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Research Paper

The Organizational Designs of R&D Activities and their Performance Implications: Empirical Evidence for Spain

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ABSTRACT Through a rich panel of Spanish manufacturing companies, this study examines the hypothesis that the formation of inter-organizational complementarities in R&D depends on the type of alliance chosen by a firm to leverage its own R&D. To test this hypothesis, the study compares the capacity of different organizational designs of internal and external R&D activities to produce complementarities. The results indicate the existence of complementarities for cases where firms combine their own R&D with research collaboration. No complementarities are found for cases where firms adopt both intramural and R&D outsourcing jointly. Additionally, a comparison of the factors driving choices on R&D reveals that the use of "innovation management practices" and the presence of "technological opportunities" relate more to the adoption of research collaboration than to the adoption of R&D outsourcing. These findings are relevant as they may explain the reported differences in the production of complementarities.

KEY WORDS: R&D activities, organizational designs, complementarities, innovative performance, count-data-panel models

1. Introduction

It has long been recognized that successful innovation depends on the firm's ability to combine old and novel sources of knowledge (Rosenkopf and Nerkar, 2001). When these sources give each other leverage in the innovation process, they are complementary in the sense that using one of them raises the returns of using the other (Milgrom and Roberts, 1990). The formation of complementarities in the production of knowledge acquires

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a strategic character, as they show that firms have found knowledge associations that raise their innovative performance. Recent studies on innovation management identify the adoption of open innovation models as an effective strategy to reach complementarities in knowledge creation (Cassiman and Veugelers, 2006; Rothaermel and Alexandre, 2009). This holds true since these models span firms' search outside their organizational boundaries, provide new technologies and capabilities, and facilitate inter-organizational learning (Chesbrough, 2003; Rosenkopf and Almeida, 2003; Laursen and Salter, 2006).

However, implementation of open innovation models requires that firms combine several R&D activities. Each combination in turn leads to different organizational designs for these activities. In some cases, firms may achieve original knowledge associations by joining their own R&D with hybrid organizational forms, such as strategic alliances and joint-venture arrangements. In other cases, firms may obtain novel knowledge combinations adopting together in-house R&D and contractual forms, such as licensing arrangements and R&D outsourcing. If so, this raises the following question: what organizational design should firms choose to maximize knowledge creation?

In this paper, I propose that the answer to this question rests on the type of knowledge provision derived from the external sourcing strategy that a firm chooses to leverage its intramural R&D. Alliances along the continuum between "hierarchies" and "markets" provide knowledge that varies depending on two factors: its complexity in terms of inter-organizational transfer, and its effectiveness in improving intramural R&D productivity. By using a rich panel of Spanish manufacturing firms for 1998–2002, this study provides evidence consistent with the premise that alliances differing on these factors have a different capacity to induce the adoption of intramural R&D, and subsequently, the production of complementarities. Surprisingly, how differences in external knowledge provision affect the formation of complementarities between internal and external R&D activities remains relatively unexplored in the extant literature on the subject.[1] Rather, previous works have focused on the interaction effects that may arise from combining multiple types of alliances (e.g. Arora and Gambardella, 1990; Belderbos *et al.*, 2006; Love and Roper, 2009); on the investigation of the interrelation of contract-based arrangements and intramural R&D (Mowery, 1983; Veugelers and Cassiman, 1999); or on how knowledge acquisition in markets and intramural R&D leverage each other in terms of innovative performance (Cassiman and Veugelers, 2006).

With the aim of extending the previous literature on complementarities in R&D, the current research focuses on the following questions: (i) Do alternative organizational designs of internal and external R&D activities have the same capacity to induce complementarities? (ii) What role do specific alliances play in determining inter-organizational complementarities in R&D? The analysis of these questions becomes relevant if we are to understand how a firm can best arrange its internal and external R&D activities to reach the maximum leverage among them in knowledge creation. Furthermore, comparing complementarities that arise from various combinations of internal and external R&D activities enables the identification of important differences in the way these activities relate to each other. This fact provides

[1] A number of studies have compared the capacity of different R&D alliances to produce inter-organizational learning (e.g. Mowery *et al.*, 1996; Gomes-Casseres *et al.*, 2006). However, these studies do not assess the effect that intramural R&D may have on the contribution of alliances to inter-organizational learning.

a more comprehensive picture regarding the manners by which different types of R&D alliances shape innovative performance.

This research contributes to the previous literature on the following aspects. This work is not only among the first in comparing complementarities derived from the combination of intramural R&D with different types of alliances, but it also conducts this evaluation using panel data analysis. Compared to cross-sectional studies on the subject (e.g. Cassiman and Veugelers, 2006; Love and Roper, 2009), the current paper assesses for complementarities in R&D allowing for the effects of unobserved heterogeneity, which has been a drawback of prior research (Athey and Stern, 1998; Leiponen, 2005b; Miravete and Pernias, 2006). Furthermore, the use of a longitudinal sample of companies improves the assessment of complementarities in R&D by accounting for the presence of well-documented feedback effects that characterize the innovation–R&D adoption relationship. In particular, this study allows for the feedbacks that arise from the dynamic nature of this relationship (Blundell *et al.*, 1995; Martínez-Ros and Labeaga, 2002), and from the fact that organizational design choices are essentially predetermined variables that may be correlated with the unobserved heterogeneity (Leiponen, 2005b). Altogether, this study provides a robust evaluation on complementarities in R&D, presenting reliable conclusions about the capacity of the compared organizational designs to enhance innovative performance.

To the best of my knowledge, only Schmiedeberg (2008) has conducted a comparative study of the complementarities between different combinations of internal and external R&D strategies, but for a cross-section sample of firms. On the other hand, Leiponen (2005b) uses panel data analysis for assessing complementarities between technical skills, innovation and R&D collaboration. However, the study about the role of different types of external R&D sources in determining the returns of technical skills is not addressed in her study.

The layout of the paper is as follows. The next section presents the theoretical foundations for studying the production of complementarities derived from alternative combinations of internal and external R&D activities. Subsequent sections describe the data, methodology and results of the study, as well as the concluding remarks.

2. Theoretical Framework

Organizational designs in which firms combine internal and external R&D activities bring not only benefits in terms of diverse knowledge, but also difficulties associated with the integration of such knowledge across organizational boundaries (Rosenkopf and Almeida, 2003). Firms implementing these organizational designs need to develop communication channels for improving knowledge sharing and to ensure assimilation of heterogeneous sources of knowledge, some of which may be far from their technological base. Furthermore, the acquisition of external R&D is a knowledge-based transaction that may be fraught with complexity and contractual problems (Pisano, 1990; Anand and Khanna, 2000). Taken together, these issues may lessen the interaction of intramural R&D with external sourcing of knowledge, thus limiting the scope of inter-organizational learning (Leiponen, 2005a).

Although the combination of internal and external R&D is costly in terms of knowledge integration, an important stream of works has documented the existence of complementarities between R&D activities implemented across firms' organizational boundaries (e.g. Mowery, 1983; Veugelers and Cassiman, 1999; Cassiman and Veugelers, 2006;

Schmiedeberg, 2008). To justify the presence of such complementarities, the majority of these studies built on Cohen and Levinthal's notion (1989) of absorptive capacity (henceforth, ACAP), defined as the firm's ability to recognize, assimilate and exploit external knowledge. According to previous research, accumulated experience in conducting R&D internally puts the firm in a better position to understand the R&D performed by external actors. In particular, the ACAP contributes to forming complementarities in R&D by enabling firms to identify technological opportunities, and by improving communication with external actors having complementary problem-solving capabilities.

However, production of complementarities in R&D requires that the firm form its ACAP from a diverse stock of knowledge. When sharing a similar and specialized knowledge background, sub-units within a firm can improve communication effectiveness, facilitating knowledge assimilation across intra-organizational boundaries. Indeed, internal communication efficiency contributes to reinforcing the firms' inward-looking ACAP (Cohen and Levinthal, 1990). Nonetheless, a lack of a diverse knowledge background also makes the firm less receptive to acquire an external source of knowledge. Less diversity in the firm's stock of knowledge affects its outward-looking ACAP (Cohen and Levinthal, 1990), which may result in the emergence of the *Not Invented Here* syndrome (Almeida *et al.*, 2003; Laursen and Salter, 2006). In the context of this study, previous arguments imply that firms with a less diverse technological background will focus their search effort on a restricted number of technological trajectories. If this search behavior is persistent, firms will see a reduced capacity to create novel knowledge associations, together with their possibilities to produce complementarities in R&D.

Drawing on the learning alliance literature (Mowery *et al.*, 1996; George *et al.*, 2001; Rosenkopf and Almeida, 2003), this study proposes that organizational designs in which firms combine internal with external R&D help them to enhance diversity of their knowledge background, thus improving their ACAP effectiveness in producing complementarities.[2] This holds true as involvement in external R&D increases the exposure of the firm's own R&D to heterogeneous knowledge that, in turn, contributes to forming a technological background in areas different from prior knowledge accumulation (Mowery *et al.*, 1996; George *et al.*, 2001). Furthermore, information provision from external links shapes ACAP by revealing the benefits of implementing new managerial practices that may improve R&D performance in knowledge creation. In that regard, Cockburn and Henderson (1998) show evidence indicating that wide connections with external actors drive the pharmaceutical companies' abilities to recognize and exploit technological opportunities. Lenox and King (2004) suggest that R&D laboratories connected to external actors are better prepared to identify the value of adopting new R&D practices. Rothaermel and Alexandre (2009) propose that joining internal and external R&D prevents search behavior that overemphasizes internal search and lessens the external exploration of new technologies. Taken together, these arguments lead to the following hypothesis:

[2] Although the role of external sources of knowledge in shaping ACAP is widely recognized in previous studies on organizational learning (e.g. Cockburn and Henderson, 1998; George *et al.*, 2001), the influence of diverse external knowledge in reinforcing the ACAP effectiveness to form complementarities remains relatively unexplored in the extant literature.

Hypothesis 1*: Organizational designs, in which firms combine internal and external R&D activities, produce complementarities in terms of knowledge creation*.

However, the intensity of these complementarities may differ depending on the external R&D activity chosen by a firm to leverage its own R&D. In particular, here I study the interaction of intramural R&D with two particular forms of alliances, research collaboration and R&D outsourcing. The former includes intentional arrangements formed among firms and external actors to co-develop innovation activities, while the latter refers to projects and services contracted in the markets for technology. While research collaboration and R&D outsourcing provide a distinct type of knowledge, these alliances can be distinguished by the fact that the adoption of each one imposes different learning requirements and generates different external knowledge exposures. Therefore, it is expected that such differences explain variation in the intensity of complementarities derived from alternative combinations of internal and external R&D activities. To investigate this fact in more detail, the following paragraphs present a description about the type of knowledge provision resulting from the adoption of R&D outsourcing and research collaboration, respectively.

Knowledge provision in R&D outsourcing is achieved by exchanges of knowledge in the technology markets. In terms of von Hippel's theory (1994) on the allocation of information and problem-solving capabilities along the innovation process, it is argued here that R&D outsourcing involves the exchange of codified knowledge about technology implementation between the adopting firm and the market R&D providers. As the adopting firm and its R&D providers codify knowledge about problems and technical solutions, R&D outsourcing may take place as successive market exchanges, and in that sense, this type of alliance is regarded as an *iterative form of learning*.[3] Thus, R&D outsourcing generates an interaction mode in which a firm links to its R&D providers by sending them codified information about technical problems and by receiving technological solutions in terms of blueprints, manuals or technological packages from them. Exchanges of codified knowledge advance until the providers' technological solutions fit the firm's technical needs. An important implication of this characterization is that these exchanges of knowledge limit the firm to learning just from the problem-solving capabilities previously codified by its R&D providers, but not from other elements embedded in their technological expertise (Lane and Lubatkin, 1998; Kale *et al*., 2000).

Alternatively, research collaboration is an *interactive form of learning*, in which a firm and its partners gain knowledge from a conjoint involvement in R&D activities. As interaction proceeds, participants share resources intentionally, but may also reach knowledge involuntarily spilled out by the others (Singh, 2005). When knowledge

[3] One of the anonymous reviewers commented that since R&D outsourcing is an arm's length transaction, the involved learning does not necessarily take place as an *iterative* exchange of knowledge. In the context of this study, I consider that an arm's length transaction involves the lowest level of iteration among partners, since providers' solutions fit the firm's technical problems immediately. However, in many other situations, firms and their R&D providers exchange information successively on the progress of a technology implementation (Weigelt and Sarkar, 2009). For instance, a firm may need additional information to solve emerging technical problems, while its providers may require the firm's feedback to improve current technology implementation. In other cases, technology solutions acquired by firms come with bundled additional services, such as training or consulting support (Arora, 1996). This fact usually results in successive exchanges of information between firms and providers.

spillovers refer to context-specific information (e.g. partners' expertise and specific practices for the functioning of particular R&D projects), research collaboration further provides the firm with tacit sources of knowledge (Lane and Lubatkin, 1998; Almeida *et al.*, 2003). In terms of knowledge provision, research collaboration then allows the firm to obtain not only standard forms of knowledge, but also knowledge hardly definable outside the R&D collaboration context (Mowery *et al.*, 1996; Powell *et al.*, 1996).

Comparing knowledge provision derived from the external R&D activities under consideration, the following conclusions can be drawn. Firstly, learning from research collaboration is more demanding than learning from R&D outsourcing since the former provides knowledge that is more complex in terms of its tacitness. Learning from tacit knowledge requires that the firm have well-developed skills in prospecting its potential outcomes and in transforming contextual into codified information for enabling knowledge assimilation (Kale *et al.*, 2002). As widely recognized by previous studies on organizational learning (e.g. Cohen and Levinthal, 1990; Arora and Gambardella, 1994), the greater the degree of external knowledge complexity is, the greater the amount of ACAP necessary to handle the involved learning process. This fact implies that firms adopting research collaboration to learn from outside knowledge will have more incentives to reinforce their ACAP, which in turn will lead them to invest more in internal R&D activities.

Secondly, learning from research collaboration enhances a firm's exposure to heterogeneous knowledge more than learning from R&D outsourcing does. This is because research collaboration allows firms to learn from knowledge with a more complex composition (e.g. codified and/or tacit knowledge). In research collaboration, interaction enables participants to learn about multiple aspects, such as lacking technologies, managerial practices, or about partners' skills and capabilities (von Hippel, 1994; Kale *et al.*, 2000). Instead, since R&D outsourcing involves market exchanges of knowledge about a technology implementation, the firm is restricted to learning from codified knowledge, but not from other aspects underlying the production of the transacted knowledge. Therefore, compared with R&D outsourcing, the adoption of research collaboration enhances the exposure to varied and complex knowledge, better preventing the emergence of locked-out effects (Tidd and Trewhella, 1997; Rosenkopf and Nerkar, 2001). These arguments imply that research collaboration is more effective than R&D outsourcing in shaping the firm's ACAP, and subsequently, in stimulating its involvement in new R&D activities. Taking into account the previous discussion, I hypothesize that:

Hypothesis 2*: Complementarities emerging from the joint adoption of in-house R&D and research collaboration are stronger than complementarities emerging from the joint adoption of in-house R&D and R&D outsourcing*.

The next section describes the methods implemented in this study to test the previously described hypotheses, paying attention to the treatment of recognized difficulties associated with the empirical evaluation of complementarities in R&D.

3. Empirical Analysis

To test for previous hypotheses, I implemented two alternative methodologies. First, I used the method of Arora and Gambardella (1990) to infer complementarities in R&D from conditional correlation coefficients.[4] These correlations come from a model in which the firm's choices on R&D are determined by observed firm and industry-specific factors. This is advantageous since this method also allows examining differences in factors that drive these choices, which in turn is informative about differences in factors influencing complementarities. Second, I tested directly for complementarities by assessing the performance effects of alternative organizational designs for R&D. To do so, I first specified a knowledge production function as being determined by exclusive combinations of the R&D activities in question. Drawing on previous empirical studies on complementarities (e.g. Leiponen, 2005b; Mohnen and Röller, 2005; Cassiman and Veugelers, 2006), I tested for the presence of supermodularity of this function as a method to assess complementarities in R&D.[5]

3.1 Correlation Analysis

Here, I aim to assess complementarities between the firm's adoption choices of alternative combinations of internal and external R&D activities. Let $X = \{x_{\mathrm{RD}}, x_{\mathrm{RC}}, x_{\mathrm{RO}}\}$ be the set of R&D activities under consideration, where "RD" represents in-house R&D, and "RC" and "RO" represent research collaboration and R&D outsourcing, respectively. For any $x_k \in X$, an activity "k" is adopted when $x_k = 1$ and not when $x_k = 0$. To infer complementarities from conditional correlation coefficients, I first regressed firms' choices of R&D activities on a set of both firm-specific and industry-specific factors.[6] Since X includes three R&D activities, my model has three equations. Finally, I estimated the correlations between residual terms derived from each equation. These correlations are conditional on the observable factors included in the analysis. For modeling the firm's adoption choices on each x_k, I implemented a multivariate probit model for pooled data (Cappellari and Jenkins, 2003). These choices are determined simultaneously according to the following specification:[7]

$$\begin{aligned} &x^*_{k,it} = Z'_{it}\beta^k + u^k_{it}, \quad x_{k,it} = 1[x^*_{k,it} > 0]; \ \ \forall k = \mathrm{RD}, \mathrm{RO}, \mathrm{RC} \\ &E[u^k] = 0, \ \ V[u^j] = 1; \ \ \forall k, j = \mathrm{RD}, \mathrm{RO}, \mathrm{RC} \\ &\mathrm{Cov}[u^k, u^j] \neq 0; \ \ \forall k \neq j. \end{aligned} \tag{1}$$

Here Z contains controls for observed firm and industry characteristics, while u^k represents residuals corresponding to equation k. In this context, positive conditional correlation coefficients are consistent with Hypothesis 1. Further, a comparison between conditional

[4] The idea behind this analysis is that under complementarities, the adoption of two strategies should be positively correlated. This implication is based on the *revealed preference principle*; that is, the fact that firms have chosen to adopt strategies together is potentially informative about the joint returns generated by them (Arora and Gambardella, 1990; Athey and Stern, 1998).

[5] Milgrom and Roberts (1990) and Topkis (1998) show that the presence of supermodularity implies the existence of complementarities.

[6] Firm-specific factors include variables, such as "firm size", "number of patents" and dummies reflecting the "use of innovation management", the "introduction of new products" or "new processes". Industry-specific factors include indicators, such as "industry export intensity" or a proxy for "industry technological opportunities". See Table 2 for a complete description of each variable.

[7] One advantage of this specification is that it takes into account potential interdependencies in the adoption of R&D activities (Gomez and Vargas, 2009). When interdependencies exist, covariances between residuals will be statistically different from zero (Arora and Gambardella, 1990).

correlations provides information to identify cases in which complementarities are stronger (Hypothesis 2). Nonetheless, the influence of unobserved factors can affect conditional correlations, which may lead either to assert complementarities between two R&D activities when in fact they are independent, or to conclude the absence of complementarities when they are actually complementary (Athey and Stern, 1998; Miravete and Pernias, 2006). Therefore, despite the informative power of Model 1 in describing drivers of choices of R&D, conclusions regarding the presence of complementarities should not be exclusively based upon the conditional correlation analysis.

3.2 Knowledge Production Analysis

In this case, complementarities are inferred directly by assessing the effects that the firms' organizational choices in R&D have on knowledge creation. To this end, I estimated a knowledge production function in which the following issues were explicitly considered. First, knowledge creation is regarded as a dynamic process in that past performance in the production of knowledge determines current performance (Blundell *et al.*, 1995). This implies that experience in knowledge creation may explain persistent unobservable differences among firms in their capacity to produce knowledge (Martínez-Ros and Labeaga, 2002). Second, the relationship between knowledge creation and R&D adoption is examined allowing for potential correlation between unobservable firm-specific characteristics (e.g. managerial skills or the firm's knowledge background) and organizational choices in R&D.[8] Finally, the firm's organizational choices in R&D are viewed as predetermined variables (Leiponen, 2005b), which allows for the presence of feedback effects in the sense that knowledge produced by the firm in the past may have an impact on its current organizational choices.[9]

The number of innovations commercialized by a firm in a given period characterizes knowledge creation, denoted here by K_{it}. Since this proxy is a non-negative integer variable, I considered the extant literature on count-data models to choose the specification that allows better for previously described issues (e.g. Hausman *et al.*, 1984; Montalvo, 1997; Blundell *et al.*, 2002). In particular, I implemented the model of Blundell *et al.* (2002), who present a linear feedback specification for a dynamic count-data-panel process. This option produces estimates for the effects of the firm's organizational choices on knowledge creation, in which a fixed-effect specification is implemented, and in which organizational choices in R&D are regarded as predetermined variables.

Hence, in this study knowledge produced by the firm "i" at year "t" is determined as follows:

$$K_{it} = \gamma K_{it-1} + \exp\left[\beta_0 + \sum_j \omega_j d_{jit} + \mathrm{W}'_{\mathrm{it}}\alpha + \eta_i + \varepsilon_t\right] + u_{it}. \tag{2}$$

[8] For instance, if the manager's aptitude to promote technological exploration is high, organizational designs with external links will probably be adopted more than others will (Rosenkopf and Nerkar, 2001).

[9] Success in previous innovation activities may raise the firm's aspiration levels, and subsequently, its willingness to be engaged in new R&D projects (Cohen and Levinthal, 1990).

The lag of the dependent variable, K_{it-1}, linearly comes into the model. A positive value for γ will indicate that the innovation behavior of firms is persistent. In this model, d_{jit} corresponds to binary variables that represent firm i's organizational choices at time "t", and where "j" is the set of organizational designs available to firm "i" (see Table 1 for a description of this set). W includes both firm and industry potential predetermined variables. In the model, η_i represents firm-specific effects, while ε_t represents time-specific effects. Finally, ω_j and α refer to parameters associated with the firm choice variables (d_{jit}) and control potential predetermined variables (W), respectively.

I tested for complementarities by examining the existence of supermodularity of K. Using the estimates of ω_j, conditions for which K is supermodular in X are defined as follows:

$$\text{Supermodularity on } x_{\text{RD}} \text{ and } x_{\text{RC}} \begin{cases} \omega_{(110)} - \omega_{(100)} \geq \omega_{(010)} - \omega_{(000)} \\ \text{and} \\ \omega_{(111)} - \omega_{(101)} \geq \omega_{(011)} - \omega_{(001)}. \end{cases} \tag{3a}$$

$$\text{Supermodularity on } x_{\text{RD}} \text{ and } x_{\text{RO}} \begin{cases} \omega_{(101)} - \omega_{(001)} \geq \omega_{(100)} - \omega_{(000)} \\ \text{and} \\ \omega_{(111)} - \omega_{(011)} \geq \omega_{(110)} - \omega_{(010)}. \end{cases} \tag{3b}$$

$$\text{Supermodularity on } x_{\text{RC}} \text{ and } x_{\text{RO}} \begin{cases} \omega_{(011)} - \omega_{(001)} \geq \omega_{(010)} - \omega_{(000)} \\ \text{and} \\ \omega_{(111)} - \omega_{(101)} \geq \omega_{(110)} - \omega_{(100)}. \end{cases} \tag{3c}$$

Note that the supermodularity of K implies the idea of complementarities between decision variables in X, since the adoption of R&D activities separately does not raise knowledge the same as implementing all of them simultaneously.

Table 1. Organizational designs for R&D

Organizational designs	The jth combination ($x_{\text{RD}}\ x_{\text{RC}}\ x_{\text{RO}}$)
No adoption setting	(000)
In-house R&D only	(100)
Research collaboration only	(010)
R&D outsourcing only	(001)
In-house R&D along with research collaboration	(110)
In-house R&D along with R&D outsourcing	(101)
Research collaboration and R&D outsourcing	(011)
In-house R&D with both external R&D activities	(111)

Note: x_k is a binary variable that is equal to one when the firm adopts the activity "k". The set "k" includes RD = in-house R&D, RC = research collaboration and RO = R&D outsourcing.

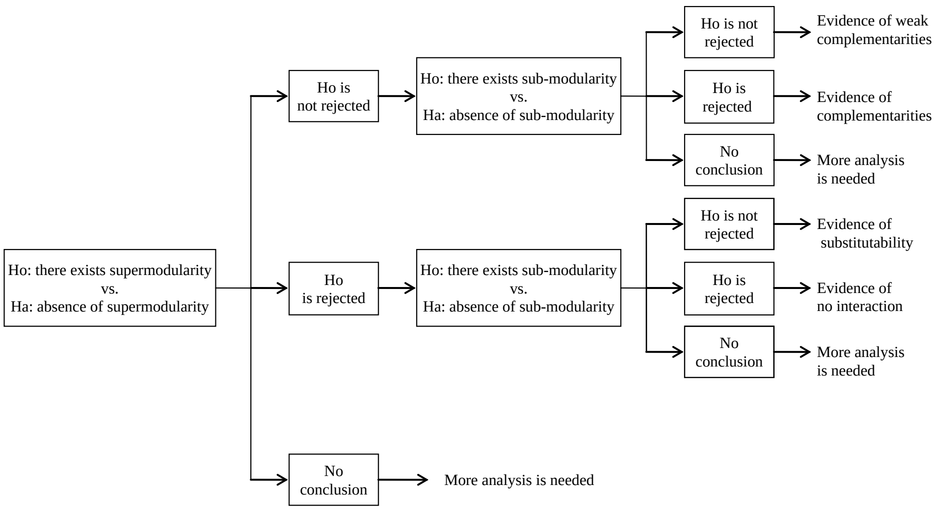

Figure 1. Hypothesis testing strategy

From the procedure developed by Kodde and Palm (1986), I tested for Conditions 3a–3c under the null hypothesis, taking each pair at a time, and considering that the test for supermodularity is a one-sided test of a given pair of inequalities.[10] To this end, I computed a distance measure that was subsequently compared with both upper and lower bounds, as provided by Kodde and Palm (1986). The decision rule applied establishes that: if the distance value is below the lower bound, the null is not rejected; if the distance value is above the upper bound, the null is rejected. Values for the distant test falling between the bounds show that the test is inconclusive. Note that a test for sub-modularity (substitution between R&D activities) can be conducted in a similar way. In this case, it is necessary to reverse the inequalities in 3a–3c and impose them as restrictions to be met under the null.

By following a procedure similar to that of Leiponen (2005b), I tested for the hypothesis of strict supermodularity as a method for assessing complementarities. For each pair, I first tested for the presence of supermodularity, and then for the presence of sub-modularity, both under the null. Non-rejection of the first and rejection of the second is considered as evidence about the presence of strict supermodularity. This fact indicates the existence of complementarities. Alternatively, non-rejection of the first with non-rejection of the second points to the presence of both supermodularity and sub-modularity, which is interpreted here as evidence that complementarities are weak. Finally, rejection of both supermodularity and sub-modularity is regarded as evidence that there is no interaction between the R&D activities under consideration. Figure 1 describes the testing strategy followed in this paper in detail. In order to complement the testing procedure previously described, I followed

[10] Restrictions in 3a–3c can be also tested under the alternative hypothesis (Kodde and Ritzen, 1988). When testing each pair of inequalities under the null, the testing problem is that inequalities have to be satisfied simultaneously, while under the alternative there are no restrictions.

Kodde and Ritzen (1988), shifting the test in such a way that the inequality testing problem (e.g. there is no interaction at all) is defined under the null against the alternative hypothesis that supermodularity (or sub-modularity) exists.[11]

3.3 Data and Variables

The analysis in this paper makes use of the *Spanish Survey of Business Strategies* (henceforth, ESEE) conducted by the Public Enterprise Foundation and the Spanish Ministry of Science and Technology since 1990. Every year, the survey collects information on an average sample of 1,800 companies. This is an unbalanced panel as some companies stopped providing information for reasons, such as mergers, closure or liquidation. Therefore, to preserve representativeness, new companies are included in the survey each year. The survey is exhaustive for firms with more than 200 workers. In the case of companies with between 10 and 200 workers, a stratified random sample by industry and size intervals is gathered. The data used in the current study covers the period 1998–2002. Attention is placed on Spanish manufacturing firms in the ESEE with complete information on their technological activities. Observations for those firms involved in any acquisition and for firms experiencing changes in their legal forms during the period of study were excluded. Additionally, no gaps in the individual time series are allowed.[12] Fulfillment of these requirements results in a balanced panel with 1,034 observations for each year.[13] This data includes companies whose principal economic activity is listed in one of the two-digit manufacturing industries of the “Classification of Economic Activities in the European Community”.[14]

3.3.1 Dependent variables. In the case of Model 1, the R&D adoption behavior of firms is characterized by three binary variables that indicate if a firm conducts in-house R&D, R&D outsourcing or research collaboration, respectively. Regarding the latter, I built this variable aggregating the information of the survey in which firms state whether they participated in joint-venture arrangements and in R&D collaboration with universities, competitors, suppliers or clients. As commented above, knowledge creation in Model 2 is measured in terms of the number of new products commercialized by a firm in each year.

[11] Under this reformulation, non-rejection of the null hypothesis provides evidence indicating that there is no interaction between the R&D activities under consideration.

[12] This requirement has to be fulfilled for estimating Model 2 with the ExpEnd Gauss routine (Windmeijer, 2002).

[13] A comparison of means between the balanced and unbalanced sample for some variables provides the following results. The null hypothesis of no differences in means for variables, such as “number of employees” and “value assets”, is rejected at conventional levels. I found that means are statistically smaller for the balanced than for the unbalanced sample. For these variables, Box plots show that the balanced sample has much fewer outliers, compared to the unbalanced sample. This fact could explain reported differences in means. A further comparison indicates insignificant differences in means for variables, such as “number of patent applications”, “number of new products commercialized” or “industry export intensity”. Finally, for the balanced sample, I classified firms by size and industry categories in order to examine how they differ in terms of variables such as, “number of patent applications” and “number of product innovations”. Then, I compared the resulting differences to those observed in the data provided by the Spanish National Statistics Institute (INE) and in the unbalanced sample provided by the Public Enterprise Foundation. I did not find substantial differences between the results derived from the balanced sample and those reported by these institutions.

[14] This classification is equivalent to the “International Standard Industrial Classification”, ISIC.

3.3.2 Explanatory and control variables. Table 2 describes regressors included in Models 1 and 2. As explanatory variables in Model 2, I used dummies that indicate the adoption of R&D activities to build exclusive combinations that characterize alternative organizational designs for R&D activities (see Table 1). On the other hand, I also included control variables that affect the R&D adoption behavior in Model 1 and/or the innovative propensity of firms in Model 2. In order to control for the fact that firms with different learning capabilities may differ in terms of their ability to generate complementarities, I considered the indicator, *Innovation Management*. This is a dummy variable that characterizes the firm utilization of management practices, such as the adoption of planning programs to address innovation activities, and the use of metrics to evaluate innovation outcomes. In Model 1, it is hypothesized that the use of innovation management practices induces the firm's adoption of R&D activities. This holds true since these practices enable firms to detect the R&D activities required for achieving predetermined innovation objectives, and to assess better the contribution of these activities to the innovation process. In the case of Model 2, I hypothesized that firms using innovation management mechanisms are better placed to harness learning rooted in R&D and therefore have a higher propensity to innovate (Huergo, 2006). In addition, in Model 2 I included the indicator, *Innovation Intensity*, measured here as the percentage of R&D expenditure to total sales. With this variable, I aim to control for the influence that differences in the technological efforts of firms may have on knowledge creation. In particular, it is expected that *Innovation Intensity* contributes positively to determining knowledge creation (Cassiman and Veugelers, 2006).

As suggested in the last section, firms with a high exposure to diverse external knowledge are those with more incentives to make R&D activities and with higher probabilities to produce complementarities in R&D. To control for these aspects, I incorporated the indicator *Technological Opportunities*, which represents external knowledge available to firms that may contribute to improving their technological performance (Cohen and Levinthal, 1989). Particularly in Model 1, it is hypothesized that *Technological Opportunities* encourage the adoption of R&D activities, since in industries with high investments in R&D, firms search more extensively to access new opportunities (e.g. Cohen and Levinthal, 1989; Veugelers, 1997; Laursen and Salter, 2006). To allow for a non-linear relationship between *Technological Opportunities* and the R&D adoption behavior, I also considered the quadratic term of *Technological Opportunities*. Additionally, in assuming the presence of diffusion spillovers, it is expected that the propensity to innovate in Model 2 is also positively associated with a high presence of *Technological Opportunities* (Klevorick *et al.*, 1995; Cincera, 1997).

To control for appropriability concerns (Kale *et al.*, 2000), I incorporated the variable *Number of Patents* granted to the firm in each year. In Model 1, it is hypothesized that firms with strong patenting capabilities are less exposed to leakage of strategic information, and for that reason, they engage more in R&D activities. Likewise, patenting capabilities positively determine knowledge creation in Model 2 because they allow firms to appropriate benefits from innovation. Alternatively, I included in each model the variable *Industrial Export Intensity*. In so doing, I aim to control for the fact that the degree of internationalization of the industry where a firm operates likely affects its adoption of R&D behavior as well as its propensity to innovate. In Model 1, it is hypothesized that firms in export industries adopt R&D activities as a method to extend their search activities to distant geographic contexts (Rosenkopf and Almeida, 2003). In Model 2, it is expected that firms operating in

Table 2. Variable description and descriptive statistics

Model	Variable	Description	Mean	SD	Min.	Max.
2	Innovation Intensity	Percentage of R&D expenditures to total sales	0.70	2.21	0	55.8
1–2	Innovation Management	Binary: 1 if the firm used plans to address its innovation activities and metrics to assess innovation outcomes	0.23	0.42	0	1
1–2	Technological Opportunities[a]	Industrial R&D stock normalized by total industrial sales (measured at the level of two-digit NACE)	1.71	2.48	0.19	20.27
1–2	Number of Patents	Number of patents granted during the year	0.35	3.93	0	150
1–2	Process Innovation	Binary: 1 if the firm conducted process innovation	0.32	0.46	0	1
1	Product Innovation	Binary: 1 if the firm conducted product innovation	0.22	0.42	0	1
1–2	Industry Export Intensity	Total industrial exports normalized by total industrial sales (measured at the level of two-digit NACE)	0.29	0.14	0.03	0.91
1–2	Value of Total Assets	Logarithm of total value assets	13.95	2.32	5.09	19.72
1	Total Public Funds	Logarithm of public resources for financing R&D activities	1.02	3.33	0	16.99
2	Knowledge Creation	Number of new products commercialized	2.59	17.18	0	426
1	Adoption of In-house R&D		0.28	0.44	0	1
1	Adoption of R&D Outsourcing	Binary: 1 when the firm adopted R&D activities	0.19	0.39	0	1
1	Adoption of Research Collaboration		0.29	0.45	0	1
2	Adoption of In-house R&D Only		0.04	0.18	0	1
2	Adoption of Research Collaboration Only		0.03	0.19	0	1
2	Adoption of R&D Outsourcing Only		0.01	0.13	0	1
2	Adoption of In-house R&D and Research Collaboration	Binary: 1 when the firm adopted exclusive combinations of R&D activities	0.09	0.28	0	1
2	Adoption of In-house R&D with R&D Outsourcing		0.02	0.12	0	1
2	Adoption of Research Collaboration and R&D Outsourcing		0.03	0.16	0	1
2	Adoption of In-house R&D with Both External R&D		0.13	0.34	0	1

[a] For each firm, I used the perpetual inventory method to determine R&D stock (Beneito, 2006; Morales, 2007). I first deflated the firm's R&D expenditures using an Industrial Price Index for durable goods, base 1998 (www.ine.es). Subsequently, for the first observation, I used the market capitalization formula: $K^{RD}_{it=1998} = R_{it=1998}/(g+\delta)$. I assumed that $\delta = 0.3$ (Martínez-Ros and Labeaga, 2002) and that $g = 0.4$ (Beneito, 2006). Finally, R&D stock for firm "i" at period "t" is derived from $K^{RD}_{it} = (1-\delta)K^{RD}_{it-1} + R_{it-1}$. Finally, I aggregated individual R&D stock at the industry level (two-digit NACE).

export industries innovate more in an attempt to compete effectively in international markets (Cassiman and Veugelers, 2006). Finally, I incorporated *Value of Total Assets* in both models as a proxy for firm size. In particular, this controls for differences in both R&D adoption behavior and the production of knowledge related to variations in the scale of operations (Henderson and Cockburn, 1996; Veugelers and Cassiman, 1999; Almeida *et al.*, 2003).

Model 1 also incorporated the following controls. Since adoption behavior may differ among innovative and non-innovative firms, I included two binary variables that state whether the firm conducted either product or process innovation. Furthermore, I incorporated the variable *Total Public Fund* received by the firm to finance R&D activities, which attempts to control for the influence of public financing extensively used in Spain to stimulate firms' R&D activities (Bayona *et al.*, 2001). Finally, I added a categorical variable into Model 2 that states whether the firm conducted process innovation. In this way, I try to take into account potential complementarities between process and product innovation during knowledge creation (Martínez-Ros and Labeaga, 2002; Reichstein and Salter, 2006). Table 3 contains the correlation matrix of previously described regressors.

3.4 Results

Table 4 shows the estimation of unconditional correlations (Spearman rank correlation). As expected, the adoption of internal and external R&D activities is positively correlated, being stronger in cases for which firms combine in-house R&D with research collaboration. Table 5 shows the estimation of both the multivariate probit model and the associated conditional correlations. It is worth mentioning that the likelihood ratio test for the null that choices on R&D activities are independent is strongly rejected (p-value < 0.001). After removing the effects of observable factors, correlations between internal and external R&D activities remain positive and statistically significant, giving support to Hypothesis 1. In favor of Hypothesis 2, the results indicate that the conditional correlation between in-house R&D and research collaboration is much larger than that observed in the case of in-house R&D and R&D outsourcing.

By examining the factors driving R&D adoption, it is observed that the majority of the estimates of the multivariate probit model have the expected signs. Consistent with Kale *et al.* (2002), the parameter for *Innovation Management* is positive and statistically significant in each equation, providing evidence that firms using management practices to address their innovation activities are prone to adopting R&D activities. The results indicate that *Technological Opportunities* has a positive and statistical, but diminishing effect on the adoption behavior of R&D activities. As expected, both product and process innovation are positively related to the likelihood of R&D adoption. As indicated by other studies (Bayona *et al.*, 2001), financing in Spain has a positive and significant impact on R&D adoption behavior. In addition, firm size is a factor positively influencing the likelihood of adopting R&D activities. These results are compatible with other studies that indicate that large firms have advantages for using both internal and external sources of knowledge (Henderson and Cockburn, 1996; Veugelers and Cassiman, 1999).

The results show important differences in factors determining the adoption of research collaboration and R&D outsourcing. As regards *Innovation Management*, it is observed that its effect is statistically stronger on the choice of research collaboration than on the choice of

Table 3. Correlation matrix

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1. Knowledge Creation	1.00																			
2. Internal R&D (dummy)	0.12	1.00																		
3. Research Collaboration (dummy)	0.08	0.54	1.00																	
4. R&D Outsourcing (dummy)	0.09	0.71	0.59	1.00																
5. Innovation Intensity	0.09	0.40	0.39	0.36	1.00															
6. Innovation Management	0.12	0.70	0.53	0.64	0.34	1.00														
7. Industry Technological Opportunities	−0.01	0.14	0.16	0.14	0.23	0.14	1.00													
8. Number of Patents	0.01	0.11	0.13	0.10	0.21	0.13	0.04	1.00												
9. Process Innovation	0.06	0.29	0.24	0.31	0.14	0.31	0.06	0.08	1.00											
10. Product Innovation	0.28	0.42	0.30	0.39	0.22	0.41	0.10	0.10	0.29	1.00										
11. Industry Export Intensity	0.01	0.16	0.16	0.16	0.15	0.16	0.49	0.01	0.10	0.08	1.00									
12. Value of Total Assets	0.07	0.49	0.42	0.51	0.23	0.47	0.11	0.10	0.27	0.23	0.14	1.00								
13. Total Public Funds	0.10	0.46	0.48	0.44	0.44	0.44	0.17	0.18	0.22	0.27	0.13	0.33	1.00							
14. Adoption of In-house R&D Only	0.03	0.31	−0.10	−0.12	0.04	0.10	0.00	−0.01	−0.01	0.08	0.01	0.07	−0.02	1.00						
15. Adoption of Research Collaboration Only	−0.02	−0.12	−0.10	0.30	−0.04	−0.05	−0.01	−0.02	0.05	0.00	0.00	0.10	−0.06	−0.04	1.00					
16. Adoption of R&D Outsourcing Only	−0.01	−0.08	0.27	−0.09	0.07	−0.04	0.02	−0.01	0.00	−0.04	0.06	0.01	−0.01	−0.03	−0.03	1.00				
17. Adoption of In-house R&D and Research Collaboration	0.04	0.51	−0.16	0.49	0.11	0.33	0.03	−0.01	0.14	0.19	0.06	0.20	0.07	−0.06	−0.06	−0.04	1.00			
18. Adoption of In-house R&D with R&D Outsourcing	0.01	0.21	0.26	−0.08	0.06	0.10	0.00	0.01	0.02	0.04	0.01	0.08	0.01	−0.03	−0.03	−0.02	−0.04	1.00		
19. Adoption of both Types of External R&D	−0.01	−0.11	0.34	0.27	0.04	0.09	0.02	−0.01	0.04	0.04	0.03	0.12	0.01	−0.03	−0.03	−0.02	−0.05	−0.02	1.00	
20. Adoption of In-house R&D with both External R&D	0.10	0.64	0.79	0.62	0.39	0.55	0.16	0.16	0.26	0.34	0.15	0.40	0.55	−0.08	−0.08	−0.05	−0.13	−0.05	−0.07	1.00

Observations ($N \times T$) $= 5{,}170$.

Table 4. Results for the unconditional correlations

	In-house R&D	Research Collaboration	R&D Outsourcing
In-house R&D	–	–	–
Research Collaboration	0.710***	–	–
R&D Outsourcing	0.541***	0.586***	–

Coefficient significant at ***1%, **5% and *10%.

Table 5. Regression results for the choice of R&D activities

Independent variables	In-house R&D (x_{RD})	Research Collaboration (x_{RC})	R&D Outsourcing (x_{RO})
Innovation Management	1.577†	1.182†	0.870†
	(0.064)	(0.061)	(0.060)
Industrial Technological Opportunities	0.220†	0.132†	0.068***
	(0.026)	(0.027)	(0.025)
Industrial Technological Opportunities Squared	−0.018†	−0.009†	−0.003**
	(0.002)	(0.002)	(0.002)
Number of Patents	0.020	0.001	0.029**
	(0.018)	(0.008)	(0.012)
Process Innovation	0.095*	0.319†	0.131***
	(0.056)	(0.052)	(0.053)
Product Innovation	0.629†	0.482†	0.263†
	(0.061)	(0.060)	(0.059)
Industry Export Intensity	0.085	0.095	0.456**
	(0.216)	(0.201)	(0.203)
Total Public Funds	0.119†	0.098†	0.089†
	(0.014)	(0.010)	(0.008)
Value of Total Assets	0.191†	0.230†	0.169†
	(0.013)	(0.013)	(0.012)
Constant	−3.999†	−4.567†	−4.009†
	(0.064)	(0.192)	(0.185)
Time Dummies	(included)	(included)	(included)
Conditional correlations			
ρ (x_{RD} and x_{RC})		0.548†	
ρ (x_{RD} and x_{RO})		0.316†	
ρ (x_{RC} and x_{RO})		0.471†	
Goodness of fit		$\chi^2(39) = 3{,}060.86$***	
Log-pseudo Likelihood		−4,494.4464	
Observation ($N \times T$)		5,170	

Robust standard errors in parentheses: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$, †$p < 0.001$.

R&D outsourcing.[15] The degree of association between the adoption of external R&D activities and the use of innovation management practices are regarded here as a signal indicating the level of complexity involved in learning from external knowledge (von Hippel, 1994; Anand and Khanna, 2000). In line with this suggestion, the results show that research collaboration is a more complex form of knowledge provision than R&D outsourcing, as the former depends more on the implementation of knowledge management. As regards *Technological Opportunities*, it is observed that increasing opportunities induce more the adoption of research collaboration than the adoption of R&D outsourcing.[16] This fact supports the idea that access to technological opportunities favors more the implementation of specific mechanisms of knowledge transfer. These results are consistent with the premise that learning from increasing technological opportunities is a difficult task that needs closer interaction between the firm and external actors than that produced by the exchange of knowledge in markets for technology (Tidd and Trewhella, 1997; Kale *et al.*, 2000). Taken together, these findings are consistent with the arguments used here to ground Hypothesis 2; that is, research collaboration and R&D outsourcing differ in the provision of knowledge derived from each one.

Table 6 shows the estimates of the parameters for the knowledge production function in Model 2. Particularly, I used a GMM estimator using Chamberlain moment conditions for the linear feedback specification in Model 2.[17] Columns 1–4 show two-step GMM estimations, in which *Innovation Intensity* and *Innovation Management* were successively incorporated as two alternative specifications for the firm's learning capabilities, and in which the linear and quadratic terms of *Technological Opportunities* were also included. In all cases, the existence of a first-order correlation of the residuals is observed, but there is no second-order autocorrelation, which shows that the model is well specified (Windmeijer, 2002). Values of the dependent variable lagged two or more periods as well as values of the explanatory variables lagged one or more periods are used as valid instruments in the study (see the notes in Table 6). As shown by the extant literature on count-data-panel models (e.g. Cincera, 1997; Montalvo, 1997), successive past values for the dependent and explanatory variables prove to be valid instruments in the quasi-differenced GMM estimator, since these values correlate with predetermined regressors in the differenced model, but not with the fixed-effect term. Table 6 also reports the Sargan test of the over-identifying restrictions. This statistic provides a test for verifying if instruments under consideration are appropriately orthogonal to the residuals. As indicated by Table 6, in all cases, the Sargan test confirms the validity of the instruments used in the estimation (via the Chamberlain moment conditions). However, as discussed by Leiponen (2005b), the capacity of panel data techniques to allow for the type of unobserved heterogeneity that affects complementarities requires the assumption that the unobserved firm characteristics keep constant over time.

[15] The Wald test for the hypothesis that the estimate of *Innovation Management* in the research collaboration equation is equal to that observed in the R&D outsourcing equation is rejected at conventional levels.

[16] The Wald test for the hypothesis that the estimate of *Technological Opportunities* in the research collaboration equation is equal to that observed in the R&D outsourcing equation is rejected at conventional levels.

[17] Estimations were carried out with ExpEnd, a Gauss code for non-linear GMM estimations of count-data models with endogenous regressors (Windmeijer, 2002).

Table 6. Regression results for the firm innovation performance (Number of New Products)

Independent variables	Model (a)	Model (b)	Model (c)	Model (d)
Lag of the Number of New Products	0.198†	0.179†	0.172†	0.159†
	(0.012)	(0.009)	(0.010)	(0.009)
Innovation Intensity	0.002	–	0.053**	0.022
	(0.028)		(0.025)	(0.024)
Innovation Management	–	0.264*	0.504†	0.395†
		(0.147)	(0.134)	(0.107)
Industrial Technological Opportunities	−0.161***	−0.209***	−0.196†	−0.375†
	(0.055)	(0.064)	(0.054)	(0.073)
Industrial Technological Opportunities Squared	–	–	–	0.025**
				(0.010)
Number of Patents	0.017***	0.017***	0.019†	0.016***
	(0.005)	(0.005)	(0.004)	(0.005)
Process Innovation	−0.988†	−0.968†	−0.977†	−1.033†
	(0.065)	(0.062)	(0.064)	(0.055)
Industry Export Intensity	1.710***	2.231†	1.798***	2.218†
	(0.593)	(0.590)	(0.549)	(0.562)
Value of Total Assets	0.208†	0.108	0.075	0.015
	(0.052)	(0.078)	(0.080)	(0.103)
Time Dummies	(included)	(included)	(included)	(included)
Organizational design adoption				
In-house R&D Only	1.487†	1.500†	1.549†	1.626†
	(0.229)	(0.242)	(0.234)	(0.203)
R&D Collaboration Only	−0.653**	−0.888**	−0.928†	−1.224†
	(0.322)	(0.267)	(0.255)	(0.186)
R&D Outsourcing Only	0.683***	0.474**	1.043†	0.894†
	(0.195)	(0.209)	(0.154)	(0.177)
In-house R&D with R&D Collaboration	1.244†	1.234†	1.132†	1.110†
	(0.082)	(0.137)	(0.139)	(0.099)
In-house R&D with R&D Outsourcing	1.732†	1.812†	1.526†	1.738†
	(0.293)	(0.295)	(0.304)	(0.289)
Both Types of External R&D	0.150	0.205	0.110	−0.154
	(0.219)	(0.207)	(0.176)	(0.177)
In-house R&D with both External R&D	1.948†	2.116†	1.827†	2.061†
	(0.201)	(0.220)	(0.219)	(0.193)
Tests for serial correlation				
First-order serial correlation	−2.423**	−2.526**	−2.468**	−2.544**
Second-order serial correlation	−0.044	−0.270	−0.203	−0.318
Overidentification test				
Sargan's test	108.7611	115.0891	112.1745	130.4854
Degree of freedom	101	101	109	117
p-value	0.2812	0.1599	0.3982	0.1859
Observation ($N \times T$)		5,170		

Notes: Parameters are two-step GMM estimators using Chamberlain moment conditions. Estimations assume that organizational choice variables as well as control variables should be taken as predetermined. Therefore, past values of all the regressors are used as instruments. Lag values of the dependent variables are also included as instruments. Four lags for the predetermined variables and three for the dependent variable were implemented. Robust standard errors in parentheses: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$, †$p < 0.001$.

Therefore, the validity of my approach to treat unobserved heterogeneity is circumscribed to this assumption.

The results from Model 2 show that organizational designs with internal and external R&D activities tend to have a greater impact on innovation propensity than those with just one R&D activity. This is consistent with the idea that the joint adoption of internal and external R&D activities enhances learning (Hypothesis 1). It is also observed that organizational designs based exclusively on research collaboration have a negative, statistical impact on innovation propensity, while organizational designs in which R&D outsourcing is adopted exclusively have a positive, statistical effect on knowledge creation. These findings suggest that learning from R&D outsourcing is possible even without the adoption of in-house R&D, while learning from research collaboration needs complementary skills in terms of in-house R&D.

Regarding the estimations for the control variables, the results are as follows. Estimates on the lagged dependent variable are positive and statistically significant in accordance with the premise that highly innovative firms tend to be so in the future. This fact reveals the presence of a persistent effect in innovation (Martínez-Ros and Labeaga, 2002; Leiponen, 2005b). Likewise, the parameter for *Innovation Management* is positive and statistically significant in all cases. As shown in model (b) of Table 6, inclusion of this variable in the analysis makes the coefficient for *Value of Total Assets* no longer statistically significant, which is consistent with the findings of Huergo (2006). That is, the effect of firm size on innovation propensity includes a large part relating to the use of mechanisms for innovation management.

It is also observed that the effect of *Technological Opportunities* is negative and statistically significant in all cases, suggesting the presence of *competitive* rather than *diffusion* spillovers (Cincera, 1997). In order to verify the existence of a non-linear relationship between *Technological Opportunities* and innovation propensity, I introduced *Technological Opportunities Squared* into model (d). The last column of Table 6 shows that the parameter for *Technological Opportunities* is negative and that the parameter for the squared term is positive, which implies that at low values of knowledge spillovers, additional *Technological Opportunities* have a negative effect on knowledge creation. At some level, the effect becomes positive, indicating that the presence of knowledge spillovers encourages knowledge creation. This finding suggests that *diffusion* spillovers prevail over *competitive* spillovers, once a certain threshold of *Technological Opportunities* is achieved. Parameters for the *Number of Patent* applications are positive and statistically significant in all cases, suggesting that firms' patenting capabilities incentivize innovation propensity.

Unexpectedly, it is observed that the adoption of process innovation is negatively related to product innovation, which is not consistent with the presence of complementarities between these activities. Further experimentation with other specifications[18] reveals that the parameter for *Process Innovation* becomes negative once the lag of the dependent variable is included in the model. This could indicate that knowledge accumulation, characterized by K_{t-1}, reflects a part of the effects attributed to *Process Innovation*. Finally, it is observed that

[18] Not shown here for space reasons, but available from the author upon request.

Industry Export Intensity is a relevant factor explaining innovation propensity, which is consistent with the premise sustaining that internationalization is a push-force inducing innovation.

Table 7 presents the values of the distance test used to assess complementarities.[19] Table 8 shows lower and upper bounds for various significant levels provided by Kodde and Palm (1986). Comparing distance measures in Table 7 with bounds in Table 8 leads to the following conclusions. There are complementarities in the case of the joint adoption of internal R&D and research collaboration, as suggested by the fact that strict supermodularity of the objective function is not rejected in any case. That is, supermodularity is not rejected while sub-modularity is strongly rejected. This result shows that internal R&D and research collaboration reinforce each other during the process of knowledge creation, giving support to Hypothesis 1.

For combinations between in-house R&D and R&D outsourcing, the results point to the existence of a substitution relationship. In all cases, sub-modularity is not rejected while the presence of supermodularity depends on the specification to be considered. In the case of models (a) and (b), the results point to the presence of weak complementarities, as both supermodularity and sub-modularity are not rejected. For these cases, I redefined the test so that under the null, no interaction is tested against supermodularity under the alternative[20] (see Kodde and Ritzen, 1988). In both settings, the null hypothesis cannot be rejected, thus, indicating these activities are independent. In the case of models (c) and (d), the test supports the existence of a substitution relationship, since supermodularity is rejected at 1 and 5 per cent, respectively, while sub-modularity cannot be rejected at 25 per cent.[21] Altogether, these results are interpreted as indicating that knowledge creation is weakly sub-modular in combinations for which firms adopt in-house R&D with R&D outsourcing. This fact reveals then the presence of a substitution relationship.

Finally, it is observed that the relationship between research collaboration and R&D outsourcing tends to be complementarity. For this combination, supermodularity in knowledge creation is not rejected while sub-modularity tends to be rejected. Since these activities are interrelated, it is of great importance not to ignore this fact when evaluating performance effects attributed to the joint adoption of internal and external R&D activities.

4. Discussion and Conclusions

This study compares complementarities derived from alternative combinations of internal and external R&D activities, using an empirical design in which conditional correlations, as well as a dynamic knowledge production model were estimated from a panel of Spanish manufacturing companies. With this empirical design, the current study is among the first

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[19] These values were obtained according to the procedure presented by Kodde and Palm (1986), in which a version of the Wald test is computed by minimizing a particular distance measure.

[20] Results for cases in which the test is inconclusive are not shown here for space reasons, but they are available from the author upon request.

[21] While inequalities are tested under the null, note that the test is more demanding as the level of significance is greater.

Table 7. Minimum distance values to be compared with the upper and lower bounds of the Kodde and Palm's test

Interaction	Combinations of R&D activities	Model (a)	Model (b)	Model (c)	Model (d)
Complementarity	In-house R&D and Research Collaboration	7.6226e−009†	2.4732e−009†	6.0081e−010†	1.3194e−009†
(Supermodularity under the null)	In-house R&D and R&D Outsourcing	1.318††	7.0283e−016†	10.813***	5.923**
	Research Collaboration and R&D Outsourcing	2.3706e−009†	8.7334e−011†	4.0554e−004†	1.8260e−009†
	In-house R&D and Research Collaboration	8.507***	7.104**	26.078***	29.992***
Substitutability	In-house R&D and R&D Outsourcing	1.7901e−010†	0.409†	1.4485e−010†	1.7891e−010†
(Sub-modularity under the null)	Research Collaboration and R&D Outsourcing	2.182†††	9.366***	6.039**	9.755***

Note: The use of asterisks indicates significant levels at which the null hypothesis is rejected. We adopt the conventional notation: ***1%, **5% and *10%. Alternatively, the use of daggers indicates significant levels at which the null hypothesis cannot be rejected. In this case, we adopt the following notation: †25%, ††10% and †††5%.

Table 8. Upper and lower bounds on the critical values of the distance test with two inequality constraints

Significant level α	0.25	0.10	0.05	0.01
Lower bound	0.455	1.642	2.706	5.412
Upper bound	2.090	3.808	5.138	8.273

Source: Kodde and Palm (1986).

in correcting for the effects of unobserved heterogeneity that may affect the assessment of complementarities among R&D activities.

The results of this study strongly support the proposed hypothesis that complementarities between R&D activities across organizational boundaries depend on whether firms leverage their intramural R&D by choosing research collaboration or R&D outsourcing. The findings indicate that while combinations between intramural R&D and research collaboration produce strong complementarities in knowledge creation, the joint adoption of intramural R&D and R&D outsourcing reduces the firm's innovative performance. The evidence here shows that the co-development of R&D among partners, rather than the acquisition of R&D in markets, proves to be an effective mechanism in reinforcing the contribution of intramural R&D to knowledge creation. Although the current research employs a different approach, the results confirm the findings reported by prior research on inter-organizational learning that alliances, such as joint ventures, are superior to contract-based arrangements in promoting inter-firm knowledge transfer (Mowery *et al.*, 1996; Gomes-Casseres *et al.*, 2006) as well as in generating learning effects (Anand and Khanna, 2000). These findings expand previous literature as they show that participation in R&D collaboration contributes to shaping innovative performance particularly by leveraging in-house R&D. Previous studies on alliance learning rarely assessed this indirect effect of alliances on innovative performance.

In order to gain further insights into the role of external sourcing in forming complementarities, I examined the drivers leading firms' R&D adoption behavior. In particular, I found that compared with R&D outsourcing, research collaboration is related more to the use of innovation management practices and to the presence of increasing technological opportunities. As expected, these results support the proposition that research collaboration is a more complex form of knowledge provision, and in this respect, its adoption incentives are more in line with the firm's implementation of in-house R&D. By considering Anand and Khanna's suggestion (2000) that the potential of a firm's learning increases with the difficulty in managing knowledge provision in alliances, the findings of this research imply that such learning should have a broader scope in research collaboration than in R&D outsourcing. These results are relevant for the literature on complementarities in R&D, since they suggest that differences in the scope of learning associated with each of the external R&D activities under consideration may have a critical role in explaining differences in the way intramural R&D interacts with research collaboration and R&D outsourcing, respectively.

However, the finding showing a substitution relationship between in-house R&D and R&D outsourcing contrasts the results provided by Schmiedeberg (2008) and by Cassiman and Veugelers (2006). While the former study reports no evidence of complementarities for a sample of German firms, the latter supports the hypothesis of complementarities between these R&D activities for a sample of Belgian firms. Alternatively, in line with the literature on open innovation (Chesbrough, 2003), my results suggest that firms could improve their learning results by specializing in R&D core activities internally or by acquiring in markets the R&D in which others have encoded knowledge expertise. Several features can be considered to explain divergences between my findings and those reported by the mentioned studies. For instance, differences across countries in the functioning and nature of markets for technology, or in the role of public policy in promoting innovation might explain discrepancies in the R&D adoption behavior (Mowery and Rosenberg, 1991). Furthermore, differences in methodology and data may result in contrasting conclusions. In this respect, important differences can exist, taking into account that the empirical design used here draws on longitudinal data for testing the hypotheses under question.

The findings of this paper have relevance for both innovation management and technology policy. As regards innovation management, the results provide indications on how firms can organize their R&D activities along their boundaries to obtain the best outcomes in terms of knowledge creation. The evidence provided by the study points to the adoption of research collaboration as the best option to enhance the returns of intramural R&D, although its benefits are only available to firms having technological and managerial skills. Alternatively, since R&D outsourcing has a positive effect on knowledge creation, it seems the right option to acquire knowledge in cases for which firms lack relevant technological assets, and for which markets for technology exist. Subcontracting of R&D may be also a suitable option in cases for which firms decide to focus their R&D effort in core R&D activities. As regards technology policy, this study supports the idea that promotion of public programs that stimulate research collaboration in sectors with high investments in R&D may cause positive externalities, considering the reinforcement effects that R&D collaboration may have on intramural R&D. Additionally, policies that improve the efficiency of markets for technology (e.g. by creating or developing property rights) may generate positive effects on the firm's innovative performance by favoring the diffusion and exploitation of available technologies. Nonetheless, one would expect that the effects of policies promoting R&D collaboration would outweigh those associated with the improvements in the functioning of markets for technology.

The results of this research are subject to some limitations, which at the same time, open new avenues for future research. As in other empirical studies on complementarities (e.g. Leiponen, 2005b; Belderbos *et al.*, 2006), the sample used here has few observations in some of the exclusive combinations of R&D activities under consideration. This fact may affect the estimation of critical coefficients, which could become less consistent and less significant. A larger sample of companies may contribute to mitigating this concern. On the other hand, since the ESEE includes observations at the firm level, complementarities in R&D may be induced by economies of scope caused by the simultaneous development of several projects (Veugelers and Cassiman, 1999). However, the results are valid even after considering the effect of the variable *Innovation Management*, which controls for a firm's ability to manage several R&D projects simultaneously (Huergo, 2006). More research may contribute to verifying whether the production of complementarities between internal and external R&D activities takes place strictly at the organizational level or whether they can appear at the level of individual R&D projects. Finally, this study does not examine specific patterns of interactions between internal R&D and research collaboration. Following the taxonomy developed by Choi *et al.* (2008), complementarities can be classified into symmetric (R&D activities are mutually reinforcing) and asymmetric (one is reinforced by the other). In this regard, more research is needed to determine whether in-house R&D and research collaboration contribute symmetrically to knowledge creation, or if one of them plays a central role while the other acts more as a moderating R&D activity. Analysis of this feature is relevant for a better understanding of the characteristics underlying the architecture of organizational designs joining internal and external R&D activities.

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