoral classification. Finally, we apply a one-sided complementarity test in order to test the incremental effect of adding an innovation activity.

Table 4. Correlation between the internal and external R&D activity.

	Internal R&D	External R&D
High-tech manufactures		
Internal R&D	1.000	
External R&D	0.336*	1.000
Low-tech manufactures		
Internal R&D	1.000	
External R&D	0.361*	1.000
KISs		
Internal R&D	1.000	
External R&D	0.449*	1.000

Source: Catalan Innovation Survey.
*Significant at 1%.

Table 5. Test for complementarity between R&D sources.

	F-value	Probability
Whole database	0.90	0.3440
High-tech manufacturing industries	3.99	0.0461
Low-tech manufacturing industries	0.69	0.4049
Knowledge-intensive services	0.02	0.8999

Note: We test the following equation: $-\text{buyonly} - \text{makeonly} + \text{makebuy} = 0$.

Table 5 shows the complementarity test classified by sectors. Our results show that carrying out internal and external R&D had a significant positive impact on productivity for high-tech manufacturing industries, whereas this positive relationship was not significant for the low-tech manufacturing and service industries.

4. Econometric methodology

4.1. Econometric model

Since Crépon, Duguet, and Mairesse's (1998) contribution, the relationship between R&D, innovation, and productivity has been widely examined at the firm level. In general, empirical studies based on cross-section data find a significant link between the adoption of R&D and innovation activities and an increase in a firm's productivity.[8] In particular, R&D generates new knowledge and brings new products to the firm and the market (Nelson and Nelson 2002); and internal R&D plays the dual role of producing new knowledge and promoting a firm's 'absorptive capacity' from external sources of information (Cohen and Levinthal 1990). Therefore R&D can affect productivity by facilitating the absorption of new technologies (Parisi, Schiatarelli, and Sembenelli 2006).

Following Crépon, Duguet, and Mairesse (1998) and Mairesse and Mohnen (2005), here we explore the relationships between two main sources of innovation – internal and external R&D – and productivity in a sample of 1612 innovative firms. It is well known that the basic CDM model consists of a system of three equations: a tobit model explaining R&D decisions, an equation linking innovation output to R&D, and an equation linking labour productivity to innovation and R&D.[9] However, the CDM framework has been extended in various directions. Here, we are interested in observing the marginal effect of internal and external R&D sources on productivity when we are moving across the productivity level.

We apply a reduced-form estimation of the CDM model to Catalonia.[10] The R&D process impacts on innovation; however, the learning process can also have an impact on the productivity, without necessarily leading to innovation. In the empirical analysis, we consider only the direct R&D-productivity relationship, not the indirect effects related to innovation output (product and process innovation, patents, new products, etc.). Thus, we focus on the relationship between sources of innovation and productivity by applying the OLS and quantile methods to the reduced-form estimation of the CDM model.

We are especially interested in observing the evolution in R&D elasticity across the entire conditional distribution of productivity with the following equation,

$$\begin{aligned} y_i = \alpha &+ \beta_1 \text{R\&Dinternal}_i + \beta_2 \text{R\&Dexternal}_i + \beta_3 \text{Size}_i \\ &+ \beta_4 \text{MarketShare}_i + \beta_5 \text{Group}_i + \beta_6 \text{Investment}_i \\ &+ \beta_7 \text{Export}_i + \beta_8 \text{SectoralDummies}_i + \varepsilon_i \end{aligned} \tag{1}$$

where for each individual firm 'i', y is productivity measured by sales per employee. This variable measures the appropriability capacity of firm production and, specifically, the capacity of R&D investment to capture the market value.[11] R&Dinternal is the internal R&D expenditure per employee; R&Dexternal is the amount of external R&D expenditure per employee; size is the firm size measured in employees; MarketShare is the firm's market share measured by firm sales divided by its industry sales, group is a dummy that indicates whether the firm belongs to a group; Investment is the physical capital investment per employee; export is a dummy variable that captures if the firm sells abroad; SectoralDummies are two-digit industry dummies that control for fixed industry effects such as some sectors having a greater tendency to present higher productivity or different technological regimes; and ε is the standard error. All variables are expressed in logs.[12] Finally, we should mention that we are aware that our database is a cross-section which avoids capturing the temporal dynamics.[13]

4.2. Econometric methodology

In our case, the quantile regression procedure allows us to give a more complete picture of the underlying relationship between sources of innovation and productivity. Quantile methods may be preferable to the more usual regression methods for several reasons. First, the standard least-squares assumption of normally distributed errors does not hold for our data because innovation expenditure and innovation intensity present a skewed distribution. Second, while conventional regressions focus on the average firm, quantile regression can describe the complete conditional distribution of the dependent variable. And third, quantile regression is more efficient at treating outliers and heavy-tailed distributions.

The initial quantile regression method was suggested by Koenker and Bassett (1978) as an alternative to OLS when errors are not normally distributed. The central idea in quantile regression is to minimize the sum of absolute residuals by giving different weights to the quantiles that are being investigated. It is a powerful tool that, given a set of explanatory variables, characterizes the entire distribution of a dependent variable in greater detail than OLS methods (see a survey in Koenker and Hallock 2001). The quantile regression method specifies the conditional quantile as a linear function of covariates. In our case, we can write the θth quantile as

$$Q_\theta(y_i|x_i) = x_i'\beta_\theta + \varepsilon_{\theta i}'$$

where y_i is the productivity level measured by sales per employee, x_i is a vector of independent variables, β_θ is an unknown vector of regression parameters associated with the θth quantile and $\varepsilon_{\theta i}$ is an unknown error term. The only necessary assumption concerning $\varepsilon_{\theta i}$ is $Q_\theta(\varepsilon_{\theta i}|x_i) = 0$. The θth regression quantile, $0 < \theta < 1$, is the solution to the minimization of the sum of absolute deviation residuals,

$$\min_\beta \frac{1}{n}\left(\sum_{i:y_i \geq x_i'\beta} |y_i - x_i'\beta|\theta + \sum_{i:y<x_i'\beta} |y_i - x_i'\beta|(1-\theta)\right)$$

which is solved by linear programming methods. When θ is continuously increased from 0 to 1, we obtain the entire conditional distribution of y conditional on x (Buchinsky 1998).[14] Our empirical evidence shows that few firms carry on R&D activities. Hence, if we restrict our analysis to firms with R&D investment, our sample may be affected by sample selection.[15] To solve this problem, Heckman (1979) describes a two-step procedure assuming that there is joint normality of the error terms in both equations. However, quantile regression assumes that errors are not normally distributed. To cope with this problem, Buchinsky (1998, 2001) applied a non-parametric methodology to estimate the sample selection equation.

Following Buchinsky (1998, 2001), Fitzenberger and Wilke (2006) and Albrecht, van Vuuren, and Vroman (2009), here we use a semiparametric estimation of the probability of investing in R&D activities which depends on firm size. Thus, our final equation will be

$$Q_\theta\,(y_i|x_i) = x_i'\beta_\theta + h_\theta'(x_1, \gamma_0) + \varepsilon_{\theta i}'$$

where $h_\theta(x_1, \gamma_0)$ controls for sample selection at the θth quantile. Thus it plays the role of the inverse of Mill's ratios, but it is quantile-specific and more general so as not to assume normality. This equation is estimated for those firms that invest in R&D, and β_θ is the true value of the coefficient correcting sample selection.

Table 7 presents the OLS results and five conditional regression quantile results for $\theta =$ 0.10, 0.25, 0.50 (hence the median), 0.75 and 0.90. The quantile regression parameters are computed using bootstrapped standard errors (200 replications). In the bootstrap resampling procedure, the quantile regression parameters remain unchanged since only estimates of standard error and significance levels are affected. Quantile regression coefficients can be interpreted as the marginal change in y at the θth conditional quantile caused by marginal change in a particular regressor, $\Delta Q_\theta\,(y_i|x_i)/\Delta x$.

5. Quantile regression results

How do R&D strategies affect labour productivity? This section presents our empirical analysis at two levels. First, we present the overall sample of innovating firms to capture the main stylized facts of the link between R&D activities and firm productivity level. Second, we classify our sample at the sectoral level to distinguish between high-tech and low-tech manufacturing industries and KISs. In both cases, we apply quantile regression techniques to control for sample selection.

We begin by looking at the matrix of contemporaneous correlations for the variables which will be introduced in our equation (Table 6). The correlations between all the variables are far from perfect. In fact the largest correlation is obtained between the dummy identifying firms belonging to a group and firm size (with a correlation equal to 0.523).

Before commenting on our results in detail, we should say that our estimations include the nonlinear estimation of Mills ratio in order to control for sample selection bias. This variable is included in our estimations (Tables 7 and 8) and has a significant impact on nearly all our equations of interest. Hence, firms investing in R&D have non-observable characteristics that must be controlled.

Table 7 shows the empirical results for the overall sample of Catalan firms that invest in R&D. First of all, we should highlight the differences between OLS and quantile regression. In OLS, the elasticity of internal R&D is equal to 3.96% but the external R&D obtains a moderate non-significant impact equal to 0.78%. However, the use of quantile regression techniques helps to identify differences in the impact of R&D sources on the distribution of productivity. In quantile regressions, the marginal effect of internal and external R&D differs as we moved across firms' productivity levels. Our results show that for low productivity levels the marginal effect of internal R&D activities is higher, but this parameter decreases as we move up to higher productivity levels. In contrast, the external R&D activities obtain smaller non-significant marginal effects for low productivity levels, but at the median of the distribution the elasticity increases and results become significant.

With respect to the individual characteristics, firm size has a positive and significant impact on productivity, in particular across the lowest productivity levels. Hence, firm size

Table 6. Contemporaneous correlations.

	Productivity	Internal R&D per worker	External R&D per worker	Firm size	Group	Market share	Investment	Export dummy
Productivity	1.000							
Internal R&D	−0.022	1.000						
External R&D	0.048	−0.113	1.000					
Firm size	0.320	−0.245	0.060	1.000				
Group	0.316	−0.080	0.155	0.523	1.000			
Market share	0.213	−0.015	0.050	0.375	0.200	1.000		
Investment	0.208	0.027	0.178	0.231	0.175	0.091	1.000	
Export dummy	0.237	−0.063	0.034	0.242	0.111	0.012	0.201	1.000

Source: Own elaboration.

Table 7. Effects of innovation sources on productivity (OLS and quantile regressions): whole database.

	OLS	Quantile regression 0.10	0.25	0.50	0.75	0.90
Internal R&D	3.9615	3.8060	3.2884	3.0584	3.1534	2.6339
	(0.8682)*	(0.9795)*	(0.7102)*	(0.9317)*	(1.1771)*	(1.2047)**
External R&D	0.7814	1.0003	0.8163	1.8378	1.8819	1.8780
	(0.5980)	(0.7193)	(0.5212)	(0.6305)*	(0.7464)**	(0.6903)*
Firm size	9.8718	26.1587	17.3058	10.3954	6.2019	9.6213
	(3.6549)*	(2.8230)*	(2.2463)*	(2.5723)*	(3.0903)**	(3.1524)*
Market share	4.6131	5.4731	4.4729	4.7720	14.1811	21.5607
	(0.8787)*	(0.6080)*	(0.6042)*	(0.5727)*	(0.5154)*	(0.3542)*
Group	33.9061	24.0126	30.0081	29.7652	30.2624	29.7686
	(4.5327)*	(5.9887)*	(4.3006)*	(5.0240)*	(6.0387)*	(5.9285)*
Investment	1.4425	1.6084	3.1602	2.4545	1.6453	1.1458
	(0.7827)***	(0.7969)**	(0.6158)*	(0.8152)*	(1.0411)	(1.0411)
Export dummy	0.1572	0.3668	0.1560	0.1441	0.0832	0.0447
	(0.0506)*	(0.0614)*	(0.0454)*	(0.0538)*	(0.0628)	(0.0574)
Mills ratio	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral dummies	Yes	Yes	Yes	Yes	Yes	Yes
[Pseudo-]R^2	0.3806	0.3220	0.2721	0.2325	0.2160	0.2433
Observations				1612		

Note: In quantile regression, bootstrapped standard errors in parentheses (200 replications). All marginal effects (dy/dx) are in percentage points. For the group dummy variable the marginal effect is the discrete change from 0 to 1. Sectoral dummies in 2-digit industries.
*Significant at 1%.
**Significant at 5%.
***Significant at 10%.

seems to be a critical variable among firms with low productivity. There is considerable evidence regarding the relationship between firm size and productivity. For instance, Pagano and Schivardi (2003) point out that being larger fosters productivity growth because it allows firms to take advantage of all the increasing returns associated with R&D. However, recently Hall, Lotti, and Mairesse (2009) found that the larger firms in a group of Italian SMEs (those between 51 and 250 employees) had a negative impact.

Market share plays an important role since it leads a firm to obtain internal financial cash to invest in R&D activities and to protect its innovations. Our results show a positive relationship between firms' market share and productivity. Additionally, the coefficient is larger when we move up to the most productive firms. Furthermore, firms that belong to a group present higher labour productivity, which means they can receive financial and technical support that may improve their performance.

Finally, investment in physical capital and export activity show a significant positive effect on productivity. Both variables show a decreasing pattern when we move towards the highest deciles. Our results for physical capital investment are in line with previous results (e.g. Hall, Lotti, and Mairesse 2009). There is also much literature analysing the relationship between export activity and firm performance. Evidence on the positive linkages on export activity and productivity can be found in Bernard and Jensen (2004).

In order to show the marginal effects of innovation sources on firm productivity in greater detail, Figure 3 shows the marginal effect patterns of internal and external R&D for the whole database.[16] Our results show that there is a nonlinear elasticity of the R&D investment on productivity. Specifically, these preliminary results confirm the decreasing pattern of the internal R&D, while the acquisition of external R&D presents an increasing pattern until at least the quantile 0.90. Finally, the shadow area stresses the greater heterogeneity of the coefficients between the extreme values of the productivity distribution.

According to Tether (2003, 2004), Salter and Tether (2006) and Freel (2006) manufacturing and service industries have different sources of R&D. These authors point out the relative roles of 'softer' and 'harder' sources of knowledge and technology within the services and manufacturing industries. In general terms, services will rely more on 'soft' sources of knowledge for innovation (such as cooperation with customers and suppliers), while manufacturing industries will rely more on 'hard' sources (such as cooperation with research centres). Thus, we can expect these differences to be reflected in the marginal

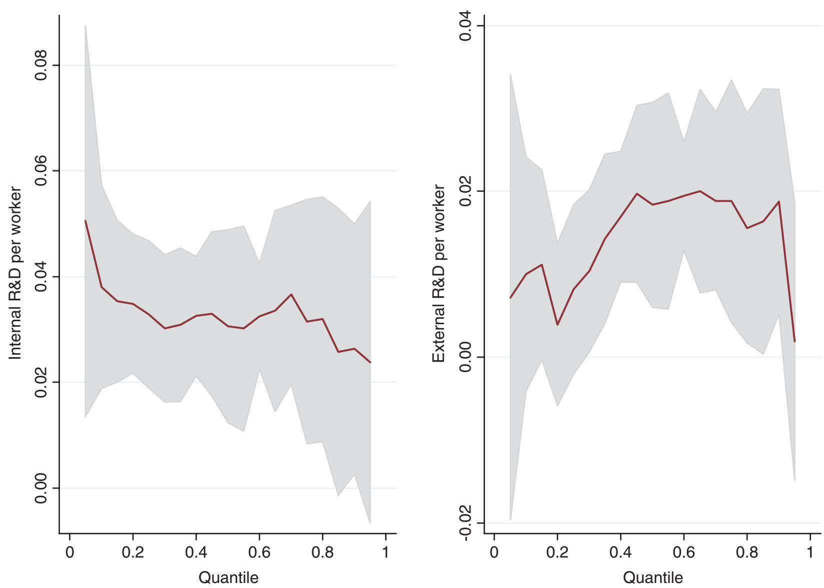

Figure 3. Marginal effects of R&D on productivity over the conditional quantiles. The figure presents internal R&D and external R&D coefficients for 90 different quantiles. The respective values are connected by a solid dark line along with an estimated 95% confidence band.

returns of R&D sources. This different sectoral behaviour may have consequences on the impact of internal and external R&D on productivity.

We will now try to disentangle the impact of internal or external R&D strategies on the labour productivity according to our three sectoral classifications. To do so, we create four different variables that are generated through the firm's internal and external R&D expenditure but that respond to three different R&D strategies depending on their R&D decision. The strategies and variables are the following:

(1) Firms with 'only internal R&D'. For those firms with only external R&D or investing in both sources, the value is equal to 0.
(2) Firms with 'only external R&D'. For those firms with only internal R&D or investing in both sources, the value is equal to 0.
(3) Firms investing in internal and external R&D simultaneously obtain two different elasticities: the effect of 'internal R&D' and the 'external R&D'. Both variables take a value equal to 0 for firms investing only in one type of R&D.

Hence, innovative firms can choose between three different strategies, but we obtain four marginal elasticities according to their specific strategy. Table 8 reports results of the quantile regressions at the sectoral level. Columns 1, 3, and 5 show the impact of internal and external R&D without considering the firms' strategies, while columns 2, 4, and 6 offer the three different strategies that Catalan firms apply to R&D activities.

The analysis of the direct impact of internal and external R&D shows interesting results. First of all, our findings show that internal R&D has a greater effect on labour productivity than external R&D. Second, for high-tech manufacturing industries, the elasticity of both R&D sources has a significantly higher impact on productivity levels than it does for low-tech industries, although both parameters have a surprisingly non-significant impact for low-tech manufacturing industries. Finally, for KIS sectors, the effect of internal R&D on productivity is considerably higher, but the marginal effect of external R&D diminishes and becomes non-significant.

The different strategies have two main results: first, the effects of R&D sources on labour productivity increase; second, a clear complementarity appears in the marginal elasticity of firms investing simultaneously in internal and external R&D. For instance, among high-tech manufacturing industries, firms that invest only in internal R&D have an increase of 10.90% in their productivity, those with only external R&D have an increase of 6.63%, whereas those investing in both R&D sources have an increase of 19.78% (the impact of both R&D investments). Comparing the three sectorial classifications, we observe that KIS firms that engage in internal and external R&D experience the highest increase in the marginal impact on productivity.

Our results are in line with Lokshin, Belderbos, and Carree (2008) who analysed the effects of internal and external R&D on labour productivity in a panel of Dutch manufacturing firms. They apply a dynamic linear panel data model and find complementarity between both R&D sources, as well as highlighting that external R&D only has an important positive impact if there is sufficient internal R&D. For these authors, their results show evidence of the role of internal R&D in promoting firm absorptive capacity and the existence of decreasing returns when the levels of internal and external R&D are high.

When considering the effect of firms' strategies, the sensibility of some variables differs. First, for low-tech manufacturing industries, the elasticity of 'group' and 'market share' on productivity considerably diminishes. Second, for high-tech manufacturing industries, the elasticity of 'firm size' and 'group' diminishes while the effect of 'market share' increases.

Table 8. Effects of innovation sources on productivity according to firm size (quantile regressions, 0.50; classification at the sectoral level).

	High-tech manufacturing industries		Low-tech manufacturing industries		KISs	
	(1)	(2)	(3)	(4)	(5)	(6)
R&D sources						
Internal R&D	2.3506		1.8970		8.6601	
	(0.9858)**		(1.4228)		(2.2528)*	
External R&D	2.2244		1.7399		0.8437	
	(0.6021)*		(1.1662)		(1.4090)	
Firms with only one strategy						
Only internal R&D		10.8995		7.1476		20.1463
		(2.2901)*		(2.3880)*		(3.7496)*
Only external R&D		6.6318		7.1749		3.5307
		(2.5386)*		(3.6746)**		(5.0941)
Firms with both R&D sources						
Internal R&D		6.1575		0.8237		16.4221
		(2.8961)**		(3.5732)		(5.2326)*
External R&D		13.6327		8.2042		17.0405
		(2.8405)*		(3.1401)*		(5.4790)*
Firm's characteristics						
Firm size	12.0469	9.3115	24.4462	23.0190	4.6505	4.5338
	(2.7707)*	(3.4616)*	(6.2289)*	(5.8434)*	(4.1594)	(3.8278)
Market share	4.1582	24.8308	9.3047	0.2657	3.5661	45.2113
	(0.5345)*	(6.2311)*	(1.2702)*	(0.0760)*	(0.8822)*	(11.1280)*
Group	25.0399	3.8381	29.1826	9.3503	44.1944	3.0047
	(5.0200)*	(0.6621)*	(8.1665)*	(1.1813)*	(12.2811)*	(0.8206)*
Investment	3.3849	2.6742	2.5714	2.4239	−0.6212	−0.6229
	(0.8252)*	(1.0214)*	(1.2750)**	(1.1956)**	(2.0210)	(0.0181)
Export dummy	0.0992	0.1206	0.2651	0.3206	−0.0952	−0.1695
	(0.0585)***	(0.0735)	(0.0883)*	(0.0826)*	(0.1091)	(0.0998)***
Mills ratio	Yes	Yes	Yes	Yes	Yes	No
Sectoral dummies	Yes	Yes	Yes	Yes	Yes	Yes
[Pseudo-]R^2	0.1937	0.2078	0.1836	0.1921	0.1751	0.1932
Observations	750	750	557	557	305	305

Note: In quantile regression, bootstrapped standard errors in parentheses (200 replications). All marginal effects (dy/dx) are in percentage points. For the group dummy variable the marginal effect is the discrete change from 0 to 1. Sectoral dummies in two-digit industries.
*Significant at 1%.
**Significant at 5%.
***Significant at 10%.

Finally, for KISs, we observe that the elasticity of the 'group' diminishes its impact on productivity, whereas 'market share' increases its impact on productivity. However, for this last group, we obtain negative but non-significant results for the variables 'investment' and 'export dummy'.

One outstanding result is the higher sensitiveness of service industries compared with R&D investment. According to Sirilli and Evangelista (1998), firms in the service industries rely on a wide variety of innovation sources. They point out that the impact of a wide range of innovation strategies becomes more important because firms usually use them simultaneously. Hence, our results for KISs may correspond to this higher impact on complementarity R&D sources. Surprisingly, firms in the KIS sector that only invest in external R&D do not present a significant impact.

To summarize, R&D has a varying effect on productivity levels. At low levels of productivity, internal R&D has a sizeable impact on productivity, while at high levels of productivity external R&D becomes more important for manufacturing industries. Furthermore, there are sectoral differences: internal R&D has a larger impact on KISs than it does on high-tech manufacturing industries, whereas the external R&D has a much greater effect on high-tech manufacturing industries than it does on KISs. Low-tech manufacturing industries experience intermediate impacts but these are not significant in the median. Finally, there is a complementarity effect between both R&D sources because they both have a larger impact on firms that invest simultaneously in internal and external R&D.

6. Concluding remarks

During the last 20 years wide-ranging economic research has appeared that directly answers a few simple questions related to the R&D. What is the rate of return on investment in R&D? What social presence do technological spillovers have? Can internal R&D complement absorptive capacity in incorporating external spillovers? Although these questions may be simple, complex analysis is required to arrive at the correct answers. In empirical research during recent years, the relationship between R&D, innovation, and productivity has been examined rigorously and while many studies, primarily empirical analyses based on cross-sectional data, have reported a significant link between innovation and productivity (Griliches and Mairesse 1998), others have failed to find an association (Hall, Mairesse, and Mohnen 2010). However, there is evidence that internal R&D has an absorptive capacity to capture external knowledge.

With a sample of innovative firms here, we analyse the relationship between sources of innovation and productivity on the basis of the understanding that a complementary relationship must exist between internal and external R&D. Catalonia is an interesting case to study the effect on R&D sources on productivity, and we use a sample with 1612 innovative firms in manufactures and KISs. We believe that the impact of both forms of R&D may differ depending on the firm's productivity level. Furthermore, we also contribute to the empirical literature by distinguishing between manufacturing and service industries according to technological intensity.

Our evidence shows that firms invest in R&D with different intensities, which is the reason why the distribution of R&D investment is highly skewed. Furthermore, the complementarity test suggests that R&D activities are mutually enhancing for high-tech manufacturing industries. Hence, productivity increases significantly more when a new R&D activity is added to a previous one than when there is no previous experience in other R&D activities.

With respect to the empirical estimations, we apply quantile regression techniques controlling for sample selection with a semi-parametric equation. Our results indicate that internal R&D has an important effect on productivity. This effect is greater at the lower conditional quantiles, but diminishes as we move up to higher productivity levels. These results indicate that in firms with relatively low levels of productivity, internal R&D activities have a considerable positive effect on firm productivity.

At the sectoral level, interesting results appear. On the one hand, the impact of the internal R&D is larger among KISs (8.66%) than among high-tech manufacturing industries (2.35%) and low-tech manufacturing industries (1.90%). On the other hand, the impact of external R&D on high-tech manufacturing industries is higher than in the remaining sectors (with an impact equal to 2.22%). Finally, for the low-tech manufacturing industries, the aggregated impact of internal and external R&D investment is not significant.

However, if we look at a firm's R&D strategy, the impacts of the R&D variables become significant for the low-tech manufacturing industries. In the first place, a complementarity effect appears because the elasticity of the internal and external R&D is larger for firms investing in both forms of R&D than for firms that only invest in one form of R&D. In the second place, firms in KISs obtain the largest joint impact, followed by high-tech and low-tech manufacturing industries.

Additionally, variables related to firm size, market share, and the fact that a firm belongs to a group have a positive impact on firm productivity. However, the impact of a firm's investment and its export activity in general terms shows a positive elasticity, except for in the case of KISs.

Our results have important policy implications for R&D and innovation. They suggest that policy-makers should promote a firm's investment in internal R&D activity because of the direct and indirect effects: investment increases productivity at low levels and increases the impact of external R&D once a high productivity level has been achieved. Furthermore, managers are in a better position to make more efficient decisions if internal R&D prevails in the case of low productivity levels and external R&D prevails in the case of high productivity levels.

Acknowledgements

This paper is part of the research done with the financial support of the Spanish Ministry of Innovation and Science in the project ECO2009-08735 and the Consolidated Group of Research 2009-SGR-907. We are grateful to Verònica Gombau-Bertomeu for her research support. The database used in this paper was provided by the Catalan Statistics Institute (IDESCAT). The usual disclaimer applies.

Notes

1. For a large sample of Spanish firms during the period 1998–2006, Segarra et al. (2008) observe that productivity per worker and wages are positively related to age and size, the heterogeneity of productivity levels decreases with firm age and size, but the differences between firms persist during years.
2. These hypotheses have been confirmed for British and French firms, where complementarity between technological and organizational changes facilitates the appearance of a more decentralized hierarchical structure (Caroli and Van Reenen 2001).
3. Stieglitz and Heine (2007) analyse the role of complementarities in appropriating innovative rents in terms of the stage of the industry.
4. Empirical evidence about the complementarity between internal and external R&D is extensive. For Spain, see Fosfuri and Tribó (2008), Arbussà and Coenders (2007), Nieto and Quevedo (2005); for Holland, Lokshin, Belderbos, and Carree (2008); for Belgium, Cassiman and Veugelers (2006); for Japan, Nakamura and Odagiri (2005); and for the UK, Love and Roper (2002).
5. In recent years Catalonia has undergone an intense process of economic opening and had its comparative advantages in traditional industries eroded, which has given rise to significant changes in its industrial mix. In 2006, the services sector accounted for 63.7% of total employment, while the manufacturing sector was responsible for only 22.7% of total employment. In Catalonia, between 1996 and 2006, employment in the manufacturing sector increased at an annual rate of 3.0%, while employment in total services increased at an annual rate of 5.8% and KIS increased by 8.1%. The Catalan economy had 540,175 employees in KIS industries in 1996 and 979,788 employees in 2006.
6. In a sample of CIS-3 Spanish firms operating in the manufacturing and service industries, Segarra and Arauzo (2008) found large differences in sources of firm innovation, in internal R&D activities, in external acquisition of services related to innovation and in cooperation agreements with other firms or public institutions. In high-tech industries, innovative firms that conduct internal R&D activities and cooperate with firms, universities and public research institutions predominate. Internal and external R&D and R&D cooperation is less frequent in low-tech manufacturing and service industries.

7. The complementarities between practices can also be confirmed by applying a static test to the adoption of technology choices. We test the null hypothesis that the unconditional correlations between each pair of choices are zero. Table 4 reports a significant and positive correlation between adoption of internal and external R&D.
8. It should be noted that empirical findings are contradictory. Some studies have found a significant link between innovation and productivity (Griliches and Mairesse 1998), whereas others have failed to find any.
9. Taken from a survey of empirical CDM application in Hall, Mairesse, and Mohnen (2010).
10. We apply a complete CDM model to Catalonia that ranges from the factors that determine firms' R&D activities to the effect that innovating firms have on productivity (Segarra 2010).
11. Thus, we aim to capture the appropriability of the value chain of R&D activities. Recently, Roper, Du, and Love (2008) estimated the impact of innovation on market value in terms of labour productivity, sales growth, and employment growth.
12. The information provided by the CIS questionnaire does not offer information related to the evolution of sales per worker.
13. Hall, Foray, and Mairesse (2007) point out an alternative equation where the sales growth is the dependent variable and the lagged investment in R&D is the explanatory variable. However, due to lack of information, we are not able to estimate this.
14. Since Koenker and Bassett's (1978) work, many applications have been described in a variety of fields: firm-size distribution (Machado and Mata 2000), barriers to entry (Mata and Machado 1996; Görg, Strobl, and Ruane 2000; Arauzo and Segarra 2005), innovation and firm growth (Coad and Rao 2006, 2008; Marsili and Salter 2005), R&D and patents (Nahm 2001; Grasjo 2005), wage differences (Mueller 1998; Papapetrou 2006), and productivity heterogeneity (Krüger 2006).
15. This problem has been previously pointed out in this literature by Lööf and Heshmati (2002). However, Roper, Du, and Love (2008) do not find significant differences among innovating and non-innovating firms.
16. Estimations were made using Stata and graphs were made using the 'GRQREG' Stata module (Azevedo 2006).

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