EXTERNAL KNOWLEDGE SOURCING AND FIRM INNOVATION EFFICIENCY

Abstract

This study examines the relationship between external knowledge sourcing and firm innovation efficiency. We build on the organizational learning theory to propose that such relationship follows an inverted U-shape: as the level of external knowledge sourcing increases from low to moderate, firm innovation efficiency increases; as the level of external knowledge sourcing increases from moderate to high, firm innovation efficiency declines. Further, we explore the moderating role of different contextual factors and contend that this inverted U-shaped relationship is flattened in firms that operate in high-tech sectors and in firms that face high internal constraints for innovation. Our empirical analysis is based on a sample of 3,204 Spanish firms over the period 2004-2015, and our results provide support to these contentions. We used Data Envelopment Analysis (DEA) methodology to estimate firm innovation efficiency relative to the industry best performers, and truncated regression models for panel data with bootstrapped confidence intervals to test our hypotheses.

Key words: data envelopment analysis, external knowledge sourcing, innovation efficiency, organizational learning

Introduction

Firms are increasingly reaching out to knowledge and ideas from beyond their boundaries to invigorate their innovation efforts and boost their innovative performance (Grigoriou and Rothaermel, 2017; Laursen and Salter, 2006; Love, Roper, and Vahter, 2014; Van de Vrande, 2013). Extant research has traditionally underscored the positive relationship between external knowledge sourcing, defined as the firm´s tendency to use knowledge from beyond its boundaries through a wide range of external channels (Escribano *et al*., 2009; Faems, De Visser, Andries, and Van Loow, 2010; Laursen and Salter, 2006; Van de Vrande, 2013), and firm-level innovative output. This relationship may exhibit diminishing returns or be contextually specific (e.g. Hung and Chou, 2013; Laursen and Salter, 2006; Leiponen and Helfat, 2010). For example, past empirical work has demonstrated that the innovation-related benefits from external knowledge sourcing are contingent on firm internal knowledge networks (Grigoriou and Rothaermel, 2017), investment in R&D and firm absorptive capacity, among others (Berchicci, 2013; Escribano, Fosfuri, and Tribó, 2009; Garcia Martinez, Zouaghi and Sanchez Garcia, 2018).

Notwithstanding these contributions, such research has focused predominantly on firm innovative output (e.g. new or significantly improved products) as a measure of firm innovative performance, saying little about how firms can harness the potential of external knowledge sourcing to enhance the *efficiency* of their innovation activities (Fu, 2012), and strengthen their competitive position (Zobel, 2017). Whereas a recent study has shown that accessing knowledge residing outside the firm boundaries is an important determinant of firm innovation efficiency (Fu, 2012), more remains to be understood about the contingent nature of this relationship and the underlying mechanisms behind it.

To fill the afore-mentioned research gap, this paper addresses the following research questions: What is the relationship between the level of external knowledge sourcing and firm innovation efficiency and what factors shape this relationship? To answer these research questions, we draw on the organizational learning theory (Levinthal and March, 1993; March, 1991) and propose a contingency-based model. In this study, *innovation efficiency* is defined as the firm-specific capability to use fewer R&D resources (inputs) to achieve certain innovation objectives (outputs) relative to the industry best performers (Hashimoto and Haneda, 2008; Hienerth, von Hippel, and Jensen, 2014), and is closely linked to a firm's competitive position (Chen, Delmas, and Lieberman, 2015).

Specifically, we argue that the relationship between the level of external knowledge sourcing and firm innovation efficiency follows a non-monotonic, inverted U-shaped pattern and can be explained by the interplay of two opposing forces—positive and negative—inherent in the learning mechanism. We underscore that, at low to medium levels of external knowledge sourcing, the exposure to external knowledge, problem-solving approaches, and management practices provides ample learning opportunities and will be positively associated with firm innovation efficiency. Nevertheless, relying too much on external knowledge sourcing will be negatively related to firm innovation efficiency. This is because with rising levels of external knowledge sourcing also come escalating diseconomies such as disruptions in firm path-dependent learning processes and R&D routines, and beyond a certain point those are likely to outweigh the potential learning benefits.

We further identify important contextual factors that likely moderate the examined relationship. Specifically, we conjecture that this inverted U-shaped curve is flattened in high-tech (cf. non-high-tech) firms and in firms that face high internal resource constraints. We test our theoretical predictions on an unbalanced panel of 3,204 firms in Spain over the period 2004-2015; a total of 12,123 firm-year observations. Our empirical findings provide support to these contentions.

Our study makes both theoretical and empirical contributions to current research in innovation management. From a theoretical standpoint, we provide a more nuanced understanding of the hidden trade-offs managers face when reaching out for external knowledge in attempts to boost firm innovation efficiency. We use insights from the organizational learning theory to extend the arguments from previous literature and shed light on the contingent nature of this relationship. Our model explains why firms in high-tech sectors and in resource constrained (cf. resource abundant) contexts may face different challenges in capitalizing on external knowledge sourcing in the pursuit of innovation efficiency gains. In doing so, our study further contributes to the ongoing scholarly debate on the implications of external knowledge sourcing on firm innovative performance (Berchicci, 2013; Garcia Martinez *et al*., 2018; Escribano *et al*., 2009; Hung and Chou, 2013; Laursen and Salter, 2006; Love *et al.*, 2014).

As an empirical contribution, our work responds to a recent call to adopt production frontier methodology to management research (Bozec, Dia and Bozec, 2010; Chen *et al.*, 2015; Devinney, Yip and Johnson, 2010), and adds to the limited number of studies that evaluate firm innovation efficiency using non-parametric approaches (Cruz-Cázares, Bayona-Sáez, and García-Marco, 2013; Fu, 2012). In doing so, this study advances our understanding of how firms can strengthen their competitive position by focusing on the efficiency with which firm innovation outcomes are achieved rather than on the introduction of new products only. Specifically, following recent research (Bozec *et al.*, 2010; Fu, 2012), we use Data Envelopment Analysis (DEA) to account for the multidimensionality of firm performance and estimate firm innovation efficiency relative to the best performers in an industry. Whereas DEA has been widely used to study the efficiency of science and technology systems at the macro level, it is a relatively novel approach to assess innovation efficiency at the firm level (e.g. Hashimoto and Haneda, 2008).

The remainder of the paper is organized as follows. The next section develops a conceptual framework and presents our main arguments, leading to our research hypotheses. Next, we describe the research methodology and the data used, and present our main findings. The paper concludes with a discussion of our main results and the implications of the study for theory, practice, and future research.

Theory and hypotheses

External knowledge sourcing and firm innovation efficiency

Firms are increasingly tapping into external sources of knowledge in their quest for revitalizing their innovation efforts. External knowledge sourcing through the *intensive* use of *diverse* channels such as universities, customers, suppliers, and competitors provides firms with access to different types of knowledge along the value chain (e.g. Van Beers and Zand, 2014), and ample opportunities to learn (Love *et al.*, 2014). For instance, through university-industry collaborations firms get access to early stage scientific discoveries and advances in basic science (Bercovitz and Feldman, 2007; Stuart, Ozdemir, and Ding, 2007), whereas firms usually cooperate with suppliers to improve input quality and production processes, and reduce costs (Belderbos, Carree, and Lokshin, 2004). Furthermore, getting feedback from customers informs firms about customers' sensitivity to market trends, their evaluations of new product concepts, and their first-hand user experiences (Candi, Roberts, Tucker, and Barczak, 2018; Chang and Taylor, 2016; Wang, Chang, and Shen, 2015). Additionally, firms can reach out to competitors to benchmark against valuable practices (Vorhies and Morgan, 2005), create new markets (Wang *et al.*, 2015), or accelerate their market penetration efforts (Miotti and Sachwald, 2003).

Below we examine the relationship between the level of external knowledge sourcing and firm innovation efficiency. Whereas a recent study suggests that the innovation efficiency gains from firm openness to external collaborations might be subject to diminishing returns (Fu, 2012), little systematic investigation addresses the mechanisms behind these effects, and the conditions under which they are stronger or more likely to occur.

When the level of external knowledge sourcing increases from low to moderate, we expect firm innovation efficiency to increase. The exposure to external partners provides firms with opportunities to learn from the best practices and remove inefficiencies in their current innovation processes. External practices serve as benchmarks against which firms evaluate their internal R&D activities and performance levels, and likely trigger firms to exert additional effort to catch up (Hamel, Doz, and Prahalad, 1989) or use their in-house resources more efficiently (Huang and Rice, 2009). Also, adopting external knowledge and problem-solving approaches increases the likelihood that firms can explore novel knowledge combinations (Ahuja and Lampert, 2001) and improve their innovation capabilities (Faems *et al*., 2010; Nieto and Santamaria, 2007).

However, as the level of external knowledge sourcing increases beyond a threshold, the innovation efficiency gains are likely to be outweighed by the escalating costs and complexity inherent in the learning mechanism. First, because organizations typically learn in a path-dependent way (Levinthal and March, 1993; Mowery, Oxley, and Silverman, 1996), sourcing too many external ideas likely slows down learning by doing, as it diverts firm learning processes from their current paths (Bettis, Bradley, and Hamel, 1992). Also, over-relying on multiple external channels can become very cumbersome as firms likely incur additional costs, time and effort to learn how to use the new technology (Kessler, Bierly, and Gopalakrishnan, 2000) and develop the necessary routines to efficiently work with these new ideas and approaches (Bridoux, Smith, and Grimm, 2013). Moreover, excessive reliance on external knowledge can divert a firm´s critical R&D resources away from its core business (Colombo, Laursen, Magnusson, and Rossi-Lamastra, 2012) and disrupt current learning processes and R&D routines. Thus, further increase in the level of external knowledge sourcing beyond a threshold will be eventually negatively associated with the efficiency in resource allocation and usage (Ahuja and Katila 2001; Leiponen and Helfat 2010).

Second, drawing too much on a wide range of external channels induces a high degree of complexity and puts an extra strain on firm absorptive capacity (De Leeuw, Lokshin, and Duysters, 2014; Duysters and Lokshin, 2011). This is because firms may need to undergo substantial partner-specific investments (Laursen and Salter, 2006) and may not get full use of all the potential learning opportunities each of these channels provides (Dong, McCarthy, and Schoenmakers, 2017). This may be aggravated by information overload (Ahuja and Lampert, 2001) and escalating complexity and coordination costs when dealing with a variety of external partners (Garcia Martinez, Zouaghi, and Sanchez Garcia, 2017).

Taken together, the above arguments suggest an inverted U-shaped relationship between the level of external knowledge sourcing and firm innovation efficiency.

H1: External knowledge sourcing is related curvilinearly (with an inverted U-shape) to firm innovation efficiency.

The moderating role of high-tech sectors

Prior scholarly work has elucidated that tapping into external knowledge has differential effects on firm innovation outputs in high-tech (cf. non-high-tech) industries, the rationale being that sectoral technological intensity creates different contexts for knowledge creation and sharing (e.g. Sáenz, Aramburu, and Rivera, 2009; Garcia Martinez et al., 2017). Following this logic, we examine how the proposed inverted U-shaped relationship between external knowledge sourcing and firm innovation efficiency is moderated in high-tech sectors.

On the one hand, we expect the innovation efficiency gains associated with lower to moderate levels of external knowledge sourcing to be less pronounced in high-tech (cf.

non-high-tech) firms. The organizational learning theory suggests that firms need to focus on learning by doing and exploitation of existing knowledge in efforts to boost efficiency (Levinthal and March, 1993; March, 1991). In turbulent environments, existing knowledge is quickly rendered obsolete and knowledge exploitation is less relevant; therefore, high-tech firms need to engage in knowledge exploration (Henderson, Miller, and Hambrick, 2006) and reach out to external knowledge to continuously innovate and keep competitive in the marketplace (Gassmann, 2006; Miotti and Sachwald, 2003). Research suggests that reducing variability through learning by doing and knowledge exploitation is less likely to ensure competitive advantage for firms in high-tech sectors, as these are characterized by rapid and unpredictable changes in the technologies, and constant disruption of the status quo (Jansen, Van Den Bosh, and Volberda, 2006; Levinthal and March, 1993; Malerba, Nelson, Orsenigo, and Winter, 2008). By contrast, knowledge exploitation is highly rewarded in relatively stable environments, where knowledge is typically accumulated in a path-dependent way (Henderson et al., 2006). Indeed, low-tech firms often source external knowledge to optimize their project development and execution, and boost efficiency (Chesbrough and Crowther, 2006).

On the other hand, we expect high-tech firms to better alleviate the potential decline in innovation efficiency when the level of external knowledge sourcing is too high. First, in high-tech sectors, firm current R&D expertise is quickly rendered obsolete (Ang, 2008; Bettis and Hitt, 1995; Wu, 2012). To keep their competitive positions, high-tech firms need to continuously revitalize their current R&D resources and routines (Escribano *et al.*, 2009; Helfat and Raubitschek, 2000; Karna, Richter, and Riesenkampff, 2015; Sirmon and Hitt, 2003) by integrating knowledge across firm boundaries (Grant, 1996; Sirmon and Hitt, 2003; Teece, Pisano, and Shuen 1997; Winter, 2003). Therefore, we expect the potential distortions of firm learning processes and R&D routines, triggered by firm excessive use of external knowledge, to be less detrimental for high-tech (cf. non-high-tech) firms. Indeed, research suggests that over-relying on external knowledge is more harmful for low-tech (cf. high-tech) firms, as it entails unnecessary risk, exhausts valuable resources, and disrupts firm efficient functioning (Wang and Li, 2008).

Second, in high-tech sectors, firms typically face complex scientific and technical challenges that often exceed the expertise of any single organization (Frishammar, Florén, and Wincent, 2011; Powell, Koput, and Smith-Doerr, 1996). To address this, high-tech firms tend to engage in inter-organizational collaborations as a norm rather than as an exception (Liebeskind, Oliver, Zucker, and Brewer, 1996). Because firms can learn from their experience in selecting and managing multiple linkages with external partners (Love *et al.*, 2014), it is reasonable to believe that high-tech (cf. non-high-tech) firms develop routines to effectively capitalize on external knowledge flows and are better off at mitigating the extra strain put on firm absorptive capacity when the level of external knowledge sourcing is too high.

Taken together, the above arguments give rise to the following hypothesis:

H2: The inverted U-shaped relationship between external knowledge sourcing and firm innovation efficiency will be flattened in high-tech sectors.

The moderating role of firm internal resource constraints

Prior work has elucidated that firm innovation likely depends on the resource constraints firm face (e.g. Van Burg *et al.*, 2012; de Araujo Burcharth *et al.*, 2015; Hoegl *et al.*, 2008). Whereas past research has advanced our understanding of the direct effects, the question of how firm internal resource constraints moderate the curvilinear relationship between external knowledge sourcing and firm innovation efficiency remains largely unaddressed.

We propose that the positive association between lower to medium levels of external knowledge sourcing and firm innovation efficiency is less pronounced when firms face high internal constraints. Firms with superior in-house R&D resources and capabilities (cf. firms facing resource constraints) are usually better off at exploring innovation undertakings of uncertain outcome (Brunswicker and Vanhaverbeke, 2015), and capitalizing on external knowledge for private innovation-related benefits (Arora and Gambardella, 1994; Berchicci, 2013; Grimpe and Kaiser, 2010; Hung and Chou, 2013). This is because investments in in-house R&D allow firms to build sufficient level of absorptive capacity to effectively screen, assimilate, and internalize external knowledge (Cohen and Levinthal, 1990; Rosenberg, 1990). Indeed, research finds that firm slack resources are positively related to both potential and realized absorptive capacity (Araujo Burcharth et al., 2015). Therefore, resource-constrained firms are likely to capitalize on fewer external opportunities to boost their innovation efficiency. Moreover, internal resource constraints may prevent firms from fully exploiting the potential complementarities between internal and external knowledge (Cassiman and Veugelers, 2006; Hagedoorn and Wang, 2012).

Nevertheless, it is also reasonable to expect that the potential negative relationship between excessive use of external knowledge and firm innovation efficiency is less pronounced in firms that face high internal constraints. Resource-constrained firms are typically attracted to opportunities that are in line with their existing resources (Van Burg, Podoynitsyna, Beck, and Lommelen, 2012). Therefore, rather than going through a more costly process of searching, they tend to acquire external knowledge that fits existing solutions, (Hoegl, Gibbert, and Mazursky, 2008). Resource-constrained firms are not only more likely to leverage and stretch their available resources more efficiently (George, 2005), but also their managerial attention is more likely to shift toward efforts to improve efficiency with familiar technologies and processes (de Araujo Burcharth, Lettl, and Ulhoi, 2015). Since resource-constrained firms tend to mobilize external complementary assets in a more focused manner and/or within the scope of their existing expertise (Teece, 1986), we expect such firms to be better-off at mitigating the costs and complexity associated with excessive external knowledge sourcing.

In light of the above arguments, we suggest the following hypothesis:

H3: The inverted U-shaped relationship between external knowledge sourcing and firm innovation efficiency will be flattened for high levels of internal constraints.

Research methods

Data and sample

Our empirical analysis is based on the Spanish Technological Innovation Panel (PITEC) database, covering the period 2004-2015. The PITEC database follows the Eurostat Community Innovation Survey (CIS) template and is administered by the Spanish National Statistics Institute (INE). It contains detailed information about the innovation activities of Spanish firms from a wide range of industrial sectors. The CIS database has been widely used in empirical scholarly work on open innovation (e.g. Garriga, von Krogh, and Spaeth, 2013; Laursen and Salter, 2006; Escribano *et al.*, 2009).

We constructed our sample by including all firms that met the following criteria and methodological restrictions. First, consistent with the methodological requirements of the first-stage DEA analysis, only firms with positive innovation inputs and outputs were included in the sample. Second, we identified outliers using the detection method proposed by Wilson (1993) and, following Fu (2012), we excluded them from our sample. Additionally, in the second-stage analysis, we used a one-year lag between our independent variable and our dependent variable. This time lag is reasonable in our setting and helps avoid potential endogeneity problems caused by simultaneity. Our final sample consists of an unbalanced panel of 3,204 firms from 2004 to 2015; a total of 12,123 firm-year observations.

Measures

First-stage analysis

Dependent variable. The dependent variable in our study is *firm innovation efficiency*, defined as the firm-specific capability to use fewer R&D resources (inputs) to achieve certain innovation objectives (outputs) relative to the best performers in an industry (Hashimoto and Haneda, 2008; Hienerth *et al*., 2014). Consistent with past research (e.g. Cruz-Cázares *et al.*, 2013; Fu, 2012), we use the DEA methodology as a non-parametric approach to measure firm innovation efficiency. DEA allows handling multiple inputs and outputs expressed in different measurement units (Chen *et al*., 2015).

Similarly to Fu (2012), the inputs in our models are R&D staff as a percentage of total headcount and total R&D expenses as a percentage of sales, whereas the outputs are the percentage of sales corresponding to products that are new to the market, and the percentage of sales of products that are new to the firm (see Table 1). Moreover, Table 1 shows inputs and outputs for high-tech and non-high-tech firms. To calculate firm innovation efficiency, we used a one-year lag between the inputs and the outputs.

Table 1. *Inputs and outputs used in the DEA first-stage analysis: descriptive statistics by type of industry.*

Variable	Mean	Std. Dev.	Min	Max	Obs. by group
products new to the company (% sales) $_{t+1}$	23.09	19.71	0.1	99	high-tech 1417 obs.
products new to the market (% sales) $_{t+1}$	23.86	22.08	0.1	99.9	
R&D expenses (% sales)	0.17	0.71	0.000830	17.67	
R&D staff (% total labor force)	52.08	28.64	1.1	100	
products new to the company (% sales) $_{t+1}$	22.21	21.04	0.1	99.9	non-high-tech 15142 obs.
products new to the market (% sales) $_{t+1}$	22.56	22.23	0.1	99.9	
R&D expenses (% sales)	0.24	1.57	0.000028	91.24	
R&D staff (% total labor force)	47.18	30.85	0.4	100	
products new to the company (% sales) $_{t+1}$	22.28	20.93	0.1	99.9	full sample 16559 obs.
products new to the market (% sales) $_{t+1}$	22.67	22.22	0.1	99.9	
R&D expenses (% sales)	0.23	1.52	0.000028	91.24	
R&D staff (% total labor force)	47.60	30.69	0.4	100	

Since innovation efficiency is industry specific, we estimated it by grouping firms in four broad categories, namely: (a) high, medium-high, medium-low and low technology manufacturing (b) knowledge intensive and less knowledge intensive services, (c) agriculture forestry and mining, and (d) energy and water sewerage and construction.

DEA is a non-parametric programming approach that allows us to generate the efficiency (or best-practice) production frontier from observed multiple inputs and outputs, and to determine a firm's innovation efficiency by its position relative to it (Fu, 2012). We use an input-oriented DEA model, which minimizes R&D resources or inputs, while innovation objectives or outputs are held constant (Hashimoto and Haneda, 2008; Hienerth *et al*., 2014). The simple mathematical form of an input-oriented DEA model with variable returns to scale (VRS) (Banker, Charnes, and Cooper, 1984) is given below:

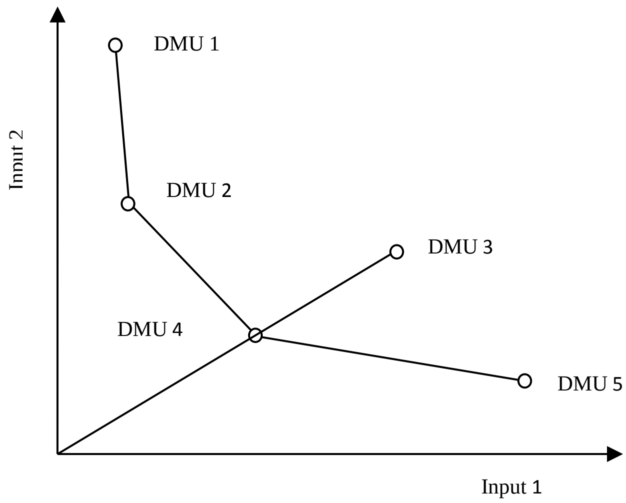
$$
\begin{aligned}
&\theta^{*} = \min \theta \\
&s.t. \\
&\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io} \quad i = 1, 2, \ldots, m; \\
&\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro} \quad r = 1, 2, \ldots, s; \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\lambda_j \geq \qquad\qquad j = 1, 2, \ldots, n.
\end{aligned}
$$

where firm *o* represents one of the *n* firms under evaluation, and x_{io} and y_{ro} are the i_{th} input and r_{th} output for firm *o*, respectively (Banker *et al.*, 1984). When θ*=1, the firm is on the efficiency frontier, indicating that there is no need to adjust its inputs; by contrast, when θ*<1, the firm is less efficient and is encompassed by the frontier.

However, DEA provides point estimates of firms' (in)efficiency without distributional properties. Bootstrapping allows investigating the sampling properties of innovation efficiency estimators providing confidence intervals (Simar and Wilson, 2000). Thus, in order to obtain unbiased innovation efficiency estimates we apply the bootstrap procedure according to Simar and Wilson (1998, 2000).

To better understand the methodological approach used to construct the dependent variables we provide a simplified example that assumes there are five firms, one fixed output, and two inputs (this is solely for illustrative purposes and is not based on mathematical calculations). Figure 1 shows different combinations of two inputs in order to produce the same amount of output, used by these five firms. While firms 1, 2, 4, and 5 are the most efficient ones defining the frontier, firm 3 is far from the frontier. This means firm 3 is less efficient, and it may enhance its efficiency by reducing one or more of the inputs while achieving the same output.

Figure 1. *Graphical representation of the input-oriented DEA model*



The descriptive statistics of the dependent variable *firm innovation efficiency* as a result of the first-stage DEA analysis are provided in Table 2. Almost 4.40% of the observations score above 0.60 in terms of efficiency, and most of the observations score below 0.40. Additionally, the overall mean and standard deviation of firm innovation efficiency is 0.18 and 0.16 respectively. Table 2 also shows the number of observations corresponding to high-tech firms as a percentage of the total observations by range of innovation efficiency. The number of observations belonging to high-tech firms with an efficiency level below 0.20 is around 21% of the total observations in the respective range up to 0.20 while this percentage falls for efficiency scores above 0.20.

Table 2. *Descriptive statistics and distribution of the dependent variable (firm innovation efficiency*

Firm Innovation Efficiency	Obs	Mean	Std. Dev.	Min	Max	% total	
	16559	0.18201	0.169	0.0037	0.9847	Overall	High-Tech
<0.10	6,758					40.81%	13.81%
0.10=<X<0.20	4,803					29.01%	6.75%
0.20=<X<0.40	3,110					18.78%	3.47%
0.40=<X<0.60	1156					6.98%	2.34%
0.60=<X<0.80	675					4.08%	3.56%
0.80=<X<1	57					0.34%	1.75%

Second-stage analysis

Independent variable. The main independent variable is *external knowledge sourcing***,** defined as a firm's use of knowledge from a wide range of external channels such as universities, customers, suppliers, and competitors (e.g. Escribano, *et al.*, 2009). It is measured as an index that captures the importance of different external knowledge sources for innovation (Escribano *et al.*, 2009; Fosfuri and Tribó, 2008). In the PITEC database, the respondents rate the importance of different sources of knowledge for their innovation activities on a four-point scale, from one (not important) to four (very important).

We use factor analysis to construct an index, based on the ratings for ten external knowledge sources: suppliers, clients, competitors, consultants and private institutes, universities, public research institutions, technological centers, conferences and exhibitions, specialized journals and meetings, professional or industrial associations. To perform the factor analysis, we use polychoric correlation matrix, as standard methods of factor analysis assume that the variables are continuous and follow a multivariate normal distribution (Kolenikov and Angeles, 2004). In the first step, the polychoric correlation of the ten aforementioned sources is derived by taking the maximum likelihood estimate of the correlation of these variables assuming an underlying normal variate for each of the variables. In the second step, we use factor analysis based on the obtained correlation matrix and we use orthogonal varimax rotation method to increase interpretability of the resulting factor.

Moderator variables. The variable *high-tech (cf. non-high-tech) sectors* is a dummy variable and takes a value of 1 if the firm operates in a high-tech sector, and 0 otherwise. To differentiate between high-tech and non-high-tech sectors, we follow Eurostat technology industry classification, which is based on the Statistical Classification of Economic Activities in the European Community (NACE Rev.2).

The variable *internal constraints* is measured as an index that accounts for different organizational obstacles that may hinder a firm's innovation efforts. It is constructed using polychoric factor analysis (Kolenikov and Angeles, 2004) including the following six constraints: lack of available funds, lack of funding sources, high innovation costs, lack of information related to technology, lack of information related to markets, and difficulty in finding business partners. The respondents rated the importance of each internal constraint on a four-point scale, from one (not important) to four (very important), and we have reversed the variables.

Control variables. Several control variables are included in the empirical analysis. First, we control for firm size, as prior work indicates that firm size affects a firm's involvement in external knowledge sourcing (e.g. Van de Vrande, De Jong, Vanhaverbeke, and De Rochemont, 2009; Van de Vrande, Vanhaverbeke, and Gassmann, 2010). We measure firm size as the logarithm of the number of employees (e.g. Escribano *et al*. 2009). Furthermore, we control for whether the firm is a start-up by including a dummy variable taking the value of 1 when a firm is a start-up and 0 otherwise; this is because being a new venture might affect a firm's incentives to innovate (Escribano *et al*., 2009). Next, we control for a firm's appropriability strategy, which reflects a firm's use of legal protection mechanisms such as patents, models/designs, trademarks, and copyrights (Gelabert, Fosfuri, and Tribó, 2009). Appropriability regimes can affect the degree to which firms can capture the profits from their innovation activities (e.g. Xu, Huang, and Gao, 2012). We operationalize this variable as an index, using factor analysis on a tetrachoric correlation matrix since the aforementioned variables are all binary. In addition, we control for internal information flows and external market-related constraints for innovation. We also control for the potential advantage of foreignness in innovation (Un, 2011) by including *private multinational* as a binary variable taking the value of 1 when a firm is private and foreign capital participates in its ownership structure, and 0 otherwise. Lastly, we include a dummy variable *group*, which takes the value of 1 if the firm belongs to a group of companies and 0 otherwise, because previous studies reveal that belonging to a business group offers access to resources under better conditions (Khanna and Yafeh, 2007). Finally, we include sector and year dummies to control for sectoral and temporal effects.

Table 3 summarizes the variables in our model, their definition, and operationalization.

Table 3. Variables and measures

Variables and definition	Measurement
Dependent variable:	
Innovation efficiency: firm-specific capability to use fewer R&D resources (inputs) to achieve certain innovation objectives (outputs) relative to the best performers in an industry	Efficiency estimates using Data Envelopment analysis in a model with two inputs (R&D staff as % of total headcount; R&D expenses as % of sales) and two outputs (Sales of products new to the firm as % of total sales; Sales of products new to the market as % of total sales)
Independent variable:	
External knowledge sourcing: a firm's use of knowledge from a range of external channels for innovation	Index obtained by factor analysis of ratings of the relative importance for innovation activities of ten external knowledge sources: suppliers, clients, competitors, consultants and private institutes, universities, public research institutions, technological centres, conferences and exhibitions, specialized journals and meetings, professional or industrial associations.
Moderators:	
High-tech sector: classification of an industry as high-tech (vs. non-high-tech)	Dummy variable taking value 1 if the industry (defined in terms of its NACE Rev.2 code) a firm declares it operates in is classified as high technology by Eurostat, and 0 otherwise.
Internal constraints: internal organizational obstacles that the firm may encounter in its innovation efforts	Index constructed using polychoric factor analysis on ordinal variables measuring the subjective importance of six different internal constraints: lack of available funds, lack of funding sources, high innovation costs, lack of information related to technology, lack of information related to markets, and difficulty in finding business partners.
Controls:	
Firm size	Logarithm of number of employees
Start-up	Dummy variable taking value 1 if the firm is a start-

	up founded in the last two years and 0 otherwise.
Appropriability: use of intellectual property rights to protect innovation outcomes	Index constructed using tetrachoric factor analysis on binary variables taking value 1 if the firm uses the following legal protection mechanisms, and 0 otherwise: patents, models/designs, trademarks, and copyrights
Private multinational	Binary variable taking value 1 if a firm is private and foreign capital participates in its ownership structure
Group	Binary variable taking the value of 1 when the firm belongs to a group of companies and 0 otherwise
Industry and year	Binary variables; industry dummies are defined according to NACE Rev.2 2-digit codes

Statistical methods

We perform the statistical analysis in two stages (see figure 2). In the first stage, firm innovation efficiency is calculated based on the input-oriented VRS modeling approach we described above. Efficiency scores vary between 0 and 1: the higher the score, the more efficient a firm is. In the second stage, we estimate the effects of external knowledge sourcing on firm innovation efficiency. DEA is a deterministic process and methodology, which does not provide the distributional properties of the calculated estimates from the first-stage analysis. In addition, second-stage regression suffers from the correlation of inputs and outputs used in the first-stage analysis with second-stage explanatory variables, and serial correlation among DEA estimates.

Figure 2. *Two-stage analysis and methodological approach*

First-stage analysis

Create the dependent variable Firm Innovation Efficiency through Data Envelopment Analysis (DEA) by applying the bootstrap procedure according to Simar and Wilson (1998, 2000), Tables 1 & 2.
Inputs: R&D expenses, R&D staff
Outputs: products new to the company (% of sales), products new to the market (% of sales)

Second-stage analysis

Hypotheses testing through truncated regression for panel data with bootstrapped confidence intervals (Simar and Wilson1 2007), Table 4.

Independent variable: External Knowledge Sourcing
Moderating variables: Internal Constraints, High-Tech

Various regression techniques have been used in the literature when exploring the impact of environmental variables on the dependent variable constructed via DEA. The majority of them use Tobit or OLS methods, but according to Simar and Wilson (2007) these techniques yield inconsistent estimators due to the above problems, even though the Tobit model has been proposed in the literature as being more appropriate than OLS because of the bounded nature of the data from the first-stage analysis. Thus, in the present paper we use a truncated regression for panel data with bootstrapped confidence intervals that overcome the above problems and allow for valid inference, as suggested by Simar and Wilson (2007).

Results

The descriptive statistics and the correlation matrix of the independent and control variables appear in Tables 4 and 5. External knowledge sourcing has a mean value of 3.20, and around 9.0% of the observations in our sample belong to the high-tech sector. The variable *internal constraints* has a mean value of 3.26 and a standard deviation of 0.76. We have conducted VIF and 1/VIF tests and we have not found evidence of multicollinearity being a problem in our models.

Table 4. *Descriptive statistics by type of industry*

		Full sample (n-12,123)					Non-high-tech (n-11,028)					High-tech (n=1,095)				
		Mean	Median	Std. dev.	Min	Max	Mean	Median	Std. dev.	Min	Max	Mean	Median	Std. dev.	Min	Max
1	External knowledge sourcing	3.2033	3.2000	0.8281	1.3518	5.4072	3.1955	3.2000	0.8312	1.3518	5.4072	3.2826	3.2529	0.7920	1.3518	5.4072
2	Internal constraints	3.2638	3.2751	0.7625	1.2807	5.1228	3.2579	3.2751	0.7605	1.2807	5.1228	3.3229	3.3258	0.7801	1.2807	5.1228
3	High-tech	0.0903	0.0000	0.2867	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	1.0000	1.0000	1.0000	1.0000
4	Size (ln)	4.4915	4.3944	1.5771	0.6931	10.6012	4.4968	4.3820	1.5903	0.6931	10.6012	4.4385	4.4188	1.4372	0.6931	7.9306
5	Appropriability	0.2452	0.1458	0.3133	0.0000	1.1072	0.2446	0.1458	0.3139	0.0000	1.1072	0.2513	0.1458	0.3067	0.0000	1.1072
6	Start-up firms	0.0379	0.0000	0.1911	0.0000	1.0000	0.0375	0.0000	0.1901	0.0000	1.0000	0.0420	0.0000	0.2007	0.0000	1.0000
7	Internal information flows	3.6835	4.0000	0.5798	1.0000	4.0000	3.6806	4.0000	0.5826	1.0000	4.0000	3.7128	4.0000	0.5506	1.0000	4.0000
8	External constraints	1.7812	1.4601	0.6384	1.0878	4.3511	1.7750	1.4601	0.6375	1.0878	4.3511	1.8429	1.5337	0.6447	1.0878	4.3511
9	Group	0.5014	1.0000	0.5000	0.0000	1.0000	0.4952	0.0000	0.5000	0.0000	1.0000	0.5635	1.0000	0.4962	0.0000	1.0000
10	Private Multinational	0.1242	0.0000	0.3299	0.0000	1.0000	0.1201	0.0000	0.3250	0.0000	1.0000	0.1662	0.0000	0.3724	0.0000	1.0000

Table 5. *Correlation matrix*

		1	2	3	4	5	6	7	8	9
1	External knowledge sourcing	1.0000								
2	Internal constraints	0.1574	1.0000							
		(0.0000)								
3	High-tech	0.0302	0.0244	1.0000						
		(0.0009)	(0.0072)							
4	Size (ln)	0.1594	-0.1593	-0.0106	1.0000					
		(0.0000)	(0.0000)	(0.2439)						
5	Appropriability	0.1147	0.0074	0.0061	0.1334	1.0000				
		(0.0000)	(0.4162)	(0.5048)	(0.0000)					
6	Start-up firms	0.0003	0.0118	0.0067	-0.0087	0.0019	1.0000			
		(0.9739)	(0.1949)	(0.4605)	(0.3361)	(0.8350)				
7	Internal information flows	0.1195	-0.0194	0.0159	0.0677	0.0433	-0.0025	1.0000		
		(0.0000)	(0.0325)	(0.0796)	(0.0000)	(0.0000)	(0.7873)			
8	External constraints	0.0169	0.2592	0.0305	-0.0343	-0.0203	0.0048	-0.0890	1.0000	
		(0.0634)	(0.0000)	(0.0008)	(0.0002)	(0.0256)	(0.5971)	(0.0000)		
9	Group	0.0941	-0.1341	0.0391	0.5017	0.0302	0.1549	0.0731	-0.0408	1.0000
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0009)	(0.0000)	(0.0000)	(0.0000)	
10	Private Multinational	-0.0372	-0.1002	0.0401	0.2391	-0.0286	-0.0696	0.0266	-0.0171	0.3006
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0016)	(0.0000)	(0.0034)	(0.0599)	(0.0000)

Notes: obs= 12123, p-values in parenthesis

The results of the second-stage regression are presented in Table 6. Model 1 is the base model and includes only the control variables. Model 2 introduces the main effects of internal constraints and high-tech variables. Model 3 is used to test the first hypothesis, predicting an inverted U-shaped relationship between external knowledge sourcing and firm innovation efficiency. The coefficient of external knowledge sourcing is positive and significant (0.1053, p = 0.0000), while the coefficient for external knowledge sourcing squared is negative and equally significant (-0.0192, p = 0.0000), which confirms our first hypothesis. Graphically, the relationship between external knowledge sourcing and innovation efficiency is presented in Figure 3. The curve reaches its maximum at a level of external knowledge sourcing equal to 2.73, with just one third (33.35%) of the observations located to the left of this point. We further evaluate the existence of the inverted U relationship between external knowledge sourcing and firm innovation efficiency by splitting the sample at the curve's turning point and estimating the slopes separately for both subsamples (Haans, Pieters, and He, 2016). The results (available upon request) confirm a positive and significant relationship between external knowledge sourcing and firm innovation efficiency to the left of the turning point, and a negative and significant one to the right turning point. In sum, these results provide support for Hypothesis 1.

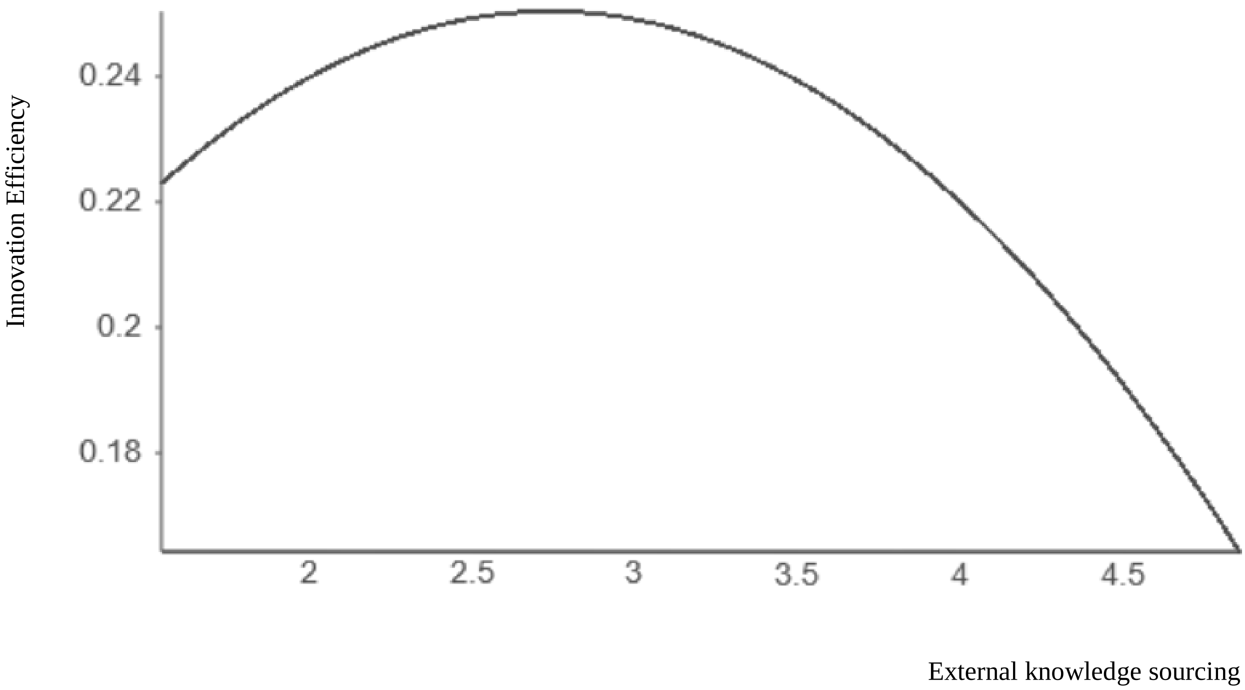
Table 6. *Econometric results from truncated regression models for panel data*

	Model 1	Model 2	Model 3	Model 4
Size (ln)	0.0350	0.0331	0.0350	0.0350
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Appropriability	-0.0346	-0.0325	-0.0291	-0.0324
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Start-up firms	0.0659	0.0654	0.0516	0.0424
	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Internal information flows	-0.0069	-0.0070	-0.0059	-0.0028
	(0.0535)	(0.0488)	(0.0961)	(0.4247)
External constraints	0.0176	0.0179	0.0184	0.0168
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Group	0.0138	0.0138	0.0151	0.0143
	(0.0061)	(0.0055)	(0.0023)	(0.0037)
Private multinational	-0.0111	-0.0052	-0.0081	-0.0041
	(0.1054)	(0.4444)	(0.2339)	(0.5415)
Internal constraints		-0.0006	0.0025	0.1211
		(0.8421)	(0.3736)	(0.0000)
High-tech		-0.1646	-0.1653	0.1114
		(0.0000)	(0.0000)	(0.2224)
External knowledge sourcing			0.1053	0.3980
			(0.0000)	(0.0000)
External knowledge sourcing^2			-0.0192	-0.0679
			(0.0000)	(0.0000)
External knowledge sourcing x Internal constraints				-0.0844
				(0.0000)
External knowledge sourcing^{2}x Internal constraints				0.0140
				(0.0000)
External knowledge sourcing x High tech				-0.1827
				(0.0010)
External knowledge sourcing^{2}x High tech				0.0286

				(0.0006)
Year dummies	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes
Intercept	-0.0599	0.0877	-0.0633)	-0.4566
	(0.0014)	(0.0005)	(0.0605	(0.0000)
logSigma	-1.5175	-1.5268	-1.5367	-1.5444
	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Notes: dependent variable: Innovation efficiency$_{t+1}$, obs: 12123, Estimation of the models is based on Simar and Wilson (2007) using 2000 bootstrap replications for the confidence intervals of the estimated coefficients.,p-values in parenthesis

Figure 3. *External knowledge sourcing and firm innovation efficiency*



Notes: The figure shows the inverted U relationship between external knowledge sourcing and firm innovation efficiency. The range of external knowledge sourcing is calculated based on its mean value plus (minus) two standard deviations. We use the coefficients from model 3 of table 6 with zero values for all dummy variables and mean values for the continuous variables.

As far as the second and the third hypotheses are concerned, Model 4 includes the relevant interaction terms. In Hypothesis 2 we predict that the inverted U-shaped relationship between external knowledge sourcing and firm innovation efficiency will be flattened in high-tech sectors. Testing for flattening is equivalent to testing whether the coefficient estimate of the interaction term between external knowledge sourcing squared and high tech is positive and significant (Haans *et al*., 2016). The coefficient estimates in Model 4 show that the interaction term of external knowledge sourcing and high tech is negative and significant (-0.1827, p = 0.001) and the interaction term with the squared knowledge sourcing is positive and significant (0.0286, p = 0.0006).

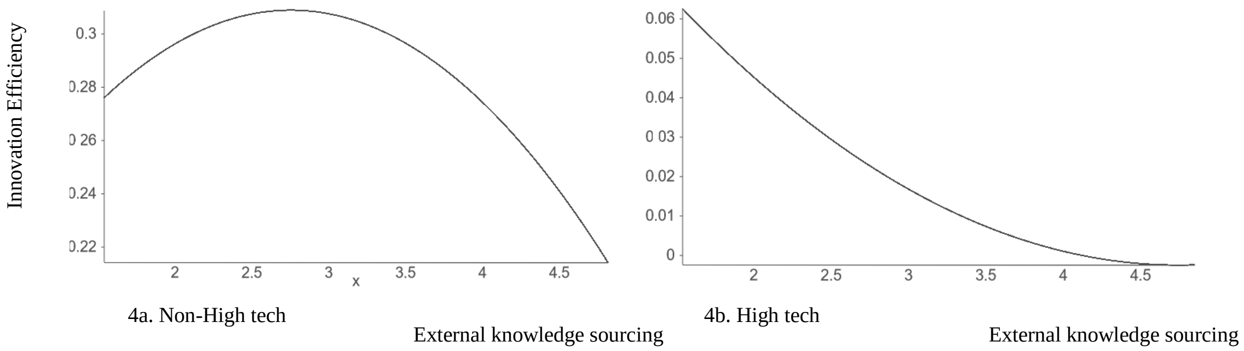
We further examine the results by determining whether a shape-flip occurs because this has important theoretical implications. The level of the moderating variable at which the shape flip occurs (where the relationship between external knowledge sourcing and firm innovation efficiency becomes linear) is determined by calculating the ratio of the coefficient of the squared main independent variable over the coefficient of the interaction between the moderator and the squared independent variable. Thus, in our case this ratio is equal to 0.77 (assuming internal constraints equal to its mean value)[1]. At this level, which theoretically is not important because high-tech sectors is a dummy variable, the shape flip occurs. When the value of the moderating variable is 1 the relationship between external knowledge sourcing and firm innovation efficiency becomes flattened. Figure 4 shows this relationship for high-tech (4b) and non-high-tech sectors (4a) when external knowledge sourcing takes values between minus and plus two standard deviations from its mean. This suggests that in high-tech sectors the positive (negative) latent mechanisms through which external knowledge sourcing influences firm innovation efficiency weaken.

Hypothesis 3 predicts that the inverted U-shaped relationship between external knowledge sourcing and firm innovation efficiency will be flattened in firms with high internal constraints. The coefficient estimates in Model 4 show that the interaction term of external knowledge sourcing and internal constraints is negative and significant (-0.0844, p = 0.0000) and the interaction term with the squared knowledge sourcing is positive and

[1] From model 4 in table 6, the ratio of the coefficients equals -(3.26*0.014 – 0.067) / (0.028) = 0.77

significant (0.0140, p = 0.0000). Thus, we can argue that a flattering of the curve occurs confirming our third hypothesis. We observe that a shape flip occurs when the moderator variable reaches 4.78 (assuming binary variable high tech is equal to zero)[2]. We plot the results in Figure 4 which shows the relationship of external knowledge sourcing (minus/plus 2 s.d.) and firm innovation efficiency for high and low levels of the moderating variables internal constraints (minus/plus 2 s.d.). The shape flip occurs marginally within the data range of the moderating variable internal constraints (mean plus two standard deviations). Thus, we cannot argue that a shape flip occurs well within our data range. The results for the third hypothesis suggest that for medium to high levels of internal constraints and medium to high levels (low) of external knowledge sourcing, weakens the negative (positive) latent mechanisms through which external knowledge sourcing influences firm innovation efficiency (figure 5).

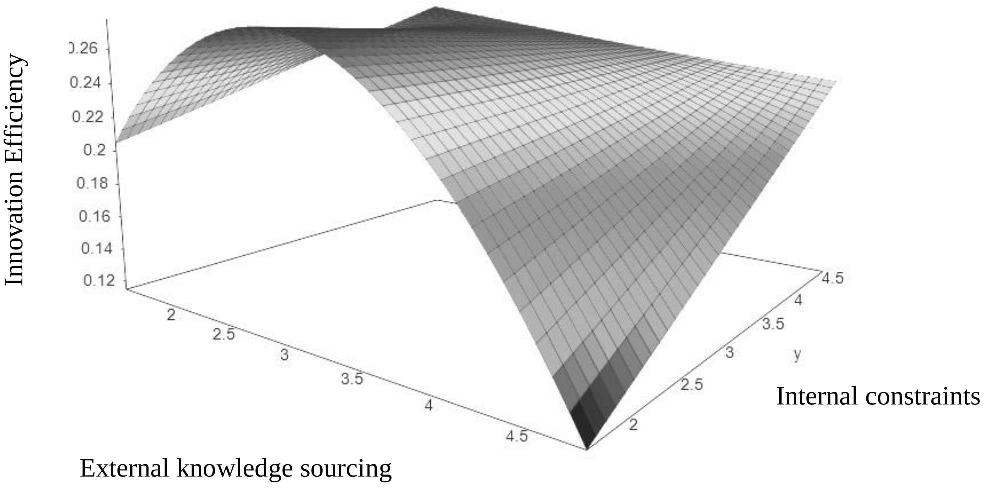
Figure 4. *External knowledge sourcing and firm innovation efficiency: the moderating effect of high-tech vs. non-high-tech industries*



Notes: The figures show the moderating effect of high-tech in the relationship between external knowledge sourcing and firm innovation efficiency. The range of external knowledge sourcing is calculated based on its mean value plus (minus) two standard deviations. We use the coefficients from model 4 of table 6 with zero values for all dummy variables and mean values for the continuous variables.

[2] From model 4 in table 6, the ratio of the coefficients equals -(-0.067) / (0.014) = 4.78

Figure 5. *External knowledge sourcing and firm innovation efficiency: the moderating effect of internal constraints*



Notes: The plot shows the moderating effect of internal constraints in the relationship between external knowledge sourcing and firm innovation efficiency. The ranges of external knowledge sourcing and internal constraints are calculated based on their mean values plus (minus) two standard deviations. We use the coefficients from model 4 of table 6 with zero values for all dummy variables and mean values for the continuous variables.

With respect to the control variables, firm size has a positive and significant coefficient across all the regression models, indicating that large firms on average outperform smaller ones in terms of innovation efficiency. Appropriability strategy has a negative and significant coefficient across all the specifications, showing that formal protection mechanisms are associated to lower efficiency. The coefficient for internal information flows is negative and insignificant in the full model while is significant in the other specifications. The variable external constraints shows a positive and significant effect on innovation efficiency, suggesting that, in the face of external constraints, firms tend to engage in more focused R&D projects with defined short-term efficiency gains. Lastly, the variable group is positive and significant, revealing that belonging to a group of companies is positively associated to firm innovation efficiency maybe due to increased availability of relevant resources.

Discussion

Theoretical Implications

In this paper, we use the lens of the organizational learning theory and delineate a non-linear and contingency-based model to better understand the relationship between the level of external knowledge sourcing and firm innovation efficiency. Our study theoretically hypothesizes and empirically finds evidence that such relationship follows of an inverted U-shaped pattern. Our findings are consistent with past work suggesting that over-engaging with external partners might have detrimental consequences on firm innovation (e.g. Garcia Martinez *et al.*, 2018; Laursen and Salter, 2006). Further, by focusing on firm innovation efficiency as a performance measure, our study extends an influential body of research on the performance-related benefits from *in-bound open innovation* (Chesbrough, 2003). Whereas past work has traditionally focused on innovation outcomes such as sales from new or improved products (Chen, Chen, and Vanhaverbeke, 2011; Laursen and Salter, 2006), number of new products (Bianchi, Cavaliere, Chiaroni, Frattini, and Chiesa, 2011; Greco, Grimaldi, and Cricelli, 2015), and patents (Caputo, Lamberti, Cammarano, and Michelino, 2016; Chen *et al*., 2011; Hagedoorn and Cloodt, 2003), our study sheds new light into how efficiently those innovation outcomes are achieved.

Our contingency-based model further elucidates that firms in high-tech sectors and in resource constrained (cf. resource abundant) contexts face different challenges in capitalizing on external knowledge sourcing. Whereas previous research has highlighted that high-tech firms can benefit from opening their innovation processes to external knowledge in order to cope with increasing demands for continuous innovation (Chesbrough, Vanhaverbeke, and West, 2006), the results of this study show that this comes at a cost, and high-tech (cf. non-high-tech) firms can better mitigate the potential drawbacks associated with excessive external knowledge sourcing. We thus contribute to an on-going debate regarding the role external knowledge flows play in industries with different levels of technological intensity (e.g. Gassmann, Enkel, and Chesbrough, 2010; Hung and Chou, 2013; Sáenz *et al*., 2009; Zouaghi, Sánchez, and García Martínez, 2018). Next, our results demonstrate that the inverted U-shaped relationship between external knowledge sourcing and firm innovation efficiency is moderated by the internal constraints firms face. In doing so, we contribute to prior scholarly work that examines how organizational slack and internal constraints create different contexts for firm innovativeness (e.g. Van Burg *et al*., 2012; de Araujo Burcharth *et al*., 2015; Hoegl *et al*., 2008).

Managerial implications

As success stories are widely shared and celebrated (e.g. Gassmann *et al*., 2010), firms have often been urged to join the "global trend" for open innovation (e.g. Lucas, 2012) and draw on external knowledge to boost their innovativeness (Chesbrough, 2003; von Hippel, 2005). This study has important implications for managers, as it contributes to a more nuanced understanding of the hidden trade-offs managers face when reaching out for external knowledge in attempts to strengthen firm competitive position. On the one hand, sourcing external knowledge is indeed positively linked to the efficiency of firm innovation activities, as firms can learn from benchmarking, external ideas, knowledge, and problem-solving approaches, and identify opportunities for innovation. On the other hand, managers must be aware that relying heavily on external knowledge may have a negative association with firm innovation efficiency because of the potential disruptions of firm R&D routines and learning by doing. Therefore, managers face a difficult task to strike the right balance for their organizations. Our findings do not negate the potential benefits that inbound knowledge flows may have on long-term innovativeness but suggest that they may be accompanied by some organizational costs and trade-offs in terms of efficiency. In addition, our study informs managers about the conditions under which firms can be more successful in capitalizing on external knowledge sourcing in the pursuit of innovation efficiency gains. Our results indicate that the examined relationship is shaped in high-tech sectors and in resource constrained (cf. resource abundant) contexts. Awareness of this can facilitate decision making and can help firms capture greater benefits from sourcing external knowledge.

Limitations and future research

This study has several limitations that can encourage future research. First, we highlight some important contingent factors—technological intensity and internal constraints—that moderate the relationship between external knowledge sourcing and firm innovation efficiency. Future research, however, can further disentangle the contingent nature of the examined relationship by exploring additional contextual factors and firm attributes. Second, whereas the use of a large-scale secondary dataset has advantages in terms of external validity, it does not allow us to directly observe the theoretical mechanisms that underlie our hypotheses. Moreover, although we followed standard research practice to address potential endogeneity and reverse causality concerns in our study (e.g. using time lag), caution about inferring causality should be observed. This prompts researchers to use alternative methodological approaches to delve deeper into how firms use external knowledge in order to deploy their R&D capital more efficiently and shed new light into the mechanisms underlying the observed relationships. Third, our measure of external knowledge sourcing is based on an aggregate subjective measure of the importance of knowledge inflows for innovation. However, knowledge sourcing is a complex phenomenon that comprises a variety of practices (Spithoven, Vanhaverbeke, and Roijakkers, 2013) and involves different challenges (Van de Vrande *et al.*, 2009). Further research may extend this work by providing a fine-grained depiction of the processes of knowledge acquisition, and their effects on innovation efficiency.

Conclusion

This study attempts to enhance our understanding of the contingent nature of the relationship between external knowledge sourcing and firm innovation efficiency, and to clarify the underlying mechanisms behind it. Drawing on insights from the organizational learning theory, we suggest that this relationship is non-monotonic, exhibits an inverted U shape, and is further moderated in high tech (cf. non-high-tech) firms and in firms that face internal constraints. Our findings unveil specific contextual factors—namely the industry technological intensity and internal organizational constraints for innovation—that pose different challenges for firms in their efforts to capitalize on external knowledge sourcing in the pursuit of innovation efficiency gains. Our empirical analysis is based on a sample of 3,204 Spanish firms over the period 2004-2015, and our results provide support to these contentions.

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