THE ROLE OF EXTRAMURAL R&D AND SCIENTIFIC KNOWLEDGE IN CREATING HIGH NOVELTY INNOVATIONS: AN EXAMINATION OF MANUFACTURING AND SERVICE FIRMS IN SPAIN[*]

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Manuscript accepted in Research Policy: https://doi.org/10.1016/j.respol.2020.104030

Cite as: Gómez, J., Salazar, I., & Vargas, P. (2020). The role of extramural R&D and scientific knowledge in creating high novelty innovations: An examination of manufacturing and service firms in Spain. *Research Policy*, 49(8), 104030.

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[*] We would like to thank participants at ACEDE and EURAM Conferences, and at a seminar at the University of Zaragoza, for their comments. We are also grateful for the helpful suggestions from the editor and two anonymous referees of this Journal. This research was supported by the Spanish Ministry of Economics, Industry and Competitiveness (project ECO2017-85451-R).

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Abstract

This paper studies the effect of extramural R&D and of scientific knowledge in the creation of high novelty innovations. We first argue that extramural R&D brings in higher benefits, but also higher costs, when trying to obtain high novelty vs. low novelty innovations. Second, we propose that extramural investments in scientific R&D allow the firm to access distant knowledge and to break the path dependence induced by its resource endowments. However, investments in scientific R&D are also subject to the risks of the 'two worlds' that result from the collaboration of firms and universities and research centres. Our hypotheses are tested with data from the Panel of Technological Innovation, which describes the innovative activities of Spanish firms from 2005 to 2013. Our results show an inverted U-shaped relationship between extramural R&D and the share of sales from new products. They also reveal that extramural R&D investments increase the proportion of sales from high novelty products more than from low novelty products (a 21% vs. a 2%). However, an excessive reliance on extramural R&D reduces more the sales from high novelty innovations than from low novelty innovations (a 52% vs. a 32%). Finally, extramural R&D performed by universities and research centres raises the share of sales from high novelty innovations. However, collaboration with non-scientific sources is more impactful than collaboration with scientific ones, no matter the nature of the innovation considered.

Keywords

Open innovation, high novelty innovation, extramural R&D, scientific sources of knowledge, high-novelty products, low-novelty products.

Classification codes

L60, L80, O31, O32, O36

1. Introduction

The decision on how openly a firm innovates is likely to have a significant impact on innovation performance (Berchicci, 2013; Grimpe and Kaiser, 2010). This has led to a substantial interest in the topic, especially in the case of inbound open innovation (Bianchi et al., 2016; Dahlander and Gann, 2010; Spithoven et al., 2011), with some authors expressing their concerns about the benefits of openness and an increasing interest in the contingencies that affect them (Bianchi et al., 2016; Monteiro et al., 2017). As a result, recent research has investigated the conditions that allow some firms to benefit from open innovation more than others (Bianchi et al., 2016; Chiaroni et al., 2010, 2011; Manzini et al., 2017; Monteiro et al., 2017). Previous papers have pointed to the role of internal research and development (R&D) (Grimpe and Kaiser, 2010; Hung and Chou, 2013; Rothaermel and Alexander, 2009), the strategic orientation (Chen and Huizingh, 2014) or the diversity of external knowledge sources from which the technological knowledge is obtained (see, for example, Chen et al., 2016; Du et al., 2014; Faems et al., 2010, Köhler et al., 2012).

In this paper we study the effect of inbound open innovation on innovation performance by focusing on two contingencies that may affect the optimal combination of extramural and internal R&D used (Manzini et al., 2017). In particular, we analyse two factors that characterize the innovation strategies[1] of firms, namely, (1) the novelty of the new products obtained from R&D investments and (2) the identity of the external partner. The literature recognizes that "different kinds of innovation … require different knowledge inputs" (Hewitt-Dundas et al., 2019). Although research suggests that open innovation may have a different effect depending on the novelty of innovation, its study has been overlooked. This is surprising, as the conclusions that result from exploring this suggestion are relevant for managers organizing their innovation investments. In this sense, it is important to underline that high novelty innovations have been related to the opportunities for creating firm competitive advantages (Garcia and Calantone, 2002; Lynn et al., 1996; McDermott and Handfield, 2000; Marsili and Slater, 2005; Barbosa et al., 2014).

Similarly, different types of partners have different impacts on the novelty of innovations (Kölher et al., 2012). The study of the effectiveness of open innovation across external actors is one of the hot topics identified by Bstieler et al., (2018) when discussing the "Emerging Research

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[1] Following Zahra and Das (1993), an innovation strategy is a multidimensional concept that embodies four dimensions (Porter, 1985; Kamm, 1987; Pearson, 1990; Ambrosio, 1991; Thurow, 1992; West, 1992): an orientation of the firm toward innovation leadership (Maidique and Patch, 1988), types of innovation (Betz, 1987) sources of innovation (Mansfield, 1988) and level of investment in innovation (Thompson and Ewer, 1989).

Themes in Innovation and New Product Development”. In this sense, the analysis of university-businesses relationships has been a constant source of concern for researchers (Conti and Gaule, 2011; Jacobsson et al., 2013) and for the European Commission (2007). Understanding the benefits and costs of scientific vs. non-scientific partners is essential if we want to break the ‘two-worlds paradox’ (Hewitt-Dundas et al., 2019) in the collaboration of businesses and universities.

We borrow from the literatures on open innovation and knowledge search directions to provide the theoretical arguments that allow us to extend the open innovation model by adding these two contingencies. We start by recognizing that investments in extramural R&D bring benefits for firms, but they also increase certain costs (Berchicci, 2013; Grimpe and Kaiser, 2010; Salge et al., 2013; Wadhwa et al., 2017). This results in the *Optimal Combination of R&D Hypothesis* that maintains that firms have to keep a balance between internal and extramural R&D investments to maximize innovation performance. Second, we suggest that the optimal combination between internal and extramural R&D investments is important not only in terms of overall innovation performance, but also regarding the type of innovation obtained. In this sense, extramural investments in R&D play a key role in assuring that firms increase their proportion of high novelty products, whereas they are less relevant when dealing with low novelty products. The reason is that firms must collect external knowledge if they want to break the path dependency induced by internal resources and capabilities (Leonard Barton, 1992, Mathews, 2003). Finally, research on external knowledge sources (Aschhoff and Schmidt, 2008; Belderbos et al., 2004; Köhler et al., 2012) shows that the identity of the external partner is important for innovative performance. Concerns on the ‘two worlds paradox’ (Hewitt-Dundas et al., 2019) lead us to pay attention to two general types of providers of knowledge, scientific and non-scientific, and on their impact on high novelty products. Our main argument is that the benefits and the costs of each of these sources is different. We suggest that a variation in the amount of investments in scientific (vs. non-scientific) sources is expected to be more critical for high novelty innovations.

We test the model on a large sample of innovative Spanish firms from 2005 to 2013. This data set was obtained from the Spanish Technological Innovation Panel (PITEC). The survey is based on the Oslo Manual and collects information on the innovative behaviour of Spanish firms. It includes information on the amount of internal and extra R&D invested, on the type of partner performing extramural R&D and on the degree of novelty of the innovation. The sample used has several advantages over the ones used in previous papers (Berchicci, 2013; Grimpe and Kaiser, 2010; Wadhwa et al., 2017): (1) it is much larger, both in terms of firms and number of observations; (2) it includes firms in both the manufacturing and service sectors and (3) it is a panel data, with a longer observation period than in previous studies. This is important in terms of the generalizability of our results and if we want to make sure that they are robust to heterogeneity and endogeneity. The richness of the information available allows us to perform additional analyses. For example, we test whether the two hypothesized relationships hold for manufacturing and service firms separately.

The paper is structured as follows. Section 2 develops the framework that allows us to develop our hypotheses. Section 3 describes the sample, the variables, and the methodology. Section 4 presents the results obtained. Section 5 draws conclusions and discusses the results.

2. Open innovation, external knowledge search and high novelty innovations

Chesbrough and Bogers (2014, p. 17) define open innovation as a *"distributed innovation process based on purposively managed knowledge flows across organizational boundaries using pecuniary and non-pecuniary mechanisms in line with the organization's business model.* Dahlander and Gann (2010) use two different dimensions to classify open innovation: the direction of the knowledge flows (inbound vs. outbound) and the use of a pecuniary or non-pecuniary mechanism. The outbound process refers to the transferring of ideas from inside the firm to the market. The inbound process refers to the use of external knowledge inside the firm. Considering the pecuniary or non-pecuniary nature of flows, Dahlander and Gann (2010) identify two categories of inbound processes (acquiring and sourcing) and two categories of outbound processes (revealing and licensing). Accordingly, there are different processes integrating the open innovation perspective.

In the case of inbound open innovation, the literature has focussed on analysing the way firms should organize their external innovation efforts. Recent research has provided new insights on different questions, such as where and how to search (Lopez-Vega et al., 2016), on the organizational characteristics that affect the ability to use crowdsourcing as a knowledge source (Polloke et al., 2019) or on the role of digital technologies (Urbinati et al., 2020), to give a few examples. Other papers focus on different aspects affecting partner selection in strategic alliances with open innovation communities (Shaikh and Levina, 2019) or on the effect of collaboration breadth and depth on innovation performance (Kobard et al., 2019). Apart from studying inbound open innovation (Stanko et al. 2017), recent research has also studied outbound open innovation processes. For example, it has investigated the paradox of openness in crowdsourcing (Foege et al., 2019) and the managerial challenges associated to outbound open innovation (Remneland and Styhre, 2019).

Despite all these research efforts, research on open innovation has been identified as one of the five emerging themes in innovation and new product development (Bstieler et al, 2018). Among other questions of interest, these authors emphasize the need to study the effectiveness of open innovation across different external actors. Although it could be argued that previous research has already focused on this, our review of the literature shows that this topic has not been studied from an inbound pecuniary perspective, when considering not only the benefits, but also the costs of open innovation. For example, Grimpe and Kaiser (2010) or Berchicci (2013) analyze the benefits and costs of open innovation, but they do not focus on the type of external provider when studying the optimal combination of internal and internal R&D investments of firms. Similarly, recent literature also emphasizes the need to study the contingencies that may affect the optimal combination of extramural and internal R&D used (Manzini et al., 2017). In this regard, we analyse two factors that characterize the innovation strategies of firms, namely, the novelty of the new products obtained from R&D investments and the identity of the external partner. Again, none of these topics have been studied from an inbound pecuniary perspective (see, for example, the two articles mentioned above). However, their investigation is critical if managers are to maximize the consequences of the R&D investments on the innovation performance of firms.

2.1. The benefits and costs of open innovation: The Optimal Combination of R&D Hypothesis

This study focuses on pecuniary inbound open innovation in Dahlander and Gann's (2010) terms, and more precisely, on how firms define their degree of openness through their investments in R&D. R&D outsourcing is a form of open innovation (Bianchi et al., 2011; Bianchi et al., 2016; Tsai and Wang, 2008, 2009) that refers to the acquisition by a firm of creative work executed by another firm or by public or private research institutions to increase the stock of technological knowledge for developing innovation (OECD, 2005a). The analysis of inbound open innovation is important, given that firms are able to reinforce their innovations by profiting from the combinations of internal and external technological knowledge (Chen et al., 2011). Competitive advantage often comes from this type of openness (Chesbrough and Kardon, 2006).

The use of inbound open innovation delivers several benefits to firms. First, it helps them to share the costs of innovative activities, which are increasing (Katz, 1986). Second, it allows firms to access knowledge that is not available internally, overcoming the constraints of internal resources (Gupta et al., 2006) and path dependency (Grimpe and Kaiser, 2010; Teece, 1986). Additionally, the simultaneous use of internal and extramural R&D in an open innovation model allows firms to obtain synergies from their combination. Investments in internal R&D create the integrative capabilities required to deploy and build upon the acquired knowledge resources (Arora and Gambardella, 1990; Beneito, 2006; Cohen and Levinthal, 1989, Helfat and Raubitschek, 2000; Nichol-Nixon and Woo, 2003; Veugelers, 1997).

However, using external knowledge also has costs. Salge et al. (2013) classify these costs into three categories: identification, assimilation and utilization costs. Identification costs arise when firms have to search and evaluate external agents in the search for the knowledge they need for their innovation projects. Assimilation costs stem from the need to persuade the external provider to reveal the relevant knowledge and to facilitate its transfer. They also include the costs to understand and assimilate external knowledge. Utilization costs are mainly created by the difficulties to integrate internal and external knowledge.

The combination of increasing benefits and costs from external knowledge creates an inverted U-shape relationship between the proportion of extramural R&D used and innovation performance (Laursen and Salter, 2006; Grimpe and Kaiser, 2010; Berchicci, 2013; Gómez et al., 2017; Wadhwa et al., 2017). To argue in terms of this relationship we use the general framework provided by Haans et al., (2016). The framework is proposed to theorize and test curvilinear relationships in which two countervailing forces, commonly expressed in terms of additive benefits/costs are related to some form of performance as the dependent variable (Haans et al., 2016). In our case, the inverted U-shape relationship results from the additive combination of two increasing latent functions capturing the benefits and costs of increasing the proportion of extramural R&D investments used as inputs in the innovation process (see Haans et al., 2016). Figure 1 represents the benefits (A), the costs (B) and the form of the innovation performance (Y) expected in our case (please, see Figure 1, Panel A in Haans et al., 2016).

Insert Figure 1 about here

For a firm using more extramural R&D, the benefits are likely to increase for the reasons explained above. Similarly, the costs are likely to raise. As the firm incorporates more extramural R&D into its innovation process, it is likely that this knowledge is further apart from the knowledge base of the firm. Therefore, the costs of identification, assimilation and utilization escalate more than proportionally. The addition of increasing benefits and costs leads to an inverted U-shape relationship between openness and innovative performance and to an optimal combination of extramural an internal R&D that produces the highest innovation output. This Optimal Combination of R&D Hypothesis is our baseline hypothesis in this paper.

2.2. Contingencies affecting the Optimal Combination of R&D Hypothesis: novelty of innovation and type of external knowledge

Recent research shows that an open innovation approach is not a one fits all approach to innovation. Taking advantage of an open innovation approach critically depends on aspects such as the availability of resources, a firm's absorptive capacity, the use of appropriability mechanisms (Monteiro et al., 2017) or investments in information technologies (Gómez et al., 2017). This has led researchers to investigate the contextual conditions that improve performance for firms choosing an open innovation model (Monteiro et al., 2017; Manzini et al., 2017). Manzini et al. (2017) suggests that the use of an open innovation model depends on a set of both internal and external factors, such as the state of technology in the industry, globalization, the appropriability regime or a firm's intellectual property and innovation strategies. These factors are likely to act as determinants of the use of open innovation models through their influence on the relative benefits and costs. In this paper, we explore two of the factors that characterise the innovation strategy of a firm by analysing the novelty of the innovations produced and by focusing on the search directions chosen by firms using an open innovation model. Our main argument is that the form of the relationship between open innovation and innovation performance will depend on (1) the degree of novelty of the innovation that a firm wants to obtain and (2) the type of providers of the extramural R&D efforts. In other words, these two contingencies affect the benefits and costs represented by the two latent functions depicted above and, consequently, the final form of the inverted U-shaped relationship.

Regarding the first dimension, we focus on the distinction between high and low novelty innovations. First, it is important to stress that new products 'represent the potential commercial value of a firm's R&D activities' (Katila and Ahuja, 2002, p.1183) and they are critically affected by knowledge sourcing decisions. As a result, they are expected to depend on the combination of R&D investment chosen. Second, new products are related to different dimensions of firm performance: they improve market share, market value and firm survival (Banbury and Mitchell, 1995; Chaney and Devinney, 1992; Katila and Ahuja, 2002). In this sense, the novelty of the innovation has been previously related to firm innovation performance (Garcia and Calantone,

2002) and to creating opportunities to access new markets (Lynn et al., 1996; McDermott and Handfield, 2000). In particular, high novelty innovations may create new markets and they offer an opportunity to potential entrants to enter them (Barbosa et al., 2014). In other words, those products that entail a higher degree of novelty are usually positively associated with higher returns (Marsili and Slater, 2005) and to competitive advantage (Barbosa et al., 2014). On the contrary, they usually require risky investments and more resources than low novelty innovations (Barbosa et al., 2014). Therefore, understanding the optimal combination of R&D is critical for managers willing to produce high novelty innovations.

Regarding the second dimension, the effects of open innovation on the novelty of new products are likely to depend not only on the combination of R&D chosen, but also on the type of external source of knowledge used. Therefore, to fully understand the consequences of extramural R&D investments on innovation, the firm has to consider the nature of the external provider of the knowledge. Not only there are many types of external providers of knowledge (see, for example, Laursen and Salter, 2006), but they are likely to differ in terms of benefits and costs associated to their use. We consider the heterogeneity of external providers of knowledge and distinguish between science-driven (Sofka and Grimpe, 2010) and other types of agents. This will allow us to contribute to better understand the ‘two-worlds paradox’ (Hewitt-Dundas et al., 2019) and the role of universities in firms’ innovation. If these sources of external knowledge differ in terms of their benefits and costs, their consequences on innovative performance will also be different.

Our focus on science driven agents aligns with the interest of the literature in disentangling the role of universities and research centres (Perkmann and Walsh, 2007; Perkmann et al., 2011; Hewitt-Dundas et al., 2019). This interest is justified by the increasing tendency of firms to engage in long-term relationships with universities (Perkmann and Walsh, 2007) and it contributes to clarify the conflicting evidence on the link between cooperation with universities and innovation performance (Belderbos et al., 2004; Vega-Jurado et al., 2010).

3. Hypotheses

3.1 Open innovation and the novelty of new products.

Although different conceptualisations and operationalisations of the degree of novelty coexist (see Garcia and Calantone, 2002, for a review), the traditional taxonomy differentiates between high and low novelty innovations.[2] Low novelty innovations are improvements, refinements, and extensions to existing systems of products or processes, usually identified as new to the firm (Garcia and Calantone, 2002), whereas high novelty innovations are major departures from existing capabilities (Ritala and Hurmelinna-Laukkane, 2013). The latter concept usually refers to products that are simultaneously new to the firm and the market (Garcia and Calantone, 2002; Barbosa et al., 2014). Low novelty innovations tend to build upon the established knowledge base utilised by firms (Argyres, 1996), and steadily improve the method or materials used to achieve the firm's objective of profitability and satisfying customers´ needs (Hill and Rothaermel, 2003). However, high novelty innovations frequently require new competencies and knowledge bases different from those used to produce traditional products (Forsman, 2011). In this sense, high novelty innovations may involve a higher degree of discontinuity in the sources of innovation. The fact that the resource endowments of firms are path-dependent and difficult to modify in the short run (Grimpe and Kaiser, 2010; Teece, 1986) make the acquisition of external knowledge a more reliable way to acquire the new competences required for innovations with a higher degree of novelty. The benefits of external knowledge are further accentuated by the fact that high novelty innovations often require the combination of different scientific or technological disciplines, a situation less likely when producing low novelty innovations.

Our main argument is that investing in extramural R&D provides higher marginal benefits and higher innovation performance in high novelty rather than in low novelty innovations. This modifies the U-inverted relationship between the proportion of extramural R&D and innovation performance. In other words, this relationship takes a different form for high novelty innovations vis a vis low novelty innovations. In particular, the U-inverted relationship will show higher values for high novelty innovations than for low novelty innovations, thanks to the higher marginal benefits provided by external knowledge in this case. This amplifies the difference between the benefits and the costs associated to each combination of R&D and results in high novelty innovations benefiting more from investments in extramural R&D, provided that they allow the firm to overcome the constrains of internal resources.

It could be argued that a higher proportion of external R&D investments could also increase the marginal costs of extramural R&D investments when dealing with high novelty innovation

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[2] The information we use in the empirical analysis uses the Oslo Manual as its framework of reference OECD (2005a). As a result, it distinguishes between product innovations that are "Only new to your firm" (low novelty innovations) and those that are "New to your market" (high novelty innovations). Therefore, minor modifications are not considered.

projects. The negative consequences of extramural R&D investments related to identification, assimilation and utilisation of external knowledge inputs (Salge et al., 2013) might be higher for high novelty innovations. As firms are more open, they substitute internal for external knowledge[3], which increases the coordination costs that stem from managing an increasing number of heterogeneous partners. Relatedly, a higher reliance in extramural R&D implies that internal R&D is reduced which makes understanding and absorbing external technology are more difficult. Similarly, as external knowledge is available to competitors, it needs to be combined with internal knowledge in order to create high novelty innovations. However, in the creation of high-novelty innovations it might be possible that a higher skill level is required, given that high-novelty innovations cannot be easily connected to current capabilities (Baldwin and Lin, 2002; Keupp and Gassmann, 2009). The creation of these distant capabilities results in higher costs, given that it is necessary to implement a learning process characterized by being stressful and with high resistance to change (Keupp and Gassmann, 2009). For low levels of extramural R&D investments, our contention is that these costs are likely to increase less than the benefits provided by the acquisition of knowledge distant from the current knowledge base of the firm. For high levels, however, they could be high enough to offset the gains from incorporating external knowledge into the innovation process.[4] Therefore, Hypothesis 1 is enunciated as follows:

Hypothesis 1. *The concavity of the relationship between the proportion of extramural R&D investments and innovative performance will be stronger for high novelty innovations than for low novelty innovations.*

3.2. External knowledge sourcing and the novelty of new products.

Hypothesis 1 studies the consequences of using different combinations of internal and extramural R&D investments on the returns of high vs. low novelty innovations. This conceptualization suggests that the external knowledge incorporated in the firm is homogeneous regarding its source (Köhler et al., 2012). However, firms may obtain external knowledge from different external agents, and these external agents are likely to differ in certain dimensions

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[3] Our assumption is that an increase in internal/extramural R&D implies a decrease in extramural/internal R&D. This would be more likely if internal and extramural R&D investments were substitutes, which is a conclusion that can be extracted from some papers (Tsai and Wang, 2009; Laursen and Salter, 2006). However, it is important to recognize that in other cases both types of investments have been found to be complementary (Cassiman and Veugelers, 2006; 2002).

[4] Hypothesis 1 assumes that the increase in marginal costs, if it takes place, is not enough to offset the marginal benefits obtained.

relevant for understanding the performance effects of open innovation models. In fact, the nature of the external provider is a relevant variable in explaining the success of open innovation (Chen et al., 2011; Köhler et al., 2012). In addition to this, firms use different knowledge sources to achieve different kinds of innovation output (Köhler et al., 2012; Tödtling et al., 2009).

Our main observation is that external agents differ in terms of the benefits and costs associated with their use in high novelty projects (Chen et al., 2011; Grimpe and Sofka, 2010). In this paper, we consider the heterogeneity of external providers of knowledge and distinguish between science-driven (Chen et al., 2016; Köhler et al., 2012; Sofka and Grimpe, 2010) and other types of agents. Therefore, the different marginal benefits and costs of science-driven vs. other types of agents should also affect the U-inverted relationship between open innovation and the innovation performance of high novelty innovations.

As an external source of knowledge, R&D activities performed by scientific agents should be mainly relevant for the creation of products with a high degree of novelty (Chen et al. 2011; Munari and Toschi, 2014; Tödtling et al., 2009). However, their marginal benefits on high-novelty innovations should be more important than that of other extramural R&D sources. The reason has to do with the type of knowledge produced by universities. Scientific partners provide access to tacit scientific knowledge and to unpublished codified knowledge that allow firms to work with the latest findings (Du et al., 2014). Furthermore, universities have a more diverse knowledge base than other external agents (Un et al., 2010). Their teaching and research interests can be expected to include multiple disciplines. In general, universities possess a more diverse set of ideas and perspectives than companies (Henard and McFadyen, 2005) and they also tend to engage in more novel research than other types of agents (Cohen et al., 2002; Hewitt-Dundas et al., 2019; Sofka and Grimpe, 2010). In addition to this, they tend to have little commercial incentives (Hewitt-Dundas et al., 2019), which reduces appropriability concerns and the fear of imitation (Giarratana and Mariani, 2014).

The available evidence is consistent with these ideas. Belderbos et al. (2004) note that university cooperation is important in producing and commercializing radical innovations. Amara and Landry (2005, p. 256) conclude "that innovations involving more radical changes require more research-based information than incremental changes….". This is why they suggest the creation of linkages between firms and universities and government laboratories. Aschhoff and Schmidt (2008) find that R&D cooperation with research institutes has a positive impact on the production of market novelties. Similarly, Hewitt-Dundas et al. (2019) find a 10.7 per cent increase in the probability of developing new to the market innovations (rather than new to the firm) when firms collaborate with universities. They also show that collaboration with universities increases the sales from new to the market products or services.

On the contrary, non-scientific providers may find difficulties in articulating tacit knowledge (Du et al., 2014), which is usually important in the early stages of the technological opportunity exploitation (Katila and Mang, 2003). Similarly, the incentives to create and appropriate value of non-scientific providers mean that unwanted knowledge spillovers are more likely in this case (Du et al., 2014).

Therefore, we argue that collaboration with universities in R&D activities is more appropriate when the objective is to create high-novelty products. This is also the reason why we expect the marginal benefits of scientific agents to be higher in the case of high novelty innovations, moving the inverted U-shaped relationship between open innovation and innovation performance upwards.

Apart for having a higher potential to generate high-novelty innovations, it could also be argued that extramural R&D investments in scientific knowledge might also imply higher marginal costs than the use of other types of agents. This would move downwards the U-shaped relationship between the extramural R&D activities conducted by scientific agents and innovative performance. One reason is that in order to apply extramural R&D to commercial ends, it requires having enough absorptive capacity to identify, assimilate and utilize it (Köhler et al., 2012; Link et al., 2007; Siegel et al., 2004). As the extent of openness increases, absorptive capacity may decrease if firms invest more in extramural R&D and less in internal R&D. This limits the ability of the firm to identify, assimilate and utilize external knowledge. Furthermore, knowledge embedded in universities tends to be more distant from a firm's current capabilities, making collaboration more difficult (Hewitt-Dundas et al., 2019). The institutionalized way of doing research in scientific institutions, based on autonomy, academic freedom and, when necessary, improvisation (Du et al., 2014) could also make collaboration difficult. In this context, non-scientific providers have the advantage of being more familiar with formal monitoring and control (Du et al., 2014). Another reason is that knowledge from scientific sources tends to be uncertain and non-codifiable, which results in high transaction costs and market failures (Cassiman and Veugelers, 2006). Finally, the fact that the objectives of scientific agents are usually different from the ones of firms may also increase the costs (Cassiman and Veugelers, 2006; Du et al., 2014; Kaufman and Tödling, 2001; Siegel et al., 2004). In fact, scientific researchers usually value reputation and non-monetary compensation rather than only monetary benefit (Du et. al., 2014). As in Hypothesis 1, our contention is that these costs are to increase less than the benefits provided by scientific sources and they are only likely to offset the higher benefits of using scientific agents for high levels of extramural R&D investments. This leads to our second hypothesis[5]:

Hypothesis 2. *The concavity of the relationship between the proportion of extramural R&D investments conducted by scientific providers and high-novelty innovations will be stronger than the concavity of the relationship between the proportion of extramural R&D investments conducted by non-scientific agents and high-novelty innovations.*

4. Empirical analysis

4.1 Sample and data

As noted previously, the empirical analysis is based on the Spanish Technological Innovation Panel (PITEC). PITEC is sponsored by the Fundación Española para la Ciencia y la Tecnología (FECYT) and the COTEC Foundation and managed by the National Institute of Statistics. This survey is based on the Oslo Manual and provides information on the innovation behaviour of Spanish firms.

PITEC contains information for a panel of more than 12,000 firms dating from 2003 and it is designed as a panel data survey. The panel is made up of four non-excludable samples: (1) firms with 200 or more employees, (2) firms with internal R&D expenditure, (3) firms with fewer than 200 employees that have extramural R&D expenditure but do not conduct internal R&D, and (4) firms with fewer than 200 employees and no innovation expenditure. It is important to note that although we have used anonymised[6] data, research has shown that they produce reliable results (López, 2011).

This dataset has been utilised in the past by several researchers with different objectives. For example, it has been used to examine the relationship between cooperation and environmental innovation (De Marchi, 2012), to analyse the extent to which internal and extramural sources affect innovation performance (Gómez et al., 2016), to understand the relationship between green

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[5] In other words, Hypothesis 2 implies that (1) there is an inverted U-shaped relationship between Scientific providers of R&D and high novelty innovations, (2) there is an inverted U-shaped relationship between Non-Scientific providers of R&D and high novelty innovations and that (3) the concavity of (1) will be stronger than the concavity of (2).

[6] The anonymisation method is based on a micro-aggregation process, which modifies the firm-level data so that the responses cannot be traced to individual firms (COTEC, 2010). For more information about PITEC see the following link: http://icono.fecyt.es/PITEC/Paginas/por_que.aspx

innovation and performance (Kunapatarawong and Martinez Ros, 2016) and to study the relationship between innovation and firm growth (Coad et al., 2016).

The primary importance of these data is that they contain information on the knowledge sourcing decision of firms. Specifically, the information collected includes the total investments of firms in internal and external research and development. Furthermore, in the case of extramural R&D, it also provides information on the type of agent that performs it. Second, among the variables provided, we can find data on the sales of new products sold by the firm. The survey also distinguishes between the sales of new products that are new to the firm and the sales of new products that are new to the market, which gives us an adequate approximation of the degree of novelty of innovations (Barbosa et al., 2014).

Table 1 presents a first approximation to the data by showing the distribution of the number of firms depending on size for the last year considered, 2013. The majority of the firms have fewer than 200 employees (around 76% of the sample fits in this category). Similarly, Table 2 shows the distribution of the number of firms according to their main activity. The dataset has a higher number of firms belonging to manufacturing, followed by firms in the service sector. Together, both groups of firms account for more than 90% of the total sample.

Insert Tables 1 and 2 about here

From these data we used information for the period 2005 to 2013[7]. We selected our sample by following three steps. First, we restricted our sample to manufacturing and service firms. Second, we dropped public firms and those that had suffered any of the following processes: start-ups, mergers and closures. Third, we also excluded those firms that did not provide the information necessary for building our variables. This means that we were left with 53,879 observations. Compared with previous samples used in studies that focus on the proportion of extramural investments in R&D ours has several advantages. It uses information on both manufacturing and services, whereas previous papers tend to concentrate just on manufacturing firms (see Berchicci, 2013, and Wadhwa et al., 2017), with Grimpe and Kaiser (2010) being the only exception. It is much larger both in terms of the number of firms and observations than the ones used in previous papers (4,564 observations were used in Grimpe and Kaiser, 2010, 2,905 in Berchicci, 2013, and

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[7] We do not use the data for 2003 and 2004 because the sample was enlarged in these years, increasing the number of firms performing intramural R&D.

506 in Wadhwa et al., 2017). Finally, it follows the same firms through a longer observation window, providing panel data. In particular, the average firm in our sample is observed 4.2 years, compared with 1.2 years in Grimpe and Kaiser (2010), 1.14 years in Berchicci (2013) and 1 year in Wadhwa et al., (2017). This allows for a better control of heterogeneity and endogeneity, and to test hypotheses on how R&D investments accumulate into the stock of knowledge.

4.2. Variable description and measurement[8]

4.2.1. Dependent variables

Three dependent variables capture the various types of innovation performance. First, we used the percentage of sales of new products (*Innovation Performance*). This variable measures the proportion of income derived from new products introduced during the previous three years. This variable has often been used in innovation studies (see, for example, Cassiman and Veugelers, 2006), because it reflects the success of new products. In addition, we created two variables to account for the novelty of innovation (Aschhoff and Schmidt, 2008; Barbosa et al., 2014). In order to measure the ability of the firm to produce innovations with a high degree of novelty, we employed the percentage of sales of new products that are new to the market (*High Novelty*). Similarly, the percentage of sales of new products that are new to the firm was utilised to measure innovations with a low degree of novelty (*Low Novelty*). These variables not only reflect a firm´s ability to introduce new products, but also their commercial success, at least in the short term.

4.2.2. Independent variables

Extramural R&D. We measured a firm's technology knowledge sourcing strategy through the proportion of the stock of extramural R&D over the stock of total R&D expenditure (which is calculated from the sum of investments in intramural and extramural R&D). Therefore, contrarily to previous papers (Grimpe and Kaiser, 2010; Berchicci, 2013; Wadhwa et al., 2017) and in consistency with the literature on innovation, we assume that investments in R&D accumulate into the stock of knowledge of a firm. To calculate the stock of both variables, the perpetual inventory method was used; a pre-sample growth rate of 5% and a depreciation rate of 15% were assumed (see Griliches, 1981 or Griliches et al., 1981). The final variable ranges from one (when all the

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[8] The original wording of the questions used to build all the variables is included in Appendix 1.

R&D activities are acquired on the market and there is no internal R&D) to zero (when all the R&D activities are performed internally) and it was used for testing Hypothesis 1.[9]

Scientific R&D and *Non-Scientific R&D*. To test Hypothesis 2, we needed information on how firms distribute their extramural R&D expenses between the different agents. Our conjecture was that research centres and universities, which focus on basic research, may be the source of more radical knowledge and, as a consequence, provide the basis for more novel innovations. To create the variable we decomposed extramural R&D into (1) the purchases of R&D, in Spain and abroad, from universities and private non-profit agents and (2) the purchases of R&D, in Spain and abroad, from other types of agents (please, see Appendix 1 for more details). The method described above was also used in order to build the stock of R&D for the two variables. The final variables are calculated as a proportion of scientific R&D investments over total R&D (*Scientific R&D*) and non-scientific R&D investments to total R&D (*Non-Scientific R&D*).

4.2.3. Control variables

When assessing the effect of a firm's technology sourcing strategy on innovative performance it is critical to control for other variables that may impact on the creation of new products. First, the size of the firm (*Size*) is one factor that it is usually under control when innovation performance is measured (Wadhwa et al., 2017). In the past, researchers have found that innovation performance may benefit from economies of scale and scope (Henderson and Cockburn, 1994). Larger firms may also benefit from the possession of more resources, including financial and human resources (Wadhwa et al., 2017). We used total sales (in 1000s of euros) as a measure of firm size. Second, we also took into account the innovation intensity of the firm (*Innovation intensity*). Firms with higher investments in innovation can be expected to show higher innovation performance (Cassiman and Veugelers, 2006) and have higher levels of absorptive capacity (Cohen and Levinthal, 1990, Wadhwa et al., 2017). This variable was calculated as a proportion by dividing the stock of the expenditure on innovation activities[10] by sales. The stock was calculated with the perpetual inventory method, on the same assumptions as those explained above. Similarly, several studies indicate that internationally exposed firms are more innovative (Cassiman and Veugelers, 2006; Wadhwa et al., 2017). We used the propensity to export, that is, the ratio of export to sales, as evidence of the extent to which a firm faces international competition

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[9] We use one lag of the Extramural R&D, Scientific R&D and Non-Scientific R&D variables.

[10] Expenditure on innovation activities includes the following: internal R&D, external R&D, acquisition of machinery, equipment and software, acquisition of external knowledge, training for innovative activities, market introduction of innovations, and design and other preparation for production and/or distribution (see Appendix 1).

(*Export intensity*). As in past research, we expected a positive relationship between innovation results and export activity.

In addition to these variables, we also included a dummy variable indicating whether the firm is part of a group (*Group*). This variable takes the value one when the firm is part of an enterprise group and zero otherwise. Those firms belonging to a group could benefit from the transfer of knowledge from other firms belonging to the same group, effectively increasing innovation performance (Cassiman and Veugelers, 2006; Wadhwa et al., 2017).

Given that the type of activity performed by the firm may be important in explaining performance, we control for sector-specific characteristics by using sector dummies (please, see Appendix 2).[11] Note that, contrarily to previous studies (see, for example, Laursen and Salter, 2006, Berchicci, 2013 or Wadhwa et al., 2017), our sample includes both manufacturing and service firms. Finally, we defined several time dummies to control for time-specific effects (*Temporal dummies*).

Table 3 contains some descriptive statistics of the variables used in the estimations. The average firm obtains 10.4% of its sales from high novelty products. This value is higher than the 2.81% reported in Laursen and Salter (2006) for the UK and lower than the 12.8% for France (Wadhwa et al., 2017). The average proportion of extramural R&D stock in our sample is 16.7%. Although the figure is not directly comparable to previous papers, given that they use a flow measure, the percentages for Italy (Berchicci, 2013) and France (Wadhwa et al., 2017) are 23.8% and 12%, respectively. Finally, please note that firms in our sample accumulate more stock of R&D from non-scientific agents (13.1%) than from scientific agents (3.6%).

Insert Table 3 about here

4.3. Methodology

Our three dependent variables were double-censored: in all cases the variable ranged between zero and 100. Accordingly, a Tobit analysis was applied (see Greene, 2000, pp. 905-926;

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[11] As an alternative approach, we also took into account the type of activity and the technological opportunity. First, we defined a dummy variable that took the value one for manufacturing firms (Manuf). Second, to take into account the technological opportunity effect we included a dummy variable that took the value of one for those firms operating in high or medium-high technology sectors (High), and zero otherwise. This classification is defined by the Spanish National Statistic Institute and takes the OECD (2005b) classification into account. The conclusions from this approach are the same as the ones commented.

see also Berchicci, 2013 and Grimpe and Kaiser, 2010). Because of the importance of maintaining the normality assumption of the residuals (Greene, 2000), and following past empirical studies, we assumed a lognormal distribution for the residuals of the Tobit model (Berchicci, 2013; Laursen and Salter, 2006). This is why our model introduces the dependent variable as a logarithmic transformation of the observed innovation performance.[12]

The *Optimal Combination of R&D Hypothesis* establishes that *Extramural R&D* will show an inverted U-shape relationship with innovation performance. Furthermore, Hypothesis 1 argues that that the relationship between external sources of knowledge and innovation is stronger for innovations with a high degree of novelty. To test both ideas, we propose Models 1 and 2:

$$Low\ Novelty_{it} = \beta_0 + \beta_1 Extramural\ R\&D_{it-1} + \beta_2 Extramural\ R\&D_{it-1}^2 + CV_{it-1} + \varepsilon_{it} \quad [1]$$

$$High\ Novelty_{it} = \beta_3 + \beta_4 Extramural\ R\&D_{it-1} + \beta_5 Extramural\ R\&D_{it-1}^2 + CV_{it-1} + \varepsilon_{it} \quad [2]$$

where CV stands for 'control variables', namely: *Innovation intensity*, *Export intensity*, *Size*, *Group and Industry and Temporal dummies*. Moreover, we introduced one time lag between the two measures of innovation performance and the independent variables in order to reduce potential endogeneity problems caused by simultaneity.[13]

To test hypothesis 1, we first have to make sure that both relationships are curvilinear. Haans et al. (2016) establish a three-step procedure. First, β_2 and β_5 *need to be significant and of the expected sign*. In our case, we expect than their sign is negative. *Second, the slope must be sufficiently steep at both ends of the data range*. That is, the slopes at the lower limit, $\beta_1 + 2 * \beta_2 * Extramural\ R\&D_L$ and $\beta_4 + 2 * \beta_5 * Extramural\ R\&D_L$, are positive and significant, and the slopes at the higher limit, $\beta_1 + 2 * \beta_2 * Extramural\ R\&D_H$ and $\beta_4 + 2 * \beta_5 * Extramural\ R\&D_H$, are negative and significant (where *H* and *L* stand for the highest and the lowest values of the ratios, respectively). Finally, *the tipping points need to be located well within the data range*.

To compare both curves, we plot the relationship between the proportion of extramural to total R&D and the share of high and low novelty innovations and we test the equality of coefficients across the two models ($\beta_1 = \beta_4$ and $\beta_2 = \beta_5$) (Laursen and Salter, 2014).[14] We also calculate the slope of the relationship for different values of extramural R&D around the tipping point for both

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[12] As Laursen and Salter (2006) point out, the lognormal transformation changes neither the signs nor the significance of the parameters of the independent variables. Nor does the transformation change the relative sizes of the parameters.

[13] We offer a more complete treatment of endogeneity in the section Robustness tests and additional analyses.

[14] To test this hypothesis, we used the *testnl* command after running a *suest* estimation procedure, using Stata 13.0.

types of innovations (Haans et al., 2016; Wadhwa et al., 2017) and compare the values. We expect the concavity of the relationship to be stronger for high novelty innovations (Hypothesis 1).

To test Hypothesis 2 we decomposed the variable *Extramural R&D* into two parts. The first part accounts for the investments in extramural R&D that are performed by universities (*Scientific R&D*). The second part considers the extramural investments that are realised by other extramural partners (*Non-scientific R&D*). To test this hypothesis we reran Model 2, taking into account that decomposition in the following way:

$$High\ Novelty_{it} = \beta_6 + \beta_7 Scientific\ R\&D_{it-1} + \beta_8 Scientific\ R\&D^2_{it-1} + \beta_9 Non - Scientific\ R\&D_{it-1} + \beta_{10} Non - Scientific\ R\&D^2_{it-1} + \beta_{11} 2xScientific\ R\&D_{it-1} x\ Non - Scientific\ R\&D_{it-1} + CV_{it-1} + \varepsilon_{it} \quad [3]$$

Hypothesis 2 suggests that the concavity of the relationship between *Scientific R&D* and high novelty innovations will be stronger than the one involving *Non-Scientific R&D*. We first check if both relationships are curvilinear, as explained above. Then, we test the following two equalities $\beta_7 = \beta_9$ and $\beta_8 = \beta_{10}$ and plot the relationship. Finally, we also calculate the slope of the relationship for different values of the two variables around the tipping point and we compare the values (Wadhwa et al., 2017). For example, in the case of *Scientific R&D* the slope is calculated as $\beta_7 + 2 * \beta_8 * Scientific\ R\&D_{i,t-1} + 2 * \beta_{11} * Non - Scientific\ R\&D_{i,t-1}$.

5. Results

Table 4 presents the results of estimating three Tobit models, over the 46,811 observations available.[15] All the models include robust standard errors.[16] The only difference between them is the dependent variable used.

Insert Table 4 about here

The results presented in Table 4 reveal that there is an inverted U-shaped relationship between *Extramural R&D* and the sales of new products (Berchicci, 2013; Grimpe and Kaiser, 2010; Wadhwa et al., 2017). *Extramural R&D* has a positive and significant coefficient in Column

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[15] The number of observation available for the analysis (46,811) is lower than the number of observations in the dataset (53,879). This is because some observations were lost when the stock variables were calculated. Additionally, we lost observations because of the lag of the independent variables.

[16] We used the clustered sandwich estimator.

1 ($\beta = 0.261$; $p<0.01$), and the square term has a negative and significant coefficient ($\beta = -0.392$; $p<0.01$). The value of the slope at the lowest level of the variable extent of openness is positive and significant ($\chi^2 = 33.21$; $p<0.01$) and the value of the slope at the highest level of the variable extent of openness is negative and significant ($\chi^2 = 75.84$; $p<0.01$). This result supports the existence of a U-inverted relationship between *Extramural R&D* and innovation performance, i.e., firms that combine internal and extramural R&D show better innovation performance. The maximum innovation performance is obtained when firms simultaneously 'buy' 33% of their R&D investment and 'make' 67%.[17]

Columns 2 and 3 show two estimations in which the dependent variable is the proportion of innovations with a low and high degree of novelty. We use these two columns to test Hypothesis 1. As one can observe, combining internal and extramural R&D is more suitable for obtaining both types of innovations, exhibiting the predicted inverted U-shaped relationship. In low-novelty innovations, the coefficient accompanying the direct effect is positive and significant ($\beta = 0.130$; $p<0.01$), whereas the one corresponding to the quadratic effect is negative and significant ($\beta = -0.220$; $p<0.01$). The value of the slope when the firm only invests in internal R&D is positive and significant ($\chi^2 = 9.63$; $p<0.01$) and it is negative and significant when all the investments in R&D are extramural ($\chi^2 = 30.74$; $p<0.01$) (Haans et al., 2016). Similarly, for high-novelty innovations the direct effect is positive and significant ($\beta = 0.343$; $p<0.01$) and the quadratic effect is negative and significant ($\beta = -0.494$; $p<0.01$). The values of the slopes at the lowest and the highest levels of the variable *Extramural R&D* are, respectively, positive and negative, and both are significant ($\chi^2 = 60.43$; $p<0.01$ and $\chi^2 = 121.51$; $p<0.01$) (Haans et al., 2016). Furthermore, the tipping point is located within the data range.

Hypothesis 1 argued that the relationship between *Extramural R&D* and innovation may be different depending on the degree of novelty of the innovation. To test Hypothesis 1 we have to show that the concavity of the curve is stronger for high-novelty rather than low-novelty innovations. First, a χ^2 test of the difference between the coefficients of the two direct effects is significant ($\chi^2 =12.79$; $p<0.01$). Similarly, a χ^2 of the difference between the two quadratic coefficients also reveals that there are significant differences between both ($\chi^2 =17.64$; $p<0.01$).

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[17] Taking a look at our sample, we can conclude that around 11% of the firms are included in the interval 33.0 % ± 10%.

Second, to confirm that the impact of *Extramural R&D* is higher on high-novelty innovations we depicted the relationship with the share of sales from new products and compared the performance for different characteristic points (Laursen and Salter, 2014). Figure 2 shows the relationship for low- and high-novelty innovations for a typical firm.[18] The inverted U-shaped relationship exists regardless of the degree of novelty of the new products. Figure 2 reveals that the concavity of the relationship is stronger for high-novelty innovations than for low-novelty innovations, supporting Hypothesis 1. This result is confirmed by looking at Table 5, which shows the slope of the relationship for different values of the extramural to total R&D variable around the tipping point. The absolute values of the slope are, in all the cases, higher for high novelty than for low novelty innovations. The share of low novelty innovations varies between 12.6% (when the firm uses no extramural R&D), 12.9% (tipping point) and 8.6% (when the firm uses no internal R&D). The share of high novelty innovations varies between 8.2% (no extramural R&D), 9.9% (tipping point) and 4% (no internal R&D).

Insert Figure 2 about here

Insert Table 5 about here

Figure 2 illustrates the consequences of an erroneous technological sourcing decision. Selecting an inadequate technological sourcing strategy will produce worse results in the case of high-novelty innovations than in the case of low-novelty innovations. The results are revealing if we look at the extremes of the distribution of *Extramural R&D*. Thus, taking the highest performance as a reference point, firms with very high levels of *Extramural R&D* are the ones with the worst performance in terms of new product sales. However, the disadvantage of firms with very low levels of *Extramural R&D* is not that important. Therefore, the opportunities, but also the costs, of a 'closed innovation approach' are much lower. This point to the importance of the internal innovation capabilities developed by firms.

Hypothesis 2 argued that *Scientific R&D* has a stronger impact on high-novelty products than *Non-Scientific R&D*. Table 6 shows the results of estimating the models presented in Table 4 by decomposing extramural R&D investments into scientific and non-scientific R&D. Column 1

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[18] For depicting Figures 2 and 3 we have set the values of the control variables at their means.

focuses on explaining the share of sales from new products, whereas Columns 2 and 3 distinguish between low- and high-novelty products.

Insert Table 6 about here

To test Hypothesis 2 we need to focus on the information shown in Column 3 and compare the impact of scientific and non-scientific providers in the production of high-novelty innovations. It reveals that both types of extramural R&D investments have a U-inverted influence on the sales of high-novelty products. The direct effect of *Scientific R&D* is positive and significant ($\beta = 0.200$; $p<0.05$) and the quadratic effect is negative and significant ($\beta = -0.302$; $p<0.01$). Similarly, the direct effect of *Non-Scientific R&D* is positive and significant ($\beta = 0.381$; $p<0.01$), whereas the quadratic effect is negative and significant ($\beta = -0.551$; $p<0.05$). An F-test of the difference between the coefficients of the two direct effects is significant (*F-test* = 10.65; $p<0.01$). Similarly, an F-test of the difference between the two quadratic coefficients also reveals that there are significant differences between both (*F-test* = 13.60; $p<0.01$).

Figure 3 depicts the relationship between the proportion of extramural R&D for high-novelty products for a typical firm, once the decomposition of extramural R&D has been done (Table 6. Column 3). The graph on the left shows the effect of *Scientific R&D* (universities and research centres), whereas the graph on the right of the figure shows the consequences of *Non-Scientific R&D*. Although both types of investments have an impact on the sales of new products, confirming the role of extramural R&D, the impact of *Non-Scientific R&D* is stronger than that of *Scientific R&D*. Table 7 confirms this observation by showing that the slopes of the relationship are always higher for *Non-Scientific R&D* than for *Scientific R&D*.[19] This result does not offer support to Hypothesis 2.

Insert Figure 3 about here

Insert Table 7 about here

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[19] To calculate the slopes, we first assume that the interaction term between Scientific R&D and Non-Scientific R&D is zero. In addition to this, we also compared the effect of both types of providers by assuming values below and above one standard deviation from the mean.

The estimations also reveal a difference in the role of extramural scientific knowledge, depending on the novelty of the innovation. Universities and research centres only have a positive influence when the firm engages in highly novel product innovation. In fact, for low novelty innovations, the results reveal a negative influence of Scientific R&D (the direct effect of *Non-Scientific R&D* is positive, but non-significant ($\beta = 0.061$; $p>0.1$), whereas the quadratic effect is negative and significant ($\beta = -0.178$; $p<0.1$)). Non-Scientific R&D investments are, however, important for all the innovation types, irrespective of their novelty. Although the results are not supportive of Hypothesis 2 they are consistent with some the arguments proposed by the papers mentioned above (Belderbos et al., 2004; Cohen et al., 2002; Henard and McFadyen, 2006; Sofka and Grimpe, 2010). First, research centres and universities are only positive for innovation when we consider market novelties. Second, an excessive use of research centres and universities will reduce innovation performance. Finally, it is also important to note that the interaction between the different types of extramural R&D is negative in the case of high-novelty innovations ($\beta = -0.324$; $p<0.05$), which seems to point to a substitution effect between them.

Finally, regarding the effect of control variables, we can observe that innovation intensity exerts a positive influence on performance in all cases. The same conclusion can be drawn for those firms that have higher export intensity and are larger. Regarding the effect of the business group, the results indicate that its effect on innovation is positive and significant in all the cases.[20]

5.1. Robustness tests and additional analyses

Two concerns over the estimations presented in Tables 4 and 6 are that (1) we do not control for heterogeneity and (2) we do not take endogeneity into account. On the one hand, heterogeneity may be associated to differences in management abilities between firms or to differences in the endowment of resources that are not explicitly considered in our model (Godfrey and Hill, 1995). In the context of Tobit models, unobserved effects may be captured through the estimation of a random effects model. On the other hand, endogeneity could bias the estimates if the error term includes unobserved factors that influence the returns to R&D (Cassiman and Valentini, 2016). For example, firms with a lower innovative performance could open their innovation model to increase the sales from new products (Cassiman and Valentini, 2016). We take endogeneity into account through a Tobit model that instruments the variables measuring the proportion of

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[20] Firms operating in high technology and manufacturing sectors have a higher level of sales than those belonging to service sectors, except when the sales of high-novelty products are considered.

extramural R&D used.[21] As in Cassiman and Valentini (2016) we also controlled for the past performance of the firm by measuring the rate of sales growth between years t-2 and t-1.

Table 8 (Table 9) shows the results of replicating the estimations presented in Table 4 (Table 6) for the three dependent variables: *Innovation Performance*, *High Novelty* and *Low Novelty*. For each variable, we estimated the model through the three different methods. First, we estimated a Tobit with random effects to control for heterogeneity. Columns 1, 4 and 7 present the results of this exercise. Second, we estimated a Tobit model that instruments the proportion of extramural R&D used (Columns 2, 5 and 8). We used the second lag of *Extramural R&D* as the instrument. Finally, we followed the approach proposed by Cassiman and Valentini (2016) and controlled for the rate of sales growth (please, see Columns 3, 6 and 9). The results are similar to the ones commented in the previous section.

Insert Tables 8 and 9 about here

In addition to these two analyses, we also re-estimated the models presented in Table 4 for different definitions of the external investments in innovation.[22] As a first step, we defined *Extramural R&D* by eliminating the investments that are the result of purchases of R&D to firms in the same group as the focal firm. In a separate estimation, we also allowed for two lags of *Extramural R&D*. In both cases, the conclusions were the same in terms of the support offered to Hypotheses 1 and 2. As a second step, we considered other innovation activities performed outside the firm. Thus, to test Hypothesis 1 we calculated our main variable by adding the expenditures incurred in the "Acquisition of external knowledge" to the ones in "External R&D" (please, see Appendix 1). The results show the U-inverted impact of external innovation investments on innovation performance and also reveal that the concavity of the relationship is stronger for high-novelty innovations than for low-novelty innovations. These results offer support for Hypothesis 1. Similarly, we recalculated the variable by adding the expenditures incurred in the "Acquisition of machinery, equipment and software" and the ones labelled "Acquisition of external knowledge" to the ones in "External R&D".[23] In this case, the results also show the U-inverted impact of

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[21] We use the second lags of the variables as instruments.

[22] We thank the reviewers for suggesting these additional analyses. They are available from the authors upon request.

[23] Therefore, the variable was calculated as (B+D)/(A+B+D) in the first case and as (B+C+D)/(A+B+C+D) in the second.

external innovation investments on innovation performance and they also offer support for Hypothesis 1.

Finally, research on open innovation tends to focus on manufacturing firms (Mina et al., 2014). However, manufacturing and service firms tend to be different in terms of the type of external providers used. For example, manufacturing firms cooperate more frequently with scientific partners than service firms (Mention, 2011), which suggest that the benefits and the costs perceived are different. We take advantage of the fact that our sample includes both manufacturing and service firms to test Hypotheses 1 and 2 separately. In the case of Hypothesis 1, the results show an inverted U-shape relationship between *Extramural R&D* and innovation performance in both subsamples. The results also show that the concavity of the relationship is higher in the case of high novelty innovation, offering support to Hypothesis 1. In the case of hypothesis 2, for manufacturing firms the results are similar to the ones previously obtained in the main text. However, in the case of service firms the results show that *Scientific R&D* does not have any impact on any of the dependent variables used. Therefore, Hypothesis 2 is not supported.

6. Discussion, conclusions and implications

This study has investigated the relationship between the R&D sourcing strategy of firms and innovation performance. In particular, we have focused on two contingencies affecting the Optimal Combination of R&D Hypothesis, the nature of the innovation and the type of external knowledge acquired.

First, our analysis confirms that the relationship between extramural R&D and innovation performance follows an inverted U-shape. In other words, the simultaneous use of both sources of knowledge outperforms the alternatives of exclusively using internal or external sources. This relationship is robust to the methods used and consistent with research on open innovation models (Berchicci, 2013; Grimpe and Kaiser, 2010; Laursen and Salter, 2006; Gómez, et al., 2017; Wadhwa et al., 2017). A first finding of our study is that the curvilinear relationship also appears when considering the degree of novelty of innovations. The maximum innovation performance is reached when combining approximately two thirds of internal and one third of extramural R&D. More precisely, the figures are 33% of extramural to total R&D investments when the sales of new products are considered and 34.7% of extramural to total R&D investments if we focus on high novelty innovations. These are similar to the ones found in previous papers: for example, the tipping point in Berchicci (2013) is reached at a 43,3% of extramural to total R&D for both types of innovations and at 32.9% in Wadhwa, et al. (2017), when we centre on new to the market innovations. Although our main purpose was not to replicate previous studies, our results provide a confirmation of the inverted U shape and show that firms reach their maximum performance at similar thresholds of extramural R&D investments. As claimed by recent papers on different areas of research (Bettis, et al., 2016; Royne, 2018; Mueller-Langer et al., 2019), this replication is important if we want to consolidate the findings of the open innovation literature.

Second, our paper is the first to distinguish between low and high novelty innovations. The results reveal that the impact of extramural R&D investments is higher on the sales of high-novelty than on low-novelty products. This is consistent with the idea that firms use extramural R&D investments to overcome the rigidities imposed by the current knowledge endowments and local processes of search (Levitt and March, 1988; March and Simon, 1958), which make it difficult to exit a given technological trajectory (Dosi, 1988). In fact, the difference is economically relevant and provides a way to create new products that have the potential to produce a competitive advantage and provide access to new markets (Barbosa et al., 2014). Our results show that increasing the proportion of extramural R&D investments from their minimum to its optimal point raises the share of sales from high novelty innovations in approximately a 21%. This illustrates the benefits from distant search (López-Vega et al., 2016). However, the data also reveals the negative consequences of relying excessively on extramural R&D investments. Moving from not engaging in extramural R&D investments to fully relying on them reduces the performance of high novelty innovations in a 52%. In comparison, these effects are much lower in the case of low novelty innovations, increasing a 2% in the first case, and decreasing a 32%, in the second. In fact, relying on extramural R&D investments when looking for low novelty innovations seems to disproportionally increase the costs vis. a vis. the benefits. In any case, it is important to emphasize that the innovation activities directed to obtain low novelty innovations are vital for firms, given that they account for a higher percentage of firm sales. In our sample, the sales from low novelty products represent a 14.4% of total sales for the typical (average firm), whereas the ones from high novelty innovations represent a 10.4%.

Third, our results also show that the main role of universities and research centres is to improve the sales from highly novel products. This is consistent with the idea that the type of knowledge managed by universities and research centres is more novel (Hewitt-Dundas et al., 2019) and diverse (Henard and McFadyen, 2005) than the one in firms. Collaboration in R&D projects with universities and research centres has the potential to increase the share of sales from high novelty products around a 7% (from 8.3% when no extramural R&D is used to 8.9% in the maximum). However, we observe again that the negative consequences of excessively relying on extramural R&D are high, with the share of high novelty products notably being reduced if no internal R&D is used (to 5.4%). In addition to this, extramural investments in R&D have a negative impact on low-novelty products, which seems to provide an additional example of the ‘two worlds’ paradox (Hewitt-Dundas et al., 2019). In other terms, when the benefits of relying on universities and research centres are low, as it is expected in the case of low novelty innovations, the costs seem to outweigh them. Reasons for these costs are differences in cultural and knowledge bases (De Wit-de Vries et al., 2018), differences in the value attributed to intellectual property and institutional and bureaucratic differences between firms and universities and research centres (Hewitt-Dundas et al., 2019), which make collaboration difficult.

Arguments based on costs may also justify why Hypothesis 2 is not supported by the data. For example, costs associated with differences in culture between firms and universities, with inflexibilities related with bureaucracy and with inefficiencies in the transference of technology (Siegel et al., 2003) may explain why the relationship between scientific R&D and innovation performance is weaker. Similarly, knowledge from scientific agents is expected to have a longer conversion process into new products (Johnson and Johnston, 2004) and this may affect the comparison of innovation performance, in general, and also when considering low and high novelty innovations.

On the contrary, non-scientific investments in R&D may be used to improve the sales of both low- and high-novelty products and their relevance to the explanation of the sales of high-novelty products is higher than in the case of universities and research centres. Extramural R&D investments in non-scientific agents move the performance of high (low) novelty innovations from 8.26% (12.5%) when no extramural R&D is used, to 10.23% (13.07%) in the optimal combination and to 3.61% (8.52%) when no internal R&D is used. Although other explanations are possible, the higher average rates of extramural R&D investments in non-scientific agents in our sample (13.1% vs. 3.6% in universities and research centres) could be the result of the higher expected returns from collaboration with non-scientific agents.

The analysis on the type of external provider deserves a final comment when high novelty innovations are considered. The results point to a substitution effect between scientific and non-scientific providers of R&D. This, again, may be explained by the different nature of both types of external providers, which may increase the complexities of managing them simultaneously.

Finally, we explore new scenarios in open innovation research and this exercise provides interesting conclusions. They show that the relationship between extramural R&D and innovation performance is stronger in the case of high novelty innovations in both manufacturing and service firms. However, manufacturing and service firms differ when we consider the different types of providers of knowledge, with Scientific R&D not having any impact on innovation in service firms.

The results of this study have several implications in terms of (1) the literature on innovation and (2) managerial practice. In terms of the literature on innovation, we theoretically argued and empirically tested for the existence of boundary conditions affecting the relationship between the sourcing decision and innovation performance. Theoretically, we identified two conditions under which the results of open innovation may be different: the novelty of the innovations generated and the type of external knowledge acquired. Empirically, the paper helps to clarify the conflicting results (Monteiro et al., 2017) found in previous literature. It confirms that the extent of openness has an inverted U-shape effect on innovation performance. Our analysis is, however, not limited to a general case: we also consider innovation sourcing in different situations. Our results indicate that the analysis of the sourcing strategy used for innovation should include the context in which firms take decisions (Hsieh and Tidd, 2012; Huizingh, 2011; Monteiro et al., 2017). Instead of attempts to explain the sometimes conflicting results ad hoc, the task of incorporating the contexts should be conducted in an ex ante manner, through context theorising (Bamberger, 2008), as in this paper. Our results reveal the potential of extramural R&D investments to be the source of high-novelty innovations. This contributes to the required evidence on the factors explaining the novelty of innovations (Barbosa, et al., 2014). Furthermore, they contribute to the explanation of the role of universities and research centres, which is not clear from the existing literature. Finally, they also highlight the costs of using extramural R&D and how they differ depending on the external providers of knowledge.

Our results also have implications for managerial practice. First, it is important that managers are aware not only of the positive effects of the complementarities between in-house and extramural R&D but also of their constraints. In this regard, it must be noted that, depending on the starting combination, an increase in either internal or extramural R&D can lead to decreased performance. In this sense, our results appear to indicate that the percentage of internal investments should be higher than those made externally (around two-thirds internal vs. one-third extramural, in general). Furthermore, managers should be aware of the negative implications of excessively relying on extramural R&D investments, especially in the case of high novelty innovations, as the innovation performance of their firms may be dramatically reduced. For low novelty innovations, the costs are also relevant, and the benefits of an open innovation approach are low. Despite this, it is also important to take into account that low novelty innovations are more important than high novelty innovations for the typical firm. Therefore, managers should pay especial attention to balance the positive/negative impacts of Non-scientific R&D and to the negative effects of Scientific R&D on low novelty innovations. Second, managers have also to be aware that the effect of using scientific sources of knowledge is important in terms of high novelty innovations. However, non-scientific sources of knowledge increase the innovative performance in terms of both low and high novelty innovations. Additionally, their contribution to the generation of high novelty innovations is more important than that of scientific sources. Finally, managers must be aware of the different costs of external providers of knowledge. For example, non-scientific sources reduce the proportion of sales from high novelty innovations more than scientific sources if they are used in isolation.

Finally, our research also has limitations that must be addressed for the appropriate interpretation of our results and conclusions. We considered only the existence of internal and extramural R&D as the main source of innovations. However, firms have other means of innovating beyond these investments. Although R&D is a fundamental source of innovation, there are other external sources that could also help firms to achieve innovation results (see, for example Laursen and Salter, 2006; Santamaria et al., 2009; Veugelers and Cassiman, 1999). Importantly, firms can also access information on new knowledge through different channels and, at the very least, it is not clear whether these efforts are included in their extramural R&D. For example, a firm may collaborate with a provider with or without performing R&D investments. Increasing the number of elements from which firms may source knowledge represents a necessary continuation of our analysis. In any case, the robustness test performed, in which we used different definitions for the external expenditures in innovation activities lead us to conclude that the results are similar when other means of innovating are considered.

Second, although we use a very large sample of innovating firms, our results only refer to one country. Therefore, our understanding of the phenomenon is confined to a given economic and institutional context. As mentioned above, this seems relevant in the face of the evidence, which shows that the actual levels of openness differ between countries. Countries not only differ in economic conditions but also in their national systems of innovation and in the extent to which institutions support markets. Research on the optimal openness of firms should take into account the context in which the firms operate. Despite this, the comparison of our results with the ones obtained using samples from Germany (Grimpe and Kaiser, 2010), Italy (Berchicci, 2013) or

France (Wadhwa et al., 2017) show consistency in the basic prediction of the Optimal Combination of R&D Hypothesis. Future research could consider studying openness in contexts that are different in terms of economic and institutional development.

Third, our research takes the R&D function as the unit of analysis. However, other possibilities are also at hand. For example, research on concurrent sourcing argues that research on firm boundaries should be performed at a disaggregate level. For example, the reason why firms combine in-house and extramural R&D investments could be because some projects are developed inside and some outside the firm limits. Therefore, future research could take research on firm boundaries into account for an understanding of technological knowledge sourcing decisions.

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Table 1. Firms by size in 2013

	Number of firms	% of firms
Size <200	6,548	76.55
Size >= 200	2,006	23.45

Table 2. Firms by activity in 2013

	Number of firms	% of firms
Agriculture	122	1.43
Extractive industry	44	0.51
Manufacturing	4,417	51.64
Water supply, sewerage, waste management and remediation activities	104	1.22
Construction	302	3.53
Service	3,565	41.68

Table 3. Descriptive analysis

	Mean	Std. Dev	Min.	Max.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Innovation performance (1)	0.247	0.352	0	1	1.000								
Low novelty (2)	0.144	0.272	0	1	0.762	1.000							
High novelty (3)	0.104	0.228	0	1	0.633	-0.019	1.000						
Extramural R&D (4)	0.167	0.272	0	1	-0.045	-0.026	-0.039	1.000					
Scientific R&D (5)	0.036	0.117	0	1	-0.012	-0.010	-0.007	0.378	1.000				
Non-scientific R&D (6)	0.131	0.252	0	1	-0.043	-0.023	-0.039	0.903	-0.056	1.000			
Innovation intensity (7)	0.103	0.171	0	1	0.161	0.064	0.173	-0.070	-0.006	-0.073	1.000		
Export intensity (8)	0.227	0.297	0	1	0.057	0.036	0.044	-0.016	0.013	-0.023	-0.050	1.000	
Size (9)	71732.89	445116.86	0.230	1.35e+07	0.012	0.005	0.012	0.072	-0.005	0.080	-0.062	0.019	1.000
Group (10)	0.396	0.489	0	1	0.003	0.008	-0.006	0.108	-0.028	0.130	-0.118	0.163	0.165

Table 4. Extramural R&D and product novelty (Tobit analysis)

	Innovation performance (1)	Low Novelty (2)	High Novelty (3)
Extramural R&D	0.261***	0.130***	0.343***
	(5.76)	(3.10)	(7.77)
Extramural R&D^{2}	-0.392***	-0.220***	-0.494***
	(-7.79)	(-4.72)	(-10.10)
Innovation intensity	0.454***	0.228***	0.430***
	(22.72)	(12.24)	(22.93)
Export intensity	0.048**	0.026*	0.044***
	(2.59)	(1.91)	(2.66)
Size	4.55e-08***	2.69e-08***	5.21e-08***
	(5.92)	(3.83)	(6.07)
Group	0.059***	0.051***	0.057***
	(7.39)	(7.01)	(7.35)
Industry dummies		Included	
Temporal dummies		Included	
Constant	-0.442***	-0.267***	-0.763***
	(-3.34)	(-2.84)	(-4.67)
No. Observations	46,811	46,811	46,811
Wald	38.66	22.51	30.21

Table 5. Slopes of the relationship between *Extramural R&D* and product novelty

Extramural R&D	**Low Novelty**	**High Novelty**
Tipping point -0.20	.0883645	.1975102
Tipping point -0.15	.0663626	.1481189
Tipping point -0.10	.0443607	.0987276
Tipping point -0.05	.0223588	.0493363
Tipping point +0.05	-.0216449	-.0494463
Tipping point +0.10	-.0436468	-.0988376
Tipping point +0.15	-.0656486	-.148229
Tipping point +0.20	-.0876505	-.1976203

Table 6. Scientific and Non-Scientific R&D and product novelty (Tobit)

	Innovation performance (1)	Low Novelty (2)	High Novelty (3)
Scientific R&D	0.146	0.061	0.200**
	(1.63)	(0.72)	(2.37)
Scientific R&D^2	-0.276**	-0.178*	-0.302***
	(-2.59)	(-1.80)	(-2.99)
Non-scientific R&D	0.291***	0.150***	0.381***
	(5.68)	(3.18)	(7.62)
Non-scientific R&D^2	-0.429***	-0.238***	-0.551***
	(-7.50)	(-4.51)	(-9.83)
Scientific R&D*Non-scientific R&D	-0.234	-0.138	-0.324**
	(1.59)	(0.95)	(-2.43)
Innovation intensity	0.454***	0.228***	0.431***
	(22.77)	(12.26)	(22.98)
Export intensity	0.047**	0.026*	0.043**
	(2.55)	(1.91)	(2.65)
Size	4.55e-08***	2.67e-08***	5.18e-08***
	(5.93)	(3.81)	(6.01)
Group	0.058***	0.051***	0.057***
	(7.30)	(6.92)	(7.32)
Industry dummies		Included	
Temporal dummies		Included	
Constant	-0.438***	-0.263***	-0.759***
	(-3.30)	(-2.80)	(-4.62)
N		46,811	
Wald	36.61	21.29	28.67

Table 7. Slopes of the relationship between Scientific/Non-Scientific R&D and high novelty products

Scientific/Non-Scientific R&D	High novelty products (Scientific R&D)	High novelty products (Non-Scientific R&D)
Tipping point -0.20	.1215476	.2217261
Tipping point -0.15	.0913331	.1666343
Tipping point -0.10	.0611186	.1115425
Tipping point-0.05	0.030904	.0564507
Tipping point +0.05	-.029525	-.0537328
Tipping point +0.10	-.0597396	-.1088246
Tipping point +0.15	-.0899541	-.1639164
Tipping point +0.20	-.1201687	-.2190082

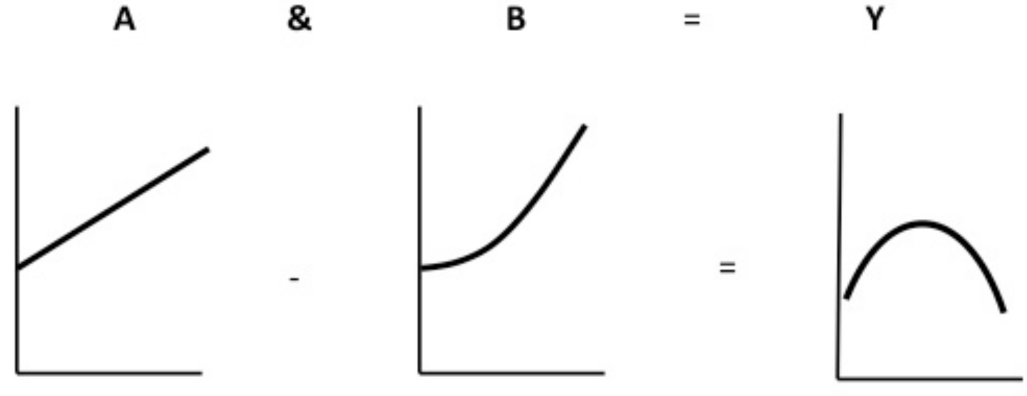
Table 8. Robustness tests (heterogeneity and endogeneity)

	Innovation performance			Low novelty			High novelty		
	Tobit (random effects)	**Tobit (endogeneity control)**	**Tobit reverse causality**	**Tobit (random effects)**	**Tobit (endogeneity control)**	**Tobit reverse causality**	**Tobit (random effects)**	**Tobit (endogeneity control)**	**Tobit reverse causality**
Extramural R&D	0.239***	0.266***	0.265***	0.133***	0.123***	0.134***	0.288***	0.359***	0.343***
	(6.08)	(8.96)	(5.80)	(3.59)	(4.42)	(3.16)	(7.43)	(12.59)	(7.67)
Extramural R&D^2	-0.353***	-0.411***	-0.404***	-0.220***	-0.226***	-0.232***	-0.412***	-0.516***	-0.496***
	(-8.33)	(-12.42)	(-7.97)	(-5.48)	(-7.29)	(-4.94)	(-9.73)	(-15.88)	(-9.98)
Innovation intensity	0.367***	0.535***	0.471***	0.214***	0.275***	0.241***	0.305***	0.490***	0.440***
	(24.55)	(33.44)	(22.75)	(14.92)	(18.35)	(12.49)	(21.75)	(33.33)	(22.67)
Export intensity	0.026***	0.0470***	0.0478**	0.018***	0.0257***	0.0261*	0.018***	0.0434***	0.0443***
	(4.77)	(8.14)	(2.56)	(3.42)	(4.76)	(1.90)	(3.93)	(8.31)	(2.62)
Size	3.06e-08***	5.15e-08***	4.60e-08***	2.48e-08***	3.26e-08***	2.79e-08***	5.21e-08***	5.49e-08***	5.18e-08***
	(3.96)	(9.28)	(5.92)	(3.46)	(6.39)	(3.93)	(6.07)	(10.99)	(6.06)
Group	0.042***	0.0630***	0.0593***	0.036***	0.0550***	0.0511***	0.040***	0.0599***	0.0581***
	(6.09)	(12.68)	(7.40)	(5.53)	(11.84)	(6.97)	(5.88)	(12.55)	(7.38)
Sales growth			0.000000278			3.24e-08			0.000000658
			(0.73)			(0.12)			(1.24)
Industry dummies	Included	Included	Included	Included	Included	Included	Included	Included	Included
Temporal dummies	Included	Included	Included	Included	Included	Included	Included	Included	Included
Constant	-0.156	-0.642***	-0.457***	-0.158	-0.438***	-0.283***	-0.455*	-0.899***	-0.776***
	(0.75)	(-4.81)	(-3.44)	(-0.84)	(-3.66)	(-2.99)	(-2.01)	(-7.06)	(-4.75)
No. Observations	46,811	40,733	45,365	46,811	40,733	45,365	46,811	40,733	45,365
F/Wald	2975.86	4196.14	37.88	1595.26	2319.40	22.23	1948.09	3266.22	29.71
Wald test of exogeneity		0.54			2.65			5.28*	

Table 9. Robustness tests (heterogeneity and endogeneity)

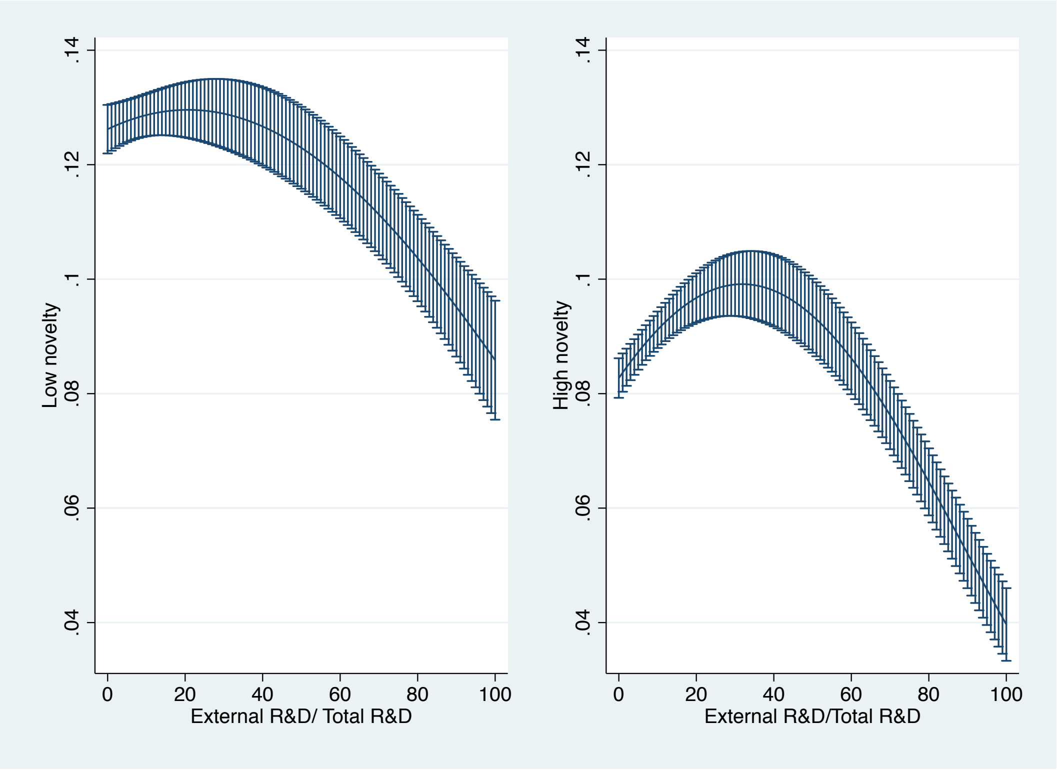
	Innovation performance			Low novelty			High novelty		
	Tobit (random effects)	Tobit (endogeneity control)	Tobit reverse causality	Tobit (random effects)	Tobit (endogeneity control)	Tobit reverse causality	Tobit (random effects)	Tobit (endogeneity control)	Tobit reverse causality
Scientific R&D	0.167**	0.171***	0.141	0.113	0.0679	0.0501	0.164**	0.230***	0.210**
	(2.24)	(2.91)	(1.56)	(1.60)	(1.23)	(0.59)	(2.24)	(4.08)	(2.45)
Scientific R&D^2	-0.240***	-0.329***	-0.273**	-0.204**	-0.207***	-0.166*	-0.179**	-0.344***	-0.314***
	(-2.84)	(-4.53)	(-2.54)	(-2.53)	(-3.02)	(-1.66)	(-2.14)	(-4.91)	(-3.08)
Non-scientific R&D	0.264***	0.288***	0.298***	0.139***	0.135***	0.157***	0.319***	0.395***	0.379***
	(5.92)	(8.50)	(5.76)	(3.30)	(4.26)	(3.32)	(7.22)	(12.15)	(7.45)
Non-scientific R&D^2	-0.388***	-0.439***	-0.445***	-0.221***	-0.238***	-0.256***	-0.476***	-0.567***	-0.550***
	(-7.97)	(-11.61)	(-7.72)	(-4.81)	(-6.72)	(-4.83)	(-9.75)	(-15.24)	(-9.65)
Scientific R&D*Non-Scientific R&D	-0.339***	-0.248***	-0.246	-0.291***	-0.113	-0.149	-0.227**	-0.384***	-0.334**
	(-3.22)	(-2.61)	(-1.63)	(-2.87)	(-1.26)	(-1.02)	(-2.14)	(-4.04)	(-2.41)
Innovation intensity	0.367***	0.536***	0.472***	0.217***	0.275***	0.242***	0.310***	0.492***	0.442***
	(24.58)	(33.45)	(22.80)	(15.16)	(18.36)	(12.52)	(22.10)	(33.40)	(22.71)
Export intensity	0.026***	0.0471***	0.0478**	0.017***	0.0258***	0.0262*	0.017***	0.0434***	0.0443***
	(4.76)	(8.15)	(2.55)	(3.24)	(4.77)	(1.90)	(2.63)	(8.31)	(2.62)
Size	3.04e-08***	5.12e-08***	4.57e-08***	2.53e-08***	3.24e-08***	2.76e-08***	3.15e-08***	5.45e-08***	5.15e-08***
	(3.95)	(9.22)	(5.87)	(3.53)	(6.35)	(3.90)	(4.30)	(10.91)	(6.00)
Group	0.042***	0.0627***	0.0589***	0.035***	0.0546***	0.0506***	0.040***	0.0597***	0.0581***
	(6.09)	(12.58)	(7.34)	(5.43)	(11.72)	(6.89)	(5.86)	(12.48)	(7.36)
Sales growth			0.0000003			4.38e-08			0.0000007
			(0.78)			(0.17)			(1.26)
Industry dummies	Included	Included	Included	Included	Included	Included	Included	Included	Included
Temporal dummies	Included	Included	Included	Included	Included	Included	Included	Included	Included
Constant	-0.155	-0.638***	-0.453***	-0.280	-0.436***	-0.280***	-0.538**	-0.894***	-0.773***
	(-0.75)	(-4.78)	(-3.40)	(-1.35)	(-3.64)	(-2.95)	(-2.39)	(-7.02)	(-4.71)
No. Observations	46,811	40,733	45,365	46,811	40,733	45,365	46,811	40,733	45,365
F/Wald	2978.44	4201.25	35.91	1553.87	2322.67	21.05	1910.48	3271.86	28.22
Wald test of exogeneity		1.25			3.22			5.47	

Figure 1. The U-inverted relationship between extramural R&D and innovative performance



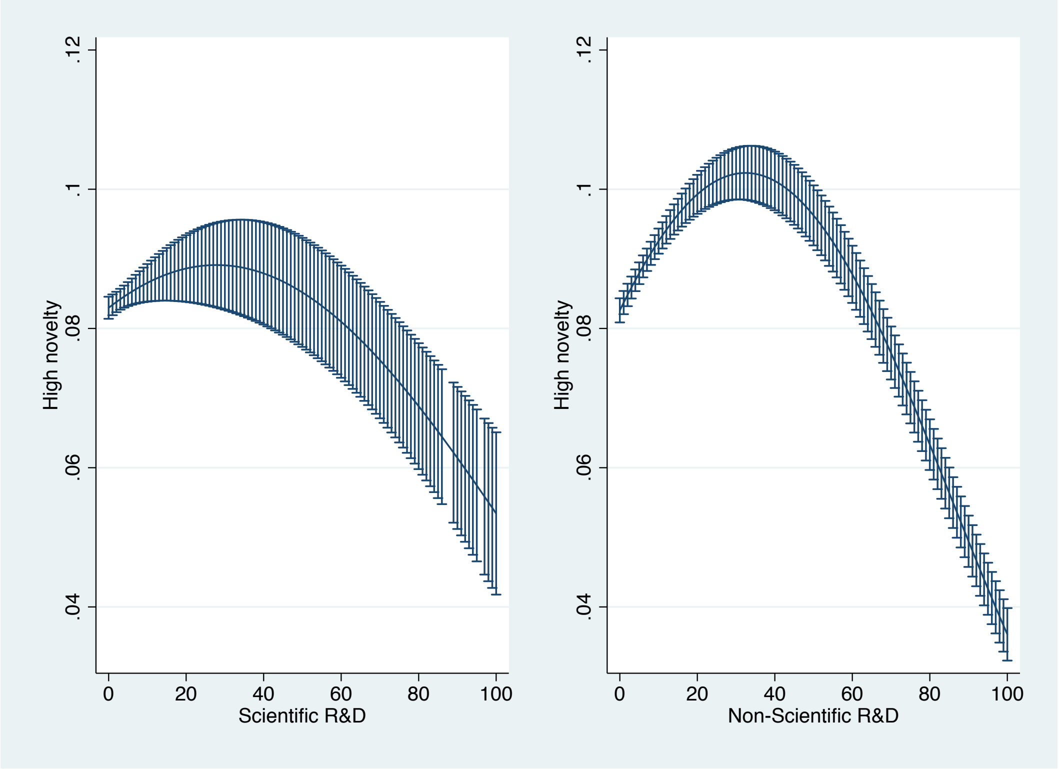
Source: Haans et al. (2016)

Figure 2. Extramural R&D and product novelty



Note: Predictive marginal effects with 95% confidence intervals

Figure 3. Scientific and Non-Scientific R&D and high novelty innovations



Note: Predictive marginal effects with 95% confidence intervals

Appendix 1. Variable description according to the original questionnaire

Dependent variables

Were any of your products innovations (goods or services) during the three years 200X to 20XX?			
		Yes	No
Only new to your firm?	Your enterprise introduced a new or significantly improved product that was already available from your competitors in the market	☐	☐
New to your market?	Your enterprise introduced a new or significantly improved product onto your market before your competitors (it may have already been available in other markets)	☐	☐

Using the definitions above, please give the percentage of your total turnover in 20XX from:	
New or significantly improved products introduced during the three years 200x to 20XX that were **new to your market**	
New or significantly improved products introduced during the three years 200X to 20XX that were **only new to your firm**	
Products that were **unchanged or only marginally modified** during the three years 200X to 20XX (include the resale of new products purchased from other enterprises)	
Total turnover in 20XX	100%

Independent variables

In 20XX, did your enterprise engage in any of following innovation activities, with the aim of obtaining new or significantly improved products (goods or services) or processes based on science, technology and other areas of knowledge?:

	No	**Yes**	**Expenditure €**
A. In-house R&D Creative work undertaken within your enterprise to increase the stock of knowledge for developing new and improved products and processes (include in-house software development that meets this requirement)	☐	☐	
B. External R&D Same activities as above, but performed by other enterprises (including other enterprises or subsidiaries within your group) or by public or private research organisations and purchased by your enterprise	☐	☐	
C. Acquisition of machinery, equipment and software Acquisition of advanced machinery, equipment (including computer hardware) or software to produce new or significantly improved products and processes	☐	☐	
D. Acquisition of external knowledge Purchase or licensing of patents and non-patented inventions, know-how, and other types of knowledge from other enterprises or organisations for the development of new or significantly improved products and processes	☐	☐	
E. Training for innovative activities Internal or external training for your personnel specifically for the development and/or introduction of new or significantly improved products and processes	☐	☐	

F. Market introduction of innovations

Activities for the market introduction of your new or significantly improved goods or services, including market research and launch advertising ☐ ☐

G. Design and other preparation for production and/or distribution (not included in R&D)

Other activities to implement new or significantly improved products and processes not included in other sections. (For example, testing, feasibility studies, routine software development, design, tooling up, industrial engineering, etc.) ☐ ☐

H. (A+B+C+D+E+F+G) Total...

Purchase of R&D in 20XX

They are motivated by the acquisition of R&D outside the firm by contract, agreement; ... institutional fees to finance other companies or research associations that do not involve a direct purchase of R and D are excluded.

A. Purchase of R and D in Spain (excluding VAT)	Total amount (€)
- Firms in the same group	Total amount (€)
- Other companies	Total amount (€)
- Research partnerships	Total amount (€)
- Public administrations	Total amount (€)
- Universities	Total amount (€)
- Private non-profit	Total amount (€)
B.Purchase of R&D abroad (excluding VAT)	
- Foreign companies in the same group	Total amount (€)
- Other foreign companies	Total amount (€)
- Foreign government agencies	Total amount (€)
- Foreign universities	Total amount (€)
- Foreign private non-profit	Total amount (€)
- Other international organisations	Total amount (€)
C. Total purchase of R&D, (external R&D)	Total amount (€)

Control variables

Is your enterprise part of an enterprise group?

Yes ☐ No ☐

Economic Performance

State total turnover of goods or services, including all taxes except VAT. For credit institutions, state interest receivable and similar income. For insurance services, state gross premiums written

	200X	**20XX**
1. Total sales		
1.1. Total turnover from European Union, AELC or candidate countries to EU*		
1.2. Export turnover (excluded 1.1)		
2. Gross investment in tangible goods		

*** Include the following countries:** Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Italy, Ireland, Latvia, Liechtenstein, Lithuania, Luxembourg, Macedonia, Malta, Netherlands, Norway, Poland, Portugal, Romania, Slovenia, Slovakia, Switzerland, Turkey, Sweden and the United Kingdom

Appendix 2. Sectorial classification

	National classification of industry activities
1. Coke and refined petroleum products	05, 06, 07, 08, 09
2. Food products, beverages, and tobacco products	10, 11, 12
3. Textiles	13
4. Wearing apparel	14
5. Leather and related products	15
6. Wood and cork	16
7. Paper and paper products	17
8. Printing and reproduction of recorded media	18
9. Chemicals	20
10.Pharmaceutical products and pharmaceutical preparations	21
11. Rubber and plastic products	22
12. Other non-metallic mineral products	23
13. Basic metals	24
14. Fabricated metal products, except machinery and equipment	25
15. Computer, electronic and optical products	26
16. Electrical equipment	27
17. Machinery and equipment	28
18. Motor vehicles, trailers and semi-trailers	29
19. Building of ships and boats	301
20. Air and spacecraft and related machinery	303
21. Other transport equipment	30 (except 301 and 303)
22. Furniture	31
23. Other manufacturing	32
24. Repair and installation of machinery and equipment	33
25. Retail trade	45, 46, 47
26. Transport, storage and communication	49, 50, 51, 52, 53
27. Hotels and restaurants	55, 56
28. Telecommunication	61
29. Software consultancy and supply	62
30. Computer and related activities	58,59,60, 63
31. Financial intermediation	64, 65, 66
32. Real estate activities	68
33. Research and development	72
34. Supporting service activities	69, 70, 71, 73, 74,75
35. Travel agencies, renting, security services	77, 78, 79,80,81, 82
36. Education	85 (except 854)
37. Health and social work	86, 87, 88
38. Recreational, cultural and sporting activities	90, 91, 92, 93
39. Other services	95, 96