Open strategies and innovation performance

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6 July 2011

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Abstract

Scholarly interest in the relationship between open strategies and innovation performance has been unfailing, and in recent years has even increased. The present paper focuses on inbound open strategies and reviews various approaches (transaction costs, competences, open innovation) dealing with firms´ decisions about these strategies. The different approaches result in different conclusions about the optimum level of openness. The different approaches are tested empirically taking account of the different degrees of openness (closed, semiopen, open, ultraopen) and their effects on sales of new–to-the-market products, and using a panel of Spanish firms from a CIS-type survey for 2004-2008. Our results show that closed and semiopen strategies are the most common among Spanish firms and that open strategies produce the best performance, while semiopen strategies are more effective than closed ones. These results hold across different subsamples based on firm size and industry, and are robust to different ways of defining the indicators and to different estimation methods.

Keywords: open innovation strategies, collaboration, transaction costs, competences, CIS surveys, R&D, technology policy.

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1. Introduction

The relationship between the utilization of external sources of knowledge and innovative performance has been a traditional area of interest for academics, managers and policy makers (Mowery, 1983; Freeman, 1991; 1994). It is beginning to attract even more research attention with some authors claiming that firms are switching from a model of closed innovation to an open strategy (Chesbrough, 2003; 2006). The evidence for this claim is mainly qualitative and based on the so-called 'high technology' industries and on US companies (Chesbrough, 2006; van de Vrande et al., 2009). Although some analyses use large databases covering several sectors and several different countries (van de Vrande et al., 2009; Barge-Gil, 2010a; 2010b), they focus on the determinants of the different open strategies followed by firms, but not on their effects. Several scholars (West et al., 2006; Spithoven et al., 2010; Lichtenthaler, 2011) have highlighted the fact that few studies focus on the effects of different open strategies on firm performance. The question of how openness influences the ability of firms to innovate and benefit from innovation is at the heart of innovation research (Dahlander and Gann, 2010) and measuring openness empirically is becoming increasingly important (Gassman et al., 2010).

In this paper, we focus on inbound open strategies, developed through formal relationships. That is, we link to a research tradition that focuses on analysing the effect of formal ties with external partner, on innovation performance (see e.g., Brouwer and Kleinknecht, 1996; Miotti and Sachwald, 2003; Mohnen et al., 2006). However, these studies focus mainly on the occurrence (not on the differing degrees) of linkages, which limits the knowledge in this area (Freel and de Jong, 2009; Tomlinson, 2010; Barge-Gil, 2010b).

More precisely, it is crucial to find the right balance between internal and external sources of innovation (Foss, 2003; Dahlander and Gann, 2010), since openness is not a binary classification (Chesbrough, 2003; Huizingh, 2010), and open strategies can be more or less enduring and intensive and involve more or less resource sharing and commitment (Freel and de Jong, 2009). Accordingly, operationalization of the degree of openness has moved on to the research agenda (Elmquist et al., 2009; Knudsen and Mortensen, 2010; Lichtenthaler, 2011).

From a theoretical point of view, the open innovation (OI) approach is closely coupled to a broader debate on firm boundaries (Dahlander and Gann, 2010), which links it to transaction cost and competences approaches. All these approaches deal with firms´ decisions about openness. However, they reach different conclusions about the optimal level of openness, thus providing contradictory guidance for practitioners. This situation makes it crucial to advance empirical analysis of the relationship between different degrees of openness and innovation performance.

In this paper, we empirically test the approaches in the literature by analysing the effect of different degrees of openness on firms´ product innovation outcomes. The study highlights a number of important features.

First, we use data from the Innovation Panel developed by the Spanish Institute of Statistics (PITEC) for the period 2004-2008, which was built on the responses to the Spanish part of the Community Innovation Survey (CIS). The PITEC database is very powerful and provides data for a large sample of firms over the five years 2004 to 2008. Its panel structure enables panel data techniques which control for individual unobservable heterogeneity not controlled for using cross sectional data. Our data provide quantitative evidence on the OI strategies of firms in all manufacturing sectors in a non-US context.

Second, we combine information gleaned from the responses to different questions in the survey to generate a measure of degree of openness, which allows us to distinguish among four different strategies: closed, semiopen, open and ultraopen. Since the survey is CIS-based, this measure can be replicated in other countries, which will enable the development of stylized facts.

Third, we use parametric techniques including single equation and two-part models, and semiparametric techniques including quantile regression, which allow us to evaluate the impact of openness strategies both for average firms and for different points on the outcomes distribution.

Fourth, we show that the results hold across different subsamples based on firm size and industry, giving generalizability to the findings.

The paper is organized as follows. Section 2 reviews the different theoretical approaches and derives some hypotheses. Section 3 reviews the empirical results from other studies that analyse openness using CIS-type data. Section 4 describes the database and variables and explains the empirical strategy. Section 5 presents the results which are discussed in Section 6. Section 7 offers some conclusions.

2. The theoretical approaches

This section looks at the relationship between open strategies and innovation, according to different approaches: transaction costs, competences, and OI. A very important point is that the different approaches reach different conclusions, leading to the formulation of opposing hypotheses. These controversies in the theory call for more empirical research.

2.1. Transaction costs

Transactions cost economics (TCE) (Williamson, 1979; 1981; 1991) provides a framework to understand the decisions of firms related to conducting an activity in-house or externally. TCE theory was proposed originally to explain why firms exist, and is based on the idea of minimizing costs: a firm will choose to be open if the cost of externalizing an activity is lower than the cost of performing it within the firm. There are three main types of costs of externalizing activities (transactions costs): the costs of potential opportunistic behaviour from other agents; coordination costs; and, in the case of innovation, unintended knowledge leakages (Ozman, 2009). On this basis, there are three key elements that influence the decision about whether to conduct an activity internally or externally: asset specificity; uncertainty; and scale economies (Williamson, 1979; 2010; Robertson and Gatignon, 1998)

Asset specificity is the most important dimension in a transaction (Williamson, 1981) and signals whether or not a 'transaction-specific` investment is warranted. Transaction specific investments cannot be redeployed to alternative uses or users without loss of value (Williamson, 1985). Partners signing a contract that involves transaction specific investment are embarking on a relationship of mutual dependence where market forces cannot easily punish opportunism or maladaptation (Robertson and Gatignon, 1998). For this reason, the need for transaction-specific investment is usually decisive in the firm's choice to carry out the activity internally.

When uncertainty is high, this means that unforeseen circumstances are likely to arise during the execution of the activities, potentially leading to conflict. If the activity is conducted in house, adaptations to original expectations can be made sequentially without the need for wide consultation or revision of interfirm agreements; conflicts can be resolved based on in-firm hierarchy (Williamson, 1979; 1981).

Scale economies are usually the result of external agents aggregating demand leading to a reduction in production costs, making the choice to externalize more attractive for the firm (Love and Roper, 2005). Scale economies will only be available if products, at least to some degree, are standardized. If there are no scale economies, then it is more likely that the firm will decide to conduct the activity internally.

Innovation usually involves investment in specific assets, major technical and economic uncertainty and few scale economies because of the level of specificity and creativity involved. In the context of product innovation, this may make the transactions costs prohibitive (Lundvall, 1993). In addition, TCE treats external sourcing and internal development as substitutes (Veugelers and Cassiman, 1999);

thus, predicting that a closed strategy is the most successful to develop innovation (Lundvall, 1993; Galende, 2006).

HIP 1: Closed strategies will be the most conducive to innovation success

2.2. The competences approach

Delmas (1999) highlights that TCE was formulated in an environment of mature physical capital-intensive industries and its application in environments where know-how is the key asset and where building rather than protecting specific assets is the main issue, may be limited. TCE is often criticized as being inappropriate in dealing with innovation (Lundvall, 1993; Foss and Klein, 2010) where learning is central to the process; critics claim that TCE focuses on minimizing costs and does not pay sufficient attention to learning. Williamson (1985; 1991) did acknowledge that TCE requires some adaptation to deal with the innovation process. In other words, the focus on cost in TCE does not recognize the differential value to be gained from being open (Madhok and Tallman, 1998) because it assumes uniform results from different governance modes (Hodgson, 1998; Noteboom, 2004), an assumption that is not made in the competences approach.

The competences approach builds on the resource-based view of the firm. It assumes that core resources are scarce, valuable, imperfectly imitable and lacking direct substitutes, so that competitive advantage is sustained (Barney, 1991). As the competences approach has evolved, the emphasis on capabilities and competences has increased with a reduced focus on pure resources (Ambrosini and Bowman, 2009). Capabilities are considered to be more important strategically than transaction costs (Noteboom, 2004): the firm's ability to foster human learning, technological innovation and research and development (R&D) in a context of uncertainty may be crucial for firm survival and a major reason why firms exist (Hodgson, 1998)

Within the competences perspective there are some arguments favouring openness, especially maximizing firm value through the pooling and utilization of valuable resources (Das and Teng, 2000). The key point in this argument is that firms have heterogeneous technological capabilities whose combination can make success more likely and can foster the accumulation of resources and learning (Sakakibara, 1997). Openness also makes organizations more flexible by enabling reversibility, which is very important since the failure rate among research projects is high (Narula, 2001).

However, there are also strong arguments for keeping activities internal. Most of the competences required for R&D are specific to the organization and are usually non tradeable (Barney, 1991; Sakakibara, 1997). Teece (1988) for example, highlights the importance of close communication between the innovation process and manufacturing, which means that its results are more likely to meet the specific needs of the firm if the innovation activity is performed internally (Beneito, 2003; 2006). Innovation capabilities do not accrue from skilfulness in exploiting external technologies, which are accessible also to competitors and therefore not sufficient to sustain competitive advantage (Barney, 1991). They accumulate as the result of in-house innovation, which implies the possession of heterogeneous and specific technological resources and the capability to generate new resources and build basic technological competence (Galende, 2006). Being closed enables firms to exploit the cumulativeness and complexity of their technological knowledge, reduce the uncertainty of the innovation search through the use of routines (Dosi, 1988) and protect their knowledge through greater control over spillovers. Another argument for integration from the competences perspective is that outsourcing can result in the dissipation of a capability that later turns out to be crucial for the utilization or replacement of elements of the firm's core competence (Noteboom, 2004).

These aspects are the basis of claims that firms should concentrate on doing in house those activities at which they excel (core activities) (Hodgson, 1998; Noteboom, 2004) and on more strategic knowledge in order to guard against unintended outflows or leakages (Cassiman and Valentini, 2009), and to outsource only 'non-core' activities or those in which they are not particularly specialized (Mowery, 1983; Mol, 2005). In other words, although exploiting external sources provides useful knowledge, a firm's product innovation processes need to be primarily internal (Oerlemans et al., 1998; Vega-Jurado et al., 2009). Firms retaining core innovation processes in house while adopting an open strategy for other activities can be described as using a 'semiopen' strategy (Barge-Gil, 2010b).

HIP 2: Semiopen strategies are the most conducive to innovation success.

2.3. Open innovation

The OI approach takes a different view. The key to OI is that external ideas and external paths to market are assigned *the same level of importance* as internal ideas and internal paths to market (Chesbrough 2006, page 1, italics are ours), and co-development of innovation is an important activity (Chesbrough and Schwartz, 2007). Firms are aware that only a small proportion of innovative people are employed in house, and that a lot of unique knowledge and abilities lie outside firm boundaries and internal R&D departments (Chesbrough 2003), but can be accessed through collaborations arrangements between firms and outside actors (Elmquist et al., 2009). Recent empirical evidence is challenging earlier approaches to innovation (Chesbrough and Appleyard, 2007). For example, Cisco is regarded as one of the world's most innovative companies, although it does very little research in house and acquires most of its technology from external sources (Gassmann, 2006). The story of its competition with Lucent is one of the outstanding examples of this new paradigm (Chesbrough 2003). Chesbrough (2006) shows that quantitatively the weight of small and medium sized enterprises (SME) in R&D spending and patents has grown considerably, showing that knowledge is increasingly distributed and providing evidence that firms should adapt to this new situation. It is suggested that more and more managers are discovering the value of openness for higher innovation rates and radically new product innovations, not just cost savings (Gassmann, 2006; Mazzanti et al., 2009).

Several factors have contributed to popularity and importance of OI (Chesbrough, 2007, Chesbrough and Appleyard, 2007; Dahlander and Gann, 2010): (i) changes in working patterns, in which professionals seek portfolio careers rather than jobs for life, and work contexts that involve increasing division of labour; (ii) improved market institutions (property rights, venture capitalists, standards) are enabling increased trading of knowledge; (iii) new technologies which ease coordination across geographical distance; and (iv) the high costs of technological development and shorter product life cycles which make it harder for companies to justify large internal investments.

The main argument for the importance of OI is its power to create value, which is related to the inherent characteristics of knowledge that it can be reused and can lead to increasing returns (Chesbrough and Appleyard, 2007). In addition, it is often not possible (or would be extremely costly and risky) to develop the knowledge internally (Lichtenthaler, 2008), making openness unavoidable. Thus, external resources are becoming part of the firm's knowledge base (Witzeman et al., 2006).

HIP3: Open strategies are the most conducive to innovation success.

Finally, some authors highlight that organizations need to guard against a preference for outsiders, which makes them waste detailed and available internal knowledge in the pursuit of less rich external knowledge (Menon and Pfeffer, 2003).[1] Even proponents of OI warn that too much openness can have a negative impact on

[1] Structure of incentives inside of organizations (internal competition) and the greater scrutiny over internal knowledge could explain this behaviour (Menon and Pfeffer, 2003).

companies' innovation success (Chesbrough and Appleyard, 2007; Enkel et al., 2009). Too much external knowledge can be damaging for four reasons. First, it could lead to loss of control and loss of core competences (Enkel et al,. 2009), especially when partners engage in "learning races" where relationships dissolve after one partner aggressively extracts knowledge from the other partner (Chesbrough and Appleyard, 2007). Second, sustaining a business model requires that a portion of the value created for innovation is captured; therefore, an effective open strategy must find a balance between value capture and value creation (Chesbrough and Appleyard, 2007). Third, too much openness can give place to over-searching and coordination problems (Katila and Ahuja, 2002; Laursen and Salter, 2006; Lazzarotti and Manzini, 2009). Fourth, some authors warn that greater external openness could damage the openness within the firm (Trott and Hartman, 2009; Knudsen and Mortensen, 2010) and negatively affect the morale of internal knowledge producers (Menon and Pfeffer, 2003). Accordingly, there can be too much openness, a finding that has been corroborated by academic research that the costs of maintaining networks increases greatly when networks pass a certain size (Hansen, 1999), resulting in reduced performance (Laursen and Salter, 2006).

HIP4: Ultra-open strategies are less conducive to innovation success.

To sum up, the different approaches predict that different degrees of openness may be more or less conducive to innovation success. This fact points to the importance of empirical exploration of the relationship between open strategies and innovation performance, which is the main goal in this paper.

3. Previous empirical work

Before presenting our empirical study, we are going to revise the previous empirical literature. There is a research tradition that focuses on analysing the effects of firms' inbound openness using large datasets (Karlsson, 1997; Oerlemans et al., 1998;

Koschatzky, 1998; Love and Roper, 1999; Vega-Jurado et al., 2009). In recent years, many studies on this topic have used CIS-type survey data. CIS survey data are popular for analysing innovation because (i) they follow the Oslo and Frascati manual guidelines, which are the result of years of work conducted by different scholars and practitioners, (ii) they allow comparable indicators to analyse intercountry and intertemporal differences and develop robust empirical evidence, and (iii) they are usually conducted by national statistics offices which are experienced at data gathering, and conduct extensive pre-testing and piloting to check interpretability, reliability and validity (Laursen and Salter, 2006).

Commonly used indicators of innovation outcome based on CIS data include percentage sales of products that are new to the market or to the firm or significantly improved compared to sales of other products. A review of the advantages and disadvantages of such indicators and some of the studies that employ them is provided by Vasquez-Urriago et al. (2011). Their main advantages are that they provide a measure of the economic success of innovations, are applicable to all sectors, allow types of innovations to be distinguished, and allow the definition of continuous variables, which contribute to the development of econometric analyses (Kleinknecht et al., 2002; Negassi, 2004). Their limitations are that they are sensitive to product life cycles and markets, which may differ in the context of competing companies (Kleinknecht et al., 2002; Frenz and Ietto-Gillies, 2009).

Table 1 presents studies analysing the effect of openness, based on these indicators[2]. All these studies use CIS-type data and some indicator of the firm's general strategy in relation to inbound openness (analyses of the effect of openness with specific types of partners or of spillovers are excluded).[3] Even within these

[2] We restrict the analysis to those works published in journals, although there are also some working papers and book chapters dealing with this issue.

[3] Some studies use indicators for formal links and for "general utilization" (not necessarily involving formal links). We show only the indicators related to formal links. E.g., Laursen and Salter (2006) focus

parameters we can see that the empirical evidence is far from conclusive. Some studies find the existence of a positive effect (Miotti and Sachwald, 2003; Caloghirou et al., 2004; Faems et al., 2005; Laursen and Salter, 2006) or no effect (Brouwer and Kleinknecht, 1996; Aschoff and Schmidt, 2008; Frenz and Ietto-Gilles, 2009; Spithoven et al., 2010), and some find a mixture of both, depending on the method of estimation (Klomp and van Leuween, 2001; Negassi, 2004), the sector analysed (Mohnen et al., 2006; Raymond et al., 2006) or the indicator for openness (Fosfuri and Tribo, 2008).

We would emphasize that, despite being very selective in terms of the studies reviewed, they present many methodological differences, in terms mainly of sample selection, estimation methods and definition of the indicators. Sample size also varies a lot. These differences make it difficult to develop robust empirical evidence. We can say only that openness is not shown to have a negative effect on sales of product innovations and that the existence or not of a positive effect of openness on results is contingent on the individual study (although there do not seem to be direct associations between the choices made and the results obtained, the effect of openness tends to be more positive if only the manufacturing sectors are included).

This lack of empirical robustness is at the root of the claims of some authors that the effect of openness on firms' innovation outcomes should receive greater attention and should take account of the different degrees of openness (West et al., 2006; Enkel et al., 2009; Spithoven et al., 2010, Knudsen and Mortensen, 2010). This call for more research would seem justified in an era when open innovation is attracting increased interest, especially from firm managers.

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mainly on the depth and breadth of open innovation in terms of "general utilization"; we do not include this part of their analysis in this review.

Table 1. Review of previous empirical studies

Authors	Data[a]	Sample	Sample Selection	Methodology	Dependent Variable[b]	Independent variables	Effect
Brouwer, Kleinknecht (1996)	CIS1 Netherlands 1992	3,505	Innovators (corrected)	Generalized Tobit	% n_firm	Dummy acquisition external knowledge	No effect
					% n_market		No effect
Klomp, Van Leeuwen (2001)	CIS2 Netherlands 1996	3,059	Innovators (corrected)	OLS	Latent logit share % n_general	Dummy cooperation	Positive
				Heckman			No effect
				FIML			No effect
Miotti, Sachwald (2003)	CIS2 France 1996	4,215	Manufacturing	nd	% n_general	Dummy cooperation	Positive
Negassi (2004)	CIS 1 and 2 France (1992 and 1996)	3,801x 7 years (Panel)	Manufacturing	Fixed Effects	LVA n_general	L VA cooperation and contracting (t-1)	No effect
				Random Effects			Positive
				2SLS			Positive
				Tobit			Positive
Caloghirou et al. (2004)	KNOW 2000 (7 countries)	558	Innovators and 5 sectors	OLS	% n_general	Dummy strategic alliance	Positive
Faems et al. (2005)	CIS 2 Belgium 1996	221	Manufacturing, innovators	Tobit	% n_general	Number of different type of partners	Positive
Mohnen et al. (2006)	CIS 1 (7 countries)	8146	Manufacturing, innovators (corrected)	Generalized Tobit	Latent logit share% n_general	Dummy cooperation	Positive (HT) No effect (LT)
Laursen, Salter (2006)	CIS 3 UK 2000	2,707	Manufacturing	Tobit	L % n_market	Dummy cooperation	Positive
					L % n_firm		Positive
					L % improved firm		Positive
					L % n_market	Number of different type of partners	Inverted U
Raymond et al. (2006)	CIS 2 Netherlands 1996	3,294	Manufacturing, innovators (corrected)	Generalized Tobit	Latent logit share% n_general	Dummy cooperation	Positive (HT) No effect (LT)
	CIS 2,5 Netherlands 1998	3,220					Positive (HT and LT)
	CIS 3 Netherlands 2000	2,104					Positive (HT and LT)
Aschhoff, Schmidt (2008)	CIS Germany 2004 and 2005	699	Innovators	Lower bound heterocedastic Tobit	% n_market	Dummy cooperation (t-1)	No effect
					% n_firm		No effect
Fosfuri, Tribó (2008)	CIS 3 Spain 2000	2,464	With innovation expenses	OLS	% n_general	Dummy cooperation	No effect
						Dummy external R&D	Positive
Frenz, Ietto-Gillies (2009)	CIS 2 and 3 UK (1998 and 2000)	679	Innovators (corrected)	OLS	L P n_general	Dummy cooperation (t-1)	No effect
				Heckman			No effect
Spithoven et al. (2010)	CIS 3 Belgium (2000)	724	Innovators (both corrected and not)	OLS	L % n_general	Dummy cooperation	No effect
				2SLS			No effect
				Tobit			No effect

[a] Some of them jointly with other surveys [b](%) Share of ___ in firm's total sales; (L) Logarithm; (VA) Absolute Value of ___ (P) productivity: value per employee; (n_firm) New products to firm; (n_market) New products to firm's market; (n_general).

4. Empirical strategy

4.1. Database

We use PITEC (2004-2008) data. PITEC is a statistical instrument for studying the innovation activities of Spanish firms over time. The PITEC database is compiled by INE, the Spanish National Statistics Institute, and sponsored by FECYT and COTEC advisory groups of university researchers. It is developed from the R&D and technological innovation surveys of Spanish firms, which makes it a CIS-type survey. Although PITEC started in 2003 we cannot use data from that year because some questions were framed in such a way as to make it impossible to derive indicators similar to those for the rest of the period. The PITEC sample is composed of various subsamples. In 2003, two subsamples were defined: one composed of all firms with 200 or more employees, and the other composed of all firms performing internal R&D. In subsequent years, some firms with different characteristics were included. Quantitative variables are anonymized.[4]

The current analysis is restricted to all innovating firms in the manufacturing sectors performing R&D in at least one year of the sample period (2004-2008). The construction of the database dictates that it is representative only of R&D performers. Our focus on the manufacturing sectors is because product innovation in services has several differential features (Sirilli and Evangelista, 1998; Pires et al., 2008). This strategy has the advantage that we do not have sample selection among these firms (all firms with these characteristics are included), but the disadvantage that our results cannot be extended to the whole population of firms. The last column in Table 2 shows the yearly composition of the final sample.

[4] More information on the database and its anonymization can be found at http://sise.fecyt.es/Estudios/PITEC.asp (in English).

4.2. Definition of the variables

4.2.1. Dependent variable

Definitions of all the variables are provided in Table 3. Following previous studies using CIS-type survey data, our dependent variable is the percentage of sales obtained in the last year of the period of analysis, from products new to the market, introduced in the previous three years. Our indicator is LNEWMK, being LNEWMK=ln (NEWMK), where NEWMK is the weight of sales of new to the market products, expressed as one per thousand. If NEWMK is equal to zero, then LNEWMK is equal to zero. In the robustness check section (5.2) other indicators will be explored.

4.2.2. Independent variables

Our independent variables are four dummy variables that capture the firm's openness strategy. We develop these variables by combining the responses to several different survey questions.[5]

First, we start by labelling those firms declaring neither collaboration for innovation nor buying external R&D. These firms do not show any formal links related to inbound open innovation and, therefore, are considered *CLOSED*. According to the transaction costs approach, this is the best choice and will allow these firms to perform better.

Second, we distinguish different degrees of openness among those declaring some formal link. We exploit the responses to another question in the innovation survey: 'How were the new products developed?' There are three possible answers: mainly by the enterprise; mainly through co-operation with other enterprises or institutions; mainly by other enterprises or institutions. Respondents were asked to choose one of these. In our view, this information allows us to derive indicators for different degrees of openness, in line with the different theoretical approaches.

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[5] We adapt the definitions in Barge-Gil (2010b).

Firms indicating formal links for inbound open innovation, but declaring that *new products were obtained mainly by the enterprise on its own,* are regarded as *SEMIOPEN*. They use external sources, but retain the bulk of the process in house. According to the competence approach, this is the best choice and these firms will achieve higher performance.

Firms indicating formal links for inbound open innovation and declaring that *new products were achieved mainly through co-operation with other organizations* are regarded as *OPEN*. They conform to the main distinguishing feature of open innovation, that is, that internal and external sources of knowledge are equally important. According to the open innovation approach, this is the best choice and will enable higher performance.

Finally, firms whose *new products are the result predominantly of the efforts of third parties* are regarded as *ULTRAOPEN*. For these firms, external sources are more important than internal sources for new products. Many authors warn about the risks in such a strategy; we want to test whether it is such a bad choice.

Table 2 shows the relative frequency of the different strategies in the period considered. We see that both the transaction cost and the competences approaches seem to perform well in explaining firm behaviour accounting respectively for 44.1% and 40.8% of the whole sample (open innovators 12.7% and ultraopen 2.3%). We see also that closed strategies are becoming more common: their weight has been increasing yearly, from 37.9% in 2004 to 47.5% in 2008, while semiopen strategies are becoming less popular, from 45.7% in 2004 to 37.6% in 2008. Table 2 shows also that open strategies are less important, decreasing from 14.7% in 2004 to 12.2% in 2008, and that ultraopen strategies increased from 1.7% to 2.7%.[6] That is, we do not observe increased firm openness despite claims that more firms are increasingly

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[6] This apparent high relative growth of ultraopen innovators in absolute numbers is a jump from 49 to 89.

adopting open innovation strategies. At least for Spanish innovators performing R&D in the manufacturing sectors, this would seem not to be the case.

Table 2. Open strategies by year

	CLOSED	SEMIOPEN	OPEN	ULTRAOPEN	TOTAL
2004	37,87%	45,70%	14,74%	1,68%	2,910
2005	43,13%	41,17%	13,57%	2,13%	3,707
2006	44,70%	40,92%	12,11%	2,27%	3,649
2007	46,73%	39,33%	11,13%	2,80%	3,323
2008	47,54%	37,59%	12,18%	2,68%	3,317
Total	44,14%	40,83%	12,71%	2,32%	16,906

4.2.3. Control variables

As control variables, and following the studies reviewed in section 3, we use firm size, R&D intensity, sector,[7] export behaviour, obstacles to innovation, and belonging to a group. Detailed definitions of the variables are provided in Table 3.

4.4. The model and estimation issues

Our specification estimates innovation output using as dependent variables a set of dummies reflecting the different strategies chosen by the firm together with a vector of controls:

$$I_{i,t} = a + \alpha_1\, SEMIOPEN_{i,t} + \alpha_2 OPEN_{i,t} + \alpha_3 ULTRAOPEN_{it} + \varphi Z_{i,t} + \varepsilon_{it})$$

where CLOSED is used as the reference category.

A first estimation issue is that we have a panel data structure, which allows us to control for unobservable individual heterogeneity. This has been shown empirically to have an effect on the firm's decision to invest in innovation (Peters, 2009; Griffiths and Webster, 2010) and, arguably, could affect the relationship between openness strategy and innovation outcome. Taking account of such individual heterogeneity is done by decomposing the error ε_{it} in two different components: c_i , which is time invariant and u_{it} .

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[7] For sector, we use the OECD (2005) classification. We tried sectoral dummies and the results (not reported here for reasons of space) were very similar.

$$I_{i,t} = a + \alpha_1 \, SEMIOPEN_{i,t} + \alpha_2 OPEN_{i,t} + \alpha_3 ULTRAOPEN_{it} + \varphi Z_{i,t} + c_i + u_{it})$$

In this work we combine panel data and pooled data analysis for comparative purposes.

Table 3. Definition of variables, mean and standard deviation

LABEL	**DESCRIPTION**	MEAN	SD
LNEWMK	Log of (NEWMK). NEWMK is the yearly weight of sales from new to the market product (introduced in the previous 3 years) over total sales, expressed as 1 in 1,000	2.78	2.64
CLOSED	Dummy variable that takes the value 1 if the firm has neither cooperated nor bought external R&D	0.44	0.50
SEMIOPEN	Dummy variable that takes the value 1 if the firm cooperated or bought external R&D but declare having developed their product innovations mainly through internal efforts	0.41	0.49
OPEN	Dummy variable that takes the value 1 if the firm has developed their product innovations mainly through joint efforts with other entities	0.13	0.33
ULTRAOPEN	Dummy variable that takes the value 1 if the firm declares that their product innovations have been mainly by third parties	0.02	0.15
LSIZE	Log of number of employees	4.16	1.32
LSIZE2	Square of LSIZE	19.04	11.92
RD_INT	R&D staff/Total number of employees	5.75	2.62
LT	Variable that takes the value 1 if the firm belongs to the following sectors: food, beverages and tobacco, textile and clothing, wood products, paper and printing.	0.25	0.43
LMT	Variable that takes the value 1 if the firm belongs to the following sectors: petroleum refining, rubber and plastic products, non-metallic mineral products, ferrous metals, non-ferrous metals, shipbuilding and other manufacturing.	0.23	0.42
MHT	Variable that takes the value 1 if the firm belongs to the following sectors: chemicals, non-electrical machinery, electrical machinery, motor vehicles and other transport equipment.	0.39	0.49
HT	Variable that takes the value 1 if the firm belongs to the following sectors: pharmaceuticals, aircraft and spacecraft, medical, precision and optical instruments, radio, television and communication equipment and office, accounting and computing machinery.	0.13	0.33
EXPORT	Dummy variable taking the value 1 if the firm has sales outside Spain	0.83	0.37
OBS_COST	Sum of the scores for the following obstacles to innovation: lack of internal funds; lack of external funds; very high innovation costs; and demand uncertainty. Rescaled between 0 (not relevant) and 1 (highly relevant)	0.61	0.29
OBS_INF	Sum of the scores for the following obstacles to innovation: lack of qualified personnel; lack of information on technology; lack of information on markets; problems to find partners. Rescaled between 0 (not relevant) and 1 (highly relevant)	0.42	0.24
GROUP	Dummy variable taking the value 1 if the firm belongs to a group	0.38	0.49

A second estimation issue is related to the characteristics of our dependent variable. Firms can have zero sales from new to the market products. We still can model their results using just one equation, as it has been done in several of the empirical analysis reviewed in Section 3 (Negassi, 2004, Faems et al., 2005; Laursen and Salter, 2006). However, a two part model can also be applied. This is developed in two steps: (i) the likelihood of obtaining any new to the market product is analysed for the whole sample, and (ii) the weight of these products over total sales is analysed for the subsample of new to the market innovators. This method shows the advantage of allowing different mechanisms to determine the likelihood of obtaining new to the market products and the percentage of sales from these products (Wooldridge, 2002; Cameron and Trivedi, 2005). Third, we could use a generalized Tobit. This model assumes that we cannot observe the sales from new to the market products of non-innovators, so it treats zeros as missing values. This means that there is a selection bias. This indicates that a two-step method would be the most appropriate, but allowing for dependence between steps following a Heckman procedure. This is the method used in Brouwer and Kleinknecht (1996), Mohnen et al. (2006) and Raymond et al. (2006). In the present work we will concentrate on the two former methods. An attempt was made to explore the generalized Tobit and the results show clearly that both equations are independent, which calls for a two part model.[8] Some authors explicitly state that in the case of the dependent variable used here the zeros observed are true zeros and not missing values (Mairesse and Mohnen, 2010), again indicating the appropriateness of a two part model.

A third issue is that dependent variables are limited (they are censored or dummy variables). Many econometrics textbooks argue that non linear models, such as Tobit or Probit should be applied in this situation. The main advantage of these models if that the predicted values are in the right intervals. However, as Angrist and Pischke (2008) highlight, if we are interested in the effect of some regressors instead of in predicting, then OLS can be used. In fact, when using Tobit or Probit, marginal effects should be computed to obtain this effect. In practice, these are close to OLS coefficients when covariates are fixed at mean values. We employed both OLS and non linear models. We will report here the OLS results, which have the advantage of

[8] Results (not reported here, but are available upon request from the authors) were very similar to those presented here, whether identification relies only on the functional form or on the regional distribution of innovation expenses are used for identification purposes.

being standard, easier to compute and allow for exploring fixed effects in panel models[9].

A fourth issue is that innovation returns are very skewed (Scherer and Harhoff, 2000; Marsili and Salter, 2005; Ebersberger et al., 2008; 2010) so that average-based methods give a biased picture and we need to pay attention to the extreme points in the distribution (McKelvey and Andriani, 2005). Quantile regression is a good tool. It examines conditional changes in different points of the distribution by minimizing a weighted sum of absolute deviations. It was proposed by Koenker and Basset (1978) and is described in detail in Buchinsky (1998). Angrist and Pischke (2008) argue that the coefficients of regressors from the second part of the two part model explained above are downward biased if the coefficients of these regressors are positive in the first part, so that a better way to address the estimation of censored variables is quantile regression. We explore the relationship for three different points in the distribution: the fifth decile (median), representing low innovation (but positive) intensity (LI); the seventh decile, representing median innovation intensity (MI) and the ninth decile, representing high innovation intensity (HI).[10] The fifth decile is the first decile with positive value of sales of new to the market products (2%); in seventh decile this rises to 12.9% and in the ninth decile it is 50%.

5. Results

5.1. Main results

Table 5 shows the main results of the analysis. Random effects panel data results are provided in columns I-III. Column I shows the results for the single equation model, column II shows the first part equation and column III shows the second part of the two part model. The same scheme applies to the pooled regressions (columns

[9]All findings hold when non linear models are employed. Results are available upon request from the authors.
[10] Note that quantile coefficients tell us about the effects on distributions not individual firms. Usually individual firms are not stable in the same point of the distribution (Angrist and Pischke, 2008).

IV-VI). Finally, quantile regression for the fifth, seventh and ninth deciles are shown in columns VII-IX. The Wald tests comparing the coefficients of the different strategies are shown below the regressions.

A first general view is provided in columns I and IV for the panel and pooled data, respectively. Results are very significant from a statistical point of view. An open strategy yields the highest payoff, while being semiopen is better than being closed. These results are robust to the consideration of panel or pooled data. Magnitude of the coefficients deserves a comment. In the more conservative panel estimations[11], an open strategy has 40 log points (around 49%) higher percentage of sales from new to the market products, compared to a close strategy. A semiopen strategy has 22 log points (around 24.6%) higher percentage of sales of new to the market products than a closed strategy.

A more detailed picture is provided by the information in the two part model (columns II-III for panel data and columns V-VI for pooled data). They show that results in colunms I-IV were driven mainly by the influence of the different strategies upon the likelihood of obtaining a new to the market product. Thus, the first part reflect the same pattern as the single equation model, since the coefficient of an open strategy is the highest and a semiopen strategy is shown to be significantly better than a closed strategy. In the panel regression, an open strategy increases the likelihood of obtaining a new to the market product by 8 percentage points and a semiopen strategy increases it by 5 percentage points, both of them compared to a closed strategy[12].

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[11] Coefficients from pooled regression are 30%-50% higher (see table 5). We also tried fixed effects regression (not reported, but available upon request). Results are qualitatively similar, although the value of the coefficient is reduced to 0.27 for open strategies and 0.12 for semiopen strategies, still different from zero (p-values of 0.001 and 0.028, respectively).

[12] Again, pool regression shows higher and significant values for the coefficients: (0.10 and 0.08) and fixed effects panel shows lower values (0.06 and 0.03), for open and semiopen strategies, respectively.

Table 5. Results of the main regressions. Dependent variable: LNEWMK

	PANEL						POOL						QUANTILE REGRESSION					
	I		II		III		IV		V		VI		VII		VIII		IX	
	Single Equation		First Part		Second Part		Single Equation		First Part		Second Part		Quantile (.50)		Quantile (.70)		Quantile (.90)	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
SEMIOPEN	0.22***	(0.05)	0.05***	(0.01)	-0.02	(0.04)	0.34***	(0.06)	0.08***	(0.01)	-0.03	(0.05)	1.01***	(0.05)	0.23***	(0.05)	0.01	(0.04)
OPEN	0.40***	(0.07)	0.08***	(0.01)	0.07	(0.05)	0.52***	(0.09)	0.10***	(0.02)	0.05	(0.06)	1.26***	(0.08)	0.39***	(0.07)	0.13*	(0.06)
ULTRAOPEN	0.14	(0.13)	0.02	(0.02)	0.13	(0.13)	-0.08	(0.19)	-0.03	(0.03)	0.12	(0.20)	-0.07	(0.16)	-0.12	(0.14)	0.34**	(0.12)
LSIZE	-0.43***	(0.11)	-0.05**	(0.02)	-0.38***	(0.08)	-0.58***	(0.11)	-0.07***	(0.02)	-0.45***	(0.08)	-0.86***	(0.09)	-0.80***	(0.08)	-0.33***	(0.07)
LSIZE2	0.05***	(0.01)	0.01***	(0.00)	0.02**	(0.01)	0.06***	(0.01)	0.01***	(0.00)	0.03***	(0.01)	0.10***	(0.01)	0.08***	(0.01)	0.03***	(0.01)
RD_INT	0.07***	(0.01)	0.01***	(0.00)	0.02**	(0.01)	0.11***	(0.01)	0.02***	(0.00)	0.03***	(0.01)	0.38***	(0.01)	0.11***	(0.01)	0.04***	(0.01)
LT	-0.33**	(0.10)	-0.04	(0.02)	-0.24**	(0.08)	-0.27*	(0.11)	-0.02	(0.02)	-0.24**	(0.08)	-0.39***	(0.08)	-0.32***	(0.07)	-0.07	(0.06)
LMT	-0.27**	(0.10)	-0.04*	(0.02)	-0.12	(0.08)	-0.18	(0.11)	-0.02	(0.02)	-0.14	(0.08)	-0.34***	(0.08)	-0.23**	(0.07)	-0.01	(0.06)
MHT	-0.23*	(0.09)	-0.03	(0.02)	-0.12	(0.07)	-0.19	(0.10)	-0.02	(0.02)	-0.12	(0.07)	-0.37***	(0.08)	-0.12	(0.07)	-0.11	(0.06)
EXPORT	0.08	(0.07)	0.02	(0.01)	-0.06	(0.05)	0.11	(0.08)	0.03	(0.02)	-0.06	(0.06)	0.08	(0.07)	0.00	(0.06)	-0.03	(0.05)
OBS_COST	0.19*	(0.08)	0.01	(0.02)	0.22**	(0.07)	0.08	(0.11)	-0.02	(0.02)	0.27***	(0.08)	-0.04	(0.09)	0.17*	(0.08)	0.22**	(0.07)
OBS_INF	0.07	(0.10)	0.02	(0.02)	0.03	(0.08)	0.09	(0.13)	0.02	(0.02)	0.02	(0.10)	0.21	(0.11)	-0.02	(0.10)	-0.15	(0.09)
GROUP	0.01	(0.06)	0.01	(0.01)	-0.06	(0.05)	-0.05	(0.07)	-0.00	(0.01)	-0.06	(0.05)	-0.05	(0.06)	-0.07	(0.05)	-0.01	(0.04)
Year Dummies	Included		Included		Included		Included		Included		Included		Included		Included		Included	
O=S	8.13**		7.12**		3.42		4.59*		2.81		1.69		11.21***		5.63*		4.14*	
O=U	3.44		4.47*		0.22		8.93**		12.39***		0.10		61.41***		11.72***		2.44	
S=U	0.38		0.96		1.49		4.70*		8.31		0.52		44.28***		6.14*		6.72**	
n	16906				16906				9917				16,906		16,906		16,906	
Chi2	323.70		208.70		775.28													
F							19.37		14.90		33.70							

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; S=SEMIOPEN; O=OPEN; U=ULTRAOPEN.

However, the second part of the two part model does not show any significant difference across strategies. We explore this second finding by using quantile regression methods (columns VII-IX), which provides a more detailed view. When these methods are applied, the general results hold for the different points in the distribution: coefficients of an open strategy are always the highest and a semiopen strategy is shown to be better than a closed strategy for LI and MI points. The only exception being HI points where semiopen and closed strategies show similar effects[13].

The results for an ultraopen strategy need to be discussed separately, since they are less stable owing to the lower number of firms adopting this strategy. Panel data single equation (column I) does not reveal a significant effect for this strategy, while the pooled regression (column IV) shows that its coefficient is not different from zero, but significantly lower than for open and semiopen strategies. The quantile regressions provide more detail. An ultraopen strategy provides poorer performance for LI and MI than an open or semiopen strategy, but for HI better performance than a semiopen or a closed strategy.

5.2. Robustness checks and further results

As already mentioned in Section 3, we cannot derive a consensus from the results of the various studies reviewed because of the different definitions of the dependent variables, the different methodologies and the different samples. Our main regressions in Table 5 show that our results are robust to the choice of different methodologies. In this section, we look at whether the results change significantly if the dependent variable is defined differently or if subgroups of firms are considered.

[13] Note that the value of the coefficients decreases sharply as we move up along the distribution. This is due to the fact that the for LI points even a small absolute increase is very high in percentage, while for HI points, a high increase is simply not feasible (because the original variable is a percentage).

5.2.1. Different dependent variables

Table 6 reports the results using two different indicators for the dependent variable.

First, we use the log of sales of products new to the market on number of employees (LNEWMK_E). This is the indicator used by Frenz and Ietto-Gilles (2009) and benefits from not being right censored, eliminating distortion caused by single product firms with 100% sales, and avoiding the accumulation of the distribution in round numbers, such as 5%, 10% or 20%.

Second, we apply a logarithmic transformation, LTNEWMK=log(newmk/(1-newmk)), where newmk is the sales per unit due to new-to-the-market products and the zero values are converted to 0.0001 and 100% becomes 0.9999. This is the indicator used by Klomp and van Leuween (2001), Mohnen et al. (2006) and Raymond et al. (2006) and benefits from being closer to a normal distribution and being symmetric.

The results using LNEWMK_E are essentially the same as the main results. An open strategy gives the highest payoff and a semiopen strategy is better than a closed one. These results are highly significant and hold for the single equation model, with panel and pooled data[14]. When this dependent variable is used, the second part of the two-part model shows that a closed strategy performs the worst. The pattern for the quantile regression is the same as for the single equation model in all the points of the distribution analysed except for the finding that there is no significant difference between an open and a semiopen strategy for LI and MI. The results for an ultraopen strategy are similar than those from table 5. An ultraopen strategy is worse than an open or a semiopen strategy for LI and MI and better than any other strategy for HI (although the difference in the coefficients is not significant compared to an open strategy).

[14] Logically, the first part would be unaffected by changes in the definition of the dependent variable.

Table 6. Results of main regression with different dependent variables

	PANEL				POOL				QUANTILE					
	Single Equation		Second Part		Single Equation		Second Part		Quantile (.50)		Quantile (.70)		Quantile (..9)	
LNEWMK_E	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**
SEMIOPEN	0.53***	(0.09)	0.10	(0.05)	0.80***	(0.12)	0.12*	(0.06)	1.48***	(0.12)	0.41***	(0.05)	0.07	(0.05)
OPEN	0.86***	(0.13)	0.21**	(0.08)	1.08***	(0.16)	0.16*	(0.08)	1.67***	(0.17)	0.39***	(0.07)	0.24***	(0.06)
ULTRAOPEN	0.34	(0.26)	0.38*	(0.18)	-0.09	(0.37)	0.35	(0.26)	-0.44	(0.36)	-0.01	(0.16)	0.35**	(0.13)
Open=Semiopen	7.48**		2.44		3.05		0.30		1.28		0.06		6.68**	
Ultraopen=Open	3.69		0.92		9.41*		0.48		31.41***		5.93*		0.63	
Ultraopen=Semiopen	0.55		2.60		5.80*		0.76		28.47***		7.15**		4.27*	
n	16906		9917		16906		9917		16906		16906		16906	
Wald Chi / F	372.14		1193.46		20.67		27.57							
LTNEWMK	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**
SEMIOPEN	0.33***	(0.09)	-0.11	(0.09)	0.52***	(0.11)	-0.13	(0.10)	1.18***	(0.08)	0.28***	(0.06)	-0.02	(0.11)
OPEN	0.71***	(0.12)	0.12	(0.12)	0.87***	(0.16)	0.07	(0.14)	1.49***	(0.11)	0.46***	(0.08)	0.34*	(0.15)
ULTRAOPEN	0.49*	(0.25)	0.76**	(0.28)	0.20	(0.40)	0.96*	(0.49)	-0.12	(0.23)	-0.08	(0.16)	1.47***	(0.31)
Open=Semiopen	10.58**		4.53*		5.67*		2.53		8.06**		5.32*		6.00*	
Ultraopen=Open	0.68		4.88*		2.68		3.21		43.26***		10.03**		11.49***	
Ultraopen=Semiopen	0.41		9.75**		0.65		5.03*		31.06***		5.01*		22.10***	
n	16906		9917		16906		9917		16906		16906		16906	
Wald Chi / F	273.58		544.18		15.53		24.33							

[a] significant at 0.01 level, [b] significant at 0.05 level;

The results using LTNEWMK follow the same main pattern and there are no qualitative differences between the panel and pooled data for the main equation. The second part or the two-part model does not show any significant difference across strategies. When quantile regression is used, results follow exactly the same pattern as those with the original indicator. Results for an ultraopen strategy are different when this indicator is used. This strategy shows the highest coefficient in the second part of the two-part model, with panel and pooled data. These results are probably driven by the transformation of the dependent variable, imposing symmetry and making observations in the tails more distant. This impression is corroborated by the quantile regression, whose results follow exactly the same pattern as those with the original indicator.

5.2.2. Regression by groups. Size

Table 7 reports the results of the main set of regressions for different groups of firms, based on size: firms with less than 30 employees (small firms), firms with 30 to 100 employees (medium firms) and firms with more than 100 employees (large firms). The cut off points were chosen to obtain groups of similar sample size.

The main results hold for the different groups of firms. For each of them, both an open strategy and a semiopen strategy have higher coefficients than a closed strategy in the single equation model and in the first part whether panel or pooled data are used. In addition, the coefficient of open is always higher than the coefficient of semiopen, although differences are sometimes non significant, due to the smaller sample size.

These results mainly hold for the quantile regressions, although there are some minor differences: For small firms, open and semiopen strategies show a similar effect for HI, and for medium sized firms, semiopen strategies show a higher coefficient than open strategies for MI. Finally, an ultraopen strategy is still the best for HI.

5.2.3. Regression by groups. Sector

Table 8 reports the results by sector following the OECD (2005) classification.

The main results hold for the different groups of sectors. For each of them, open and semiopen strategies show significantly higher coefficients than a closed strategy in the single equation and the first part models and with panel or pooled data. The coefficient of an open strategy is always higher than the coefficient of a semiopen one, although differences are sometimes non significant, due to the smaller sample size.

Concerning the second part, no significant differences emerge across strategies, except for high tech sectors, where an open strategy has a higher coefficient than closed and semiopen for both the panel and pooled data. The quantile regressions show the same pattern of general regression for LI and MI. The only difference is that an open strategy is only shown to be better than the all the other strategies for HI among LMT firms. Finally, an ultraopen strategy is the best strategy for HI only for firms in the MHT sectors.

Table 7. Results of main regressions by size of the firm

	PANEL						POOL						QUANTILE (POOL)					
	Single Equation		First Part		Second Part		Single Equation		First Part		Second Part		Quantile (.50)		Quantile (.70)		Quantile (.90)	
Small Firms	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**
SEMIOPEN	0.27^{**}	(0.08)	0.05^{**}	(0.02)	0.01	(0.06)	0.48^{***}	(0.11)	0.08^{***}	(0.02)	0.11	(0.08)	1.21^{***}	(0.19)	0.36^{***}	(0.08)	0.16^{*}	(0.06)
OPEN	0.57^{***}	(0.12)	0.11^{***}	(0.02)	0.10	(0.08)	0.66^{***}	(0.15)	0.12^{***}	(0.03)	0.12	(0.10)	1.60^{***}	(0.25)	0.54^{***}	(0.11)	0.15	(0.09)
ULTRAOPEN	-0.24	(0.25)	-0.04	(0.05)	0.11	(0.23)	-0.58	(0.32)	-0.14^{*}	(0.05)	0.39	(0.31)	-0.70	(0.57)	-0.76^{**}	(0.25)	0.24	(0.18)
Open=Semiopen	6.34^{*}		7.49^{**}		1.11		1.43		1.40		0.02		2.09		2.52		0.02	
Ultraopen=Open	9.09^{**}		9.49^{**}		0.00		13.66^{***}		20.07^{***}		0.73		14.60^{***}		23.86^{***}		0.22	
Ultraopen=Semiopen	3.96^{*}		3.84		0.18		10.32^{**}		16.06^{***}		0.85		10.89^{**}		18.92^{***}		0.18	
n	5,465		5,465		3,110		5,465		5,465		3,110		5,465		5,465		5,465	
Medium Firms	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**
SEMIOPEN	0.22^{**}	(0.08)	0.06^{***}	(0.01)	-0.09	(0.06)	0.29^{**}	(0.10)	0.07^{***}	(0.02)	-0.10	(0.08)	1.11^{***}	(0.10)	0.16^{*}	(0.07)	-0.05	(0.06)
OPEN	0.34^{**}	(0.12)	0.08^{***}	(0.02)	-0.04	(0.10)	0.42^{**}	(0.15)	0.11^{***}	(0.03)	-0.14	(0.12)	1.24^{***}	(0.15)	0.08	(0.11)	0.25^{**}	(0.09)
ULTRAOPEN	0.18	(0.22)	0.04	(0.04)	0.09	(0.22)	-0.06	(0.30)	-0.03	(0.06)	0.15	(0.29)	-0.07	(0.29)	-0.09	(0.21)	0.41^{*}	(0.18)
Open=Semiopen	1.04		1.34		0.38		0.78		1.37		0.11		0.65		0.56		9.94^{**}	
Ultraopen=Open	0.42		1.13		0.31		2.15		5.08^{*}		0.86		17.71^{***}		0.54		0.61	
Ultraopen=Semiopen	0.03		0.29		0.71		1.23		3.16		0.70		16.52^{***}		1.38		6.26^{*}	
n	5,798		5,798		3,280		5,798		5,798		3,280		5,798		5,798		5,798	
Large Firms	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**
SEMIOPEN	0.26^{**}	(0.08)	0.05^{**}	(0.02)	0.05	(0.07)	0.26^{*}	(0.10)	0.07^{**}	(0.02)	-0.05	(0.08)	0.81^{***}	(0.15)	0.18^{*}	(0.07)	-0.07	(0.08)
OPEN	0.39^{***}	(0.11)	0.07^{**}	(0.02)	0.19	(0.10)	0.43^{**}	(0.14)	0.08^{**}	(0.03)	0.11	(0.11)	1.04^{***}	(0.21)	0.39^{***}	(0.09)	0.12	(0.11)
ULTRAOPEN	0.46^{*}	(0.23)	0.07	(0.04)	0.20	(0.22)	0.35	(0.34)	0.09	(0.06)	-0.04	(0.35)	0.50	(0.44)	0.33	(0.20)	0.75^{**}	(0.23)
Open=Semiopen	1.91		0.90		2.68		1.67		0.36		2.63		1.41		5.84^{*}		3.19	
Ultraopen=Open	0.07		0.01		0.00		0.05		0.02		0.20		1.31		0.07		6.57^{*}	
Ultraopen=Semiopen	0.75		0.24		0.50		0.07		0.15		0.00		0.47		0.60		12.32^{***}	
n	5,643		5,643		3,527		5,643		5,643		3,527		5,643		5,643		5,643	

[a] significant at 0.01 level, [b] significant at 0.05 level;

Table 8. Results of main regressions by sector

	PANEL						POOL						QUANTILE (POOL)					
	Single Equation		First Part		Second Part		Single Equation		First Part		Second Part		Quantile (.50)		Quantile (.70)		Quantile (.90)	
LT	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**
SEMIOPEN	0.25**	(0.09)	0.05**	(0.02)	0.03	(0.08)	0.40***	(0.12)	0.09***	(0.02)	-0.01	(0.09)	1.61***	(0.18)	0.33**	(0.12)	-0.03	(0.09)
OPEN	0.44***	(0.13)	0.11***	(0.02)	-0.07	(0.11)	0.42*	(0.17)	0.10**	(0.03)	-0.10	(0.13)	1.55***	(0.25)	0.30	(0.16)	-0.06	(0.12)
ULTRAOPEN	0.31	(0.24)	0.06	(0.04)	-0.12	(0.23)	-0.13	(0.32)	-0.03	(0.06)	-0.03	(0.36)	-0.26	(0.48)	-0.17	(0.32)	0.14	(0.24)
Open=Semiopen	2.53		6.92**		0.83		0.01		0.20		0.51		0.07		0.04		0.05	
Ultraopen=Open	0.27		1.13		0.04		2.61		4.28*		0.04		12.47***		1.88		0.57	
Ultraopen=Semiopen	0.07		0.95		0.38		2.63		3.69		0.00		14.92***		2.39		0.46	
n	4,249		4,249		2,429		4,249		4,249		2,429		4,249		4,249		4,249	
LMT	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**
SEMIOPEN	0.25**	(0.10)	0.05**	(0.02)	-0.03	(0.08)	0.36**	(0.13)	0.07**	(0.02)	-0.01	(0.10)	1.16***	(0.20)	0.20	(0.12)	0.12	(0.08)
OPEN	0.50***	(0.13)	0.10***	(0.02)	0.05	(0.11)	0.61***	(0.17)	0.12***	(0.03)	0.07	(0.14)	1.60***	(0.26)	0.46**	(0.15)	0.41***	(0.11)
ULTRAOPEN	0.03	(0.23)	-0.01	(0.04)	0.22	(0.22)	-0.24	(0.30)	-0.06	(0.06)	0.23	(0.25)	-0.09	(0.47)	-0.36	(0.28)	0.12	(0.20)
Open=Semiopen	4.22*		3.73		0.76		2.43		2.07		0.38		2.85		2.97		6.52**	
Ultraopen=Open	3.74		5.58*		0.54		6.93**		8.80**		0.33		10.92**		7.39**		1.70	
Ultraopen=Semiopen	0.92		2.18		1.26		3.67		5.35*		0.84		6.67**		3.79		0.00	
n	3,916		3,916		2,238		3,916		3,916		2,238		3,916		3,916		3,916	
MHT	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**
SEMIOPEN	0.18*	(0.07)	0.04**	(0.01)	-0.05	(0.06)	0.29**	(0.10)	0.07***	(0.02)	-0.10	(0.07)	0.89***	(0.15)	0.21**	(0.07)	0.04	(0.08)
OPEN	0.27*	(0.11)	0.05**	(0.02)	0.07	(0.09)	0.52***	(0.14)	0.10***	(0.03)	0.07	(0.10)	1.28***	(0.23)	0.35***	(0.10)	0.18	(0.11)
ULTRAOPEN	-0.07	(0.26)	-0.03	(0.05)	0.42	(0.25)	-0.05	(0.44)	-0.05	(0.07)	0.48	(0.39)	-0.27	(0.54)	0.00	(0.25)	0.92***	(0.25)
Open=Semiopen	0.74		0.45		1.79		2.76		0.93		3.23		2.97		1.72		1.80	
Ultraopen=Open	1.58		2.80		1.92		1.61		4.30*		1.11		7.35**		1.73		7.56**	
Ultraopen=Semiopen	0.92		2.16		3.59		0.70		3.16		2.22		4.46*		0.68		11.90***	
n	6,578		6,578		3,873		6,578		6,578		3,873		6,578		6,578		6,578	
HT	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**
SEMIOPEN	0.32*	(0.14)	0.07**	(0.02)	0.03	(0.10)	0.42*	(0.19)	0.07*	(0.03)	0.13	(0.13)	0.62**	(0.21)	0.27*	(0.13)	-0.09	(0.08)
OPEN	0.63**	(0.20)	0.08*	(0.04)	0.39**	(0.15)	0.77**	(0.27)	0.11*	(0.05)	0.35*	(0.17)	0.87**	(0.31)	0.50*	(0.20)	0.01	(0.11)
ULTRAOPEN	0.62	(0.49)	0.19*	(0.09)	-0.11	(0.35)	0.49	(0.67)	0.19	(0.12)	-0.49	(0.63)	0.37	(0.77)	0.17	(0.49)	-0.42	(0.24)
Open=Semiopen	3.00		0.07		7.92**		2.15		0.86		2.57		0.71		1.48		1.06	
Ultraopen=Open	0.00		1.43		2.00		0.18		0.41		1.75		0.39		0.40		3.02	
Ultraopen=Semiopen	0.39		1.78		0.16		0.01		0.99		0.98		0.11		0.04		1.90	
n	2,163		2,163		1,377		2,163		2,163		1,377		2,163		2,163		2,163	

[a] significant at 0.01 level, [b] significant at 0.05 level;

6. Discussion of results

We see that the majority of the analysed firms (around 85%) use a closed or semiopen strategy to innovate, as predicted by the transaction costs and competences approaches. The tendency for open innovation has not increased in recent years. However, we found that an open strategy provides higher payoffs in terms of product innovation than semiopen or closed strategies, with the last performing worst. This result is very robust and holds with different estimation methods, dependent variable definitions and sample groups. More precisely, it holds for firms of different sizes and for firms from different sectors, thus providing empirical proof of the generalizability of the open innovation approach. This result provides empirical evidence to the debate about the differential effect of openness on firms of different sizes (see e.g., Veugelers, 1998; Nieto and Santamaría, 2010) and on firms from different sectors (see e.g. Chesbrough and Crowther, 2006; Santamaría et al., 2009).

Parametric estimations produce the same results also for the likelihood of new to the market products, but do not distinguish between the effects of different strategies on sales of these products. Quantile regression methods allow more in depth investigation of this issue, and show that for low and medium innovation intensity points in the distribution (fifth and seventh decile), the general pattern holds and that it is only for the high innovation intensity points (ninth decile) where there is generally no significant difference among semiopen and closed strategies, being both of them worse than an open strategy. An ultraopen strategy has the highest coefficient for this decile and the lower for the rest. However, due to the small number of firms that adopt this strategy, results for ultraopen strategies should be considered with caution.

This work has several limitations. First, we analyse the impact of an open strategy on R&D performers only. However, many firms not performing R&D are innovative and use an open strategy (Hall et al., 2009; Ortega-Argilés et al., 2009; Santamaría et al., 2009; Barge-Gil et al., 2011a). However, the characteristics of our database do not allow us to include these firms. Second, we analyse the effect of open strategy only on product innovation. However, an open strategy can have an effect on process or organizational innovation. Our data do not provide a measure of how much process innovation is obtained or how organizational innovation is achieved. Third, it is possible that products developed using different strategies have different life cycles, yielding different levels of sales over different time spans. Implicitly, our analysis assumes that this is not the case. Fourth, as Jaffe (2008) highlights, we are analysing average rather than marginal effects so that there is no evidence that former closed or semiopen innovators will achieve the same results as current ones. Related to this, it could be argued that choices are endogenous and some non-observable factors are affecting strategic choice and innovation performance. However, utilization of panel data alleviates, to some extent, this problem. Fifth, it is likely that many firms use a mix of strategies, open for some projects, semi-open for others and closed for others. Unfortunately, we can only measure the openness of an entire firm, but analysis of project data would provide complementary and very interesting additional information. Sixth, we focus on formal inbound open strategies. However, we would point out that formal links are the results of strategic choice while informal relationships are not (Bodas-Freitas et al, 2010). Finally, our analysis applies only to the Spanish case. Although existing studies do not provide specific results for Spain (Griffith et al., 2006; Abramovsky et al., 2009) on the relationship between innovation and productivity or the determinants of cooperation, evidence from other countries would be useful.

Despite these limitations, we believe that this study adds to the knowledge on the effect of different degrees of openness for firms` innovation performance, a topic of increasing interest to academics, managers and policy-makers. We show that an open strategy produces higher payoffs than a semiopen one, which in turn produces higher payoffs than a closed strategy for product innovation performance.

This leaves the important question of why firms do not more frequently use an open strategy. This is beyond the scope of the present paper, but it should be remembered that we analyse the benefits of open strategy and not whether it is more costly for firms. Several studies highlight that the costs of search and coordination can be very high (Gulati and Singh, 1998; Lazzaroti and Mancini, 2009; Huizingh, 2010) so that this could be one explanation. However, an alternative explanation would be that many firms overestimate the costs of openness before they try it. The empirical evidence suggests that there are clear barriers to adopt open innovation strategies since some empirical facts are: (i) firms collaborate in two projects rather than one (Fontana et al., 2006); (ii) public initiatives to fund collaboration are unlikely to motive firms with no history of involvement in some kind of partnership (Vence, 1998; Heijs, 2005); and (iii) the existence of a previous relationship (with any different agent) is a good indicator of the establishment of a new relationship (Love and Roper, 2001). This evidence could be explained by transactions costs as well as cultural factors (Dodgson et al., 2006; Elmiquist et al., 2009) or also by simply "lack of awareness" of the existence of better management practices (Bloom and Van Reenen, 2010). The process involved in firms becoming open is a very important research topic (Chiaroni et al., 2009; Elmquist et al., 2009; Bianchi et al., 2010).

From a policy point of view it would seem crucial to know how to help firms to become open. There is no easy answer and encouraging openness from outside is a difficult task (Massa and Testa, 2008; Tomlinson, 2010). However, it is also clear that standard policy tools (such as subsidies) are not very effective (Vence, 1998; Heijs, 2005). Indirect measures might be more successful than direct ones (Lambrecht and Pirnay, 2005; Vega-Jurado et al., 2008; Barge-Gil, 2010a). For example, demonstrations of the benefits of openness or the existence of suitable partners (such as technology institutes) or environments (such as technology parks) (Barge-Gil et al., 2011b; Vasquez-Urriago et al., 2011). An examination of the different policy tools that could be used to encourage firm openness would be an important line for future research.

Concluding remarks

Our objective was to analyse the relationship between openness and innovation performance, testing the predictions of different theoretical approaches: transactions costs, competences and open innovation. We defined four degrees of openness: closed, semiopen, open, and ultraopen. This line of research is important because the different theoretical approaches reach different conclusions and empirical evidence from large databases has been inconclusive so far.

The choices made by the firms in our sample support transaction costs and competence approaches since most of the firms (around 85%) are shown to be either closed or semiopen innovators. We observed no tendency for open innovation.

The results for the impact of the different strategies provide a very different picture. An open strategy performs better than a semiopen strategy, which in turn performs better than a closed strategy, when sales of new-to-the-market products are analyzed. This result is robust to different estimation methods and different indicators. It is also quite general and holds for firms of different sizes or from different sectors. When the volume of sales from new to the market products is analysed using parametric techniques the results are less clear and the effects of the different strategies are found to be very similar. However, a quantile regression technique enables a more detailed approach and shows that the main results hold for the points in the distribution characterized by different innovation intensities (fifth, seventh and ninth deciles, respectively). It is only for the high innovation intensity point (ninth decile) where differences between semiopen and closed strategies become non-significant.

Thus, our main findings highlight an apparent paradox: open strategies yield higher payoffs but are used by a small minority firms. To understand why would be a very interesting line for future research.

Acknowledgment

The author wants to acknowledge financial support from project 08SEC008201PR (Xunta de Galicia), and from UAM-Accenture Economics and Innovation Management Award. The usual disclaimers apply.

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