European Management Journal xxx (2016) 1–16

Contents lists available at ScienceDirect

European Management Journal

journal homepage: www.elsevier.com/locate/emj

An analysis of the open innovation effect on firm performance

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A R T I C L E I N F O

Article history:
Received 13 May 2015
Received in revised form
28 January 2016
Accepted 11 February 2016
Available online xxx

Keywords:
Open innovation
Innovation performance
Coupled open innovation
Inbound open innovation
Search depth
Search breadth

A B S T R A C T

The open innovation (OI) paradigm describes how firms innovate by interacting with other organizations. Several authors found that specific OI strategies have a positive effect on economic and industrial innovation performance. Nevertheless, over-search and over-collaboration phenomena might reduce the OI marginal returns when a firm resorts to additional external innovation partners. This article hypothesizes that the variety of external innovation channels (search breadth) used by a firm, the extent to which a firm draws deeply from them (search depth) and the extent to which a firm collaborates through different external channels (coupled OI) are curvilinearly related with innovation performance. The empirical models are estimated using 84,919 firms from Eurostat's Community Innovation Survey, which was conducted in 2008 across European countries. The results suggest that search breadth is curvilinearly related with all the measures of innovation performance, whereas search depth is not subject to diminishing marginal returns in most cases. Furthermore, this article shows that coupled OI is curvilinearly related with the development and commercialization of radically new products. The findings of this study make several contributions both in a practical perspective, showing how managers can put into practice different OI strategies to influence innovation performance, and in a theoretical perspective, suggesting a number of recommendations for future research.

1. Introduction

Open innovation (OI) deals with the innovating capability of a firm deriving from the interaction with other firms (Chesbrough, 2003). The origin of the term lays in its ideally opposite meaning with respect to closed innovation, which incurs when all the organizational innovations are produced by means of internal Research & Development (R&D) efforts (Chesbrough, 2003). Firms can adopt OI resorting to one or more strategies: inbound OI, which describes internal use of external knowledge; outbound OI, which describes external use of internal knowledge; and coupled OI, which describes active collaboration with partners to innovate (Cheng & Huizingh, 2014; Gassmann & Enkel, 2004) and ideally results from the combination of inbound and outbound OI activities (Gassmann & Enkel, 2004).

The access to external knowledge through OI is increasingly recognized as a critical source of the firms innovativeness (Duysters & Lokshin, 2011). The literature focussing on OI is mainly devoted to explore how such strategies can affect a firm's innovation performance, both in economic (e.g. turnover share from innovative products) and industrial terms (e.g. development of innovations). Therefore, according to recent reviews, the study of the relationships between OI strategies and firms' innovation performance has roused much interest in the literature (Schroll & Mild, 2012; West & Bogers, 2014). Most authors hypothesized and demonstrated that OI strategies have a positive effect on innovation performance. The rationale behind such hypotheses is quite intuitive: the more a firm interacts with other organizations, the higher will be its access to external ideas, competences, knowledge, technologies and other intangible assets, the higher will be its chances to innovate successfully. In particular, many authors explored the effect on innovation performance of general OI strategies such as inbound, coupled or outbound OI (Cheng & Huizingh, 2014; Chiang & Hung, 2010; Frishammar, Lichtenthaler, & Rundquist, 2012; Hernández-Espallardo, Sánchez-Pérez, & Segovia-López, 2011; Leiponen, 2012; Martini, Aloini, & Neirotti, 2012; Ortiz–de–Urbina–Criado, Montoro–Sánchez, & Mora–Valentín, 2012). Other authors verified the effect of collaborating with specific typologies of external partners, such as customers, suppliers, research institutions and competitors (Czarnitzki & Thorwarth, 2012; Sofka & Grimpe, 2010; Un, Cuervo-Cazurra, & Asakawa, 2010; Vega-jurado, Gutiérrez-

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http://dx.doi.org/10.1016/j.emj.2016.02.008
0263-2373/

Gracia, & Fernández-de-Lucio, 2009).

Nevertheless, firms' resources are typically limited, and interacting with external subjects is a costly activity (Koput, 1997). Indeed, active collaborations require large maintenance costs (Duysters & Lokshin, 2011; Kang & Kang, 2009; Lin, 2014). Therefore, in a cost/benefit perspective, the OI approach may have, after certain levels, diminishing marginal returns on innovation performance, or even a negative effect on it (Lin, 2014). Following this lead some authors demonstrated an inverted U-shaped relationship between OI (in terms of inbound or coupled strategies) and innovation performance (Duysters & Lokshin, 2011; Kang & Kang, 2009; Laursen & Salter, 2006; Lin, 2014). Most of them measured innovation performance in terms of turnover share from radically and/or incrementally innovative products, whereas Kang and Kang (2009) measured it in terms of the number of product innovations introduced. These articles analysed country-specific large samples (Netherlands, Korea, United Kingdom and Taiwan, respectively) whose cultural and macroeconomic peculiarities may have affected the external validity of the results.

Overall, as described above, studying the link between OI and innovation performance is pivotal in the OI literature. Most authors demonstrated a positive effect of several OI strategies on innovation performance, whereas only few authors found relationships taking an inverted U-shape. Nevertheless, such lack of agreement is probably due to authors' methodological choices rather than to the real characteristics of the phenomenon. Indeed, the vast majority of studies did not hypothesize, and consequently did not test, inverted U-shaped relationships between OI and innovation performance (Greco, Grimaldi, & Cricelli, 2015). All of the existing empirical evidence supporting U-shaped relationships resorted to country-specific samples. Most of them also measured only one or two OI strategies. In fact, the synergistic effect of coupled and inbound OI on innovation performance has not been explored yet, the effect of the two strategies having always been studied separately. Nevertheless, the inbound and coupled OI often coexist in the same firm, and their concurrent effect may differ from their individual ones (Mazzola, Bruccoleri, & Perrone, 2012).

Therefore, this study aims to fill the gap in the literature by answering to the following research question:

RQ. *"Are OI strategies curvilinearly (taking an inverted U-shape form) related with innovation performance in European firms?"*

The importance of a comprehensive and convincing answer to our research question lays both in its practical and theoretical implications. Indeed, managers are likely to benefit from knowing accurately which effect OI is likely to have on their firms' innovation performance. Providing an answer to our research question may also help scholars to produce more fine-grained researches comparing the results of different countries, industries or exploring the effect of specific OI sources in a different perspective from previous studies.

In order to answer to our research question properly we needed to analyse an appropriate amount of firms, covering multiple countries, sectors and sizes. The difficulty in identifying and contacting a vast, representative sample of the firms' population in a wide number of countries and sectors brought us to use high-quality secondary data collected by Eurostat. Thus, this article explores the relation between OI and innovation performance on a European scale, by means of the most recent micro data of the Community Innovation Survey (CIS), which is released by Eurostat for research purposes. The refined sample used in this article includes 84′919 firms from 14 European countries. To the best of our knowledge, this is the most extensive sample ever used in the OI literature.

The paper is structured as follows. Section 2 reviews the theoretical background, while Section 3 presents the hypotheses of the study. Section 4 describes the dataset and the research methodology. The results of the study are shown in Section 5 and discussed in Section 6. Finally, Section 7 identifies the implications for academics and managers, suggesting future developments.

2. Theoretical background

Firms have always been prompted to develop innovations in order to achieve competitive advantage (Lengnick-Hall, 1992). To this aim, for much of the 20th century firms' internal R&D laboratories were considered the main sources of technological innovation (West & Bogers, 2014). Nevertheless, far before the term "Open Innovation" was introduced by Chesbrough (2003), firms were already interacting with other organizations such as universities and suppliers in order to improve their innovation performance (Vanhaverbeke, West, & Chesbrough, 2014). According to the OI paradigm, firms are becoming increasingly aware of the need to interact with their abundant underlying knowledge landscape to integrate their internal Research & Development (R&D) efforts and of the importance of managing their outbound flows of knowledge and technology (Chesbrough, 2006). In this perspective, internal R&D is just as important as gathering external knowledge from other sources, whereas in the past the latter approach had a somewhat supplementary and limited role in shaping most firms' innovation strategy (Chesbrough, 2006).

In several industries even the largest firms need to open their innovation activities by collaborating with other organizations in order to keep pace with technological developments (Brusoni, Prencipe, & Pavitt, 2001; Chen, Chen, & Vanhaverbeke, 2011). A firm whose internal innovation process involves external organizations may insource some of their knowledge, competences and technology (inbound OI), or may actively collaborate with them (coupled OI).

When resorting to an inbound OI strategy, a firm tries to search outside of its boundaries the skills, competences or technologies that it does not own, and that would take too much cost, effort and time to be developed internally. A large amount of external subjects such as research institutions, suppliers, customers, consultants and competitors may provide the firm with the knowledge it needs (Faems, Van Looy, & Debackere, 2005; Tether & Tajar, 2008). The variety of external sources used by a firm describes its external search breadth (SB), whereas the extent to which a firm draws deeply from different external sources describes its external search depth (SD) (Laursen & Salter, 2006). According to a recent study, a remarkably high percentage of European firms were already adopting the inbound OI mode before Chesbrough's seminal work on OI itself (77% in 2001), and after a steep increase measured in 2004, the percentage remained stable on very high levels (around 90%) (Cricelli, Greco, & Grimaldi, 2016). This reinforces the perception that inbound OI strategies are considered very effective to enhance firms' innovativeness, and are already widespread in most industries.

Similarly to inbound OI, coupled strategy may imply collaborations with several partners of different types (Un et al., 2010), to a higher or lower degree of intensity (Kang & Kang, 2009). A firm may want to collaborate with external subjects in order to achieve several business goals, such as increasing its profitability, shortening the time-to-market, enhancing innovation capability, creating greater flexibility in internal R&D or expanding market access (Chesbrough & Schwartz, 2007). On the one hand, collaborating with external subjects requires additional efforts and costs with respect to merely acquiring know-how from them. Firms may sustain costs of coordination when interacting with other organizations (Faems, De Visser, Andries, & Van Looy, 2010), and an

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excessive number of relationships may lead to a diversion of managerial attention (Dahlander & Gann, 2010). Furthermore, additional costs may emerge from the risk that one actor would act opportunistically in bad faith, and from the need to protect ideas and know-how to which others have access (Dahlander & Gann, 2010). On the other hand collaborations can enhance the interchange of tacit and explicit knowledge (Faems, Janssens, & van Looy, 2007; Mowery, Oxley, & Silverman, 1996), may reduce technology market inefficiencies (Lichtenthaler, 2013) and some of the risks and costs of technological activities (Belderbos, Faems, Leten, & Van Looy, 2010).

The debate about the effect of SB, SD and coupled OI strategies on innovation performance is very much alive. In most cases, research articles explored the effect of one or two of such strategies, often limiting their scope of analysis to specific industries, countries, or to specific typologies of the external sources/partners (e.g. in terms of links with universities, links with foreign organizations, links with customers, link with competitors …). Such heterogeneity in the characteristics of the samples and of the independent variables, matched with remarkable differences in the approaches used to measure innovation performance, resulted in a lack of agreement, in generic terms, on the effect of SB, SD and coupled OI on innovation performance (Greco et al., 2015). The articles related to the OI literature measured innovation performance through two main approaches: industrial innovation performance (IIP) and economic-financial innovation performance (EIP).

IIP refers to the development of new products or services, regardless their market success. IIP has been operationalized by verifying the successful introduction of an innovation regardless to its novelty (Mention, 2011; Revilla, Sáenz, & Knoppen, 2013; Trigo & Vence, 2012; Vega-jurado et al., 2009). Some authors distinguished between the introduction of an innovation new to the market (radical IIP) (Ebersberger & Herstad, 2011; Inauen & Schenker-Wicki, 2012; Nieto & Santamaría, 2007), or only new to the firm (incremental IIP) (Inauen & Schenker-Wicki, 2012; Nieto & Santamaría, 2007). Other authors measure IIP through patents count (Belussi, Sammarra, & Sedita, 2010; Hussler & Rondé, 2009; van de Vrande, Vanhaverbeke, & Duysters, 2011) or patents citations (Messeni Petruzzelli, 2011).

EIP refers to the economic impact of the innovation process. The most popular EIP measure takes into account the turnover share deriving from radical innovations (Grimpe & Sofka, 2009; Köhler, Sofka, & Grimpe, 2012; Laursen, 2011; Laursen & Salter, 2006;Martini et al., 2012; Neyens, Faems, & Sels, 2010; Sofka & Grimpe, 2010) or from incremental ones (Köhler et al., 2012; Laursen, 2011; Laursen & Salter, 2006; Neyens et al., 2010). Other authors used the turnover deriving from innovative products regardless to their degree of novelty (Czarnitzki & Thorwarth, 2012; Faems et al., 2010; Kuittinen, Puumalainen, Jantunen, Kyläheiko, & Pätäri, 2013; Leiponen, 2012).

3. Open innovation and innovation performance: hypotheses development

This section introduces the hypotheses of the study with respect to SB, SD and coupled OI effect on innovation performance.

3.1. External search breadth

A firm can benefit from a high SB, as having several external channels to gather knowledge may grant it access to innovations or innovation-producing capabilities that the firm does not hold (West & Bogers, 2014). A firm may find existing ideas or technologies outside its organizational boundaries and use them to initiate or enhance internal R&D activities (Dahlander & Gann, 2010). As a result, those firms that are prepared for taking advantage of external sources of knowledge may be more successful in introducing innovations with different levels of radicalness (Chiang & Hung, 2010) and in generating additional sales. In fact, they can access to additional resources that they do not own (Grimpe & Kaiser, 2010; Weigelt, 2009), increasing their problem solving arsenal (Duysters & Lokshin, 2011) and enabling new paths to existing market, or favouring the creation of standards in emerging markets (Dahlander & Gann, 2010).

Indeed, several authors have shown a positive effect of SB on the development of radical innovations (Chiang & Hung, 2010), on radical EIP (Grimpe & Kaiser, 2010) and EIP and IIP in more generic terms (Duysters & Lokshin, 2011; Schweitzer, Gassmann, & Gaubinger, 2011). Nevertheless, to the best of our knowledge no previous study demonstrated a positive effect of SB on incremental IIP. In fact, Chiang and Hung (2010), who tested such effect, did not obtain statistically significant results.

Despite the empirical evidence backing the positive effect of SB on innovation performance, using an excessive number of channels can turn into an "over-search" that may also have a negative effect on the focal firm's innovation performance (Koput, 1997; Laursen & Salter, 2006). Indeed, a firm may be overwhelmed by an excessive number of innovation ideas, methods or strategies, facing costs to choose among them or not paying enough attention to bring all of them into implementation (Koput, 1997). Moreover, each channel "*can be seen as a separate search space, encompassing different institutional norms, habits and rules; often requiring different organizational practices in order to render the search processes effective within the particular knowledge domain*" (Laursen, 2011, p. 715). Thus, using additional search channels may cause specific costs related to the peculiarities of each channel. Following this lead, Laursen and Salter (2006) and Laursen (2011) demonstrated that SB was curvilinearly (taking an inverted U-shape) related to EIP deriving from products new to the market (radical innovations) and from products new to the firm (incremental innovations). Nevertheless, their results are still isolated in literature and their hypotheses have not been tested on multiple-country samples yet. Consequently, we hypothesize that:

Hp. 1a. *The external search breadth is curvilinearly related (taking an inverted U-shape) with the turnover share from radical innovations*

Hp. 1b. *The external search breadth is curvilinearly related (taking an inverted U-shape) with the turnover share from incremental innovations*

The over-search problem grounding Hp. 1a and Hp. 1b is expected to have a negative effect on the innovation productivity of the focal firm, because it might reduce the firm potential to develop innovations by dispersing its limited resources. Nevertheless, the turnover share from innovative products is a measure of their market acceptance (Köhler et al., 2012). Firms with a high turnover share from innovative products suggest an external observer that they are successful innovators, whereas there is a chance that their market success has depended on massive marketing investments, on the introduction of marketing innovations (such as new design, packaging, promotion, placement or pricing methods) or on external socio-economic circumstances. Moreover, by construction, turnover share measures the ratio between turnover from innovative products and total turnover, thus not taking into consideration any of the costs related to the development of the products, which may have risen in the case of over-search proportionally more than sales. Thus, we want to explore whether the curvilinearly effect of SB on innovation performance can be measured in terms of IIP, which only verifies whether a firm successfully developed an innovation, without considering its market success. Therefore, we test whether the external search activities succeeded in their main goal of producing a tangible output that can be industrialized and commercialized. As firms have limited resources, the beneficial effect of SB may be counterbalanced by the time and effort dedicated to the search and selection of external ideas, reducing the odds of developing successful product innovations. Therefore, we posit:

Hp. 2a. *The external search breadth is curvilinearly related (taking an inverted U-shape) with the introduction of radical product innovations*

Hp. 2b. *The external search breadth is curvilinearly related (taking an inverted U-shape) with the introduction of incremental product innovations*

3.2. External search depth

Inbound OI does not involve, of course, only searching for different channels to draw in innovations, knowledge and competences. Indeed, once a channel is found, the focal firm may benefit from drawing deeply from it, taking advantage of lower transaction costs and long-term relationships. Furthermore, the firm will be increasingly able to communicate effectively with its favoured external sources (Ferreras-Méndez, Newell, Fernández-Mesa, & Alegre, 2015). The difficulties in establishing purposive interactions with external sources encompassing different institutional norms, habits and rules, may be somewhat less pronounced when the firm is used to interact in a certain context. For example, a firm may find difficult to interact with an academic institution in the early stages of their relationships, exploring its bureaucracy, its organisational structure and culture and its specific communication patterns, nevertheless, as the intensity of their interactions increases, the firm will move swiftly in the counterpart's field. External SD, which measures how intensively the focal firm draws knowledge from different channels, is therefore likely to have a positive effect on innovation performance. Indeed, some authors demonstrated a positive effect of SD on the development of radical innovations (Martini et al., 2012) and incremental innovations (Chiang & Hung, 2010). As discussed by Ferreras-Méndez et al. (2015), the positive effect of SD on EIP and IIP is most likely influenced by the focal firm's absorptive capacity, i.e. by its capability to comprehend and retain the inputs drawn from external sources.

As previously discussed for SB, we expect that the limited economic and human resources of the focal firm might reduce its chances to successfully draw knowledge and competences from too many privileged channels. Following this lead, Laursen and Salter (2006) verified that SD was curvilinearly (taking an inverted U-shape) related to turnover share deriving from radical and incremental innovations. Nevertheless, Lee (2010), who tested the same relationships in Korea's Information Technology Industry, did not find support for their hypothesis. Thus, Laursen and Salter's contribution remain rather isolated in the literature and appears quite focused on a specific economic context (manufacturing firms in the UK), which may not be safely generalized. Therefore, we replicate their study by formulating the following hypotheses:

Hp. 3a. *The external search depth is curvilinearly related (taking an inverted U-shape) with the turnover share from radical innovations*

Hp. 3b. *The external search depth is curvilinearly related (taking an inverted U-shape) with the turnover share from incremental innovations*

Again, in consideration of the limitations of the turnover share from innovative products that we discussed before (i.e. potential distortive effect of marketing activities and potentially biased interpretation of the share of innovation sales when the corresponding share of innovation costs is not considered) we formulate the following hypotheses:

Hp. 4a. *The external search depth is curvilinearly related (taking an inverted U-shape) with the introduction of radical product innovations*

Hp. 4b. *The external search depth is curvilinearly related (taking an inverted U-shape) with the introduction of incremental product innovations*

3.3. Coupled OI

Firms can take fully advantage of the OI paradigm by collaborating with other organizations rather than merely importing knowledge, competences and innovations. Indeed, collaboration may favour the exchange of tacit and explicit knowledge (Faems et al., 2007; Mowery et al., 1996), especially when intensive communications are maintained among the partners (Teirlinck & Spithoven, 2013). Furthermore, it may reduce some technology market inefficiencies (Lichtenthaler, 2013) and some of the risks and costs of technological activities, possibly increasing their chances to be successful (Belderbos et al., 2010). In other words, co-development can increase the return from the focal firm's internal R&D by leveraging it partners' capabilities (Chesbrough & Schwartz, 2007). Indeed, many authors demonstrated the positive effect of collaborating with specific categories of partners (such as customers, universities, suppliers) on innovation performance (Czarnitzki & Thorwarth, 2012; Faems et al., 2005; Knudsen, 2007; Laursen, 2011; Mention, 2011; Trigo & Vence, 2012; Un et al., 2010; van de Vrande et al., 2011). Nonetheless, collaborating with external partners from many different channels is likely to be even more challenging than merely sourcing knowledge from them, although it is also likely to be more rewarding. Therefore, having too many active collaboration channels may disperse resources, requiring large maintenance costs (Kang & Kang, 2009) to sustain the coordination complexity (Duysters & Lokshin, 2011; Narula, 2004), and may cause diminishing returns on innovation performance. Furthermore, co-developing innovations requires additional efforts to protect the focal firm's intellectual property or ideas from its partners' potentially opportunistic behaviour (Dahlander & Gann, 2010; Zhao, Sun, & Xu, 2015). Consistently with this, some authors observed an inverted-U-shape relationship between the extent of using R&D collaboration and innovation performance in terms of the perceived number of product innovations (Kang & Kang, 2009) and in terms of share of sales due to new products introduced by a firm (Duysters & Lokshin, 2011). In both cases the authors did not distinguish between radical and incremental innovations and explored country-specific samples (Korean and Dutch firms, respectively) leaving much space for additional studies. Thus, we hypothesize the following:

Hp. 5a. *Coupled OI is curvilinearly related (taking an inverted U-shape) with the turnover share from radical innovations*

Hp. 5b. *Coupled OI is curvilinearly related (taking an inverted U-shape) with the turnover share from incremental innovations*

While the mainstream measure of EIP used to verify hypotheses 5a and 5b is very effective to understand the effectiveness of coupled OI in improving firms' sales, still an IIP measure is needed to understand how such OI practice can enhance firms' innovativeness. In fact, as discussed before, turnover share may be affected by the firm's own marketing activities, but also – in the case of coupled OI – by the marketing efforts of the focal firm's partners (Bhalla, 2010). Therefore, the positive effect of coupled OI on EIP

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measures might be stronger than that observable on IIP measures, although we expect an inverted U-shape in both cases. Therefore, we hypothesize:

Hp. 6a. *Coupled OI is curvilinearly related (taking an inverted U-shape) with the introduction of radical product innovations*

Hp. 6b. *Coupled OI is curvilinearly related (taking an inverted U-shape) with the introduction of incremental product innovations*

Fig. 1 synoptically summarizes all the hypotheses of the study.

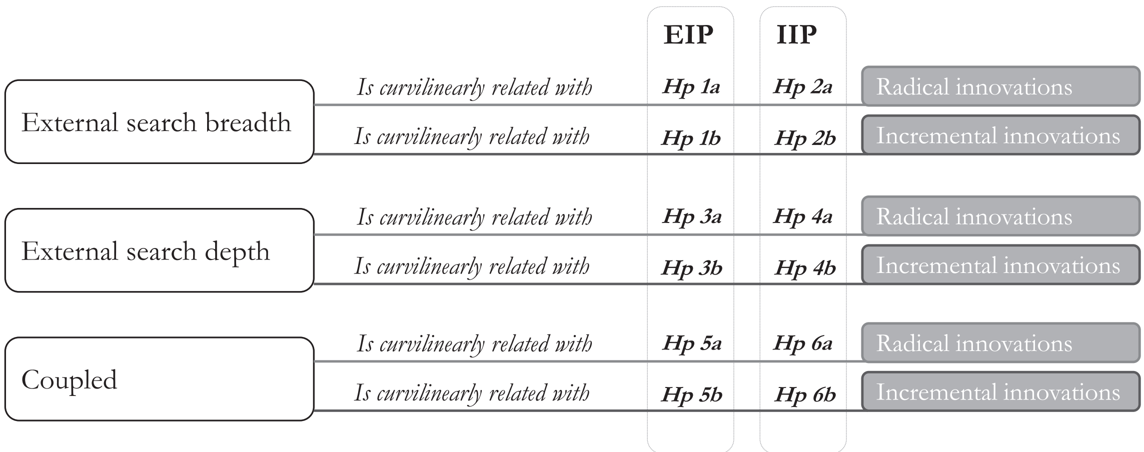

Fig. 1. Synoptic view of the hypotheses of the study.

4. Methodology

This section defines the variables that are analysed in the article, the methodological approach adopted to answer the research question and the characteristics of the sample.

4.1. Measures

This article aims to measure the OI impact on organizational innovation performance, both in an IIP and EIP perspective.

In a IIP perspective, many authors used dichotomous variables in their studies on OI, most of the times measuring whether a new product had been developed by a firm, or not, regardless to its degree of novelty (Ortiz–de–Urbina–Criado et al., 2012; Trigo & Vence, 2012; Vega-jurado et al., 2009; Wagner, 2011). Mention (2011) used a dichotomous variable taking the value of 1 in case of radical innovations introduced, and 0 in case of only incremental innovations introduced. In order to identify clearer results about the potentially different effect of OI on radical and incremental IIP we used the two variables *NEWMKT* and *NEWFRM* (Ebersberger & Herstad, 2011; Inauen & Schenker-Wicki, 2012; Nieto & Santamaría, 2007). *NEWMKT* takes the value 1 if during the three years 2006–2008 the company introduced a new or significantly improved good or service onto its market before its competitors (it may have already been available in other markets), 0 otherwise. *NEWFRM* takes the value 1 if during the three years 2006–2008 the company introduced a new or significantly improved good or service that was already available from its competitors in its market, 0 otherwise.

EIP, consistently with previous empirical studies (Grimpe & Sofka, 2009; Köhler et al., 2012; Laursen, 2011; Laursen & Salter, 2006; Martini et al., 2012; Neyens et al., 2010; Sofka & Grimpe, 2010) is measured through the variables TURNMAR (the share of 2008 total turnover from radical innovations implemented from 2006 to 2008) and TURNIN (the share of 2008 total turnover from incremental innovations implemented from 2006 to 2008). The two variables aim to assess the firm's radical and incremental EIP, respectively.

This article studies three independent variables to describe SB, SD and coupled OI.

BREADTH and *DEPTH* are measures of SB and SD as defined by Laursen and Salter (2006), which had been widely used or adapted in the literature (Chen et al., 2011; Chiang & Hung, 2010; Schroll, Andreas, & Mild, 2011; Schweitzer et al., 2011).

BREADTH of the i-th company is defined as:

$$BREADTH_i = \sum_{k=1}^{9} dummy - breadth_{ki} \; \forall \; i$$
$$with \;\; dummy - breadth_{ki} = \begin{cases} 1 \quad if \;\; the \;\; k - th \;\; source \;\; has \;\; been \;\; used \;\; by \;\; the \;\; i - th \;\; company \\ \qquad 0 \quad otherwise \end{cases} \tag{1}$$

DEPTH of the i-th company is defined as:

$$BREADTH_i = \sum_{k=1}^{9} dummy - depth_{ki} \; \forall \; i$$
$$with \; dummy - depth_{ki} = \begin{cases} 1 \; if \;\; the \;\; k - th \;\; source \;\; has \;\; been \;\; used \;\; by \;\; the \;\; i - th \;\; company \;\; to \;\; a \;\; high \;\; degree \\ \qquad 0 \quad otherwise \end{cases} \tag{2}$$

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The 9 sources considered to calculate *BREADTH* and *DEPTH* are the following: Suppliers of equipment, materials, components, or software; Clients or customers; Competitors or other enterprises in the focal firm's sector; Consultants, commercial labs, or private R&D institutes; Universities or other higher education institutions; Government or public research institutes; Conferences, trade fairs, exhibitions; Scientific journals and trade/technical publications; Professional and industry associations. Therefore, both *BREADTH* and *DEPTH* can take values in a range from 0 to 9.

The third independent variable, coupled OI, is measured by means of questionnaire items about cooperation partners. Respondents had to specify the type of organisation and location in case of active cooperation arrangements on innovation activities with other enterprises or institutions. The measure is similar to that introduced by Laursen and Salter (2006), who defined a similar proxy as *DEPTH-COLLAB*, implicitly emphasizing that the mere existence of a collaboration underpins an in-depth interaction with partners.

COUPLED of the i-th company is defined as:

$$COUPLED_{\mathrm{i}} = \sum_{k=1}^{6} dummy - coupled_{ki} \ \forall \ i \\ with \ dummy - coupled_{ki} = \begin{cases} 1 \ if \ the \ i-th \ company \ collaborated \ with \ the \ k-th \ source \\ \qquad 0 \ otherwise \end{cases} \tag{3}$$

The six sources of coupled OI are the following: Suppliers of equipment, materials, components, or software; Clients or customers; Competitors or other enterprises in the focal firm's sector; Consultants, commercial labs, or private R&D institutes; Universities or other higher education institutions; Government or public research institutes. Therefore, the variable takes values in the range 0–6 for each company. Noticeably, we did not include a seventh collaboration partner reported in the CIS questionnaire and labelled as “Other enterprises within your enterprise group”. In fact, collaboration among firms within the same group may be considered more a physiological phenomenon rather than a sign of openness of the focal firm. Indeed, collaborating with firms within the same group raises both less concerns related to potential spillovers of knowledge, and related to the transaction costs underpinned in collaborations with external subjects. Nevertheless, being part of a group may facilitate a firm in finding external sources of innovation or external partners, both due to the physiologically larger network of a group rather than that of a single firm, and due to the attractiveness of a firm member of a group for external organizations that may want to gain visibility with the holding company. Therefore, we introduced the dummy GRP that takes the value 1 if the focal firm declared to be part of a group and 0 vice-versa.

Several other control variables may influence the dependent variables. They are described as follows.

The R&D intensity (*RDINT*), defined in terms of the ratio of total internal R&D expenditures on sales (Hurmelinna-Laukkanen, Olander, Blomqvist, & Panfilii, 2012; Un et al., 2010), or of total R&D expenditures on sales (Cappelli, Czarnitzki, & Kraft, 2014; Ebersberger & Herstad, 2011; Kang & Kang, 2009; Leiponen, 2012; Michelino, Lamberti, Cammarano, & Caputo, 2015) is frequently adopted as a control variable in the innovation output equation, being independent of size effects (Ebersberger & Herstad, 2011). Indeed, it represents the firm's internal effort for R&D (Kang & Kang, 2009) and its absorptive capacity (Cohen & Levinthal, 1990). Therefore, it can both represent a driver that attracts external partners (a firm investing much in internal R&D may be considered a desirable partner in an OI perspective) and an enabler and enhancer of the OI contribution to the innovation development process. *RDINT* is very skewed in the economy, and extreme variables are likely to affect the mean value of its distribution, therefore we performed a logarithmic transformation of the ratio of total R&D expenditures and sales (Aerts & Schmidt, 2008; Hurmelinna-Laukkanen et al., 2012; Li & Tang, 2010). Including the squared R&D intensity in the regression ($RDINT^2$) allows controlling for a nonlinear relationship (Czarnitzki & Thorwarth, 2012).

Firm size is also likely to have an impact on firms innovativeness (Cheng & Huizingh, 2014), therefore, consistently with previous studies (Huggins & Johnston, 2010; Ortiz–de–Urbina–Criado et al., 2012), we have introduced the *SIZE* ordinal control variable, which takes the value 0 for companies with a number of employees in the range 10–49 employees (small), 1 for the range 50–249 employees (medium-sized), and 2 for more than 249 employees (large).

As different industries and different home countries may underpin different strategies to innovate we have also introduced fourteen sectorial dummy variables (one for each NACE section included in the sample) and fourteen country dummy variables (one for each European country included in the sample). Industry dummies are often included in multi-sectorial studies (Belderbos et al., 2010; Czarnitzki & Thorwarth, 2012; Kang & Kang, 2009; Laursen & Salter, 2006; Un et al., 2010), and country dummies are often included in articles studying multiple countries (Belderbos et al., 2010; Köhler et al., 2012; Messeni Petruzzelli, 2011; Sofka & Grimpe, 2010).

The turnover share associated to new products is likely to be influenced by the implementation of a new marketing concept or strategy. In order to control for this factor we have introduced the dummy *MKT*, which takes the value 1 if the firm introduced one or more marketing innovations (i.e. new design, packaging, promotion, placement or pricing method), 0 if it did not introduce any marketing innovations.

Finally, the receipt of public subsidies may induce – or even require – firms to cooperate with external organizations or to draw innovation from them. Indeed, several empirical studies exploring the behavioural additionality of public subsidies have demonstrated that firms with access to such funds are more likely to cooperate with other organizations (Gallego, Rubalcaba, & Suárez, 2013; Miotti & Sachwald, 2003; Negassi, 2004; Segarra-Blasco & Arauzo-Carod, 2008). Furthermore, public funds may also generate output additionality, improving the target organization's odds to develop an innovation-related output (Clarysse, Wright, & Mustar, 2009), such as an higher degree of innovation in firms (Hummel, Karcher, & Schultz, 2013) or an improved patenting activity (Czarnitzki, Ebersberger, & Fier, 2007). Therefore, we introduce the dummy *FUND*, which takes the value 1 if the firm benefited from public financial support from local, regional, central governments or from the European Union in the years from 2006 to 2008, 0 if the firm did not receive any public subsidy.

Table 1
Overview of dependent, independent and control variables.

Variable	Definition	Variable type
TURNMAR	Share of turnover deriving from new or significantly improved goods and services introduced during 2006–2008 that were new to the focal firm's market	Continuous dependent v.
TURNIN	Share of turnover deriving from new or significantly improved goods and services introduced during 2006–2008 that were new to the focal firm's but not to its market	Continuous dependent v.
NEWMKT	New to the market product introduced in the triennium 2006–2008	Binary dependent v.
NEWFRM	New to the firm product introduced in the triennium 2006–2008	Binary dependent v.
BREADTH	Number of categories of innovation sources used to low, medium or high degree	Discrete independent v. (0–9)
DEPTH	Number of categories of innovation sources used to a high degree	Discrete independent v. (0–9)
COUPLED	Number of categories of partners used to any degree	Discrete independent v. (0–30)
RDINT	Logarithmic transformation of the ratio of the firm's total R&D investments on the firm's turnover	Continuous control v.
GRP	The firm is part of a group, or not	Binary control v.
FUND	The firm benefited from public subsidies in the triennium 2006–2008, or not	Binary control v.
MKT	Marketing innovations introduced in the triennium 2006–2008, or not	Binary control v.
SIZE	Size of the focal firm	Ordinal not metric control v. (0, 1, 2)
NACE	NACE section of the firm	14 binary control v.
COUNTRY	Country of the firm	14 binary control v.

Table 1 provides an overview of dependent, independent and control variables.

4.2. Data

We requested access to the results of Eurostat Community Innovation Survey (CIS) in order to test our hypotheses on the largest number of firms, countries and sectors. We analysed the micro-aggregated data available in the CD-ROM release of CIS2008, which is based on the 2008 reference year. The CIS 2010 and CIS 2012 CD-ROMs, which are the most recent CIS waves, were still unavailable at the date of our study. The CIS statistics are part of the EU science and technology statistics. The surveys are carried out with two years frequency by voluntary EU member states and some European Social Survey member countries (European Commission, 2015). The harmonized CIS survey aims to provide information about several aspects of innovation within organizations.

Possibly the most relevant disadvantage of using secondary data collected by a reputed international institution lays in that they may not include all the variables of interest for a study (Vartanian, 2010). Nevertheless, in our case, CIS micro data allows measuring the variables of interest, as demonstrated by the large number of scholars using CIS to explore various aspects of OI (Barge-Gil, 2010; Ghisetti, Marzucchi, & Montresor, 2015; Köhler et al., 2012; Laursen, 2011; Laursen & Salter, 2006; Leiponen, 2012; Sofka & Grimpe, 2010). Another limit observed in most datasets, including previous CIS waves, is related to the potential selection bias that may arise by requesting only to innovative firms to compile the entire questionnaire. In CIS 2008 the sample is drawn from the "*total population of enterprises in NACE Rev. 2 sections A to M*" (Eurostat, 2009, p. 1) and also almost 40% of the firms that did not perform internal R&D (more than 70% of our sample) or did not develop product innovations (more than 81% of our sample) answered properly to the OI questions. Therefore, a large number of firms that may not be considered "innovative" in this article perspective (i.e. in terms of product innovation) are included in the analysed sample, tackling the selection bias problem in this study.

We have excluded Ireland and Norway from our sample because the inbound OI questionnaire items were not filled in. In addition, we have excluded all the companies that declared a 2008 null turnover in order to avoid measuring inactive companies, and all companies whose R&D expenses answers were missing. Therefore, the original sample of 120′613 firms has been reduced to the final one of 84′919. Table 2 describes the final sample by the firms' NACE (the statistical classification of economic activities in the European Community) section and country. It turns out that several NACE sections, such as "Agriculture, forestry and fishing", "Construction", "Accommodation and food service activities", "Real estate activities" and "Administrative and support service activities", are not widely represented in each country of our sample.

Table 2
Number of companies in the refined sample, classified according to their countries and NACE section.

Country	A	B	C	D	E	F	G	H	I	J	K	L	M	N	Total
Bulgaria (BG)		22	2′185	16	16		378	126		183	63		85		3′074
Cyprus (CY)		7	237	1	15		94	29		25	59		8		475
Czech Republic (CZ)		31	1′501	43	79	115	214	103	42	255	116	13	218	99	2′829
Germany(DE)		85	3′135	153	275		192	392		417	243		554	285	5′731
Estonia (EE)			1′306	56	88		170	182		188	108		126	16	2′240
Spain (ES)	947	390	15′974	115	523	2′990	5′428	2′119	1′370	2′150	571	199	2′480	2′131	37′387
Hungary (HU)		14	828	38	64	66	110	85		99	102		48		1′454
Italy (IT)		172	6′483	184	513	4′368	3′307	1′234	1′473	630	703	128	300	72	19′567
Lithuania (LT)		21	522	46	83	127	211	51		124	17		201		1′403
Latvia (LV)		2	89	4	4		36	13		19	16		4		187
Portugal (PT)		130	3′681	33	225	45	892	477		348	289		389		6′509
Romania (RO)		28	1′400	31	82		347	121		112	125		167		2′413
Slovenia (SI)		10	615	11	24		94	54		97	52		43		1′000
Slovakia (SK)		15	325	26	23	59	80	33		33	36		20		650
Total	947	927	38′281	757	2′014	7′770	11′553	5′019	2′885	4′680	2′500	340	4′643	2′603	84′919

Notes: NACE sections legend: A Agriculture, forestry and fishing; B Mining and quarrying; C Manufacturing; D Electricity, gas, steam and air conditioning supply; E Water supply; sewerage, waste management and remediation activities; F Construction; G Wholesale and retail trade; repair of motor vehicles and motorcycles; H Transportation and storage; I Accommodation and food service activities; J Information and communication; K Financial and insurance activities; L Real estate activities; M Professional, scientific and technical activities; N Administrative and support service activities.

Please cite this article in press as: Greco, M., et al., An analysis of the open innovation effect on firm performance, European Management Journal (2016), http://dx.doi.org/10.1016/j.emj.2016.02.008

5. Results

This section presents the correlation analysis of the variables and the regression models aimed to test the hypotheses of the study.

The discriminant validity has been assessed by means of Pearson correlation ratios between the constructs, which are shown in Table 3. As expected, *TURNMAR* is positively related with *NEWMKT*, and *TURNIN* is positively related with *NEWFRM*. Indeed, the turnover ratios from radical or incremental innovation are reasonable consequences of the respective types of innovation. The correlation values between the independent and control variables never fall above a 0.70 threshold that would suggest multi-collinearity. Such result is also confirmed by the analysis of variance inflation factors.

In order to test our hypotheses, we applied several regression models that are often used in literature to describe the chosen dependent variables, such as standard ordinary least squares, Tobit, Logit and Probit regressions. This subsection shows the models that fitted with the data the best. We analysed *TURNMAR* and *TURNIN* through Tobit regressions, whereas we used Logit regressions for the binary dependent variables (*NEWMKT, NEWFRM*). The regressions were also repeated for a sub-sample including the most innovative NACE sections (C, D, E, G, H, J, K and M), obtaining the same results obtained for the whole sample, therefore we did not include them in the paper for the sake of brevity.

Tobit models are used in the OI literature (Du, Leten, & Vanhaverbeke, 2014; Keupp & Gassmann, 2009; Köhler et al., 2012; Laursen & Salter, 2006) for single or double censored continuous dependent variables such as TURNMAR and TURNIN, whose minimum is 0 and maximum is 1 (being by definition percentages of a firm's sales). We control for heteroscedasticity by using robust standard errors. Logit models are used in the OI literature (Lasagni, 2012; Lichtenthaler & Ernst, 2008; Mention, 2011) to describe binary dependent variables similar to those chosen in this study. The standardized regression coefficients in Logit models refer to a standard deviation change in the logit of the dependent variable and not in the dependent variable itself (Lichtenthaler & Ernst, 2008).

The hypothesized inverted U-shaped relationships are tested through the computation of the quadratic terms of *BREADTH*, *DEPTH* and *COUPLED.* If the sign of the quadratic terms is negative and statistically significant, and the extremum point falls within the data range, then Lind and Melhum's (2010) test is implemented to check whether the relationship actually is inverted U-shaped rather than merely convex.

Fig. 2 synoptically resumes the rationale behind the models that will be discussed hereafter. Models 0, 4, 8, and 12 are baselines that load the control variables only. Models 1, 5, 9, and 13 load the explanatory independent variables of inbound OI (*BREADTH* and *DEPTH*) and their squared terms to verify curvilinear relationships between the dependent and independent variables. Similarly, Models 2, 6, 10, and 14 measure the impact of *COUPLED* and its squared term on the dependent variables. As stated before, this article advances several previous researches by studying the effect of both coupled and inbound OI (Models 3, 7, 11 and 15). In this perspective, the two sets of models, which measure inbound (1, 5, 9, 13) and coupled OI (2, 6, 10, 14), are useful to verify whether our approach contributes to describe the effect of OI on innovation performance more accurately.

Table 4 shows the effect of the independent variables on the EIP dependent variable *TURNMAR.* The Hp. 1a, which hypothesizes a curvilinear relationship between *BREADTH* and radical EIP, is

Table 3
Descriptive statistics and correlations.

	Variable	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	*TURNMAR*	.04	.15								
(2)	*TURNIN*	.07	.20	0.10							
(3)	*NEWMKT*	.31	.46	0.60	0.02						
(4)	*NEWFRM*	.42	.49	0.06	0.58	0.21					
(5)	*BREADTH*	5.07	2.98	0.14	0.10	0.23	0.19				
(6)	*DEPTH*	1.00	1.37	0.12	0.08	0.13	0.11	0.42			
(7)	*COUPLED*	.82	2.01	0.14	0.05	0.21	0.11	0.32	0.29		
(8)	*RDINT*	.01	.13	0.14	0.06	0.12	0.06	0.09	0.09	0.12	
(9)	*SIZE*	.65	.74	0.07	−0.06	0.19	0.18	0.17	0.08	0.20	−0.02

Notes: all correlations statistically significant at the 0.000 level.

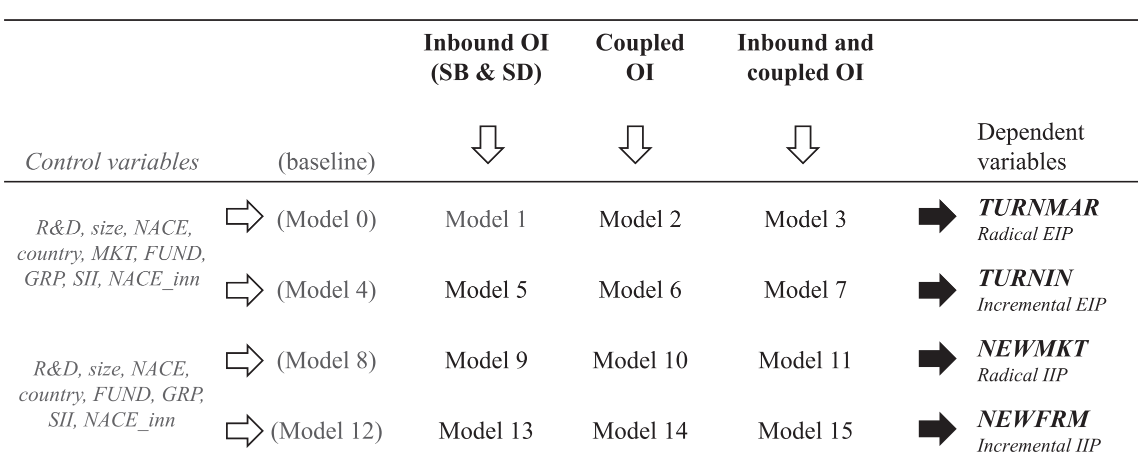

Fig. 2. Overview of the regression models.

Table 4
Regression results of Tobit models on *TURNMAR*.

	Model 0		Model 1		Model 2		Model 3		Sign. U-shaped Test (ext. point)
	Coeff. (SE)	Sign	Coeff. (SE)	Sign	Coeff. (SE)	Sign	Coeff. (SE)	Sign	
BREADTH			0.062 (0.004)	***			0.065 (0.004)	***	*** (7.34)
BREADTH^2			−0.004 (0.000)	***			−0.004 (0.000)	***	
DEPTH			0.017 (0.005)	***			0.011 (0.005)	*	na
DEPTH^2			−0.001 (0.001)	ns			0.000 (0.001)	ns	
COUPLED					0.043 (0.003)	***	0.031 (0.003)	***	*** (12.3)
COUPLED^2					−0.002 (0.000)	***	−0.001 (0.000)	***	
RDINT	0.468 (0.048)	***	0.285 (0.038)	***	0.288 (0.037)	***	0.259 (0.036)	***	
RDINT^2	−0.039 (0.014)	**	−0.022 (0.01)	*	−0.023 (0.009)	*	−0.020 (0.009)	*	
GRP	0.068 (0.007)	***	0.036 (0.007)	***	0.033 (0.007)	***	0.029 (0.007)	***	
FUND	0.236 (0.008)	***	0.084 (0.007)	***	0.094 (0.007)	***	0.067 (0.007)	***	
MKT	0.248 (0.007)	***	0.136 (0.006)	***	0.158 (0.006)	***	0.129 (0.006)	***	
SIZE (with respect to 0)									
1	0.024 (0.007)	***	−0.001 (0.007)	ns	0.002 (0.007)	ns	−0.004 (0.007)	ns	
2	0.057 (0.009)	***	0.019 (0.009)	*	0.014 (0.009)	ns	0.003 (0.009)	ns	
NACE dummies included	Yes	***	Yes	***	Yes	***	Yes	***	
COUNTRY dummies included	Yes	***	Yes	***	Yes	***	Yes	***	
AIC	39,830		33,957		34,476		33,764		
Pseudo R squared	0.237		0.135		0.136		0.139		
Observations	55,875		33,933		34,803		33,923		
Censored obs.	44,856		22,921		23,790		22,916		

Notes: *** indicates p < .001significance, ** indicates p < .01, * indicates p < .05, ns indicates that the coefficient is not statistically significant; na indicates that Lind & Mehlum test could not be performed due to not significant and/or non-negative quadratic terms; the overall effect is displayed for dummies.

supported by both Models 1 and 3. Indeed, *BREADTH* terms have a positive and statistically significant effect on radical EIP, whereas the squared terms of *BREADTH* have a negative and statistically significant effect on it and Lind and Melhum's (2010) test, implemented on Model 3, is statistically significant. Therefore, although *BREADTH* is likely to have a positive effect on the turnover share from radical innovations, using too many channels is likely to cause diminishing marginal returns on radical EIP. Instead, the Hp. 3a, which hypothesizes a curvilinear relationship between *DEPTH* and EIP, is not supported by Model 1 nor Model 3, the squared terms of *DEPTH* being not statistically significant. It seems, therefore, that drawing deeply from additional channels is not subject to diminishing returns on the turnover share from radical innovations. The Hp. 5a, posing that *COUPLED* is curvilinearly related with radical EIP, is supported by both Models 2 and 3, confirming that too many active collaboration channels may disperse resources and cause diminishing returns.

Fig. 3 shows the marginal effect of the three independent variables *BREADTH*, *DEPTH* and *COUPLED* on *TURNMAR*. According to the figure, the diminishing returns to *BREADTH* on *TURNMAR* incur only

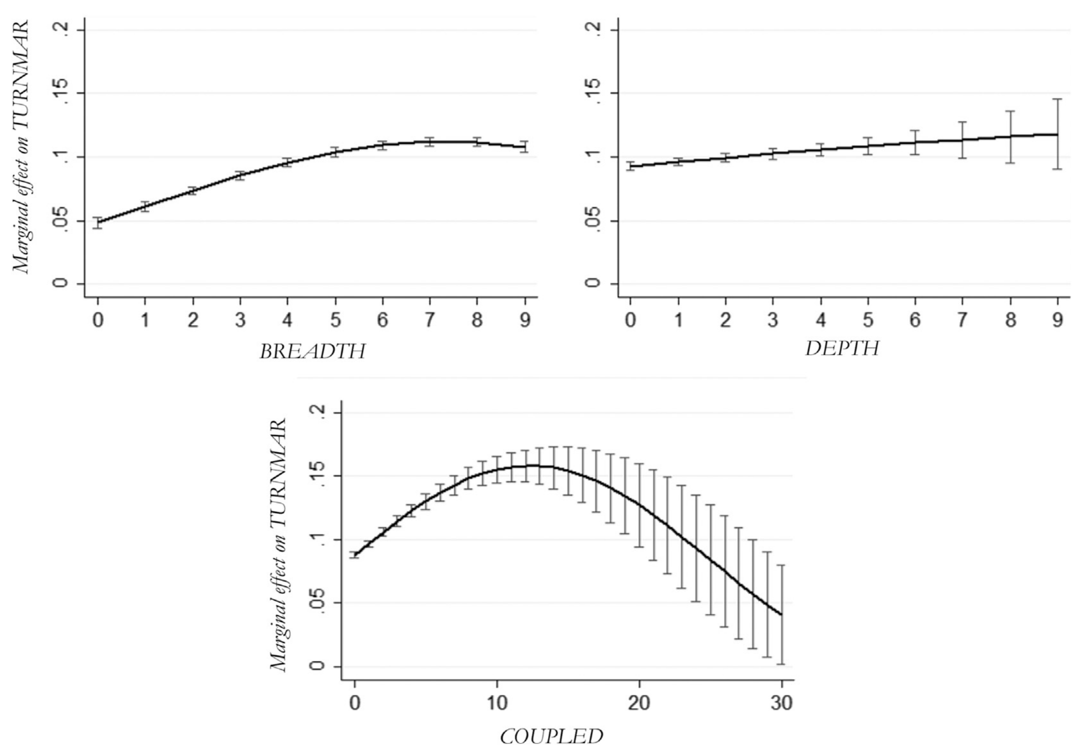

Fig. 3. Marginal effect of the independent variables *BREADTH*, *DEPTH* and *COUPLED* on *TURNMAR* and confidence intervals.

Table 5
Regression results of Tobit models on *TURNIN*.

	Model 4		Model 5		Model 6		Model 7		Sign. U-shaped Test (ext. point)
	Coeff. (SE)	Sign	Coeff. (SE)	Sign	Coeff. (SE)	Sign	Coeff. (SE)	Sign	
BREADTH			0.079 (0.005)	***			0.081 (0.005)	***	*** (7.26)
BREADTH²			−0.005 (0.000)	***			−0.006 (0.000)	***	
DEPTH			0.014 (0.005)	**			0.012 (0.005)	*	na
DEPTH²			−0.001 (0.001)	ns			−0.001 (0.001)	ns	
COUPLED					0.024 (0.003)	***	0.009 (0.003)	**	na
COUPLED²					−0.001 (0.000)	***	0.000 (0.000)	ns	
RDINT	0.610 (0.067)	***	0.144 (0.043)	**	0.187 (0.045)	***	0.125 (0.043)	**	
RDINT²	−0.163 (0.036)	***	−0.043 (0.016)	**	−0.053 (0.018)	**	−0.038 (0.016)	*	
GRP	0.075 (0.008)	***	0.025 (0.008)	**	0.029 (0.008)	***	0.023 (0.008)	**	
FUND	0.230 (0.009)	***	0.020 (0.008)	**	0.052 (0.008)	***	0.015 (0.008)	ns	
MKT	0.265 (0.007)	***	0.105 (0.007)	***	0.141 (0.007)	***	0.103 (0.007)	***	
SIZE (with respect to 0)									
1	0.004 (0.008)	ns	−0.034 (0.008)	***	−0.028 (0.008)	***	−0.035 (0.008)	***	
2	0.028 (0.011)	**	−0.024 (0.010)	*	−0.017 (0.011)	ns	−0.030 (0.011)	**	
NACE dummies included	Yes	***	Yes	***	Yes	***	Yes	***	
COUNTRY dummies included	Yes	***	Yes	***	Yes	***	Yes	***	
AIC	56,084		45,915		46,899		45,896		
Pseudo R squared	0.155		0.059		0.057		0.060		
Observations	55,880		33,942		34,808		33,931		
Censored obs.	42,322		20,396		21,260		20,392		

Notes: *** indicates p < .001significance, ** indicates p < .01, * indicates p < .05, ns indicates that the coefficient is not statistically significant; na indicates that Lind & Mehlum test could not be performed due to not significant and/or non-negative quadratic terms; the overall effect is displayed for dummies.

when the average focal firm resorts to more than 7 external sources, and the section of the curve characterized by a negative slope decreases gradually and slightly. On the other hand, the diminishing returns to *COUPLED* on *TURNMAR* after 12 partner types describe a marked fall, although confidence intervals are large for above-average levels of *COUPLED*.

The analysis of the control variables suggests that, as expected, firms that are members of a group, firms that obtained public subsidies and firms that implemented marketing innovations are likely to experience higher levels of turnover share from radically new products. Finally, consistently with previous studies, we find that R&D investments have diminishing marginal returns on *TURNMAR* (Czarnitzki & Thorwarth, 2012).

Table 5 presents the effect of the independent variables on the EIP dependent variable *TURNIN*. The Hp. 1b, suggesting a curvilinear relationship between *BREADTH* and incremental EIP, is supported by both Models 5 and 7. Therefore, although *BREADTH* is likely to have a positive effect on the turnover share from incremental innovations, using too many channels is as well likely to cause diminishing marginal returns. Instead, the Hp. 3b, suggesting a curvilinear relationship between *DEPTH* and incremental EIP, is not supported by Model 5 nor Model 7, the squared terms of *DEPTH* being not statistically significant. It seems, therefore, that drawing deeply from additional channels does not exhibit diminishing returns on the share of turnover resulting from incremental innovations. Similarly, Model 7 does not support the Hp. 5b, which poses that *COUPLED* is curvilinearly related with incremental EIP. This suggests that increasing the number of active collaboration channels is not likely to cause diminishing returns on *TURNIN*, possibly because the benefits of collaboration overdo the costs that can arise when incremental innovations are co-developed.

As observed for *TURNMAR*, firms that are members of a group and firms that implemented marketing innovations are likely to experience higher levels of turnover share from incremental innovations. In this case, the effect of public subsidies is not statistically significant, possibly because R&D public funding are usually assigned to very innovative projects. All the models show that R&D investments exhibit diminishing marginal returns, whereas small firms are likely to have a larger share of turnover from incremental innovations than medium and large ones.

Table 6 describes the effect of the independent variables on the IIP dependent variable *NEWMKT*. Both Models 9 and 11 support the Hp. 2a, suggesting a curvilinear relationship between *BREADTH* and radical IIP. Therefore, *BREADTH* is curvilinearly related with both economic and industrial measures of innovation performance. The Hp. 4a, suggesting a curvilinear relationship between *DEPTH* and radical IIP, is not supported by both Models 9 and 11, the squared term of *DEPTH* being not statistically significant. It seems, therefore, that drawing deeply from additional channels is not likely to exhibit diminishing returns both on the share of turnover resulting from radical innovations and on the chances to develop a radical innovation. The Hp. 6a, posing that *COUPLED* is curvilinearly related with radical IIP, is supported by Model 10 (test statistically significant with p < .001) but only weakly supported by Model 11 (p < .07). This result seem to confirm that too many active collaboration channels may disperse resources and cause diminishing returns on the odds of developing radical innovations. Fig. 4 shows the probability of introducing a new the market product at various levels of *BREADTH*, *DEPTH* and *COUPLED*. It is apparent that the slope of *BREADTH* only slightly decrease in case of 8 or 9 external sources, whereas the positive effect of *DEPTH* seems weak with respect to *BREADTH* (using the same scale of probability for both measures of inbound OI, the curve appears almost flat). *COUPLED* marginal effect on radical IIP starts to decrease only after 21 collaboration channels, and rather slightly, especially if we compare the curve with the one described in Fig. 3 (which steadily decreases after 12 channels). Therefore, the inefficiencies caused by too many collaboration channels come into view only for very high levels of *COUPLED*, and provoke gradually diminishing returns.

All Models confirmed that firms that are members of a group and firms that benefited from public subsidies have higher odds of developing a radical innovation. Finally, all the models show that R&D investments have diminishing marginal returns, whereas they show that the larger a firm is, the greater are its prospects to develop radical innovations.

Table 7 shows the effect of the independent variables on the IIP dependent variable *NEWFRM*. The Hp. 2b, suggesting a curvilinear relationship between *BREADTH* and incremental IIP, is supported by both Models 13 and 15. Therefore, *BREADTH* is curvilinearly related with both economic and industrial measures of innovation

Table 6
Regression results of Logit models on *NEWMKT*.

	Model 8		Model 9		Model 10		Model 11		Sign. U-shaped Test (ext. point)
	Coeff. (SE)	Sign	Coeff. (SE)	Sign	Coeff. (SE)	Sign	Coeff. (SE)	Sign	
BREADTH			0.258 (0.019)	***			0.275 (0.019)	***	** (7.74)
BREADTH²			−0.014 (0.002)	***			−0.018 (0.002)	***	
DEPTH			0.089 (0.022)	***			0.060 (0.023)	**	na
DEPTH²			−0.007 (0.004)	ns			−0.006 (0.004)	ns	
COUPLED					0.232 (0.013)	***	0.171 (0.013)	***	! (21.19)
COUPLED²					−0.007 (0.001)	***	−0.004 (0.001)	***	
RDINT	2.036 (0.351)	***	1.483 (0.294)	***	1.450 (0.303)	***	1.164 (0.266)	***	
RDINT²	−0.153 (0.027)	***	−0.113 (0.023)	***	−0.116 (0.024)	***	−0.095 (0.021)	**	
GRP	0.184 (0.032)	***	0.143 (0.033)	***	0.118 (0.032)	***	0.102 (0.033)	***	
FUND	0.572 (0.032)	***	0.373 (0.033)	***	0.403 (0.033)	***	0.278 (0.033)	***	
SIZE (with respect to 0)									
1	0.185 (0.032)	***	0.133 (0.033)	***	0.154 (0.032)	***	0.118 (0.033)	***	
2	0.554 (0.044)	***	0.398 (0.045)	***	0.364 (0.045)	***	0.298 (0.046)	***	
NACE dummies included	Yes	***	Yes	***	Yes	***	Yes	***	
COUNTRY dummies included	Yes	***	Yes	***	Yes	***	Yes	***	
AIC	33,473		32,301		32,668		31,962		
Pseudo R squared	0.119		0.121		0.136		0.130		
Observations	27,637		26,608		27,483		26,592		

Notes: *** indicates p < .001significance, ** indicates p < .01, * indicates p < .05; ! indicates p < .07, ns indicates that the coefficient is not statistically significant; na indicates that Lind & Mehlum test could not be performed due to not significant and/or non-negative quadratic terms; the overall effect is displayed for dummies.

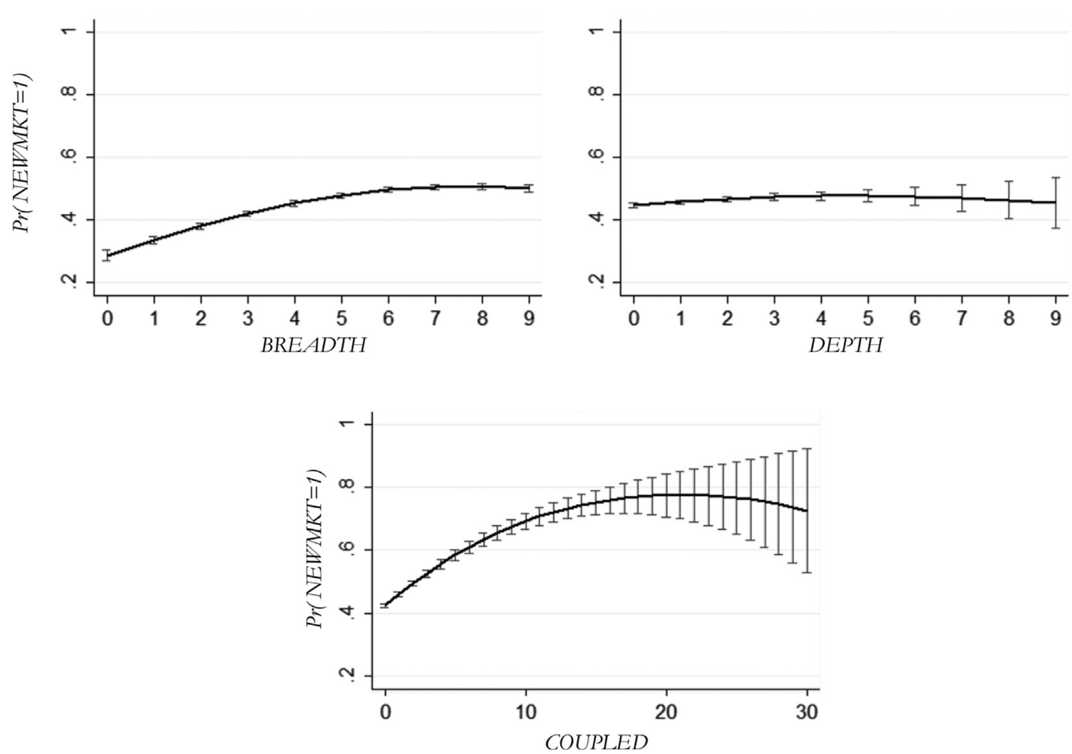

Fig. 4. Probability of NEWMKT = 1 at various levels of the independent variables *BREADTH, DEPTH* and *COUPLED* and confidence intervals.

performance. The Hp. 4b, suggesting a curvilinear relationship between *DEPTH* and incremental IIP, is supported by both Models 13 and 15. Thus, drawing deeply from additional channels is likely to have diminishing returns on the chances to develop an incremental innovation. The Hp. 6b, posing that *COUPLED* is curvilinearly related with incremental IIP, is not supported by both Models 14 and 15. Furthermore, in Model 15 neither the positive effect of *COUPLED* on *NEWFRM* is statistically significant. The result suggests that inbound OI plays a more important role than coupled OI in the development of incremental innovations.

All Models confirmed that firms that are members of a group have higher odds of developing an incremental innovation. Conversely, benefiting from public subsidies does not show a statistically significant effect on *NEWFRM*. All the models show that R&D investments exhibit negative returns, whereas the larger a firm is, the better are its chances of developing radical innovations.

6. Discussion

The results of the study, which are summarized in Fig. 5 supported or weakly supported the hypotheses of the study in 7 cases

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Table 7
Regression results of Logit models on *NEWFRM*.

	Model 8		Model 9		Model 10		Model 11		Sign. U-shaped Test (ext. point)
	Coeff. (SE)	Sign	Coeff. (SE)	Sign	Coeff. (SE)	Sign	Coeff. (SE)	Sign	
BREADTH			0.339 (0.018)	***			0.344 (0.018)	***	*** (7.18)
BREADTH^2			−0.023 (0.002)	***			−0.024 (0.002)	***	
DEPTH			0.082 (0.024)	**			0.079 (0.024)	**	** (2.68)
DEPTH^2			−0.014 (0.004)	**			−0.015 (0.005)	**	
COUPLED					0.089 (0.016)	***	0.017 (0.016)	ns	na
COUPLED^2					−0.002 (0.001)	ns	0.002 (0.001)	ns	
RDINT	−0.338 (0.121)	***	−0.577 (0.123)	***	−0.494 (0.125)	***	−0.636 (0.127)	***	
RDINT^2	0.011 (0.012)	***	0.032 (0.012)	**	0.022 (0.012)	ns	0.035 (0.013)	**	
GRP	0.146 (0.033)	ns	0.105 (0.034)	**	0.116 (0.033)	***	0.095 (0.034)	**	
FUND	0.275 (0.034)	ns	0.034 (0.035)	ns	0.197 (0.035)	***	0.014 (0.036)	ns	
SIZE (with respect to 0)									
1	−0.028 (0.045)	ns	−0.078 (0.034)	*	−0.038 (0.033)	ns	−0.080 (0.034)	*	
2	0.207 (0.220)	***	0.062 (0.046)	ns	0.108 (0.046)	*	0.033 (0.047)	ns	
NACE dummies included	Yes	***	Yes	***	Yes	***	Yes	***	
COUNTRY dummies included	Yes	***	Yes	***	Yes	***	Yes	***	
AIC	32,280		30,950		32,018		30,905		
Pseudo R squared	0.141		0.137		0.144		0.137		
Observations	27,607		26,608		27,481		26,588		

Notes: *** indicates p < .001significance, ** indicates p < .01, * indicates p < .05, ns indicates that the coefficient is not statistically significant; na indicates that Lind & Mehlum test could not be performed due to not significant and/or non-negative quadratic terms; the overall effect is displayed for dummies.

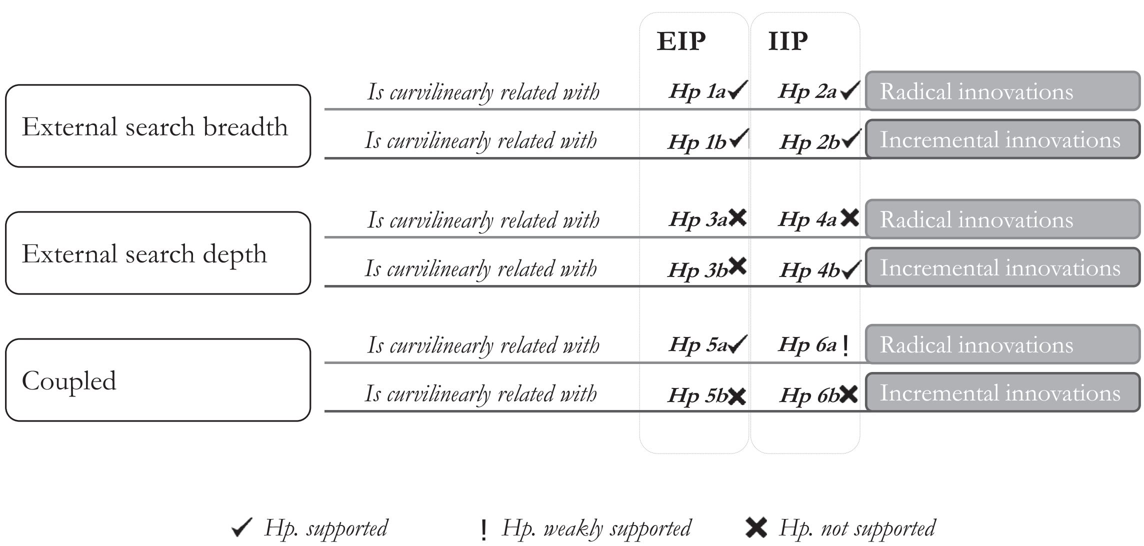

Fig. 5. Synoptic view of the support found for the hypotheses of the study.

out of 12, providing interesting insights with respect to earlier studies.

We found strong support for all the hypotheses stating that SB is curvilinearly related with EIP and IIP, in terms of radical or incremental OI. Therefore, we can infer that the over-search practice has diminishing marginal returns on innovation performance. Thus, a firm may be harmed by interacting with an excessive number of innovation channels, consequently reducing its effectiveness in bringing innovation ideas into implementation. Indeed, a firm that considers too many innovation ideas and knowledge, gathered from different innovation sources, risks dispersing time and resources in the effort. To the best of our knowledge, this is the first study that successfully demonstrates an inverted U-shaped relationship between SB and measure of incremental IIP. Very much interestingly, the optimal number of sources to enhance each of the four innovation performance measures is 7. This information suggests that the potentially negative effects of over-search described before emerge only for very high levels of SB. In Laursen (2011) the top level of *BREADTH* was 6, on a maximum of 9. The difference with Laursen's result, which was calculated on a sample drawn from the Danish CIS4 questionnaire (reference year 2005), might suggest that firms are getting increasingly capable to draw benefits from SB. Longitudinal or repeated cross-sectional studies should address this point to verify whether firms are actually increasing their skills in managing OI and obtaining better innovation performance.

We observed a curvilinear relationship between SD and the development of incremental innovations, whereas squared terms of *DEPTH* were not statistically significant in the models estimating the other dependent variables. The findings suggest that once a firm has chosen some channels to insource knowledge from external organizations, drawing deeply from them does not necessarily exhibit diminishing returns. Indeed, maintaining stable relationships with and insourcing from organizations within a specific channel can guarantee both managerial and relational benefits. An in-depth knowledge of the relational patterns embedded in an innovation channel is likely to enhance the firm's capability to successfully innovate and counterbalance the over-search shortcomings. The results confirm those obtained by Lee (2010), who tested the effect of SD on radical and incremental EIP, in Korea's Information Technology Industry, and by Ghisetti et al. (2015), who tested the effect of SD on the development of environmental innovations in Europe. This suggests that the diminishing returns to SD on innovation performance, as observed by Laursen and Salter (2006), might no longer be a major issue in the OI management in developed countries. There is a possibility, as the one suggested for SB, that firms are becoming more and more OI-savy, increasing their capability to interact with external knowledge sources maintaining a good balance of benefits and costs.

The regressions supported the hypotheses of diminishing returns to *COUPLED* on radical EIP and IIP. Conversely, they did not support neither the hypothesis of diminishing returns to *COUPLED* on incremental EIP, nor the one hypothesizing curvilinear effect on incremental IIP. Thus, coupled OI is not likely to have a remarkable effect on the development of incremental innovations, although it may concur to their market success. On the one hand, Figs. 3 and 4, which describe the marginal effect of the three independent variables on radical EIP and IIP, suggest that coupled OI has a strongest potential than inbound OI to enhance the development and commercialization of new products. On the other hand, Fig. 4 emphasizes how “over-collaborating” may be strongly counter-productive and even detrimental to the odds of developing a new to the market product (for example, the probability of NEWMKT = 1 is 8.78% for *COUPLED* = 0, 9.67% for *COUPLED* = 1, and 8.40% for *COUPLED* = 25). As a matter of fact, alliances and collaborations are among the firms' favourite means to share the risks and costs related to novelties, including R&D activities, development, distribution and marketing costs (Nieto & Santamaría, 2007; Papadopoulos, Stamati, Nikolaidou, & Anagnostopoulos, 2013).

As expected, being part of a group improves all the measures of innovation performance. In fact, group members may share the experiences of other members in interacting with external subjects, learn from their group best practices, be introduced to more potential partners and benefit from the attractiveness of the group's image, which can encourage external subjects to be more open and helpful.

Another expected result was the statistically significant positive effect of the introduction of marketing innovations on the turnover share stemming from both radical innovations and incremental innovations.

We found evidence that public subsidies have a positive effect on radical EIP and IIP, but do not exhibit a statistically significant impact on either incremental EIP or IIP. These results may have been influenced by most R&D public subsidies structure, which often requires the beneficiaries to successful develop prototypes of new products as final outputs of their projects.

Finally, R&D intensity has shown a positive effect on the development of radical innovations, as well on the turnover from radical and incremental innovations, consistently with previous studies (Cappelli et al., 2014; Ebersberger & Herstad, 2011; Laursen & Salter, 2006; Un et al., 2010). Nevertheless, we also found that such positive effect is subject to diminishing returns, further supporting the findings of other articles (Czarnitzki & Thorwarth, 2012; Ebersberger & Herstad, 2011). It is somewhat surprising that we found a negative effect of R&D intensity on the incremental IIP, suggesting that other practices are more likely to influence the incremental innovation development, such as external search breadth and depth. Caution must be applied as, although some studies found not statistically significant effect of R&D intensity on incremental EIP (Czarnitzki & Thorwarth, 2012; Hurmelinna-Laukkanen, Sainio, & Jauhiainen, 2008) or on IIP regardless to the degree of novelty (Kang & Kang, 2009), this is to the best of our knowledge the first time that a negative coefficient is discussed in literature.

7. Conclusions

This study comprehensively analysed the effect of OI on innovation performance, hypothesizing that several OI strategies – namely external search breadth, external search depth and coupled OI – are curvilinearly related with economic and industrial innovation performance. We tested the hypotheses of the study through Tobit and Logit regressions on data drawn from the 2008 CIS wave.

The findings show that most OI strategies are subject to diminishing marginal returns on industrial and economic innovation performance. In particular, external search breadth is curvilinearly related with all the measures of innovation performance; coupled OI is curvilinearly related with the development and commercialization of radical innovations; whereas external search depth is not subject to diminishing marginal returns in most cases, with the exception of industrial innovation performance from incremental innovations. These results have implications for both theory and practice.

7.1. Theoretical implications

In a theoretical perspective, this article casts new light on the debate between the branch of literature hypothesizing that benefits from OI strategies are subject to diminishing returns (Duysters & Lokshin, 2011; Kang & Kang, 2009; Laursen & Salter, 2006; Lin, 2014) and the branch not hypothesizing diminishing returns (Cheng & Huizingh, 2014; Chiang & Hung, 2010; Frishammar et al., 2012; Hernández-Espallardo et al., 2011; Leiponen, 2012; Martini et al., 2012; Ortiz–de–Urbina–Criado et al., 2012).

Our results collocate this study in-between the two branches of literature. In fact, coherently with the first one, we demonstrated diminishing returns to external search breadth on each of the innovation performance measures. Furthermore, we showed diminishing returns to coupled OI on the development and commercialization of radical innovations, whereas we did not observe diminishing returns on incremental economic innovation performance and neither observed a direct positive effect on incremental industrial innovation performance. We also found that benefits from external search depth are subject to diminishing marginal returns on incremental industrial innovation performance only. Indeed, in accordance with the second branch of literature, the regressions demonstrated that external search depth has a positive effect on incremental economic innovation performance as well as radical economic and industrial innovation performance, not experiencing diminishing returns. Given such results, further studies may verify how the entity of diminishing returns to different OI strategies vary across different industries, countries and firm sizes.

Noticeably, the adopted economic innovation performance independent variables describe the benefits (i.e. the turnover) obtained by a firm resorting to the OI paradigm. Therefore, the diminishing marginal returns discussed before highlight that the corresponding OI strategies are less effective in producing benefits when over-search or over-collaboration happen. Instead, the regressions on the turnover shares cannot describe the characteristics of marginal costs. Although the industrial innovation performance independent variables used in this article indirectly assess the costs embedded in the innovation development process, further studies might analyse the effect of OI on economic innovation performance in a comprehensive cost/benefit perspective. We expect that the curvilinearly relationship between OI and economic innovation

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performance might further increase its peakedness.

7.2. Practical implications

The results discussed in this article may enhance firms' capability to adopt an appropriate OI strategy according to their short-term objectives, in a temporal horizon of three years.

OI can improve both industrial and economic innovation performance in the short-term, although some OI strategies can be more effective than others in achieving specific targets. We showed that coupled OI strategies can have a remarkable effect on both the development and commercialization of radical innovations, whereas their impact on the development of incremental innovations is somewhat nuisance. Therefore, if the management wants to improve the development and market success of radical innovations, we suggest actively collaborating with external organizations, adopting a "collaborative innovation strategy" or a "network-based collaboration strategy" (Saebi & Foss, 2014). According to the former strategy, the company should enter into collaborative agreements with a few knowledge-intensive partners, ensuring frequent interactions that may favour the transfer of knowledge across organizational boundaries (Saebi & Foss, 2014). The latter strategy is appropriate when the required knowledge is widely distributed outside a firm's organizational boundaries, encouraging the firm to engage and maintain a network of relationships with many external partners (Saebi & Foss, 2014).

Conversely, if managers want to improve the development and market success of incremental innovations, we suggest exploring different channels to draw knowledge from external organizations, eventually adopting a "crowd-based innovation strategy", in which the knowledge input is sourced from a large number of actors, outsourcing a task to a "crowd" rather than to a specific external subject (Saebi & Foss, 2014).

In both cases, as diminishing marginal returns exist, firms should avoid over-search (Koput, 1997; Laursen & Salter, 2006) and over-collaboration (Bader & Enkel, 2014; Duysters & Lokshin, 2011). Further studies may verify which channels should be privileged according to the focal firm's sector and to its innovation performance strategic targets. Although drawing deeply from the external sources is in most cases not subject to diminishing returns, further studies on economic innovation performance might verify whether the marginal costs associated with drawing deeply from external sources are balanced by marginal benefits.

7.3. Limitations of the study

We are aware of three relevant limitations that affect this article and that may as well represent future research opportunities for the OI literature.

Firstly, although the sample used in this article is considerably larger than those that had been used by most of the previous studies, as well as more extensive in terms of sectors and countries covered, still its external validity may require further investigation. In fact, the results may change in studies outside Europe according to specific macroeconomic or cultural factors. Therefore, researchers are encouraged to investigate homogeneous economic and cultural macro-areas to verify the existence of differences with respect to those presented in this article.

Secondly, this article explores the effect of external search breadth, depth and coupled OI on innovation performance in terms of the most relevant channels that may enhance innovation development. Nevertheless, it does not include an analysis of external search depth-ness, breadth-ness and collaborations within the same channel (e.g., it does not verify, within the "supplier" channel, how many suppliers are involved in the innovation process and to which degree). This is an important issue for future researches, and quite difficult to overcame in a holistic perspective by means of standardized questionnaires. Indeed, exploring each channel in-depth, especially for large firms with dozens or hundreds of different innovation partners, may result in overwhelmingly long questionnaires. Thus, studying each channel separately might be recommended for future researches.

Thirdly, in the absence of panel data we could not control for unobserved heterogeneity. Thus, some unobserved differences among the firms in our sample may have an unobserved effect on firms' innovation performance. Therefore, we paid close attention to the definition of an adequate amount of control variables in order to mitigate as much as possible the degree of unobserved heterogeneity (Belderbos, Gilsing, & Lokshin, 2011; Cainelli, 2006; Czarnitzki, Etro, & Kraft, 2014).

Acknowledgements

The authors wish to thank the anonymous reviewers for their thorough revisions and insightful comments. Furthermore, the authors wish to thank Prof. Jo Thori Lind and Prof. Alan Neustadtl for their valuable suggestions. Finally, the authors wish to thank Eurostat for providing access to the anonymised Community Innovation Survey micro data. The authors also emphasize that the results and conclusions cannot be attributed to Eurostat, the European Commission or any of the national authorities whose data has been used.

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Please cite this article in press as: Greco, M., et al., An analysis of the open innovation effect on firm performance, European Management Journal (2016), http://dx.doi.org/10.1016/j.emj.2016.02.008