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Open, Semi-Open and Closed Innovators: Towards an Explanation of Degree of Openness

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ABSTRACT There is much controversy in the literature over the relationship between the openness of firms' innovation strategies and firm characteristics such as size, R&D intensity and sector. We argue that the controversy arises because, both theoretically and empirically, only a binary, open vs. closed, strategy has been considered. In this paper, we distinguish among three firm strategies: open, semi-open and closed, drawing upon a panel of Spanish firms (2004–2006) using data from Community Innovation Survey (CIS)-type surveys, and two different indicators of openness. Our results show that open innovators are smaller and less R&D intensive than semi-open ones, although larger and more R&D intensive than closed innovators. These results reduce some of the controversies, and show that two conflicting forces, absorptive capacity and a "need" effect, are at stake in open innovation strategies.

KEY WORDS: Open innovation strategies, collaboration, size, R&D, sector, technology policy

1. Introduction

The motivation for this paper is twofold. On the one hand, it aims to respond to some fundamental questions posed by scholars on Open Innovation (OI). On the other, it tries to reconcile the opposing arguments developed over a long period by scholars based on their analyses of the importance of external sources of knowledge for innovation.

First, it has been argued that in recent years many innovative firms are shifting from a closed to an open model of innovation, within a paradigm that assumes that firms can and should use external as well as internal ideas, and internal and external paths to the market, as they look to advance their technology. This approach places external ideas and external paths to the market on the same level of importance as that reserved for internal ideas and

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paths to the market in the earlier era (Chesbrough, 2003, 2006). This broad definition allows the OI paradigm to link to a long tradition of studies focused on the importance of external knowledge to firms' innovation processes. However, the OI paradigm is broader because it includes not only inbound, but also outbound open strategies as well as pecuniary and non-pecuniary approaches (Chesbrough, 2006; van de Vrande *et al.*, 2009; Dahlander and Gann, 2010). OI has gained in popularity for at least three reasons (Dahlander and Gann, 2010): (i) it reflects the changes to work patterns where professionals are seeking portfolio careers rather than a job-for-life, and work contexts that involve increasing divisions of labour; (ii) improved market institutions (property rights, venture capitalists, standards) are enabling increased trade knowledge; and (iii) new technologies are easing coordination across geographical distance. However, evidence of this new paradigm to advance firm technology is almost exclusively based on qualitative evidence on the so-called "high technology" industries and US companies (Chesbrough, 2006; van de Vrande *et al.*, 2009). The limited amount of empirical research based on large data-sets and on areas outside the USA leaves many questions unanswered, and especially questions about underlying decision processes (Dahlander and Gann, 2010). For example, do large firms differ from small firms in their adoption of OI? Do firms with relatively greater investment in internal research and development (R&D) differ from those with little or no investment in R&D? Do we see significant variation in adoption of OI within industries? (West *et al.*, 2006).

Second, for many years, scholars from various disciplines, such as industrial organization, management and geography, have been analysing inbound OI, that is, how and why firms resort to external sources of knowledge for their innovation processes. More precisely, this literature mainly focuses on the effect of size, R&D intensity and sector on the cooperation strategies of firms, which has resulted in controversy from both the theoretical and empirical viewpoints. Theoretically, opposing arguments have been developed to explain the relationship between several firm characteristics, such as size, R&D or sector, and cooperation. Empirically, previous studies have produced mixed results; the literature reaches no common understanding about these relationships, in terms of stylized facts or evidence. Accordingly, the questions posed by researchers interested in OI (West *et al.*, 2006) remain unresolved and proposing some solutions is important for academic study in order to try to reconcile the different points of view that have been put forward.[1]

This topic is not only of interest to academic debate, but is also relevant for policy makers, since innovation policy is increasingly focused on cooperation among agents (Bozeman, 2000), and especially for the design of targeted policies. Managers will also find it of help to decide about the openness strategies best suited to the characteristics of their firms.

This paper aims to advance the strand of research that examines the determinants of OI strategies from the firm's perspective and to make some strides towards a resolution of the theoretical and empirical controversies revealed by the literature, by examining the relationship between size, R&D intensity, and firm sector and openness; it provides some novelties compared to previous analyses.

First, we integrate the opposing arguments proposed in the literature within a common framework. We argue that it is the utilization of binary concepts and variables that is the core

[1] Note that the questions related to OI refer to all its modes. Here we focus only on inbound OI; thus, in this paper, OI strategies refer only to this mode.

of these controversies and put forward three possible strategies for firm innovation—open, semi-open and closed—which allow us to investigate the existence of non-linearities. There is a consensus that OI strategies are a continuum, however the empirical literature is biased towards an open vs. closed dichotomy (Chesbrough, 2003; Dahlander and Gann, 2010). Although a continuous indicator would be preferable, our data do not enable its estimation. However, we show that our approach of analysing three different OI strategies is helpful for advancing our knowledge and for reconciling the controversies that arise from the literature.

Second, we use data from the Innovation Panel in the Spanish Institute of Statistics (PITEC) for the period 2004–2006. This allows us to use multinomial logit panel data with random effects which take account of individual unobservable heterogeneity that cannot be controlled for with cross-sectional data. This heterogeneity has been shown empirically to have a profound effect on the firm's decision to invest in innovation (Peters, 2009; Griffiths and Webster, 2010) and, arguably, might also influence decisions related to the degree of openness. Our data also reveal quantitative evidence on firms' open innovation strategies covering all manufacturing sectors and in a non-US context.

Third, we employ two different indicators to study the innovation strategy adopted by firms, based on information derived from two questions in the Community Innovation Survey (CIS). CIS data have been used in many studies in economics and management (e.g. Cassiman and Veugelers, 2002; Laursen and Salter, 2006).[2] As openness is a broad term encompassing various definitions and practices (Dahlander and Gann, 2010), we use two different indicators to measure it in order to establish those results that are more general and do not change with the different definitions of openness, and to delve into the differences between more narrow and more broad definitions.

Section 2 reviews the literature and positions the present paper in this research stream. In the succeeding sections of this paper we explain our empirical strategy, define the variables employed, present our results and provide a discussion and conclusions.

2. The Theoretical Framework and the Literature

This section is split into three sub-sections. First, we review the theoretical arguments posed by the literature to explain the relationship between size, R&D, sector and openness. Second, we show how our paper is positioned within this literature. Third, we review the existing empirical evidence.

2.1 Theoretical Arguments

The aim of this sub-section is to briefly review the causal logics explaining the links between firm characteristics and openness. That is, we focus on why certain relationships can be expected to emerge, showing that there are logical arguments to support these different relationships, and to justify the existence of the greater (lesser) benefits and lower (higher) costs of openness for firms with specific characteristics, that result in their being more open (closed) to external sources of knowledge.

[2] The method and type of questions are described in the *Oslo Manual* (OECD, 1997, 2005).

2.1.1 Size. Many scholars support the idea that openness is more relevant for big firms, based on their greater resources and complementary capacities, which ease the search for partners and the management of collaboration agreements and means that such firms are better placed to exploit its benefits (Veugelers, 1998). Firm resources include information services, libraries and pools of qualified or specialist staff (Rothwell and Dodgson, 1991; Tether, 2002). Thus, larger firms will face lower costs and will be likely to benefit more from greater openness.

On the other hand, there is a growing body of work suggesting that openness creates unique benefits and challenges for small firms (Zahra *et al.,* 2002; Nieto and Santamaría, 2010). Due to their lack of internal resources small firms have a greater need to be open to the environment to develop innovation activities. They use external knowledge strategically (Mazzanti, 2008) because they do not have the critical mass to be able to cope on their own with certain projects (Bayona *et al.*, 2001; Tether, 2002) and they are more affected by the uncertainty of innovation projects, as failure could compromise the future of the entire firm. In this sense, openness could help to reduce the irreversible costs of the innovation process. In addition, it has been suggested that small and medium-sized firms enjoy behavioural advantages, such as flexibility and rapid response, which help them to benefit more from openness (Rothwell and Dodgson, 1994). Thus, there are arguments supporting the view that smaller firms face lower costs and are likely to benefit more from being open. This has led some authors to conclude that openness is more important for small firms (Freel, 2000; Rogers, 2004).

2.1.2 R&D. The relationship between R&D and openness is also controversial as shown by the existing debate about the complementarity or substitutability of internal and external R&D (Veugelers and Cassiman, 1999; Cassiman and Veugelers, 2006; Watkins and Paff, 2009).

The traditional view of the relationship between R&D and openness is based on Cohen and Levinthal's absorptive capacity theory (1989, 1990), which holds that the benefit a firm can obtain from external knowledge is highly dependent on the firm's existing knowledge. Absorptive capacity can be defined as the firm's ability to acknowledge the value of new, external information, to assimilate it and apply it to its activities (Cohen and Levinthal, 1990). The presence of absorptive capacity reduces the costs of openness, by reducing search and assimilation costs, and increases profits by its better application to in-house activities. R&D is generally used as a proxy for absorptive capacity (Lane *et al.*, 2006). Accordingly, firms with higher levels of internal R&D activity will find open innovation more relevant than firms with low internal R&D capabilities, which implies an essential complementarity between internal and external sources of knowledge.

However, some authors argue that from the perspective of the literature on resources and capabilities, firms with highly developed R&D capabilities can benefit from internal economies of scale (Mol, 2005) so that they find it less necessary to involve external partners in their R&D processes (Bayona *et al.*, 2001; Cassiman and Valentini, 2009), similar to Pittaway *et al.*'s argument (2004) that firms with high levels of technical competence do not see the value of networks for innovation. Conversely, firms with a limited pool of internal knowledge can greatly benefit from establishing external links (Santoro and Chakrabarti, 2002). That is, according to these authors the benefits from being open will be lower for R&D-intensive firms. In addition, R&D-intensive firms are often subject to the

"Not Invented Here" syndrome, which refers to the conviction that they have a monopoly on the knowledge and thus reject ideas from external sources to the detriment of their performance (Katz and Allen, 1982). That is, the costs of being open might be higher for R&D-intensive firms with strong internal R&D departments.

2.1.3 Sector. On the one hand, openness is thought to be particularly important in those sectors described as "high-tech" (Tödtling *et al.*, 2006) because more technological opportunities exist and firms will often need to search more widely and deeply in order to gain access to critical resources (Klevorick *et al.*, 1995; Laursen and Salter, 2006). As a consequence, high-tech sector firms are unlikely to encompass all the capacities needed to develop their innovations (Narula and Hagedoorn, 1999; Gassmann, 2006) and will need to be open to the environment, in particular, to enable them to follow several lines of research simultaneously (Bayona *et al.*, 2001). There is also greater turbulence in these sectors, making external knowledge critical because an inward-looking attitude would attract large penalties (Escríbano *et al.*, 2009). That is, new knowledge is being developed every day and everywhere so that awareness of the environment is especially crucial.

However, some authors (Tether, 2002) maintain that when other factors are taken into account, it is not entirely clear that openness for innovation is more important for firms performing in high-tech sectors, and some (Pittaway *et al.*, 2004; Chesbrough and Crowther, 2006) suggest that this view is influenced by the bias in open innovation studies towards high-tech sectors. The knowledge bases in the low-tech sector are very distributed (Hirsch-Kreinsen, 2009) and innovation performance in this sector is highly dependent on the knowledge coming from high-tech industries (Robertson and Patel, 2007). This could explain why some open innovation modes have been found to be more conducive to innovation in low-tech industries (Santamaría *et al.*, 2009).

Thus, the influence of sector on openness is not clear. Also, many authors highlight that the main influence of the sectoral context could be to mediate the relationship between size or R&D and openness, as both the quantity and type of external knowledge available to firms, and the appropriability characteristics, differ greatly between sectors (e.g. Klevorick *et al.*, 1995; Escríbano *et al.*, 2009).

2.2 Positioning this Work in the Literature: Towards an Integrative Framework

As we have seen, the theoretical arguments do not offer a clear picture of the relationships between size, R&D and sector for firms' openness. On the contrary, arguments can be found to support opposing views. This confusion is at the root of the claims made by authors developing the OI paradigm that research should be focused on the decision processes related to openness (Dahlander and Gann, 2010) and that large data-sets should be used to explore the relationship between several firm characteristics and openness, from a general perspective.

We investigate this issue by considering the possible existence of non-linearities affecting these relationships.[3] The arguments reviewed above focus on the open–closed dichotomy, which we would argue is at the heart of the disagreement. Although an empirical

[3] We refer to non-linearities related to *degree* not likelihood of openness.

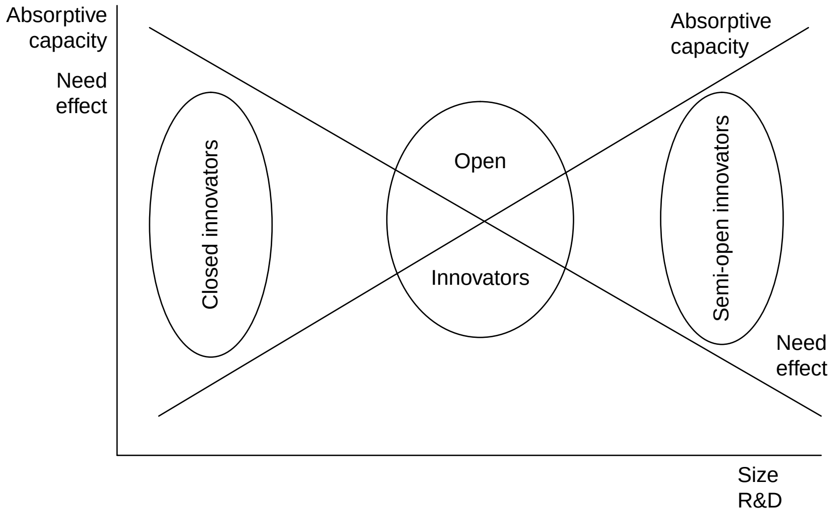

Figure 1. Conflicting forces in the relationship between size, R&D and openness

study based on the continuum of openness would be preferable, we are able only to develop variables for the three categories of open, semi-open and closed. However, the simplicity of this classification should help to clarify our arguments.

Although different arguments have been put forward in the theoretical discussion, we could sum the bulk of them up as the existence of two main conflicting forces underlying the relationship between size and R&D intensity, and openness. On the one hand, the firm's capacity to absorb external knowledge increases with size and R&D intensity.[4] On the other hand, the need for external knowledge is higher for smaller, less R&D-intensive firms, and decreases as size and R&D intensity grow. These conflicting forces are represented in Figure 1.[5]

According to this framework, we can distinguish three broad regions, corresponding to three types of firms. First, firms with a smaller capacity to absorb external knowledge but which have a great need for external knowledge. Second, firms with better (but not very high) absorptive capacity, which have a need for external knowledge. Finally, firms with very high absorptive capacity, but less need for external knowledge.

We argue that the first group of firms enjoys very high *potential* benefits from external knowledge (as the need effect is very high). However, the firms in this group do not have the *capacities* to reap these benefits (absorptive capacity is low). Thus, the adoption of an open

[4] Size could be considered a proxy for some dimensions of absorptive capacity as it is usually an indicator of better developed R&D management practices (Huergo, 2006), which facilitate the recognition, assimiliation and application of external knowledge for commercial ends.

[5] This framework does not include sector for two reasons. First, the relationship between "need effect" and sector is unclear, second, and more important, we explore the mediating role of sector on the framework proposed (Section 5.3).

strategy will not allow them to realize the potential benefits and they will choose a closed strategy.

H1: Smaller firms and less R&D-intensive firms will opt for closed strategies.

The second group of firms has quite high potential benefits from external knowledge and also have the absorptive capacities required to realize them. Thus, they will choose an open strategy.

H2: Medium-sized firms and firms with medium R&D intensity will opt for open strategies.

The situation faced by the third group of firms is that they have the absorptive capacities to benefit from external knowledge, but the potential benefits are lower. The lack of a need effect will lead them to choose semi-open strategies.

H3: Larger firms and more R&D-intensive firms will opt for semi-open strategies.

In this context, semi-open means that firms exploit external knowledge, but that this knowledge is not crucial for their innovation process (they are not open-based innovators). For example, and related to cooperative relationships, we can distinguish among non-cooperating firms (closed), firms that cooperate but retain the core of their innovation processes in house (semi-open) and firms that cooperate in the core blocks of their innovation processes (open). This last group is aligned to Chesbrough's idea (2006) that open innovators assign the same importance to internal and external sources of knowledge.

The idea of a group of semi-open innovators is crucial for reconciling the arguments in the literature. If we distinguish only between open and closed innovators, the "absorptive capacity" argument will prevail. However, in distinguishing among different open strategies, we reveal the existence and importance of the "need effect". Those in more need of external knowledge will be more open if they possess the capabilities required to realize the potential benefits from such openness.

2.3 Previous Empirical Results

In this section we review the existing empirical results and analyse the relationship between size, R&D, sector and openness, using data from CIS-type surveys.[6] The main advantage of restricting our review to these parameters is that these studies use large samples of firms and similar sets of indicators, thus allowing for detailed comparison of results and a clearer view of the phenomenon than would be possible if the (nevertheless very valuable) studies that focus on analysing very specific situations using "ad-hoc" surveys, were included. In addition, and owing to the fact that we are going to use a CIS-type survey, they are of help in defining our independent and control variables.

One of the limitations in the studies reviewed is that the focus of analysis is mainly on what determines the existence of cooperation,[7] based on an analysis of the firm characteristics that lead to cooperation. Exceptions include Becker and Dietz (2004), Negassi (2004), Barge-Gil

[6] Although not all are official surveys, they employ similar questions to those in the CIS.

[7] We focus here on studies that analyse cooperation in general, and not with a specific type of partner.

(2010) and de Faria *et al.* (2010), who analyse the determinants of other measures of cooperation, such as number of relationships, budget and the importance of cooperation.

Table 1 summarizes the previous empirical evidence. It suggests that the results obtained, to an extent, are dependent on the estimation method, definition of the variables and countries involved. Firm size is found generally to affect the likelihood of cooperation (in line with our arguments in Section 2.2, if the dependent variable is binary only the "absorptive capacity" effect is revealed). However, some studies point to a non-linear relationship (between size and the likelihood of cooperation, not its degree) (Cassiman and Veugelers, 2002; López, 2008; Abramovsky *et al.*, 2009) while others show a non-significant one (Kleinknecht and Reijnen, 1992; Abramovsky *et al.*, 2009). The effect of R&D is usually positive (again, only the "absorptive capacity" effect is "revealed"), but some studies find no

Table 1. Studies analysing the determinants of cooperation using surveys based on the *Oslo Manual*[a]

	Dependent variable	Size	R&D	Technological level of sector
Kleinknecht and Rejinen (1992)	Dummy cooperation	Non-significant	Positive/non-significant*	
Bayona *et al.* (2001)	Dummy cooperation	Positive	Positive	Positive
Tether (2002)	Dummy cooperation	Positive	Positive	Non-significant
Cassiman and Veugelers (2002)	Dummy cooperation	Inverted U	Positive	
Miotti and Sachwald (2003)	Dummy cooperation	Positive	Positive	Positive
Becker and Dietz (2004)	Dummy cooperation	Positive	Positive	Negative
Kaiser (2002)	Dummy cooperation	Positive		
López (2008)	Dummy cooperation	Inverted U	Positive	
Arranz and Fernandez de Arroyabe (2008)	Dummy cooperation	Positive	Positive	Positive
Segarra-Blasco and Arauzo-Carod (2008)	Dummy cooperation	Positive	Positive	Positive
Abramovsky *et al.* (2009)	Dummy cooperation	Inverted U/non-significant***	Negative/non-significant/positive***	
Barge-Gil (2010)	Dummy cooperation	Positive	Positive	
	Importance of cooperation	Negative	Negative	Negative
de Faria *et al.* (2010)	Dummy cooperation	Positive	Positive/inverted U	Non-significant
	Importance of cooperation		Positive/inverted U	Positive/ non-significant
Becker and Dietz (2004)	Dummy cooperation	Positive	Positive	Negative
	Number of cooperation partners	Positive	Positive	Negative
Negassi (2004)	Cooperation budget	Positive	Positive	

[a] Studies that report the results of determinants of cooperation with specific types of agents only (and not cooperation in general) are not included.

*Depending on the indicator used.

***Depending on the country.

influence (Abramovsky *et al.*, 2009) or, even a negative relationship.[8] Finally, evidence concerning the relationship between the technological level of the sector and cooperation is very mixed. Some studies find that firms in the high-tech sector are more open (Bayona *et al.*, 2001; Miotti and Sachwald, 2003; Arranz and Fernandez de Arroyabe, 2008), while Becker and Dietz (2004) find the reverse and Tether (2002) finds an absence of any influence.

It should be noted that two very recent papers (Barge-Gil, 2010; de Faria *et al.*, 2010) consider the likelihood of cooperation and also some measures of its importance. Barge-Gil (2010) finds that cooperation is more important for smaller, less R&D-intensive firms in the low- and medium-tech sectors; de Faria *et al.* (2010) find that the cooperation is more important for more R&D-intensive, high-tech sector firms (although this effect depends on the specification).[9]

Finally, it is important to note that this mixed empirical evidence does not only affect studies employing CIS surveys, but has been highlighted in reviews based on broader parameters (see, e.g. Veugelers, 1997 or Segarra-Blasco and Arauzo-Carod, 2008).

3. The Data

3.1 Description of the Sample

We use the PITEC (Technological Innovation Panel) database (2004–2006). 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 and an advisory group of university researchers. Although the PITEC starts in 2003 we cannot use data from this year because information required to develop our dependent variable was not included in that year or the questions were framed in such a way as to make it impossible to derive similar indicators. 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 of all firms performing internal R&D. In subsequent years, firms performing only external R&D were included, as well as a sample of non-R&D performing firms. Quantitative variables are anonymized.[10]

The construction of the database dictates that we restrict our analysis to all innovating firms performing R&D, in the manufacturing industries, from 2004 to 2006. This has the advantage that we do not have sample selection among firms (all firms with these characteristics are included), but the disadvantage that our results cannot be extended to the whole population of firms. Our final sample is composed of 10,875 observations (Table 2).

3.2 Definition of Variables and Descriptive Statistics

Detailed definitions of the variables are presented in Table 3. One novelty of our paper is how we define openness. Openness encompasses many different practices, and is operationalized differently by different authors. In this paper, we use two measures

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[8] In the French case, and only after instrumenting the variable (Abramovsky *et al.*, 2009).

[9] The reason is probably that Barge-Gil (2010) measures the importance of cooperation in relative terms (to the internal processes) while de Faria *et al.* (2010) measure it in absolute terms.

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

Table 2. Number of observations

Year	Number of firms
2004	3,368
2005	3,953
2006	3,554
Total	10,875

of openness—one narrow and one very broad—based on two questions in the CIS survey. For both we identify three possible strategies: being open, being semi-open and being closed.

First, we analyse the question of how innovations are achieved. Firms were asked how their innovations were developed (mainly by the enterprise or group, mainly through collaboration, or mainly by third parties). This question, combined with information on firm behaviour, allows us to distinguish three types of innovation strategies (variable *OPENNESS_IMP*).

- Open innovators: firms with innovations developed mainly through collaboration with other entities or mainly by other entities.[11]
- Semi-open innovators: firms whose innovations were developed mainly through in-house efforts, but having cooperated or bought external R&D.
- Closed innovators: firms whose innovations were developed mainly through their own efforts and which have neither cooperated nor bought external R&D.

That is, closed innovators are those firms that neither cooperated nor bought external R&D. Among those involved in one or other of these activities, we can distinguish two groups of firms. Those that, although having cooperated and/or bought in external R&D, declare their innovations as being achieved mainly by in-house efforts (semi-open innovators) and those that innovate mainly through collaboration with other entities or by subcontracting (open innovators).[12] Based on these definitions, 20.6 per cent of firms are open innovators, 34.8 per cent are semi-open innovators and 44.5 per cent are closed innovators.

Second, we analyse the question related to the subjective importance of different sources of information to innovate. Firms were asked to rate the importance, on a four-point scale, of different information sources (internal knowledge and 10 external sources). Again, we can distinguish three types of strategies (variable *OPENNESS_SOUR*):

- an open innovator: at least one external source is more important than the internal knowledge;

[11] The question was asked separately for product and process innovations. Here, we consider that a firm is an open innovator if product or process innovation were developed mainly through collaboration with other entities or mainly by other entities. (See Tables A2(a) and (b) in the Appendix for separate estimations for product and process innovators.)
[12] Using *OPENNESS_IMP* improves the dummy variable of cooperation used in existing studies as it distinguishes between those firms that innovate mainly through cooperation from those that, although cooperating, innovate mainly through their own efforts (Barge-Gil, 2010) and allows to measure not only the existence of ties but also their strength, which is an issue deserving more attention (Tomlinson, 2010).

Table 3. Definition of variables, mean and standard deviations

Label	Description	Mean	SD
OPENNESS_IMP	Variable that takes the value 3 if innovations are developed mainly through collaboration with other entities or mainly by other entities, 2 if firms developed innovations mainly through their own efforts but that have cooperated or bought external R&D, and 1 if firms developed innovations through in-house efforts and neither cooperated nor bought external R&D	1.76	0.77
OPENNES_SOUR	Variable that takes the value 3 if any external source is more important than the internal knowledge, 2 if the most important external source is as important as the internal knowledge, and 1 if the most important external source is less important than the internal knowledge	1.98	0.63
LSIZE	Log of number of employees	4.14	1.35
RD_INT	R&D staff/total number of employees	0.15	0.20
LOWTECH	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	0.26	0.43
LOWMEDIUMTECH	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	0.24	0.42
MEDIUMHIGHTECH	Variable that takes the value 1 if the firm belongs to the following sectors: chemicals, non-electrical machinery, electrical machinery, scientific instruments, motor vehicles and other transport equipment	0.38	0.49
EXPORT	Exports/total sales	0.18	0.30
RADICAL	Sales of products new to the market/total sales	10.35	24.05
DEVELOPMENT	Expenditure on development in total R&D expenses	0.51	0.41
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)	0.50	0.18
OBS_INFORMATION	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)	0.39	0.13

- a semi-open innovator: the most important external source is as important as the internal knowledge;
- a closed innovator: the most important external source is less important than the internal knowledge.

Note that the indicator we develop here has the advantage that it does not compare valuations among individuals, which we know could potentially be problematic since some individuals might be “optimistic” and value every item very high while others could be overly “pessimistic” and assign low values to each item. Instead, we compare values for each individual, thus eliminating this individual bias. Note also that, by operationalizing the variable in this way we obtain the degree of openness of each firm, in its own relative

Table 4. Cross tabulation of *OPENNESS_IMP* and *OPENNESS_SOUR*

		OPENNESS_SOUR		
$N = 10{,}875$		Open	Semi-open	Closed
OPENNESS_IMP	Open	1,584 (14.57%)	2,206 (20.29%)	1,054 (9.69%)
	Semi-open	890 (8.18%)	2,152 (19.79%)	745 (6.85%)
	Closed	336 (3.09%)	1,249 (11.49%)	659 (6.06%)

terms. That is, if some firms value their internal knowledge more than external knowledge, we categorize it as closed, regardless of how high or low these values are.[13] Also, this indicator focuses on the depth rather than the breadth of openness. That is, the firm is considered to be open if at least one external source is more important than the internal knowledge, but semi-open if many external sources are valued as equally important as internal knowledge and none is seen as more important.[14] We believe that defining the indicator in this way makes it, to an extent, more comparable to OPENNESS_IMP, which also is related to depth of openness. Based on these definitions, 22.6 per cent of firms are open innovators, 51.6 per cent are semi-open innovators and only 25.8 per cent are closed innovators.

The main differences between these measures are that: *OPENNESS_IMP* involves the formalization of open innovation (cooperation or contracting with external partners) while this does not necessarily apply to *OPENNESS_SOUR* (Escríbano *et al.*, 2009). Although probably influenced very much by formal agreements (Belderbos *et al.*, 2004), *OPENNESS_SOUR* also includes all open innovation practices and the importance of spillovers from other organizations and available external knowledge. In addition, *OPENNESS_IMP* is more focused, since it takes account only of the importance of openness for the attainment of innovation (from an *ex post* perspective) while *OPENNESS_SOUR* takes account of the importance of external sources for innovation activities. That is, it includes all external knowledge that is in any way involved in the innovation process. Thus, in our view, *OPENNESS_SOUR* is a much broader indicator of openness.

Despite these differences, both measures show a significant positive correlation (chi2 $= 321.85$; p-value $= 0.000$). Cross tabulation is shown in Table 4. Based on *OPENNESS_IMP*, it might be concluded that open innovation is not such a common phenomenon, since almost half of the firms are shown to be closed innovators and only 20 per cent open innovators. This finding confirms the results from previous studies. For example, Lichtenthaler (2008) finds that most firms are closed innovators, even when smaller firms are excluded. The values are slightly higher if *OPENNESS_SOUR* is taken into account. From this perspective the percentage of closed innovators is around 25 per cent, which is logical since, as discussed above, this measure is broader.

[13] To confirm the adequacy of this method, we tested our results by dropping those firms assigning no or low importance to every source. The results are almost identical (see Tables A3(a) and (b) in the Appendix).

[14] We want to thank an anonymous referee for raising this important point. For analyses focused on breadth, see, for example, Laursen and Salter (2006), Nieto and Santamaría (2007) or Vega-Jurado *et al.* (2009).

In terms of the independent variables, we measure size as the log of number of employees *LSIZE*), R&D intensity as the percentage of R&D staff (*RD_INT*) and use dummy variables to indicate belonging to low-tech (LT), low- to medium-tech (LMT), medium- to high-tech (MHT) or high-tech sectors (HT), following the OECD classification (OECD, 2005). We should note here that, although the OECD classification is elaborated according to R&D ratios, R&D-intensive firms occur in low-tech sectors and non-R&D-intensive firms occur in high-tech sectors (Kirner *et al.*, 2009; Santamaría *et al.*, 2009). Also, as previously noted, sector could be a mediating factor in the relationships between size and R&D and openness: the sector to which the firm belongs influences the availability of external partners and information sources and the appropriability of knowledge: in Section 5.3 we develop separate analyses for each sector.

We also control for several firm-specific factors, such as exports (measured as a percentage of sales abroad), belonging to a group (measured by a dummy variable), orientation of R&D activities (measured as a percentage of internal development expenses over total internal R&D) and existence of cost or information obstacles to innovation (defined following the procedure described in Cassiman and Veugelers, 2002) (see Table 3).[15]

3.3 Descriptive Analysis

Table 5 shows that the characteristics of open, semi-open and closed innovators differ. More precisely, semi-open innovators are larger, more R&D intensive and more frequently belong to high-tech sectors than either open or closed innovators whatever variable is used. *OPENNESS_IMP* indicates that closed innovators are the smallest and least R&D-intensive firms, but the relationship is less clear if we use *OPENNESS_SOUR*. These exploratory findings support the relevance of accounting for degree of openness, and of using two different measures. In what follows, we conduct econometric analysis of these results.

4. Econometric Method

For the econometric analysis, we use panel data, and a dependent variable that can take three different values, representing open, semi-open and closed strategies. Thus, we estimate the determinants of firm choice using a multinomial logit panel data model with random intercepts. The model is formulated as follows (Rabe-Hesketh *et al.*, 2004).

Let a index the three possible categories of the dependent variables. Multinomial logit models are defined by the "linear predictor" V_{it}^{a}, so that the multinomial probability of the response category h (the probability that h is chosen) for firm i in a period t is

$$\Pr(h_{it}) = \frac{\exp\left(V_{it}^{h}\right)}{\sum_{a=1}^{3}\exp\left(V_{it}^{a}\right)}. \tag{1}$$

This probability model can be derived by assuming that an unobserved "utility" U_{it}^{a} is associated with each alternative, in each period, and that the one with the highest utility is the

[15] Independent variables for the period covered by dependent variables. We tried them also with 1 lag and the results (unreported, available upon request) were qualitatively unchanged.

Table 5. Descriptive statistics

	All sample		*OPENNESS_IMP*							*OPENNESS_SOUR*						
			Open		Semi		Closed			Open		Semi		Closed		
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Differences[a]	Mean	SD	Mean	SD	Mean	SD	Differences
LSIZE	4.16	1.35	4.28	1.40	4.41	1.42	3.90	1.21	***	4.02	1.26	4.20	1.37	4.19	1.37	***
RD_INT	0.15	0.20	0.15	0.19	0.16	0.22	0.13	0.18	***	0.15	0.20	0.15	0.20	0.14	0.21	***
LT	0.25	0.43	0.28	0.45	0.22	0.41	0.27	0.44	***	0.27	0.44	0.25	0.43	0.24	0.43	
LMT	0.23	0.42	0.27	0.45	0.22	0.42	0.23	0.42	***	0.26	0.44	0.22	0.42	0.24	0.43	**
MHT	0.38	0.49	0.34	0.47	0.38	0.49	0.40	0.49		0.36	0.48	0.38	0.49	0.39	0.49	
HT	0.13	0.34	0.11	0.31	0.17	0.38	0.11	0.31	***	0.12	0.32	0.14	0.35	0.13	0.33	***
EXPORTS	0.17	0.30	0.19	0.39	0.17	0.28	0.15	0.26	***	0.16	0.30	0.17	0.31	0.17	0.28	
GROUP	0.38	0.48	0.41	0.49	0.47	0.50	0.29	0.45	***	0.32	0.47	0.39	0.49	0.40	0.49	**
DEV	0.52	0.41	0.55	0.40	0.53	0.40	0.51	0.42	***	0.52	0.42	0.53	0.41	0.52	0.41	
COST	0.50	0.18	0.51	0.18	0.50	0.18	0.50	0.19	*	0.51	0.18	0.51	0.19	0.48	0.18	***
INFORM	0.39	0.13	0.41	0.13	0.39	0.12	0.39	0.12	***	0.41	0.13	0.40	0.13	0.37	0.12	***

[a] Differences are tested using Bonferroni test or Chi-square (depending on the characteristics of the variables). ***p-value < 0.01, **p-value < 0.05, *p-value < 0.1.

one selected. This utility is modelled as

$$U_{it}^{h} = V_{it}^{a} + \varepsilon_{it}^{a}.$$

The alternative *h* will be selected if

$$U_{it}^{h} > U_{it}^{g} \quad \text{for all } g \neq h$$

or, equivalently

$$U_{it}^{h} - U_{it}^{g} = V_{it}^{h} - V_{it}^{g} + \left(\varepsilon_{it}^{h} - \varepsilon_{it}^{g}\right) > 0.$$

If the error term ε_{it}^{a} has an extreme value distribution of type I (Gumbel), then the differences $\left(\varepsilon_{it}^{h} - \varepsilon_{it}^{g}\right)$ have a logistic distribution and Equation 1 follows (McFadden, 1973).

The linear predictor depends on observed characteristics X_{it} that vary among individuals and over time, and unobserved individual effects α_{i}^{a}, that are time constant:

$$V_{it}^{a} = X_{it}\beta^{a} + \alpha_{i}^{a}.$$

As the choice of probabilities is conditioned on α_{i}^{a} it is necessary to integrate over the distribution of unobserved heterogeneity. Thus, the sample likelihood for the multinomial logit with random intercepts has the following form:

$$L = \prod_{i=1}^{N} \int_{-\infty}^{\infty} \prod_{t=1}^{T} \prod_{a=1}^{3} \left(\frac{\exp(X_{it}\beta^{a} + \alpha_{i}^{a})}{\sum_{h=1}^{A} \exp(X_{it}\beta^{h} + \alpha_{i}^{h})} \right)^{d_{iat}} f(\alpha)d\alpha$$

where $d_{iat} = 1$ if firm *i* chooses alternative *a* at time *t* and zero otherwise.

There is no analytical solution of the integral. In the literature various methods for integral approximation are suggested and discussed (Haan and Uhlendorff, 2006). Here, we use adaptive Gaussian quadrature. The idea behind this is to approximate an integral by a specified number of discrete points. Adaptive Gaussian quadrature is a Bayesian method that extends Gauss Hermite quadrature by making use of the posterior distribution of the unobserved heterogeneity, significantly increasing the accuracy of integration. This method is discussed and compared with other methods in Rabe-Hesketh *et al.* (2002), who developed a program to run it with Stata.

5. Results

5.1 General Results

The results are presented in Table 6(a). Semi-open innovators are the reference group. In Model 1 *OPENNESS_IMP* is the dependent variable; in Model 2 it is *OPENNESS_SOUR*.[16]

From Model 1, we observe that all three characteristics show similar patterns. In analysing the probability of being an open innovator, *LSIZE* shows a negative and

[16] We also tried binary logit regressions eliminating every alternative. Results (not reported here, but available upon request) were qualitatively similar, indicating that the assumption of independence of irrelevant alternatives (IIA) holds. We decided to employ this method since recent studies tend to conclude that IIA tests are not suited to applied work as they often reject the assumption when alternatives seem distinct, and often fail to reject it when alternatives can reasonably be viewed as close substitutes (Chen and Long, 2007).

Table 6(a). Results of multinomial logit panel data model with random intercepts (reference category = SEMI-OPEN)

	Model 1 (dependent variable: *OPENNESS_IMP*)		Model 2 (dependent variable: *OPENNES_SOUR*)	
	Coef.	Std error	Coef.	Std error
Dependent variable = 3 (OPEN)				
LSIZE	−0.29***	0.05	−0.17***	0.04
RD_INT	−1.14***	0.27	−0.68***	0.24
LOWTECH	1.17***	0.17	0.20	0.16
LOWMEDIUMTECH	0.99***	0.17	0.37**	0.16
MEDIUMHIGHTECH	0.59***	0.16	0.06	0.15
EXPORT	0.31**	0.12	−0.05	0.12
GROUP	−0.29***	0.11	−0.22**	0.11
DEVELOPMENT	0.18*	0.10	−0.12	0.10
OBS_COST	−0.20	0.26	−0.65***	0.24
OBS_INFORMATION	0.90**	0.36	0.25	0.34
Constant	0.36	0.31	0.15	0.28
Dependent variable = 1 (CLOSED)				
LSIZE	−0.61***	0.05	−0.14***	0.04
RD_INT	−3.06***	0.27	−0.73***	0.24
LOWTECH	0.94***	0.16	0.03	0.16
LOWMEDIUMTECH	0.67***	0.16	0.24	0.16
MEDIUMHIGHTECH	0.63***	0.15	0.10	0.15
EXPORT	0.14	0.12	−0.09	0.12
GROUP	−0.58***	0.10	0.07	0.10
DEVELOPMENT	−0.01	0.10	−0.12	0.09
OBS_COST	−0.26	0.24	−0.79***	0.24
OBS_INFORMATION	−0.86**	0.34	−1.65***	0.35
Constant	3.80***	0.29	0.96***	0.28
	Log likelihood = −10,356.295 Number of level 1 units = 10,875; number of level 2 units = 4,922		Log likelihood = −10,321.846 Number of level 1 units = 10,875; number of level 2 units = 4,922	

***p-value < 0.01, **p-value < 0.05, *p-value < 0.1.

significant coefficient (p-value = 0.000) and the same applies to *RD_INT*. Also, the probability of adopting an open innovation strategy is positively related to belonging to a low-tech, medium- to low-tech and medium- to high-tech sector, compared to a high-tech one (in the three cases the p-value is equal to 0.000). Interestingly, *LSIZE* and *RD_INT* have a negative and significant coefficient for explaining the probability of being a closed innovator (p-value = 0.000), and belonging to a low-tech, medium- to low-tech or medium- to high-tech sector is also positively related to being a closed innovator. These results suggest that closed and open innovators share some characteristics related to size, R&D intensity and sector of activity, compared to semi-open innovators. To

Table 6(b). Results of multinomial logit panel data model with random intercepts (reference category = CLOSED)

	Model 1 (dependent variable: *OPENNESS_IMP*)		Model 2 (dependent variable: *OPENNES_SOUR*)	
	Coef.	Std error	Coef.	Std error
Results for dependent variable = 3 (OPEN)				
LSIZE	0.64***	0.06	0.03	0.05
RD_INT	2.92***	0.34	0.04	0.34
LOWTECH	−0.16	0.21	0.24	0.20
LOWMEDIUMTECH	0.11	0.21	0.07	0.21
MEDIUMHIGHTECH	−0.37*	0.19	−0.06	0.19
EXPORT	0.13	0.14	−0.04	0.15
GROUP	0.65***	0.13	−0.43***	0.13
DEVELOPMENT	0.25**	0.11	0.02	0.11
OBS_COST	0.21	0.29	0.18	0.30
OBS_INFORMATION	2.11***	0.41	2.86***	0.43
Constant	−4.78***	0.36	−0.18	0.35

****p*-value < 0.01, ***p*-value < 0.05, **p*-value < 0.1.

explore these characteristics, we made the reference group closed innovators (see Table 6(b))[17] and found that open innovators are larger and more R&D intensive than closed ones (p-values = 0.000).

The results of Model 2 show again that *LSIZE* is negatively related to being an open innovator (p-value = 0.000) as is *RD_INT* (p-value = 0.000). However, the influence of sector is less clear. The signs of the coefficients are negative, but not statistically significant, except in the case of medium- to low-tech sectors. For the likelihood of being a closed innovator, *LSIZE* and *RD_INT* show negative coefficients (p-value of 0.001 in both cases) and sector influence is not statistically significant. In this case, we do not observe significant differences between closed and open innovators (Table 6(b)).

5.2 Robustness Checks

To test the sensitivity of our results to how we define the dependent variables, we performed some robustness checks.

First, in our definition of *OPENNESS_IMP* we merge two different categories of openness: cooperation and contracting. There is some debate in the literature on the existence or not of a sharp distinction between these activities (Ham and Mowery, 1998; Barge-Gil and Modrego-Rico, 2006; Cassiman *et al.*, 2010). It is possible that those firms

[17] Only coefficients for the comparison between open and closed innovators are shown, as the comparison between closed and semi-open is already provided in Table 6(a).

that innovate mainly by subcontracting are actually "passive adopters". To test whether the results are influenced by this, we repeated the regressions but dropping those firms (70 or 0.64 per cent of the sample). The results are similar (see Tables A1(a) and (b) in the Appendix).

Second, in our definition of *OPENNESS_IMP*, and in line with our aim to obtain a measure of openness for the entire firm, we aggregate product innovation and process innovation openness and for the entire firm select the one that reflects greater openness (i.e. has the highest value). To test whether this aggregation is influencing our results, we ran separate regressions for product and process innovation. The pattern of the results was very similar (see Tables A2(a) and (b) in the Appendix).

Third, we tested whether the results related to *OPENNESS_SOUR* are sensitive to the existence of some firms assigning low or null importance to all information sources, by dropping them (260 firms or 2.4 per cent of the sample). The results are qualitatively similar (see Tables A3(a) and (b) in the Appendix).

5.3 Results by Sector

The technological level of the sector influences the quantity and type of external knowledge that is available to firms; thus, it can influence the factors leading to the decision over degree of openness. In what follows, we analyse the openness of firms' strategies by sector, following the OECD classification. Table 7 shows the percentage of firms in each sector that adopt an open innovation strategy. We observe that HT firms are more likely to be semi-open innovators according to both measures.

The regressions are shown in Table 8(a). In Model 3, *OPENNESS_IMP* is the dependent variable; in Model 4 it is *OPENNESS_SOUR*. Results across sectors are quite similar to the results for the whole sample. From Model 3, we can see that generally both *LSIZE* and *RD_INT* have a negative and significant coefficient, explaining the adoption of both open and closed innovation strategies (p-value = 0.000); the exception is low- and low- to medium-tech sectors where we find no significant relationship between *RD_INT* and open innovation. If open and closed innovators are compared (see Table 8(b)) we see that the latter are smaller and less R&D intensive in all sectors.

Table 7. Openness of firms by sector (OECD classification)

	OPENNESS_IMP				*OPENNES_SOUR*			
	Closed	Semi	Open	Total	Closed	Semi	Open	Total
Low-tech	47%	30.2%	22.8%	100%	24.6%	51.4%	24%	100%
Low- to medium-tech	42.9%	33.1%	24%	100%	26.4%	49%	24.6%	100%
Medium- to high-tech	46.3%	35.2%	18.5%	100%	26.8%	52%	21.2%	100%
High-tech	37.4%	45.9%	16.8%	100%	24.7%	55.1%	20.2%	100%
	Pearson $chi^2(4) = 27.4897$, Prob = 0.000				Pearson $chi^2(6) = 25.3332$, Prob = 0.000			

Table 8(a). Results of multinomial logit panel data model with random intercepts by sector (OECD classification)

	Model 3 (dependent variable: *OPENNESS_IMP*)								Model 4 (dependent variable: *OPENNES_SOUR*)							
	Low-tech		Medium- to low-tech		Medium- to high-tech		High-tech		Low-tech		Medium- to low-tech		Medium- to high-tech		High-tech	
	Coef.	Std error	Coef.	Std error	Coef.	Std error	Coef.	Std error	Coef.	Std error	Coef.	Std error	Coef.	Std error	Coef.	Std error
Dependent variable = 3																
LSIZE	−0.23***	0.09	−0.33***	0.10	−0.34***	0.08	−0.33***	0.14	−0.16*	0.08	0.00	0.08	−0.32***	0.08	−0.34**	0.13
RD_INT	−0.67	0.55	−0.46	0.43	−2.14***	0.53	−1.70***	0.61	−0.54	0.57	−0.38	0.46	−1.84***	0.51	0.04	0.59
EXPORT	−0.08	0.31	0.58***	0.22	0.38*	0.23	0.00	0.35	0.00	0.29	−0.17	0.19	0.01	0.23	−0.01	0.32
GROUP	−0.20	0.19	−0.29	0.22	−0.34*	0.19	−0.38	0.36	−0.53***	0.19	−0.39	0.20	−0.10	0.18	0.77**	0.35
DEVELOPMENT	0.20	0.19	0.10	0.20	0.09	0.18	0.59**	0.33	−0.03	0.18	−0.17	0.18	−0.21	0.16	−0.01	0.32
OBS_COST	−0.49	0.50	−0.44	0.53	−0.39	0.43	1.43**	0.73	−0.92**	0.47	−0.65	0.48	−0.30	0.40	−1.14	0.76
OBS_INFORMATION	0.19	0.68	1.19*	0.72	1.41**	0.60	−0.30	1.14	0.49	0.64	−0.18	0.63	0.74	0.56	−1.20	1.20
Constant	1.56***	0.54	1.42**	0.56	1.26***	0.48	0.12	0.81	0.38	0.48	0.07	0.48	0.61	0.44	0.85	0.81
Dependent variable = 1																
LSIZE	−0.45***	0.08	−0.59***	0.10	−0.71***	0.08	−0.80***	0.13	−0.09	0.08	−0.02	0.08	−0.29***	0.08	−0.21	0.13
RD_INT	−2.43***	0.55	−1.93***	0.51	−4.24***	0.51	−3.94***	0.62	−0.05	0.56	−0.61	0.48	−1.95***	0.50	0.05	0.58
EXPORT	−0.11	0.28	0.23	0.23	0.18	0.22	0.28	0.32	0.01	0.29	−0.26	0.20	0.07	0.22	−0.23	0.33
GROUP	−0.50***	0.18	−0.26	0.21	−0.80	0.18	−0.80**	0.34	−0.12	0.19	0.09	0.20	0.15	0.18	0.40	0.35
DEVELOPMENT	−0.15	0.17	−0.16	0.19	0.01	0.16	0.68**	0.31	−0.20	0.18	−0.30*	0.18	−0.02	0.16	−0.10	0.32
OBS_COST	−0.49	0.46	−0.51	0.50	−0.21	0.39	0.74	0.69	−1.12**	0.47	−0.43	0.48	−0.74*	0.40	−0.89	0.75
OBS_INFORMATION	−0.66	0.65	−1.26*	0.71	−0.78*	0.57	−1.06	1.06	−0.95	0.68	−2.44**	0.67	−1.16**	0.58	−3.20***	1.23
Constant	4.00***	0.51	4.47***	0.55	5.02***	0.45	3.96***	0.76	0.68	0.48	0.92	0.48	1.50***	0.43	1.42*	0.81
Log likelihood	−2,719.2065		−2,524.6044		−3,821.2923		−1,251.7156		−2,656.1644		−2,503.5774		−3,862.9331		−1,270.0529	
Number of level 1 units	2,750		2,554		4,138		1,433		2,750		2,554		4,138		1,433	
Number of level 2 units	1,345		1,221		1,843		601		1,345		1,221		1,843		601	

****p*-value $<$ 0.01, ***p*-value $<$ 0.05, **p*-value $<$ 0.1.

Table 8(b). Results of multinomial logit panel data model with random intercepts by sector (OECD classification) (reference category = CLOSED)

	Low-tech		Medium- to low-tech		Medium- to high-tech		High-tech	
	Coef.	Std error	Coef.	Std error	Coef.	Std error	Coef.	Std error
			Model 3 (dependent variable: *OPENNESS_IMP*)					
Results for dependent variable = 3 (OPEN)								
LSIZE	0.45***	0.11	0.47***	0.11	0.76***	0.11	0.93***	0.19
RD_INT	3.04***	0.64	1.48***	0.55	3.72***	0.62	3.29***	0.82
EXPORT	0.02	0.33	0.35	0.25	0.13	0.26	−0.35	0.43
GROUP	0.61***	0.24	0.06	0.25	1.09***	0.23	0.88**	0.39
DEVELOPMENT	0.57**	0.20	0.21	0.22	0.08	0.20	0.07	0.39
OBS_COST	0.44	0.56	0.38	0.56	−0.37	0.51	0.50	0.89
OBS_INFORMATION	1.00	0.79	3.43***	0.83	2.61***	0.67	0.23	1.37
Constant	−3.96***	0.60	−4.22***	0.61	−5.78***	0.57	−5.23***	1.14
			Model 4 (dependent variable: *OPENNES_SOUR*)					
Results for dependent variable = 3 (OPEN)								
LSIZE	−0.02	0.10	0.00	0.10	0.05	0.09	−0.02	0.13
RD_INT	−0.75	0.68	−0.02	0.41	0.54	0.61	1.13	0.72
EXPORT	−0.04	0.35	0.02	0.24	−0.30	0.27	0.34	0.43
GROUP	−0.49	0.23	−0.64**	0.25	−0.45**	0.23	0.22	0.38
DEVELOPMENT	0.10	0.21	0.14	0.22	−0.14	0.19	0.12	0.38
OBS_COST	0.20	0.57	−0.15	0.60	0.36	0.51	0.02	0.88
OBS_INFORMATION	2.03**	0.81	3.12***	0.82	3.12***	0.72	3.94***	1.43
Constant	0.43	0.59	−0.08	0.59	−0.30	0.55	5.96	3.79

***p-value < 0.01, **p-value < 0.05, *p-value < 0.1.

The picture for the dependent variable *OPENNESS_SOUR* is less clear. Generally, semi-open innovators are larger and more R&D intensive than either open or closed innovators, but in several cases the coefficients, although retaining their negative sign, are not significant.[18] In addition, differences between open and closed innovators are very small and not significant from a statistical point of view.

6. Discussion and Conclusions

A pattern emerges from the above results concerning the relationship between size and R&D intensity, and openness, especially when the dependent variable is *OPENNESS_IMP*. Based on the three strategies (open, semi-open and closed), we find that firms that are open innovators are smaller and less R&D intensive than semi-open ones, although they are larger and more R&D intensive than closed innovators. This result seems to be robust as it is fairly stable across industries.

These results clearly follow the pattern shown in Figure 1, confirming our hypotheses. First, it seems that smaller, less R&D-intensive firms have a greater need for external knowledge, but very low capacity to absorb it. Thus, they cannot benefit from it and decide to adopt a closed strategy. Second, the biggest and most R&D-intensive firms are likely to have great capacity to absorb external knowledge, but their need for it is usually smaller. Thus, they exploit it, but it is not at the core of their innovation assets. That is to say, they choose to be semi-open. Finally, between these two groups are firms with the capacity to benefit from external knowledge and a considerable need for it: they make the decision to be open innovators.

These results are less clear cut when the variable is *OPENNESS_SOUR*. Although the signs are mostly the same, they are frequently not significant, especially in the sector analysis. We interpret this as meaning that the difference is related to the different scope of the two indicators. *OPENNESS_SOUR* is much broader, and includes all open innovation practices as well as the importance of free, external knowledge and of knowledge not specifically related to the achievement of new products and processes. Thus, on the one hand, the capacity required to absorb this type of knowledge may be lower (especially in terms of management, as no formal relationship is involved) so that smaller, less R&D-intensive firms can benefit more easily. On the other hand, the need for general external knowledge does not decrease as sharply as size and R&D increase, since even the bigger and more R&D-intensive firms would need to monitor and use the external pool of knowledge. These two characteristics produce less clear results than in the case of *OPENNESS_IMP*.

Concerning the influence of sector on openness, if the dependent variable is *OPENNESS_IMP* a clear pattern emerges for the sector variables. Both open and closed innovators are usually outside the high-tech sectors,[19] where firms are much more frequently semi-open innovators. However, if the dependent variable is *OPENNESS_SOUR*, there is no clear pattern. As discussed above, *OPENNESS_IMP* reflects formal collaboration aimed at obtaining new products and processes while *OPENNESS_SOUR* reflects a much more general behaviour among firms in terms of exploiting external knowledge. This result

[18] The same robustness checks were performed for the sectoral regressions, being results qualitatively unchanged. They are not provided here for reasons of space but are available from the authors upon request.

[19] In this case, no systematic differences were found between open and closed innovators.

suggests that non-high-tech sectors are (relatively) more open if only more formal arrangements are taken into account. This confirms the views expressed by some authors that low-tech innovation depends greatly on the knowledge developed in high-tech sectors, which usually flows through formal relationships (Robertson and Patel, 2007).[20] In any case, it is clear from our results that open innovation is a general phenomenon that affects all manufacturing sectors, and not just high-tech ones. In addition we find no strong mediating effect of sector in the relationship between size and R&D and openness: the patterns observed are very stable across sectors.

One implication of these results is that the framework proposed is able to integrate and reconcile the arguments in the literature and fits with the empirical evidence, especially when formal relationships are analysed. Both the “need” and “absorptive capacity” effects are important, and jointly determine firms’ decisions about openness when a straight choice between open and closed is abandoned and some measure of degree of openness is considered. Firms that are more in need of external knowledge do not engage in open innovation because of their lower capabilities to absorb external knowledge. However, firms with slightly more developed capabilities will select an open strategy, in contrast to the bigger and more R&D-intensive firms that choose a semi-open strategy. In an era of innovation policy focused very much on cooperation (Bozeman, 2000), it is this latter group of firms (i.e. that choose a semi-open strategy) that benefit the most from policies that provide incentives for collaboration (see Vence, 1998; Heijs, 2002, 2005 among others).[21] That is, the firms that would potentially benefit more from openness are not being reached by these policies, which should be of concern for the design of future initiatives.

This work has several limitations. First, we use a nominal variable for openness. A continuous one would be preferred, but it is not available based on the data gleaned from CIS-type surveys. Second, it is likely that many firms use a mix of strategies, being open in some projects, semi-open in others and closed in yet others. Unfortunately, we can only measure openness of the entire firm, but an analysis of project data would provide complementary and very interesting additional information. Third, we do not analyse the openness strategies of non-R&D performing firms. Many such firms are innovative (Hall *et al.*, 2009; Ortega-Argilés *et al.*, 2009; Barge-Gil *et al.*, 2011) and little is known about their innovation strategies: the characteristics of our database do not allow us to analyse this issue. Fourth, we study the adoption of more or less open strategies, but do not investigate what are the results of the strategies chosen, or how much these results may be contingent on the influence of different variables. These would be interesting areas for future research. Nevertheless, we believe that the present study adds to the knowledge on firms’ decisions about whether or not to be open and their relationship with size, R&D intensiveness and sector.

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[20] Note that this means that firms in HT sectors would be outbound open innovators.

[21] Other studies that are not precisely focused on this issue, derive similar conclusions. For example, de Jong and Marsili (2006) find that innovation subsidies are much more frequent in clusters of “science-based” firms.

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References

Abramovsky, L., Kremp, E., López, A., Schmidt, T. and Simpson, H. (2009) Understanding co-operative innovative activity: evidence from four European countries, *Economics of Innovation and New Technology*, 18(3), pp. 243–265.

Arranz, N. and Fernandez de Arroyabe, J. C. (2008) The choice of partners in R&D cooperation: an empirical analysis of Spanish firms, *Technovation*, 28(1/2), pp. 88–100.

Barge-Gil, A. (2010) Cooperation-based innovators and peripheral cooperators: an empirical analysis of their characteristics and behaviour, *Technovation*, 30(3), pp. 195–206.

Barge-Gil, A. and Modrego-Rico, A. (2006) Firms' utilisation of knowledge external sources: towards an holistic approach, paper presented at the 2006 Annual Conference of Technology Transfer Society, Georgia Tech, Atlanta, USA. Available at: http://www.cherry.gatech.edu/t2s2006/papers/barge-gil-1034-T.pdf

Barge-Gil, A., Nieto, M. J. and Santamaría, L. (2011) Hidden innovators: the role of non R&D activities, *Technology Analysis & Strategic Management*, 23(4).

Bayona, C., García-Marco, T. and Huerta, E. (2001) Firms' motivations for cooperative R&D: an empirical analysis of Spanish firms, *Research Policy*, 30, pp. 1289–1307.

Becker, W. and Dietz, J. (2004) R&D cooperation and innovation activities of firms—evidence for the German manufacturing industry, *Research Policy*, 33, pp. 209–223.

Belderbos, R., Carree, M., Diederen, B., Lokshin, B. and Veugelers, R. (2004) Heterogeneity in R&D cooperation strategies, *International Journal of Industrial Organization*, 22, pp. 1237–1263.

Bozeman, B. (2000) Technology transfer and public policy: a review of research and theory, *Research Policy*, 29, pp. 627–655.

Cassiman, B., di Guardo, M. C. and Valentini, G. (2010) Organizing links with science: cooperate or contract?: a project-level analysis, *Research Policy*, 39(7), pp. 882–892.

Cassiman, B. and Valentini, G. (2009) Strategic organization of R&D: the choice of basicness and openness, *Strategic Organization*, 7(1), pp. 43–73.

Cassiman, B. and Veugelers, R. (2002) R&D cooperation and spillovers: some empirical evidence from Belgium, *American Economic Review*, 92(4), pp. 1169–1184.

Cassiman, B. and Veugelers, R. (2006) In search of complementarity in innovation strategy: internal R&D and external knowledge acquisition, *Management Science*, 52(1), pp. 69–82.

Chen, S. and Long, J. S. (2007) Testing for IIA in the multinomial logit model, *Sociological Methods & Research*, 35(4), pp. 583–600.

Chesbrough, H. (2003) *Open Innovation* (Cambridge, MA: Harvard University Press).

Chesbrough, H. (2006) Open innovation: a new paradigm for understanding industrial innovation, in: H. Chesbrough, W. Wanhaverbeke & J. West (Eds) *Open Innovation: Researching a New Paradigm*, pp. 1–12 (New York: Oxford University Press).

Chesbrough, H. and Crowther, A. (2006) Beyond high tech: early adopters of open innovation in other industries, *R&D Management*, 36(3), pp. 229–236.

Cohen, W. and Levinthal, D. (1989) Innovation and learning: the two faces of R&D, *The Economic Journal*, 99(397), pp. 569–596.

Cohen, W. and Levinthal, D. (1990) Absorptive capacity: a new perspective on learning and innovation, *Administrative Science Quarterly*, 35(1), pp. 128–152.

Dahlander, L. and Gann, D. M. (2010) How open is innovation?, *Research Policy*, 39(6), pp. 699–709.

de Faria, P., Lima, F. and Santos, R. (2010) Cooperation in innovation activities: the importance of partners, *Research Policy*, 39(8), pp. 1082–1092.

de Jong, J. and Marsili, O. (2006) The fruit flies of innovations: a taxonomy of innovative small firms, *Research Policy*, 35, pp. 213–229.

Escríbano, A., Fosfuri, A. and Tribo, J. (2009) Managing external knowledge flows: the moderating role of absorptive capacity, *Research Policy*, 38, pp. 96–105.

Freel, M. (2000) External linkages and product innovation in small manufacturing firms, *Entrepreneurship & Regional Development*, 12, pp. 245–266.

Gassmann, O. (2006) Opening up the innovation process: towards an agenda, *R&D Management*, 36(3), pp. 223–228.

Griffiths, W. and Webster, E. (2010) What governs firm-level R&D: internal or external factors?, *Technovation*, 30(7/8), pp. 471–481.

Haan, P. and Uhlendorff, A. (2006) Estimation of multinomial logit models with unobserved heterogeneity using maximum simulated likelihood, *Stata Journal*, 6(2), pp. 229–245.

Hall, B., Lotti, F. and Mairesse, J. (2009) Innovation and productivity in SMEs: empirical evidence for Italy, *Small Business Economics*, 33, pp. 13–33.

Ham, R. M. and Mowery, D. (1998) Improving the effectiveness of public–private R&D collaborations: case studies at a US weapons laboratory, *Research Policy*, 26, pp. 661–675.

Heijs, J. (2002) Efectividad de las políticas de innovación en el fomento de la cooperación, *Economía Industrial*, 346, pp. 97–114.

Heijs, J. (2005) Identification of firms sorted by technology policies: the case of Spanish low interest credits, *Science and Public Policy*, 32(3), pp. 219–230.

Hirsch-Kreinsen, H. (2009) “Low-tech” innovations, *Industry and Innovation*, 15(1), pp. 19–43.

Huergo, E. (2006) The role of technological management as a source of innovation: evidence from Spanish manufacturing firms, *Research Policy*, 35, pp. 1377–1388.

Kaiser, U. (2002) An empirical test of models explaining research expenditures and research cooperation: evidence for the German service sector, *International Journal of Industrial Organization*, 20(6), pp. 747–774.

Katz, R. and Allen, T. J. (1982) Investigating the Not Invented Here (NIH) syndrome: a look at the performance, tenure and communication partners of 50 R&D project groups, *R&D Management*, 12(1), pp. 7–20.

Kirner, E., Kinkel, S. and Jaeger, A. (2009) Innovation paths and the innovation performance of low-technology firms—an empirical analysis of German industry, *Research Policy*, 38, pp. 447–458.

Kleinknecht, A. and Reijnen, J. (1992) Why do firms cooperate on R&D? An empirical study, *Research Policy*, 21(4), pp. 347–360.

Klevorick, A., Levin, R., Nelson, R. and Winter, S. (1995) On the sources and significance of interindustry differences in technological opportunities, *Research Policy*, 24, pp. 185–205.

Lane, P., Koka, B. and Pathak, S. (2006) The reification of absorptive capacity: a critical review and rejuvenation of the construct, *Academy of Management Review*, 31(4), pp. 833–863.

Laursen, K. and Salter, A. (2006) Open for innovation: the role of openness in explaining innovation performance among U.K. manufacturing firms, *Strategic Management Journal*, 27, pp. 131–150.

Lichtenthaler, U. (2008) Open innovation in practice: an analysis of strategic approaches to technology transaction, *IEEE Transactions on Engineering Management*, 55(1), pp. 148–157.

López, A. (2008) Determinants for R&D cooperation: evidence from Spanish manufacturing firms, *International Journal of Industrial Organization*, 26(1), pp. 113–136.

Mazzanti, M. (2008) What drives (or hampers) outsourcing? Evidence for a local production system in Emilia Romagna, *Industry and Innovation*, 16(3), pp. 331–365.

McFadden, D. (1973) Conditional logit analysis of qualitative choice behaviour, in: P. Zarembka (Ed.) *Frontiers in Econometrics*, pp. 105–142 (New York: Academic Press).

Miotti, L. and Sachwald, F. (2003) Co-operative R&D: why and with whom? An integrated framework of analysis, *Research Policy*, 32, pp. 1481–1499.

Mol, M. (2005) Does being R&D intensive still discourage outsourcing? Evidence from Dutch manufacturing, *Research Policy*, 34, pp. 571–582.

Narula, R. and Hagedoorn, J. (1999) Innovating through strategic alliances: moving towards international partnerships and contractual agreements, *Technovation*, 19, pp. 283–294.

Negassi, S. (2004) R&D cooperation and innovation a microeconometric study on French firms, *Research Policy*, 33, pp. 365–384.

Nieto, M. J. and Santamaría, L. (2007) The importance of diverse collaborative networks for the novelty of product innovation, *Technovation*, 27(6/7), pp. 367–377.

Nieto, M. J. and Santamaría, L. (2010) Technological collaboration: bridging the innovation gap between small and large firms, *Journal of Small Business Management*, 48(1), pp. 44–69.

OECD (1997) *Oslo Manual. Proposed Guidelines for Collecting and Interpreting Technological Innovation Data*, 2nd edn (Paris: OECD Publications).

OECD (2005) *Oslo Manual. Guidelines for Collecting and Interpreting Innovation*, 3rd edn (Paris: OECD Publications).

Ortega-Argilés, R., Vivarelli, M. and Voigt, P. (2009) R&D in SMEs: a paradox?, *Small Business Economics*, 33, pp. 3–11.

Peters, B. (2009) Persistence of innovation: stylised facts and panel data evidence, *Journal of Technology Transfer*, 34, pp. 226–243.

Pittaway, L., Robertson, M., Munir, K., Denyer, D. and Neely, A. (2004) Networking and innovation: a systematic review of the evidence, *International Journal of Management Reviews*, 5/6(3/4), pp. 137–168.

Rabe-Hesketh, S., Skrondal, A. and Pickles, A. (2002) Reliable estimation of generalized linear models using adaptative quadrature, *The Stata Journal*, 2(1), pp. 1–21.

Rabe-Hesketh, S., Skrondal, A. and Pickles, A. (2004) *GLLAMM Manual* (Berkeley: California University Press).

Robertson, P. and Patel, P. (2007) New wine in old bottles: technological diffusion in developed economies, *Research Policy*, 36, pp. 708–721.

Rogers, M. (2004) Networks, firm size and innovation, *Small Business Economics*, 22, pp. 141–153.

Rothwell, R. and Dodgson, M. (1991) External linkages and innovation in small and medium-sized enterprises, *R&D Management*, 21, pp. 125–137.

Rothwell, R. and Dodgson, M. (1994) Innovation and size of firm, in: M. Dodgson & R. Rothwell (Eds) *The Handbook of Industrial Innovation*, pp. 310–324 (Aldershot, Hants.: Edward Elgar).

Santamaría, L., Nieto, M. J. and Barge-Gil, A. (2009) Beyond formal R&D: taking advantage of other sources of innovation in low- and medium-technology industries, *Research Policy*, 38, pp. 507–517.

Santoro, M. and Chakrabarti, A. (2002) Firm size and technology centrality in industry–university interaction, *Research Policy*, 31, pp. 1163–1180.

Segarra-Blasco, A. and Arauzo-Carod, J. M. (2008) Sources of innovation and industry–university interaction: evidence from Spanish firms, *Research Policy*, 37, pp. 1283–1295.

Tether, B. (2002) Who cooperates for innovation, and why. An empirical analysis, *Research Policy*, 31, pp. 947–967.

Tödtling, F., Lehner, P. and Tril, M. (2006) Innovation in knowledge intensive industries: the nature and geography of knowledge links, *European Planning Studies*, 14(8), pp. 1035–1058.

Tomlinson, P. R. (2010) Co-operative ties and innovation: some new evidence for UK manufacturing, *Research Policy*, 39(6), pp. 762–775.

van de Vrande, V., de Jong, J., Vanhaverbeke, W. and de Rochemont, M. (2009) Open innovation in SMEs: trends, motives and management challenges, *Technovation*, 29, pp. 423–437.

Vega-Jurado, J., Gutierrez-Gracia, A. and Fernandez-de-Lucio, I. (2009) Does external knowledge sourcing matter for innovation? Evidence from the Spanish manufacturing industry, *Industrial and Corporate Change*, 18(4), pp. 637–670.

Vence, X. (1998) *La política tecnológica comunitaria y la cohesión regional. Los retos de los sistemas de innovación periféricos* (Madrid: Civitas).

Veugelers, R. (1997) Internal R&D expenditures and external technology sourcing, *Research Policy*, 26(3), pp. 303–315.

Veugelers, R. (1998) Collaboration in R&D: an assessment of theoretical and empirical findings, *The Economist*, 149, pp. 419–443.

Veugelers, R. and Cassiman, B. (1999) Make and buy in innovation strategies: evidence from Belgian manufacturing firms, *Research Policy*, 28, pp. 63–80.

Watkins, T. A. and Paff, L. A. (2009) Absorptive capacity and R&D tax policy: are in-house and external contract R&D substitutes or complements?, *Small Business Economics*, 33, pp. 207–227.

West, J., Vanhaverbeke, W. and Chesbrough, H. (2006) Open innovation: a research agenda, in: H. Chesbrough, W. Wanhaverbeke & J. West (Eds) *Open Innovation: Researching a New Paradigm*, pp. 285–307 (New York: Oxford University Press).

Zahra, S. A., Ireland, R. D. and Hitt, M. A. (2000) International expansion by new venture firms: international diversity, mode of market entry, technological learning, and performance, *Academy of Management Journal*, 43(5), pp. 925–950.

Appendix

Table A1(a). Results of multinomial logit panel data model with random intercepts, excluding firms whose main innovation mode is subcontracting (reference category = SEMI-OPEN)

	Model 1 (dependent variable: *OPENNESS_IMP*)	
	Coef.	Std error
Dependent variable = 3 (OPEN)		
LSIZE	−0.29***	0.05
RD_INT	−1.07***	0.27
LOWTECH	1.17***	0.17
LOWMEDIUMTECH	0.98***	0.17
MEDIUMHIGHTECH	0.59***	0.16
EXPORT	0.33***	0.12
GROUP	−0.26**	0.11
DEVELOPMENT	0.18*	0.10
OBS_COST	−0.19	0.26
OBS_INFORMATION	0.94***	0.36
Constant	0.25	0.31
Dependent variable = 1 (CLOSED)		
LSIZE	−0.62***	0.05
RD_INT	−3.08***	0.27
LOWTECH	0.95***	0.16
LOWMEDIUMTECH	0.67***	0.16
MEDIUMHIGHTECH	0.63***	0.15
EXPORT	0.13	0.12
GROUP	−0.58***	0.10
DEVELOPMENT	−0.01	0.10
OBS_COST	−0.23	0.24
OBS_INFORMATION	−0.84**	0.34
Constant	3.79***	0.29
	Log likelihood = −10,209.3	
	Number of level 1 units = 10,805; number of level 2 units = 4,896	

***p-value < 0.01, **p-value < 0.05, *p-value < 0.1.

Table A1(b). Results of multinomial logit panel data model with random intercepts, excluding firms whose main innovation mode is subcontracting (reference category = CLOSED)

	Model 1 (dependent variable: *OPENNESS_IMP*)	
	Coef.	Std error
Dependent variable = 3 (OPEN)		
LSIZE	0.64***	0.06
RD_INT	3.02***	0.34
LOWTECH	−0.19	0.20
LOWMEDIUMTECH	0.09	0.21
MEDIUMHIGHTECH	−0.40**	0.19
EXPORT	0.18	0.14
GROUP	0.69***	0.13
DEVELOPMENT	0.24**	0.11
OBS_COST	0.17	0.30
OBS_INFORMATION	2.11***	0.40
Constant	−4.88***	0.36

***p-value < 0.01, **p-value < 0.05, *p-value < 0.1.

Table A2(a). Results of multinomial logit panel data model with random intercepts by product and process innovator (reference category = SEMI-OPEN)

	Model 1 (*OPENNESS_IMP*) Product innovation		Model 1 (*OPENNES_IMP*) Process innovation	
	Coef.	Std error	Coef.	Std error
Dependent variable = 3 (OPEN)				
LSIZE	−0.42***	0.05	−0.21***	0.05
RD_INT	−0.91***	0.29	−1.23***	0.30
LOWTECH	0.96***	0.19	0.93***	0.19
LOWMEDIUMTECH	0.90***	0.19	0.77***	0.19
MEDIUMHIGHTECH	0.53***	0.17	0.48***	0.18
EXPORT	0.34**	0.14	0.15	0.14
GROUP	−0.52***	0.13	−0.31***	0.12
DEVELOPMENT	0.06	0.12	0.25**	0.11
OBS_COST	0.14	0.29	−0.34	0.28
OBS_INFORMATION	0.78**	0.39	0.53	0.38
Constant	0.11	0.34	0.27	0.34
Dependent variable = 1 (CLOSED)				
LSIZE	−0.71***	0.05	−0.50***	0.05
RD_INT	−2.91***	0.29	−3.06***	0.32
LOWTECH	0.80***	0.17	0.82***	0.18
LOWMEDIUMTECH	0.48***	0.18	0.67***	0.19
MEDIUMHIGHTECH	0.66***	0.16	0.67***	0.18
EXPORT	0.04	0.13	−0.05	0.14
GROUP	−0.72***	0.12	−0.64***	0.12
DEVELOPMENT	−0.05	0.10	0.04	0.11
OBS_COST	−0.20	0.26	−0.20	0.27
OBS_INFORMATION	−0.92**	0.37	−1.49	0.38
Constant	3.67***	0.32	3.13***	0.33
	Log likelihood = −8,253.94 Number of level 1 units = 9,203; number of level 2 units = 4,293		Log likelihood = −8,376.75 Number of level 1 units = 8,527; number of level 2 units = 4,048	

***p-value < 0.01, **p-value < 0.05, *p-value < 0.1.

Table A2(b). Results of multinomial logit panel data model with random intercepts by product and process innovator (reference category = CLOSED)

	Model 1 (*OPENNESS_IMP*) Product innovation		Model 1 (*OPENNES_IMP*) Process innovation	
	Coef.	Std error	Coef.	Std error
Dependent variable = 3 (OPEN)				
LSIZE	0.69***	0.07	0.59***	0.07
RD_INT	3.10***	0.38	3.14***	0.43
LOWTECH	−0.27	0.23	−0.29	0.23
LOWMEDIUMTECH	0.23	0.23	−0.13	0.23
MEDIUMHIGHTECH	−0.57***	0.22	−0.56**	0.22
EXPORT	0.25	0.17	0.26	0.17
GROUP	0.59***	0.15	0.60***	0.14
DEVELOPMENT	0.12	0.13	0.20	0.13
OBS_COST	0.48	0.34	−0.06	0.32
OBS_INFORMATION	2.10***	0.48	2.71***	0.46
Constant	−4.94***	0.42	−3.80***	0.41

***p-value < 0.01, **p-value < 0.05, *p-value < 0.1.

Table A3(a). Results of multinomial logit panel data model with random intercepts excluding firms assigning null or low importance to all information sources (reference category = SEMI-OPEN)

	Model 2 (*OPENNESS_SOUR*)	
	Coef.	Std error
Dependent variable = 3 (OPEN)		
LSIZE	−0.17***	0.05
RD_INT	−0.65***	0.25
LOWTECH	0.17	0.17
LOWMEDIUMTECH	0.35**	0.17
MEDIUMHIGHTECH	0.00	0.15
EXPORT	−0.03	0.13
GROUP	−0.23**	0.11
DEVELOPMENT	−0.10	0.10
OBS_COST	−0.71***	0.25
OBS_INFORMATION	0.38	0.35
Constant	0.15	0.29
Dependent variable = 1 (CLOSED)		
LSIZE	−0.14***	0.05
RD_INT	−0.73***	0.25
LOWTECH	0.02	0.16
LOWMEDIUMTECH	0.24	0.17
MEDIUMHIGHTECH	0.05	0.15
EXPORT	−0.08	0.12
GROUP	0.05	0.11
DEVELOPMENT	−0.10	0.10
OBS_COST	−0.88***	0.25
OBS_INFORMATION	−1.69***	0.37
Constant	1.05***	0.29
	Log likelihood = −10,038.9	
	Number of level 1 units = 10,615; number of level 2 units = 4,872	

***p-value < 0.01, **p-value < 0.05, *p-value < 0.1.

Table A3(b). Results of multinomial logit panel data model with random intercepts excluding firms assigning null or low importance to all information sources (reference category = CLOSED)

	Model 1 (*OPENNESS_SOUR*)	
	Coef.	Std error
Dependent variable = 3 (OPEN)		
LSIZE	0.02	0.05
RD_INT	0.08	0.34
LOWTECH	0.31	0.21
LOWMEDIUMTECH	0.12	0.21
MEDIUMHIGHTECH	0.01	0.20
EXPORT	−0.06	0.15
GROUP	−0.38***	0.13
DEVELOPMENT	0.00	0.12
OBS_COST	0.32	0.31
OBS_INFORMATION	3.09***	0.45
Constant	−0.29	0.37

***p-value < 0.01, **p-value < 0.05, *p-value < 0.1.