Network Embeddedness and New Product Development in the Biopharmaceutical Industry: The Moderating Role of Open Innovation Flow

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ABSTRACT

This paper explores the role of centrality and structural holes positions on the likelihood to develop new products and the moderating role of the open innovation flow, a measure of the net knowledge flow crossing the firm's boundaries, on the aforementioned relation. We argue that network positions provide the information content to the firm, whilst open innovation flow describes how the firm uses such content, thus the combination of these two concepts has a significant impact on new product development. We test the theoretical framework on a large sample of 544 public companies and data from 1758 agreements among 1890 bio-pharmaceutical firms through the period 2006-2010. Our results show that being centrally located in the network positively affects the new product development process, while having a structural holes position has no effect on the aforementioned performance. However, the interaction of the two network positions with the open innovation flow has a positive impact on the likelihood to develop new products.

Keywords: Inter-firm networks; Open Innovation; New Product Development

1. Introduction

Social Capital (SC) scholars highlight how structural network embeddedness influences the ability of the firm to develop innovations such as patents (Ahuja, 2000; Schilling and Phelps, 2007; Phelps, 2010), significant improved products/services (Pèrez-Luño et al., 2011) and new product awards (Soh, 2003). Open Innovation (OI) scholars (Chesbrough, 2003) evidence how the incoming flow of knowledge provided through inbound OI practices (West and Bogers, 2013), such as in-licensing, acquisition of R&D services and technologies, influences the firm's innovation performance such as patent development (Sampson, 2007), patent citations (Li and Tang, 2010) and new product development (Un et al., 2010).

By analyzing the aforementioned contributes two interesting issues emerge. First, while OI scholars enhance our understanding of how openness improves new product development, to the best of our knowledge, SC literature has not examined specifically whether and how structural network embeddedness, i.e. the firm's network position, is able to improve the ability of the firm to develop new products. This omission is glaring, especially in the bio-pharmaceutical industry, where developing new products allows achieving monopoly rents for several years ahead.

Second, a more relevant issue concerns the relation between the information asset provided by the network position and the use of such resources provided by the direction of the knowledge flow that the firm builds through OI practices. Indeed, while SC scholars point out the information dimension of network embeddedness by evidencing how information volume, diversity and richness, provided by different network positions, can enhance firm's performance, they fall short on tackling the potential benefits springing out from the actual use of such information in term of knowledge flow creation or dissipation (Koka and Prescott, 2002; 2008). On the other hand, OI scholars evidence the effect of an inflow of knowledge, provided by inbound practices, on innovation performance, however they ignore the role of firm's structural position as a source of information asset, enhancing the developing of the knowledge flow. Thus, the second contribute of this research is understanding how the direction of the knowledge flow across the organizational boundaries provided by OI practices is able to enhance (or deteriorate) the positive effect that some network positions have on innovation performance. The importance of such contributes to the literature is recently highlighted by an editorial of a special issue on OI research where the authors affirm: "While research on strategic alliances has profited greatly from a network perspective, the link between open innovation and social capital is underdeveloped" (West et al., 2014: 809).

In order to accomplish these aims, we define a measure of the net knowledge flow crossing the firm boundaries. We define open innovation flow as the attitude of a firm of balancing inflow of knowledge and outflow of knowledge through the prevalence of inbound and outbound practices; it is positive when inflow of knowledge is greater than outflow of knowledge and vice versa. Thus, the open innovation flow provides insights on how the firm uses the information content provided by its network position to enhance (or deteriorate) its capacity to develop new products. We build a theoretical framework and we test it within the bio-pharmaceutical context. We gather data on a network of inter-firm relations among bio-pharmaceutical firms through 2006 to 2010 using information from the BioWorld database. We construct the network characteristics by collecting a total amount of 1758 agreements among 1890 bio-pharmaceutical firms in the period 2006-2010. We collect data on patents, new products and firm attributes for a sample of 544 public companies belonging to the aforementioned network using multiple sources of other data.

Our results show that, although structural embeddedness positions (centrality and structural holes) have a direct positive influence in the process of new product development, the effect is significantly amplified when a net positive knowledge flow is involved.

The paper is organized as it follows. In section two, we develop the theoretical framework. Then, we describe the development of the dataset and explain the estimation models. Next, the empirical findings are presented. Finally, the paper concludes with a discussion of the theoretical and managerial implications of the study, some limitations of the research and suggestions for future research directions.

2. Conceptual development and hypotheses

2.1. Structural network embeddedness and new product development

As structural network embeddedness (Granovetter, 1992; Moran, 2005) we mean the "impersonal configuration of linkage between network actors" (Nahapiet and Ghoshal, 1998: 244) such as the presence or absence of ties, connectivity, centrality and hierarchy. SC scholars associate structural embeddedness with the extent of information a firm can obtain from its network of relations (Koka and Prescott, 2002; 2008). According to this view, structural embeddedness is analyzed along two network features. The first is centrality (Borgatti et al., 2002; Koka and Prescott, 2008); having a central network position provides the ego firm with information volume, i.e. a dimension emphasizing the quantity of information that a firm can access and acquire through its position in the network of inter-firm ties (Koka and Prescott, 2002).

The second feature - structural holes - highlights the brokerage opportunities created by an open social structure (Burt, 1992). Structural holes are open and not densely tied network structures that provide the ego firm with entrepreneurial opportunities, i.e. the possibility to act as bridges between the different parts of the network (Koka and Prescott, 2008). Thus, by occupying a structural holes position a firm access to information diversity, i.e. the variety and to a somewhat lesser extent quantity of information that a firm can access through its relationships (Koka and Prescott, 2002).

From the seminal work of Uzzi (1996), several scholars have tried to understand how structural network embeddedness influences organization's performance. Through an in-depth review of SC empirical studies, we examine scientific papers that have empirically investigated the role of the network embeddedness in explaining innovation and organizational performance. Table 1 summarizes the results of the literature review. From the literature analysis, we found several scholars that evaluate the impact of network embeddedness on economic-financial performance of the firm (Koka and Prescott, 2002; Bae and Gargiulo, 2004; Zaheer and Bell, 2005; Maurer and Ebers, 2006; Shipilov, 2006; Acquaah, 2007; Goerzen, 2007; Shipilov and Li, 2008; Wu, 2008;

Malik, 2012) and some other scholars dealing with innovation performance (Ahujia, 2000; Soh, 2003; Salman and Saives, 2005; Shilling and Phelps, 2007; Gilsing et al., 2008; Padula, 2008; Pieters et al. 2009; Vanhaverbeke et al., 2009; Phelps, 2010; Pèrez-Luño et al., 2011; Karamanos, 2012; Vanhaverbeke et al., 2012). Specifically, Ahuja (2000) finds a positive effect of direct and indirect centrality of the firm on patent prolificacy, while structure hole positions seem to have a negative effect on the same performance. Soh (2003) evidences how a company improves the number of awards obtained for its products when it increases the number of repeated partners and centrality position relative to others. Salman and Saives (2005) find that by occupying a central position in a network of indirect ties, a firm is more likely to increase innovation performance (patent count). Schilling and Phelps (2007) empirically find that firms embedded in alliance networks, that exhibit both high clustering and high reach centrality, have greater patent performance. Gilsing et al.'s (2008) findings clearly indicate that the number of explorative patents depends on other two dimensions of embeddedness, namely technological distance and network density. The study of Padula (2008) suggests that the development of a dual alliance network structure, made up of both cohesive and sparse relationships, provides higher rates of innovation performance (count of patents) than those from either pattern alone. Vanhaverbeke et al. (2009) find that firms can boost both explorative and exploitative patent count by shaping the degree of redundancy and density in their local alliance. Phelps (2010) evidences how the technological diversity of a firm's alliance partners increases its exploratory innovation (patent citations) and that network density among partners strengthens the influence of diversity. Karamanos (2012) empirically investigates how the interaction between a firm's alliance portfolio structure and the industry alliance network structure may be affecting the exploratory innovation outcome of network participating firms in the biotechnology industry. Finally, Vanhaverbeke et al. (2012) explain how direct ties have an inverted U-shaped effect on both core and noncore technology and, moreover, indirect ties play a positive role in noncore technology development.

Authors	*Performance measures*	*Operationalization*
Acquaah, 2007	Organizational performance	Sales and revenues, Net Income, Return on Assets, Return on Sales, Growth in productivity
Ahuja, 2000	Innovation output	Number of successful patent applications
Bae and Gargiulo, 2004	Organizational profitability	Return on Investment, Return on Asset
Gilsing et al., 2008	Explorative innovation performance	Number of patents
Goerzen, 2007	Economic performance	Operating return on sale, Return on Asset, Operating return on capital
Karamanos, 2012	Innovation performance	Number of patents
Koka and Prescott, 2002	Firm performance	Sales per employees
Pèrez-Luño et al., 2011	Radical innovation	Five-item scale regarding new or significant improved products/services
Malik, 2012	Firm performance	Return on Revenue
Maurer and Ebers, 2006	Firm performance	Revenue and employment growth, Patenting rate
Molina-Morales et al., 2010	Innovation performance	Innovation in processes and products
Padula, 2008	Rates of innovation	Number of successful patent applications
Phelps, 2010	Degree of exploratory innovation	Number of patent citations
Pieters et al. 2009	Innovative performance	Weighted patent counts
Salman and Saives, 2005	Innovation performance	Number of patents
Shilling and Phelps, 2007	Knowledge creation	Number of successful patent applications
Shipilov and Li, 2008	Firm's market performance	Revenue-generation abilities
Shipilov, 2006	Firm performance	Market Share
Soh, 2003	New product performance	Number of new product awards.
Vanhaverbeke et al., 2009	Exploitative/explorative technology innovation	Weighted patent counts
Vanhaverbeke et al., 2012	Core/Non core technology	Number of patent citations
Wu, 2008	Firm competitiveness	Three items scale regarding firm's competitors, products/services quality, reaction to market demand.
Zaheer and Bell, 2005	Firm performance	Market Share

Table 1. Literature review on SC and firm performance

All the aforementioned SC studies basically focus their researches on patents as measure of innovation performance. However, new product development is a quite common measure of firm's innovation performance both in OI (Fey and Birkinshaw, 2005; Laursen and Salter, 2006; Vega-Jurado et al., 2009; Un et al., 2010; Bianchi et al., 2011; Tomlinson and Fai, 2013; Bianchi et al., 2014) and alliance literatures (Deeds and Hill, 1996; Rothaermel and Deeds, 2004; Kalaignanam et al., 2007). As shown in Table 1, none of the previous works adopt a new product development perspective as measure of innovation. There are two possible exceptions, i.e. Soh (2003) who however considers awards obtained by products, and Molina-Morales et al., (2010) who study, from a relational/cognitive perspective, the role played by the dimensions of social capital, measured as social interactions, trust, shared vision and involvement of local institutions, in process and product innovation. However, none of the two works consider the impact of network embeddedness measures on the count of new products developed. Thus, while it is well recognized in innovation management literature that new product development is necessary for firm survival and competitive advantage, especially in the high-tech industry, the SC literature disregards the effect of firm's network positions on the likelihood to develop new products (Deeds and Hill, 1996; Rothaermel and Deeds, 2004; Kalaignanam et al., 2007; Vega-Jurado et al., 2009; Un et al., 2010; Bianchi et al., 2011; Tomlinson and Fai, 2013). This omission is glaring, especially in the bio-pharmaceutical industry, where developing new products allows achieving monopoly rents for several years ahead. Thus, our analysis reveals a flaw in the SC literature: while OI and alliance literatures have considered the impact of OI practices and research collaborations on the new product development to measure the innovation performance, the SC literature has, until now, neglected this kind of performance. Thus, in order to fill this gap in literature, we discuss in the following how the aforementioned network positions, centrality and structural holes, impact on the likelihood to develop new products.

2.1.1 Centrality

Three kinds of benefits that arise from a central position have been associated to a positive impact on innovation outputs: knowledge gathering, knowledge accumulation, and scale (Ahuja, 2000).

First, firms centrally located in a network of inter-firm ties are able to gather large quantities of information about successes and failures and screen the most appropriate, and consequently, they are apprised to more information, and potentially have a greater capacity of monitoring their external environment and finding new information and knowledge (Ahuja, 2000). Second, Cohen and Levinthal (1990) show that the accumulation of knowledge enhances companies' abilities to recognize and assimilate new ideas, as well as their ability to convert this knowledge into further innovations. Following their absorptive capacity concept, companies that are more centrally located accumulate greater knowledge and information and, thus, will be in a better position to convert this knowledge into further innovations. Finally, being centrally positioned in a network allows scale economies in research that arise when larger projects generate significantly more knowledge than smaller projects (Ahuja, 2000). Of course, centrality also affects new product development capabilities of the firm. First of all, the firm can reduce the search costs for finding those external resources able to improve the product development process. For instance, by being centrally located, the firm can easily reach suppliers providing the best knowledge and capabilities for making the new product development process more successful (Ragatz et al., 2003; Mazzola and Perrone, 2013), or even they can select the most aligned patent or technology able to trigger or strengthen the new product development process (Geum et al., 2013), or finally getting in contact with potential customers whose commercial needs trigger new product development processes (He et al., 2014). Furthermore, a central position in the network allows accessing partners whose knowledge/technological base is not distant from the ego firm's, so that the firm could reduce the performance risk of unsuccessful technology acquisitions related with product development (Pisano, 1990; Billitteri et al., 2013). Finally, the learning capabilities provided by high information volume allow developing capability in dealing with inter-firm relationships that can be useful to improve collaborative product development processes (Kale and Singh, 2007). Under these circumstances, the above arguments lead to the first hypothesis.

Hypothesis 1: Being centrally located in a network of inter-firm relationships is positively related to the likelihood to develop new products.

2.1.2 Structural Holes

Structural holes are gaps in information flows between partners linked to the same ego network but not linked to each other (Zaheer and Bell, 2005). This structure implies access to mutually unconnected partners, and consequently, to many different information flows (Burt, 1992). The underlying mechanism posited by Burt (1992) is that firms bridging structural holes are able to access novel and diverse information from unconnected parts of the network.

Traditional studies on networks suggest that structural holes are likely to be important to the firm's rate of innovation (Burt, 1992; Ahuja, 2000; Baum et al., 2000; Koput and Powell, 2003; Zaheer and Bell, 2005; Padula, 2008). For example, Baum et al., (2000) empirically investigate how Canadian companies in biotechnology industry that had heterogeneous mix of alliance partners enjoy faster revenue growth and a significant advantage in developing patents. Moreover, Koput and Powell (2003) show higher earnings and survival chances of those biotechnology firms that have more kinds of activities in alliances with different kinds of partners. Structural holes, providing connections with unusual ties operating in different industries, markets or technologies, promote diverse and non-redundant information that - by means of re-combination mechanisms - might help companies to develop new ideas and technologies for developing new products (Burt, 1992; Ahuja, 2000; Rothaermael and Deeds, 2004; Gilsing and Nooteboom, 2005; Dittrich and Duysters, 2007; Gilsing et al., 2008; Koka and Prescott, 2008).

A clear example of this is the IDEO case analyzed by Hargadon and Sutton (1997). Specifically, they describe processes by which a firm, IDEO, uses brainstorming to create new products. The firm's employees work for clients in diverse industries, so that in the brainstorming sessions, they use technological solutions from one industry to solve client issues in other industries where the solutions are rare or unknown. Thus, a firm bridging structural holes acts as the employees in the

Hargadon and Sutton (1997) example; it acts as a technology broker in different industries improving in this way the likelihood to develop new products. Galunic and Rodan (1998) build on the work of Hargadon and Sutton (1997) and found that a firm brokering several industries with its inter-firm relationships is able to broker the knowledge derived from the multiple industries to create new business concepts. They noted that when bridging structural holes, existing ideas and already developed technologies from a partner might appear new to the other, and vice versa, resulting in potentially new products or services. Zaheer and Bell (2005) found a positive relationship between structural holes and the extent to which companies improve their market share. Actors who bridge structural holes are able to developing new understandings, especially regarding emerging threats and opportunities, and efficiently and quickly learning about novel responses to industry trends in a manner that is not possible to those who do not bridge such holes (Zaheer and Bell, 2005). They posit that network position, as access to structural holes, exerts a multiplicity of positive influences on firm's performance, including enhanced efficiency, better access to information or knowledge, and better identification of and responses to threats and opportunities.

Hence, according to the above reasoning we formulate the second hypothesis of the study.

Hypothesis 2: Having a bridging structural holes position in a network of inter-firm relationships is positively related to the likelihood to develop new products.

2.2 Structural embeddedness and new product development: the moderating role of the open innovation flow

OI scholars focus on measuring how much the firm is open (Chiaroni et al., 2010; Dahlander and Gann, 2010), how and why the firm commercializes external sources of innovations (West and Borges, 2013), and how differentiated (breadth) or intensively exploited (depth) are the external search channels of the firm (Laursen and Salter, 2006). However, they have not taken into account, so far, the net flow of knowledge crossing the firm's boundaries. Thus, we define open innovation flow (OI_Flow) as the attitude of a firm of balancing inflow of knowledge coming from the use of inbound practices and outflow of knowledge deriving from the application of outbound practices through the prevalence of inbound and outbound practices. In the case, where the firm is involved in more inbound practices than outbound ones, we say that the attitude of the firm of doing inbound of knowledge regards outbound of knowledge is prevalent and therefore the OI_Flow is positive. On the other hand, if the firm is engaged in more outbound practices than inbound ones, we say that the attitude of the firm of doing outbound of knowledge regards inbound of knowledge is prevalent and therefore the OI_Flow is negative. Finally, if the firm is involved in the same amount of inbound and outbound practices, we say that the attitude of the firm of doing inbound of knowledge regards outbound of knowledge it is equivalent and so the OI_Flow is neutral. Hence, our measure of OI_Flow accounts for how the firm uses the information content provided by its network position. SC scholars have acknowledged that having a central position provides the firm with a high volume of information, while having a structural holes position delivers high information diversity. In H1 and H2 we have hypothesized how being central or having a structural holes position in a network positively influences the likelihood to develop new products.

However, a further important question concerns how the firm uses the information content provided by its network position and, in particular, whether a different use of such information in terms of in-flowing or out-flowing of knowledge strengths or weakens the relation between network positions and the likelihood to develop new products.

We argue that if a firm mostly applies in-bound practices, i.e. the OI_Flow is positive, it means that the firm mostly uses the available information content provided by its central position to create an inflow of knowledge that strengths the development of new products (Fey and Birkinshaw, 2005; Vega-Jurado et al., 2009; Un et al., 2010; Tomlinson and Fai, 2013). For instance, having a central position in the network possible means that the firm is in contact with several potential suppliers of technologies, patents and services; this occurrence, by its own is able to improve the likelihood to develop new products as stated in H1; however, if the firm uses such information to build in-bound knowledge relationships with its possible suppliers, it uses its information content to involve such suppliers in the new product development process and this further increases the probability to develop new products (Ragatz et al., 2003; He at al., 2014). Thus, if the firm associates a positive OI_Flow to its central position, its ability to develop new products is strengthen.

On the contrary, if a firm mostly applies outbound practices, i.e. out-licensing, selling of R&D services and technologies, it uses its information content, provided by its central position, mostly to outflow knowledge to other firms; thus, if the firm is more focused on selling intermediate innovation products, like patents, technologies or services, then it is less likely to develop new final products on its own (Mazzola et al., 2012; Bianchi et al., 2014). Also, in this case, the high information volume provided by its central position allows the firm to easily find customers for selling its patents, technologies and R&D services. Consequently, the firm specializes itself in providing intermediate innovation products and fails to acquire those skills needed to develop final products. Thus, we expect that the more a firm creates an incoming OI_Flow the more it is able to use the volume of information provided by its central position in order to develop new products. On the other hand, the more a firm generates an out-going OI_Flow, the more the volume of information provided by its central position is used to sell intermediate innovations and this adversely affects the possibility to develop new final products.

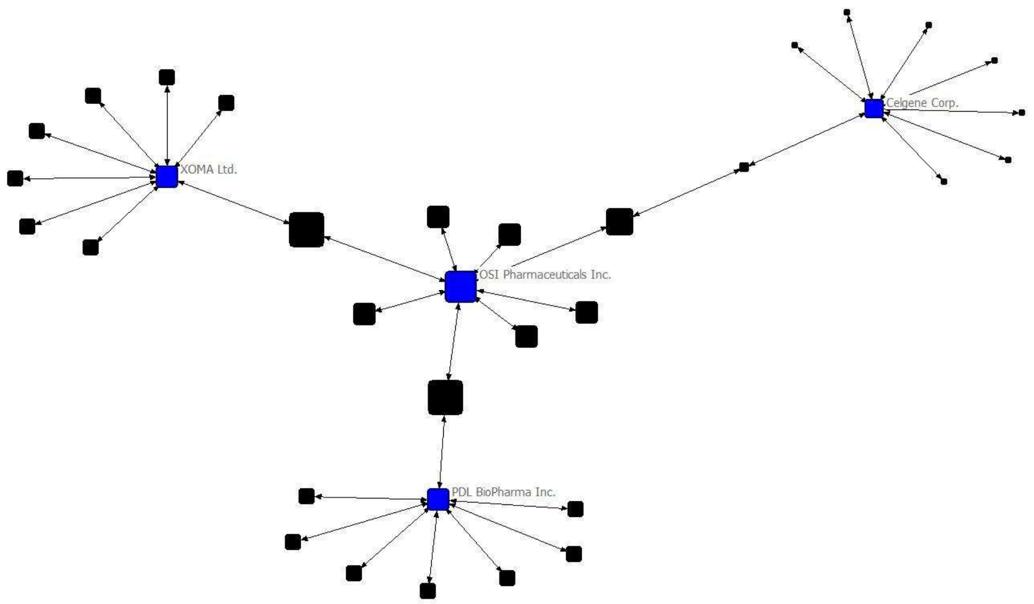

Figure 1. Anecdotal evidence of the interaction between centrality and OI_Flow

Figure 1 provides evidences concerning the previous considerations. It represents the 1-step network of 3 bio-pharmaceutical firms, i.e. Celgene Corp., PDL Biopharma Inc. and Xoma Ltd., during the period 2006-2010. The size of the node in the picture is proportional to the firm's eigenvector centrality, i.e. it accounts for direct and indirect centrality; thus, as the reader can notice they have the same eigenvector centrality. However, in the period 2006-2010, of its 8 ties, Celgene Corp. has performed 5 inbound practices with 5 different partners, while it has not performed any outbound practices. Thus, the net effect is a knowledge inflow (5-0>0), i.e. a positive OI_Flow. Celgene Corp. has developed two new products in the observed period. PDL Biopharma Inc., has performed 4 inbound and 4 outbound practices, thus it has a neutral OI_Flow (4-4=0) and it has not developed any product in the same period. Finally, Xoma Ltd. has performed 3 outbound practices and only 1 inbound practice in the period 2006-2010, thus it has an outflow of knowledge (1-3<0), i.e. a negative OI_Flow. It has not developed any product in the period. Hence, according to the above reasoning and the anecdotal evidences shown above, we formulate the third hypothesis of the model.

Hypothesis 3: Open innovation flow moderates the relation between centrality and new product development; in particular, a positive open innovation flow, i.e. an inflow of knowledge, further increases the likelihood to develop new products.

The positive effect of having a structural holes position in a network derives from the possibility to bridge diverse information that can allow the firm to find new applications for its technology, or new markets, or new business opportunities (Gilsing and Nooteboom, 2005; Dittrich and Duysters, 2007). However, in order to exploit such information for the new product development process, the firm has to acquire technologies, patents or services, related with these information, that allow it to effectively develop new products. This consideration is quite similar to the new product development process proposed by Hargadon and Sutton (1997) for the IDEO's case study. Indeed, the two scholars identify a process of new product development through the combination of different ideas brought by the brokering position of IDEO. The first step in this process is the definition of a structural holes position of the firm, and the second step is the acquisition of the knowledge that we identify with an incoming flow of knowledge, i.e. a positive OI_Flow.

This is especially true in high-tech industries, such as the bio-pharmaceutical one. Let us consider for instance a common case in the bio-pharmaceutical market. Company “A” is a bio-pharmaceutical firm possessing a technology platform that is already being used to develop products in a given therapeutic area. “A” could potentially get in contact with company “B”, who has developed and patented a new gene that can be modified through the “A” ‘s technological platform to develop a new drug. However, in order to develop the product, “A” needs to perform proper tests in the new therapeutic area and it does not possess the skill to do it. So, it could get in contact with the company “C” to acquire proper trial services. Thus, “A” could act as a bridge between “B” and “C” and getting the idea to use the gene from B to develop a new product in the therapeutic area of “C”. But, is having such information, provided by its structural holes position, enough to develop the new product? Of course not. In order to develop products “A” has to perform an inbound relation with its partners: it needs to buy the gene from “B” and trial services from “C”. Thus, just having the information provided by a structural holes position could be not enough to develop new products; the structural holes position has to be associated with an incoming knowledge flow (Figure 2a). What happens if “A” does not bridge the structural hole between “B” and “C” as in Figure 2b? In this case “A” loses the exclusivity of the information, so the possibility to exploit the information for its own purposes decreases. Indeed, “B” being in contact with “C”, could grow the idea to develop a new product for the therapeutic area of “C” on its own, or by acquiring technology services directly from “A”.

Also in this case we can provide evidences shown in Figure 3. Millenium Pharmaceutical Inc. and Monogram Bioscience Inc. have the same constraint measure equal to 0.167, while Sequenom being constrained in a closed loop (clique) has a higher measure of constraint equal to 0.175. Thus, Millenium and Monogram receive more exclusive information than Sequenom, i.e. they act as structural holes more than Sequenom. Of its 6 ties, Millennium Pharmaceutical has performed 4 inbound practices and 1 outbound thorough 2006-2010. So, it has positive OI_Flow (4-1>0) and it has developed 3 products in the period. Monogram Bioscience Inc. has performed 4 outbound and 2 inbound practices in the period 2006-2010, thus it has negative OI_Flow (2-4<0) and has not developed any product in the same period. Finally, Sequenom Inc. has performed 4 inbound and 1 outbound practices in the period 2006-2012, and, even if its OI_Flow is positive (4-1>0), being more constrained, it has not developed any product in the period 2010-2012.

a) Structural holes with incoming OI_Flow

b) No structural holes

Figure 2. Structural holes and OI_Flow

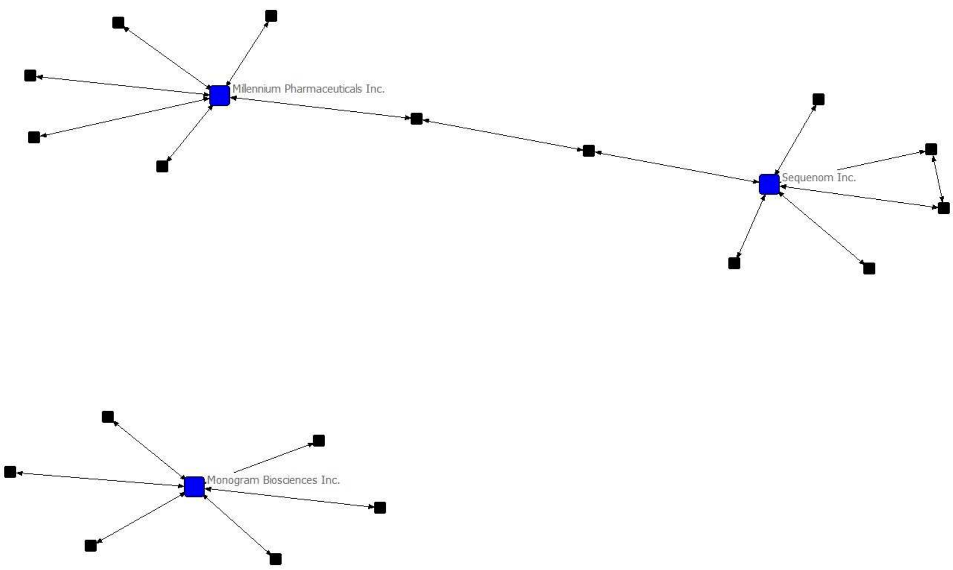

Figure 3. Anecdotal evidence of the interaction between structural holes and OI_Flow

Hence, according with the above discussions and anecdotal evidences, we formulate the fourth hypothesis of the model.

Hypothesis 4: Open innovation flow moderates the relation between structural holes position and new product development; in particular, a positive open innovation flow, i.e. an inflow of knowledge, further increases the likelihood to develop new products.

3. Research method

3.1 Sample and Data

Since the mid 1970s the bio-pharmaceutical industry has been characterized by an increasing recourse to inter-firm agreements between big pharmaceutical firms and small new biotechnology firms. The basic explanation for the increasing number of inter-firm relationships in the industry is related to the extent of strong asset complementarities between the two types of firms (Billitteri et al., 2013). For these reasons, and because it is characterized by a high level of innovation openness, we chose the bio-pharmaceutical industry as the research setting of this study.

We collect data on inter-firm collaborations between bio-pharmaceutical companies in the years 2006-2010 through the BioWorld database, an online information service providing daily news and analysis, company coverage, patent reports, and other biotechnology information. The full dataset, in the observed period, includes 1758 agreements among 1890 firms that, accordingly with OI literature, are categorized into inbound, outbound and coupled practices (Chesbrough, 2003). By inbound practices we mean any agreement concerning in-licensing, acquisition of services, acquisition of technologies and assets, partial and full acquisitions. By outbound practices we mean any agreement concerning out-licensing, selling of services, selling of technologies, assets and divesting. By coupled practices we mean any agreement in which the firm co-makes something with a partner (co-developing, co-manufacturing, co-distribute), i.e. an agreement in which is not possible to identify a clear direction of the knowledge flow and the OI_Flow is indeed neutral. We use the full dataset to find out the OI practices and the structural embeddedness network data of each firm. Then, from this dataset, we select all the public companies in it, specifically 544 firms, to ensure the availability and reliability of firm-attribute data. Thus, by selecting all the public firms in the dataset, no selection bias is present in our sample. We collect data about new products, patenting, and firm-attributes of this sample. We retrieve data on new product development from the "Biotech Products" section of BioWorld database. The patenting data are retrieved from the US Patents Office database. Finally, we collect firm-attribute data from the companies' annual reports.

3.2 Measures

3.2.1 Dependent variables

In the innovation management literature, we find a long history of conflict within the theme of measuring firms' innovation performance. Scholars have employed several kinds of measures to capture firms' innovative performance, such as R&D inputs, patent counts, patent citations, counts of new product introductions, or more specific survey-based measurements (Ahuja, 2000; Soh, 2003; Bae and Gargiulo, 2004). In literature, the two most applied measured are patents (counts, citations and so on) and the number of products developed. We acknowledge that substantial differences exist in measuring innovation performance as patents or new products. These two measures indicate the achievement in the innovation path from conception and development of new ideas (patenting) up to the introduction of an invention into the market (new product development). Specifically, we focus on product perspective disregarding the patent point of view, and the comparison between the two innovation measures, due to the following rationales. Firstly, SC literature has specifically investigated the effect of network positions on patent propensity of a firm, not considering if network positions differently impact others kinds of innovation performance, such as new product development. Secondly, considering the industrial context under analysis, a consistent part of the literature analysing innovation performance in the bio-pharmaceutical industry focuses on new products as a direct measure of how well a firm performs within a new technological paradigm. As already highlighted by Pisano (1990), developing new products is increasingly a focal point of competition and often requires the development and successful implementation of novel process technologies. Especially in the bio-pharmaceutical industry, by introducing a new drug in the market the firm gains a temporary monopoly profits for 10-15 years ensuring in this way cash, market share and getting reputation among physicians, customers and government agencies (Lieberman and Montgomery, 1988). Thus, several scholars within this industry assume the number of new products developed as a measure of innovation performance (Rothaermel, 2001; Rothaermel and Deeds, 2004; Kalaignanam et al., 2007; Bianchi et al., 2011).

Nevertheless, since developing new drugs is a long and costly process (DiMasi and Grabowski, 2007), in order to measure the ability of the firm to develop new bio-pharmaceutical products, we operationalize the dependent variable of this study in two ways: how the firm is prolific in developing many products during the period 2010-2012, NewBioProd_c, and whether the firm has developed at least one new bio-pharmaceutical product in the observed period, *New*BioProd_d. Thus, NewBioProd_d is a binary variable that is one when the company introduces at least one new product in the period 2010-2012, zero otherwise; while, NewBioProd_c is a count variable obtained by summing all the products developed by the firm in that period.

Because of bio-pharma companies may not have a new drug marketed every year, to assess different lag specifications between the investigation variables and the dependent one we adopt an approach quite applied in literature (Rothaermel and Deeds, 2004; Salman and Saives, 2005; Padula, 2008; Phelps, 2010; Vanhaverbeke et al., 2012); according to this approach, both the dependent variables are calculated considering the 3 years succeeding the 5 years bio-pharmaceutical company agreements' observations, that is the period 2010-2012.

3.2.2 Independent variables

As the structural embeddedness network variables, we use two explanatory variables: Centrality and Structural Holes. To calculate these two network measures we first collect Bioworld data and define an inter-firm collaborations' matrix, containing all the agreements established among the 1890 bio-pharmaceutical firms throughout 2006 to 2010. Among the different network measures that have been utilized to capture the notion of centrality, we use the Eigenvector Centrality (Eigen) that accounts for both direct and indirect company ties. The most central companies are those linked to many firms, which are in turn linked to several other firms. We choose eigenvector centrality since it is a good measure of information volume (Koka and Prescott, 2002), that is what, in our perspective (see hypothesis 1), influences the new product development, and also because, in literature, it has been often related to innovation performance (Ahuja, 2000; Salman and Saives, 2005; Padula, 2008). To evaluate eigenvector centrality and structural holes measures we use UCINET VI (Borgatti et al., 2002), a network analysis program that computes network variables by using dyadic data. Following prior literature, we measure Structural Holes (Str_holes) as one minus the firm's constraint score (in cases where constraint was non-zero) and zero for all other cases, because a score of zero in our network happens only when the firm is unconnected to others, so it has no access to structural holes. Constraint is the far most used measure for accounting of structure hole positions in literature (Ahuja, 2000; Zaheer and Bell, 2005; Shipilov, 2006; Shipilov and Li, 2008). Furthermore, the measure has been associated to information diversity (Koka and Prescott, 2002), which indeed is what we would like to capture.

With regards to the OI measures the issue of how measuring OI is a hot topic among innovation scholars (Dahlander and Gann, 2010). This is also highlighted by the editors of the recently Research Policy special issue on Open Innovation (West et al., 2014) that define how measuring OI is one of key trends in OI research (Belderbos et al., 2014). OI scholars focus on measuring how much the firm is open (Chiaroni et al., 2010) and how differentiated (*breadth*) or intensively exploited (*depth*) are the external search channels of the firm (Laursen and Salter, 2006). More recently several authors have assumed a "practice-based" perspective for measuring the degree of openness of a firm (Dahlander and Gann, 2010; Mazzola et al., 2012; Burcharth et al., 2014; Dahlander and Piezunka, 2014; Mina et al., 2014). This measure consists on counting the number of practices of inbound and/or outbound a firm adopts. By choosing this approach in here we are able to consider in one measure the multifaceted nature of the OI concept. However, since the concept of OI is both transactional and relational (Laursen and Salter, 2006), in order to decide which OI practices to consider in measuring the OI_Flow we follow the taxonomy proposed by Dahlander and Gann (2010). In particular, they define "sourcing" category as the *inbound innovation-nonpecuniary* option, whereas "acquiring" category is the *inbound innovation-pecuniary* choice. In addition, they define "revealing" category as the *outbound innovation- nonpecuniary* option, while "selling" category is the *outbound innovation- pecuniary* option. For the purpose of this research, we find appropriate to limit the discussion to the "pecuniary" side of OI, considering both inbound and outbound strategies. The *acquiring* category (*inbound innovation-pecuniary*) captures those OI activities in which a firm acquires input to innovation processes in exchange for market prices. The *selling* category (*outbound innovation-pecuniary*) captures those OI activities in which a firm commercializes internally already developed knowledge outside its boundaries in exchange for market prices. By focusing on those kinds of OI practices we assume a transactional perspective of the OI exchange that allows making inbound and outbound practices more comparable each other. Practically, to construct *OI_Flow* variable, we count how many times each company is involved, in the period 2006-2010, in the following inbound acquiring practices: in licensing, i.e. the purchasing of IP assets (Tsai, 2009); purchasing of services (including R&D and manufacturing) and purchasing of technologies and assets (Tsai, 2009; Chiaroni et al., 2010; Un et al., 2010); partial and full acquisitions of other firms (Vanhaverbeke et al., 2002). While as category of outbound selling we have considered those OI practices through which a firm can commercialize its inventions and technologies through selling or licensing out resources that are developed within the organizations (Bianchi et al., 2014). Specifically, we count how many times, in 2006-2010, each company is involved in the following outbound selling practices: out-licensing, i.e. the selling of firm's IP (Lichtenthaler, 2009); supply of scientific, technological, and manufacturing services (Tsai, 2009; Chiaroni et al., 2010); external technology commercialization, i.e. the numbers of agreements for commercialization and distribution the firm engages in that period (Kutvonen, 2011); divesting, i.e. the number of divisions, business unit and products lines the firm sells from 2006 to 2010 (Lee and Madhavan, 2010).

As already mentioned, with the OI_Flow we would like to measure the net knowledge flow crossing the firm boundaries; it is equal to +1 if the firm has realized in the period 2006-2010 more inbound practices than outbound ones; thus, +1 identifies an attitude of the firm to build a net incoming knowledge flow in the period. Conversely, OI_Flow is -1 in case the firm has more outbound practices than inbound ones, so that -1 identifies a net out-going knowledge flow. Finally, OI_Flow is 0 if the number of inbound practices is equal to the number of outbound practices in the period or if the company has realized only coupled practices throughout 2006-2010. Thus, 0 identifies a neutral OI_Flow, either coming from an equal number of inbound and outbound practices or from coupled practices. Some necessary clarifications are needed about the measure of the open innovation flow we assume in here. Firstly, even if we compare OI practices that are transactional based (inbound acquiring and outbound selling), we do not assume a strictly compensation between inbound and outbound flows, thus we dichotomize the variable. Indeed, by measuring the OI_Flow as the difference between the number of inbound and outbound practices it would have meant to assume a strict compensation among practices; vice versa, the dichotomized variable simply indicates that a firm playing more inbound than outbound it is more likely to have an inflow of knowledge. Secondly, in our measure, coupled practices, i.e. alliances, have no impact on OI_Flow, since, as said, they are neutral; however, this does not mean that alliances have no effect on innovation performance of the firm, which, indeed, is a quite acknowledged result in alliance literature (Deeds and Hill, 1996; Rothaermel and Deeds, 2004). We would like to recall here that our hypotheses 3 and 4 are related to a moderator effect of the OI_Flow on the direct relationship between centrality/structure holes and new product development, thus no direct effect of the OI_Flow on performance is hypothesized in this study. Finally, our measure of OI_Flow relies on the same data we used to calculate eigenvector centrality and structure holes measures;

however, it is a diverse measure as the anecdotal examples clearly show and how the low correlation values reported in Table 2 confirms.

3.2.3 Control variables

Many other factors may influence the likelihood to develop new biotechnological products. One important control variable we include is Patent stock. Patent stock reflects the level of technological capital, absorptive capacity and R&D know-how of a company (Vanhaverbeke et al., 2009; Phelps, 2010) and thus we may expect a positive relation of this variable on new product development. However, we can also expect a negative influence of the patent stock on the dependent variable, in case the firm specializes itself on developing and selling patents and, in this way, it neglects the development of new products (Phelps, 2010). We control for the number of patents a firm obtains in the thirty years up to 2010. Since R&D expenditures are a significant determinant of innovation outcomes (Bae and Gargiulo, 2004; Phelps, 2010), we introduce the second control variable, i.e. R&D Expenditures. We operationalize firm's R&D expenses as the natural logarithm of average R&D expenditures in the years 2006-2010. Moreover, we include the variable Pipeline as control. Indeed, products in the pipeline represent accumulated stocks of knowledge (Decarolis and Deeds, 1999), and they could have a direct relationship to innovation outcome, even if in the biopharmaceutical industry products under development are often sold as intermediate innovation products. We count the number of products in the firm's pipeline up to 2010. We include an Industry dummy variable to indicate whether a company is a pure biotechnological or a bio-pharmaceutical one (Vanhaverbeke et al., 2009). Indeed, the more a biotech firm is integrated downstream in the development of drugs, the higher the likelihood to develop new products (Billitteri et al., 2013). Finally, we include the Nationality of the firm as control (Ahuja, 2000); this is a dummy variable that is one if the company is US one, zero otherwise. Indeed, 341 out of 544 of the firms in our sample are American, a market that is more developed for biopharmaceutical products, thus we expect that being located in the US has a positive impact on the likelihood to develop new products (Phelps, 2010; Vanhaverbeke et al., 2012). We had originally introduced also a control for the size of the firm measured as the natural logarithm of the average employees of each firm in the period 2006-2010 (Ahuja, 2000). However, this variable showed serious collinearity problems with the variable R&D Expenditures, so we decided to drop Size and to keep the R&D Expenditures because this last variable is more fitting the model.

4. Results

Table 2 provides the descriptive statistics and the correlations between all the variables. The correlation coefficients between the independent variables are quite low. Also, the VIF (variance inflation factor) value is below the critical level, indicating that the explanatory variables can simultaneously be included in the models (Stevens, 1992; Gujarati, 1995). It is interesting to notice how the correlations between Eigen, Str_holes and OI_Flow are respectively 0.00 and 0.04, evidencing how the network variables measure a completely different concept than OI_Flow, even if they are derived by the same dataset.

	Mean	SD	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1. NewBioProd_d	0.11	0.31	0	1	1.00									
2. NewBioProd_c	0.18	0.71	0	11	0.71	1.00								
3. Patent stock	76.73	327.38	0	3359	0.16	0.40	1.00							
4. R&D Expenditures	2.69	1.78	0	9	0.33	0.33	0.43	1.00						
5. Pipeline	5.84	11.25	0	150	0.21	0.32	0.34	0.32	1.00					
6. Industry	0.61	0.498	0	1	0.10	0.01	0.03	0.08	0.03	1.00				
7. Nationality	0.37	0.48	0	1	-0.06	-0.07	-0.04	-0.08	0.09	-0.09	1.00			
8. Eigen	1.06	3.48	0	47.1	0.19	0.50	0.32	0.25	0.23	-0.14	-0.01	1.00		
9. Str_holes	0.35	0.34	0	1	0.12	0.16	0.18	0.23	0.12	-0.1	0.00	0.35	1.00	
10. OI_Flow	0.03	0.83	-1	1	0.07	0.11	0.09	0.13	0.11	0.01	0.00	0.00	0.04	1.00

Table 2. Descriptive statistics and correlation matrix

4.1. Probit models

NewBioProd_d is a dichotomous variable, thus we use a "probit" model (Hoetker, 2007). The probit and logit regression models tend to produce very similar predictions and the choice between the logit and probit models is largely one of convenience and convention, since the substantive results are generally indistinguishable (Long, 1997).

Table 3, models 1-4, provides an overview of the results of the probit model. Model 1 contains all the control variables. Model 2 evaluates the main effects of centrality and structural holes. Since the interaction term may be highly correlated with the first-order predictor variables from which it is derived, to create all the interaction items we mean-centered the first-order variables Eigen, Str_holes, OI_Flow to reduce the potential multicollinearity (Little et al., 2006). Furthermore, we sequentially and separately include the two interaction effects in Models 3 and 4 in order to track coefficients and significance levels (Dalal and Zickar, 2012). Indeed, by looking at the overall fit of each of the models, we observe that the introduction of structural embeddedness network measures in model 2 significantly improves the fit. Another significant improvement occurs in models 3 and 4, with the introduction of the two interaction effects.

As expected, R&D Expenditures has a positive and significant effect in all the models. The Patent stock coefficient is negative and significant in models 2, 3 and 4. This confirms that the more a bio-pharmaceutical firm is specialized in the upstream phase of the supply chain, the research phase, the more its business model is based on producing and selling patents and technological services instead of developing new products. The Industry coefficient is positive and significant in all the models; as expected, the more a company is downstream integrated in the pharmaceutical market, the higher is the likelihood to develop new products. Finally, Nationality and Pipeline do not achieve statistical significance.

Model 2 introduces the *Eigen* and *Str_holes* as explanatory variables. According to H1, we expect a positive relation between centrality and new product development propensity. As shown in model 2, the coefficient of *Eigen* is significant and the sign is as predicted; this means that being centrally located in a network increases the likelihood to develop new biotech products.

According to H2, we hypothesize a positive relation between structural holes and new product development. As depicted in model 2 the coefficient for *Str_holes* is positive, as expected, but it is not significant.

Model 3 introduces the pairwise interaction term between Eigen and OI_Flow in order to test H3; we expect a positive interaction effect between centrality and open innovation flow. As model 3 shows, the interaction term (EigenXOI_Flow) is positive and significant, so, H3 is confirmed.

Finally, Model 4 introduces the pairwise interaction term between Str_holes and OI_Flow in order to test H4; we predict a positive interaction effect between structural holes and open innovation flow. As shown in model 4, the interaction term (Str_holesXOI_Flow) is positive and significant, so also H4 is confirmed.

As highlighted by Hoetker (2007), interaction terms in probit and logit models should be carefully interpreted. Indeed, in this case, the marginal effect of a change in both interacted variables is not equal to the marginal effect of changing just the interaction term as normally applies in linear models. More surprisingly, the sign may be different for different observations, thus the appraisal of the interaction term cannot only be determined from significance of the z-statistic reported in the regression output. In this case, besides the interpretation of the significance of the z-statistic of the coefficient, a graphical presentation of the interaction term for the different observations is almost required (Hoetker, 2007). For this reason, we apply the STATA's inteff command (Norton et al., 2004) to our dataset in order to verify that the sign of the z-statistic of the coefficient of the interaction term is the same as that of the z-statistic of the observations. Results from the application of the command are reported in Figures 4 (a-d). As shown in Figure 4a and 4b, all the interaction effects of the observations, with the exception of 3, are positive, and all the z-statistics of the single observation, except 3, are also positive. This confirms the probit results. Also the analysis of the z-statistic significance is quite good; indeed, looking at Figure 4b, when moving from a probability to develop a product close to zero, the z-statistics are above the red line delimiting the significance area; furthermore, the few negative z-statistics are all not significant.

Moving to the interaction effect between Str_holes and OI_Flow, by looking at Figures 4c and 4d the same considerations of above hold.

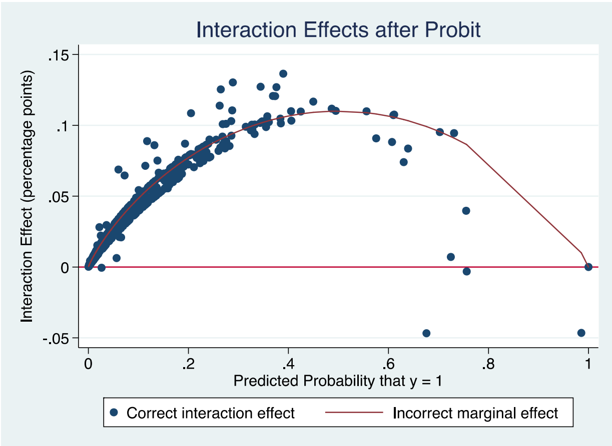

Figure 4a. Interaction effects of EigenXOI_Flow

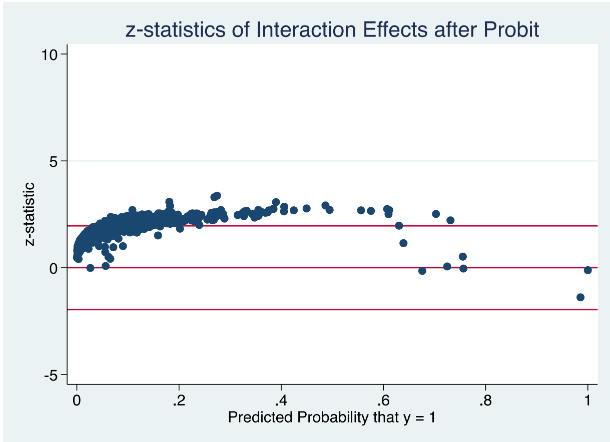

Figure 4b. z-statistics of the interaction effects of EigenXOI_Flow

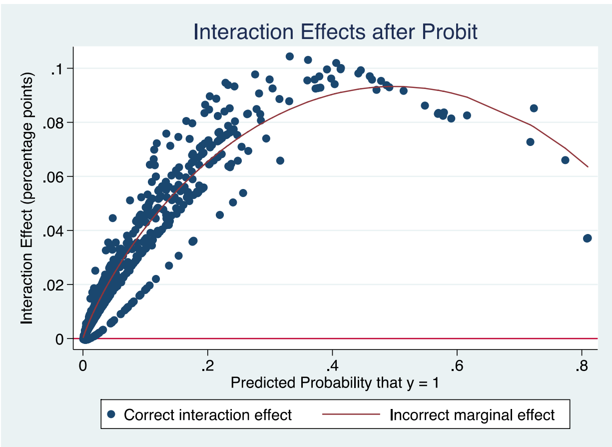

Figure 4c. Interaction effects of Str_HolesXOI_Flow

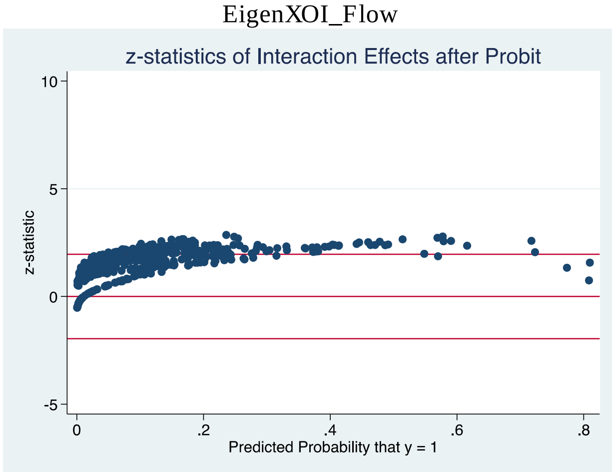

Figure 4d. z-statistics of the interaction effects of Str_HolesXOI_Flow

4.2 Negative binomial models

NewBioProd_c is a count variable that takes only non-negative integer values. Since the dependent variable indicates over-dispersion, as depicted in Table 2, (mean of 0.18 and S.D. of 0.71), a negative binomial estimation provides the better fit for count data than the more restrictive Poisson model. Table 3, models 5-8, provides an overview of the results of the negative binomial models. Also in this case, the likelihood ratio tests reported in Table 3 indicates that each model represents a significant improvement over the baseline model (Model 5).

Starting from the control variables, the results are the same of the logit model for the variables Patent Stock, R&D expenditures and Industry. Differently from the logit model, we find that the Nationality variable is negative and significant in all the models; meaning that US firms, as expected, develop more biotech products. Finally, the coefficient Pipeline is significant and positive in all the models; so, as expected, having a rich pipeline influences positively the number of products developed.

In Model 6 the coefficient of *Eigen* is significant and the sign is as predicted; this result corroborated H1. Moreover, also in this case, *Str_holes* has a positive coefficient but is not significant. In models 7 and 8 the coefficients of the interaction terms EigenXOI_Flow and Str_holesXOI_Flow are both positive and significant as expected; so, also H3 and H4 receive, from the binomial model, a corroborated confirmation.

5. Discussion and conclusions

The results of the empirical analysis show a consistent support to our theoretical framework and contribute significantly to the literature on the issue.

In hypothesis 1 we posit how having a central position in a network of inter-firm relationships has a positive impact on the likelihood to develop new products. The positive coefficient in all the models of Tables 3 of the eigenvector centrality (Eigen) confirms our intuition that accessing a high volume of information allows the firm to find more suitable supplier collaborations (Ragatz et al., 2003; Tsai, 2009; He at al., 2014) and/or to locate intermediate innovation products (patents, technologies, services etc.) that better fit the product development projects of the firm (Geum et al., 2013). Although this result is quite in line with other empirical works concerning other innovation performance (Ahuja, 2000; Soh, 2003), to the best of our knowledge, it is the first showing the positive influence of a central position on the effectiveness of the new product development process; thus, our results strengthen the importance of being central in a network of inter-firm ties to gain innovation performance.

In hypothesis 2 we predict a positive relation between structural holes position and the likelihood to develop new products. Although the sign of the coefficient in the models is positive, it never turns out significant. This finding reflects the dualistic debate in literature that offers different explanations for the role of structural holes. Following Burt (1992), several scholars have hypothesized a positive influence of structure holes on firm performance. Most of the empirical confirmations about this position are obtained for economic and financial performance (Zaheer and Bell, 2005; Shipilov, 2006; Shipilov and Li, 2008). However, according to Coleman (1988) searching through structural holes might lead to deteriorate the innovative propensity of a firm. Indeed, having a structural holes position exposes the firm to a higher volume of diverse information (Gnyawali and Madhavan, 2001); to recognize, assimilate, transform, and exploit these information for creating new products, a firm must put greater effort and resources (Cohen and Levinthal, 1990). The problem is that there is a limit to the absorptive capacity of a focal firm. Moreover, when knowledge components become more diverse, the lack of specialization and focus makes the recombination of this knowledge in new valuable ideas difficult, thus decreasing the innovation rate. Thus, when dealing with innovation performance, absorptive capacity problems become highly significant; indeed, Ahuja (2000) empirically finds a negative influence between structural holes and patent propensity of a company. On the other hand, Padula (2008) finds that a firm occupying a position that bridges network clusters is able to improve its patent propensity. The basic conclusion that emerges from the contrasting result between Ahuja’s (2000) and Padula’s (2008) studies is that whether structural holes are good, bad, or irrelevant is a function of the context under analysis. Thus, considering the nature of ties and the innovation performance measured, in our hypothesis we have predicted a positive effect of structural holes on new product development. Indeed, focusing on new product development point of view, in a network consisting of competitive linkages between firms belonging to the same industry, bio-pharmaceutical companies act as technology brokers (Hargadon and Sutton, 1997). This brokerage position increase the probability to develop new products due to the ability of the firm to collect different information that can be useful in finding new applications of existing technologies, or new business opportunities for existing products. Our results show that, diversely from patents (Ahuja, 2000; Padula, 2008), having a structural holes position does not have any effect on new product development. So we might conclude that brokering different information, if from one hand has an effect (discordant) on patent propensity, it is not enough to improve the new product development rate of a company. Most important, as we are going to explain in the following, we found that in a network of competitors the structural holes position has a positive effect on developing new products due to the *OI_Flow* activation. Thus, only by associating an incoming flow with a structural holes position a firm can increase its propensity to develop new products.

As concerns the interactions between structural network embeddedness and OI_Flow, the former provides information content to the firm, while the latter indicates whether such information content results in an entering knowledge flow (inbound) or an exiting one (outbound). In hypothesis 3 we hypothesize how an incoming flow of knowledge further increases the likelihood to develop new products, while an outgoing flow of knowledge decreases the likelihood to develop new products. The positive and significant sign of the interactions between Eigen and OI_Flow in model 3 (the logit model) and model 7 (the binomial model) confirms the prediction that when the OI_Flow is positive, the likelihood to develop a new product, as well as the number of new products developed, increases. In Figures 5a and 5c we plot, respectively, the predicted probability to develop a new product and the predicted number of products developed when the eigenvector centrality increases in two cases: OI_Flow = -1, +1. When high centrality is associated with an outgoing flow (OI_Flow = -1), the probability to develop new product is lower and slightly decreasing with the centrality. This confirms our intuition that the availability of a high volume of information and an attitude of the firm to perform outbound selling practices allows the firm to easily finding possible customers for selling its intermediate innovation products (patents, technologies or services). This focalizes the firm on selling intermediate innovation, reducing the likelihood to develop final products. On the contrary, when high centrality is associated with inbound acquiring practices, i.e. an incoming knowledge flow (OI_Flow = +1), the predicted probabilities highly increase with the eigenvector centrality because, the firm uses the available information to acquire new knowledge and innovation assets that can be used to develop new products.

In hypothesis 4 we predict a positive effect of the interaction between structural holes and open innovation flow. Again, the positive and significant sign of the interaction between Str_holes and OI_Flow both in models 4 and 8 confirms this prediction. Figures 5b and 5d plot, respectively, the predicted probability to develop a new product and the predicted number of products developed when Str_holes increases in two cases: OI_Flow = -1, +1. Also in this case, when structural holes positions are associated with outbound practices (OI_Flow = -1), the predicted probabilities decrease with the strengthening of the position of structural holes. On the other hand, when structural holes position is associated with an inbound flow (OI_Flow = +1), the probability to develop new product is higher and it increases with a stronger structural holes position.

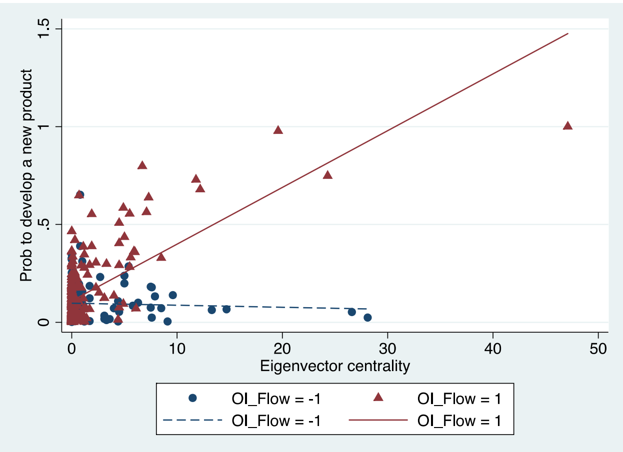

Figure 5a. Interaction EigenXOI_Flow - Predicted probability of developing a new product

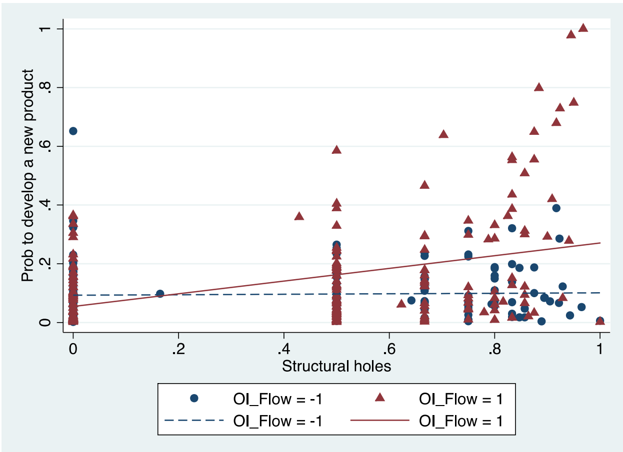

Figure 5b. Interaction Str_holesXOI_Flow - Predicted probability of developing a new product

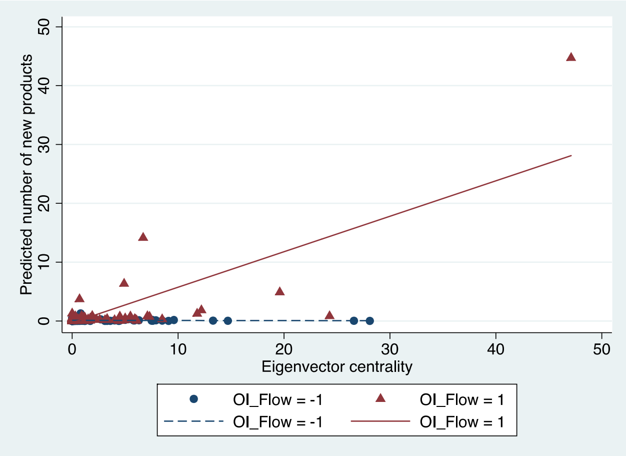

Figure 5c. Interaction EigenXOI_Flow - Predicted number of new products developed

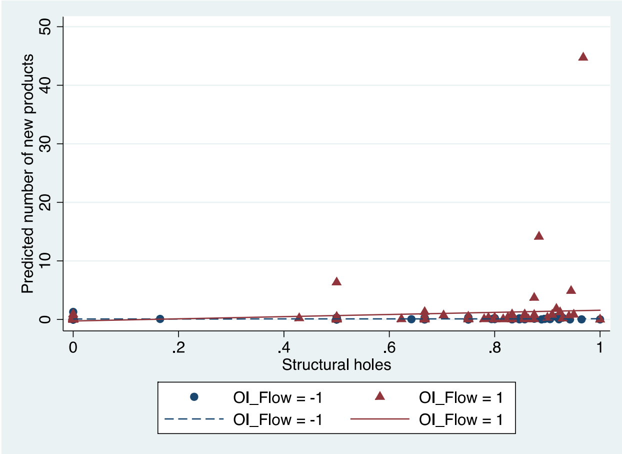

Figure 5d. Interaction Str_holesXOI_Flow - Predicted probability of new products developed

This result is quite interesting if considering the empirical results we get for the principal effect, i.e. structural holes position does not influence alone the probability to develop new products. Thus, only by associating an incoming flow with a structural holes position a firm increases the probability to develop new products. This result is quite in line with the consideration proposed by Hargadon and Sutton (1997) for IDEO case study; the authors find that initially the firm assumes a network position able to bridge diverse information and afterwards inbounds the knowledge coming from these diverse information. Our results strengthen this case study analysis also within the same industrial context. Thus, besides the context issue, raised by Ahuja (2000) to explain why in a network of competitors structural holes positions are associated with negative performance (patents) while in a network of complementors are associated with a positive performance (new products) (Hargadon and Sutton, 1997), we highlight here another important issue: how the firm uses the information asset provided by its network position. The open innovation flow concept is a measure of how the firm uses its network information; that is to create an incoming flow of knowledge or an outgoing one. Here we show that the association between network position, i.e. the information the firm has, and the OI_Flow, i.e. how it uses such information, does have an impact on product development.

Our study has important theoretical and managerial implications. Firstly, our results are robust and confirmed through two different operationalization of new product development. Secondly, we bridge a gap between SC and OI literatures. SC scholars have pointed out the importance of the information asset provided by the structural embeddedness for the firm's innovation performance (e.g. Ahuja, 2000; Schilling and Phelps, 2007; Perez-Luño et al., 2011). OI scholars have shown how the knowledge flow, due to inbound practices, positively impacts on innovation performance (e.g. Fey and Birkinshaw, 2005; Vega-Jurado et al., 2009; Un et al., 2010). Both SC and OI literatures advantage significantly from this study; indeed, we propose a combination of the information asset, provided by network embeddedness, and how the firm uses the information available on its network in term of inflowing or outflowing of knowledge, a main focus of OI scholars. We show how the two things are related: firm's innovation performance, as new product development, depends on the interaction between the information assets provided by the network position and the use of such asset measured through the open innovation flow.

Our results significantly impact in terms of managerial perspectives, firstly in the bio-pharmaceutical context, but also in other industries. Indeed, several studies have signaled to managers the strategic importance of product development in bio-pharmaceutical context as a mean for acquiring monopoly positions and reduce the "functional incompleteness" of biotech companies (Pisano, 1990; Kalaignanam et al., 2007). Furthermore, other studies evidenced how alliances and OI practices can improve the ability of the firm to develop new products (Deeds and Hill, 1996; Rothaermel and Deeds, 2004). Our findings suggest further directions to bio-pharmaceutical managers for improving new product development. Firstly, network positions matter, especially centrality (both direct and indirect); indeed, while building a direct central position takes time, since the firm has to sign several inter-firm relationships, having an high eigenvector centrality is relatively easier since the firm needs to sign an agreement with a highly centrally located firm in the network. This, according to our results, seems to put the firm in a position of improving its product development performance. Secondly, managers can take advantage by combining structural network embeddedness and open innovation flow. According to what evidenced in Figures 5a and 5c, a firm wishing to improve its product development rate should build, year by year, its central position in the network and exploit it by using inbound practices. On the other hand, if a firm wishes to improve its financial performance by selling intermediate innovation products (patents, technologies, services) it should exploit its centrality through outbound practices; of course, this will reduce the probability to develop new products. Thirdly, while our study provides a neutral expectation from gaining structural holes position in a network of inter-firm ties, at least with regard to product development processes, we signal how inbound practices seem to activate the potentiality gained from the different information that a structural holes position provides.

5.1 Limitations and further research

The results and the contributions of this study should be considered in light of its limitations. Firstly, this study focuses on the bio-pharmaceutical industry (traditionally involved in innovation processes) and excludes other types of industries. Although this approach is appropriate, it would be unwise to generalize the findings too broadly to other industries and cultural contexts. Secondly, since the analysis is built upon cross-sectional data, the long-term effects could not be investigated. The gathering of longitudinal data in which time lags between variables are present would be an important step for further investigations. Moroever, as the measure of open innovation (OI_Flow) has been newly developed for this study, it requires further validation in future researches. In addition, researchers often capture innovation performance with both new developed products and number of patents (or other innovation outcomes). We used only new developed products. Thus, not only the performance results can be somewhat biased, but also the interpretation of them can be different in cases where other innovation measures are employed. Finally, in this study, we start this debate by addressing only one dimension of the social capital, i.e. the structural embeddedness, and therefore neglecting the relational embeddedness, that has been widely proved to influence firm's performance (Gulati, 1995; Soh, 2003). Furthermore, Uzzi (1997) developed the notion of "overembeddedness" suggesting that inter-firm networks composed mostly of strong ties may threaten innovation, rather than enhance it; this theory has obtained some empirical support both in

OI (Laursen and Salter, 2006) and SC (Phelps, 2010; Vanhaverbeke et al., 2012) literatures. Here we have neglected the impact of "overembeddedness" on the interaction between network positions and open innovation flow. Future research might take these considerations into account.

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	Model 1	Model 2	Model 3	Model 4	*Model 5*	*Model 6*	*Model 7*	*Model 8*
	NewBioProd_d - Probit model				*NewBioProd_c - Binomial model*			
Patent Stock	-.00028	-.00042*	-.00057*	-.00045†	.2.51e-06	-.00049*	-.00070*	-.00058*
	(.00021)	(.00021)	(.00022)	(.00021)	(.00025)	(.000254)	(.00028)	(.00025)
R&D Expenditures	.325***	.317***	.339***	.313***	.4823***	.4905***	.5183***	.4838***
	(.0549)	(.0532)	(.0534)	(.0529)	(.0992)	(.0869)	(.0841)	(.0874)
Pipeline	.01123	.00926	.00637	.00819	.0392**	.0303*	.0255†	.0277*
	(.0073)	(.0072)	(.0074)	(.0075)	(.0783)	(.0157)	(.01617)	(.0166)
Industry	.354*	.497**	.470*	.485**	.3014	.6036*	.5521*	.5408*
	(.170)	(.185)	(.186)	(.189)	(.2566)	(.2924)	(.2918)	(.3017)
Nationality	-.273	-.259	-.244	-.274	-.7627*	-.7856*	-.7813**	-.8311**
	(.187)	(.188)	(.189)	(.191)	(.3353)	(.3254)	(.3230)	(.324)
Eigen		.0436*	.0491†	.0463*		.0642*	.0075	.0601*
		(.0207)	(.0272)	(.0206)		(.0257)	(.0478)	(.0231)
Str_holes		.183	.180	.175		.4699	.5854	.3659
		(.255)	(.259)	(.269)		(.4149)	(.4334)	(.4546)
OI_Flow			-.0225	-.0445			.0380	.0117
			(.0964)	(.102)			(.1581)	(.1834)
EigenXOI_Flow			.222**				.2698*	
			(.0793)				(.376)	
Str_holesXOI_Flow				.193*				.2699**
				(.0788)				(.1378)
Constant	-2.51***	-2.70***	-2.73***	-2.68***	-3.892***	-4.357***	-4.359***	-4.249***
	(.233)	(.251)	(.249)	(.250)	(.409)	(.388)	(.382)	(.388)
N	544	544	544	544	544	544	544	544
Wald χ^2	56.69***	73.32***	73.34***	75.49***	110.78***	134.26***	98.45***	146.78***
Log- (psedudo) likelihood	-153.66	-150.30	-145.73	-147.29	-207.29	-202.56	-199.56	-200.23
Likelihood ratio test					-	6.054***	2.002***	2.134**
Psudo R^2	.1863	.2041	.2283	.2200				

Robust standard errors in parentheses † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3. Results of the empirical analysis