Accumulated stock of knowledge and current search practices: the impact on patent quality

ABSTRACT

The paper suggests a multidimensional patent-based framework that investigates the relationships among accumulated stock of knowledge, current knowledge search practices and quality of innovation output. More specifically, the work intends to examine how the recourse to specific technological strategies, the previous open innovation adoption, the use of external sources of inspiration and the engagement of external actors for knowledge search affect both the market and the technological value of patented inventions. The methodology is tested on 61,042 patents filed by 157 R&D intense bio-pharmaceutical and technology hardware & equipment companies. Results show that technological specialization leads to high value technologies and is stimulated by the use of external sources of inspiration. Moreover, firms search for new knowledge by engaging external actors when they aim at exploring new technical areas. Finally, when companies largely employ open innovation to accumulate knowledge, they achieve high quality in future R&D efforts.

HIGHLIGHTS

- A patent-based framework for studying knowledge search after multiple perspectives
- Relationships among accumulated knowledge stock, current search and patent quality
- Technological specialization is stimulated by the use of external sources of inspiration
- Exploration strategies are pursued by engaging external actors
- Knowledge accumulated with open innovation practices favors high quality inventions

KEYWORDS

Knowledge search; technological strategy; open innovation; stock of knowledge; sources of knowledge; patent data

1. INTRODUCTION

The capability of accurately managing knowledge is a strategic asset in R&D intense sectors, where actors recombine and integrate information and expertise belonging to a wide range of technical fields and dynamically expand their stock of knowledge over time (Miller, 2004). Knowledge search (KS) is the part of the R&D process through which firms search for new solutions and technological ideas, solving problems by combining knowledge elements with the aim of creating new products (Katila, 2002). Companies can adopt different search strategies for the development of new technologies and not only employ their internal know-how, but also capture knowledge spillovers from third parties. Actually, even though firms' innovation capability depends on their existing stock of knowledge, companies also employ external sources in order to access knowledge. Firms can rely either on sources of inspiration and information - such as scientific articles and patent documents - or on external actors directly involved in the R&D process, such as industrial and scientific partners.

A central issue in knowledge management studies is the effect of KS strategies on innovation performance. Firms accurately select the KS practice that may improve the output of the R&D process (Xie *et al.*, 2016). Indeed, many scholars suggested that both the existing stock of knowledge and the current search strategies affect the quality of innovation output and innovation performance (Ferreras-Mendez *et al.*, 2015; Hwang and Lee, 2010; Laursen and Salter, 2006; Wu *et al.*, 2014), positively contributing to the companies' future financial returns and, then, to their market value (Hall *et al.*, 2005).

Actually, companies use their internal knowledge about customer preferences, technologies, product design or market requirements to search for new solutions and develop new products. Therefore, firms' professional background, expertise, prior knowledge and experience within specific technical areas inspire future R&D efforts (Arts, 2012; Callaert *et al.*, 2014; Hung and Tang, 2008). Path dependence theory suggests that previous R&D efforts address the future ones. Older and already established knowledge is valuable and companies have to learn from distant times (Katila, 2002; Katila and Ahuja, 2002).

Nevertheless, to our knowledge no scientific contribution regarding the direct dependence of current KS activities from previous search strategies is available.

In addition, prior research concentrated its attention on the study of KS from a one-dimensional perspective, e.g. by considering only the nature of the sources employed, the actors engaged, the interaction mechanisms, the organizational practices or the managerial practices.

In this work, we aim at contributing to the current literature by providing a multidimensional patent-based framework that investigates the impact of KS strategies on innovation performance, measured by patent quality. In particular, we intend to understand: 1) how the stock of knowledge deriving from past search strategies and involved in current development processes affects the present search practices selection, 2) the effect of both existing stock of knowledge and current search practices on innovation performance.

Since innovation is a complex topic, we aim at investigating such dimensions from a multidimensional perspective, by considering *where* and *how* to search for knowledge and information, *who* is involved in the search process and *how* previous experience affects the efforts under investigation.

A further contribution regards our operationalization, since we studied KS exclusively employing patent statistics. Hence, the suggested framework has been built exploiting information deriving from a valuable source, publicly available, containing objective and standardized data, and widely acknowledged by scientific literature (Belderbos *et al.*, 2010; Burhan *et al.*, 2016; Griliches, 1990; Grupp, 1992; Johnstone *et al.*, 2012).

2. RESEARCH QUESTIONS

This work aims at answering three research questions (Figure 1):

RQ1: how accumulated stock of knowledge is related to current search practices;

RQ2: how stock of knowledge is related to quality of innovation output;

RQ3: how search practices are related to quality of innovation output.

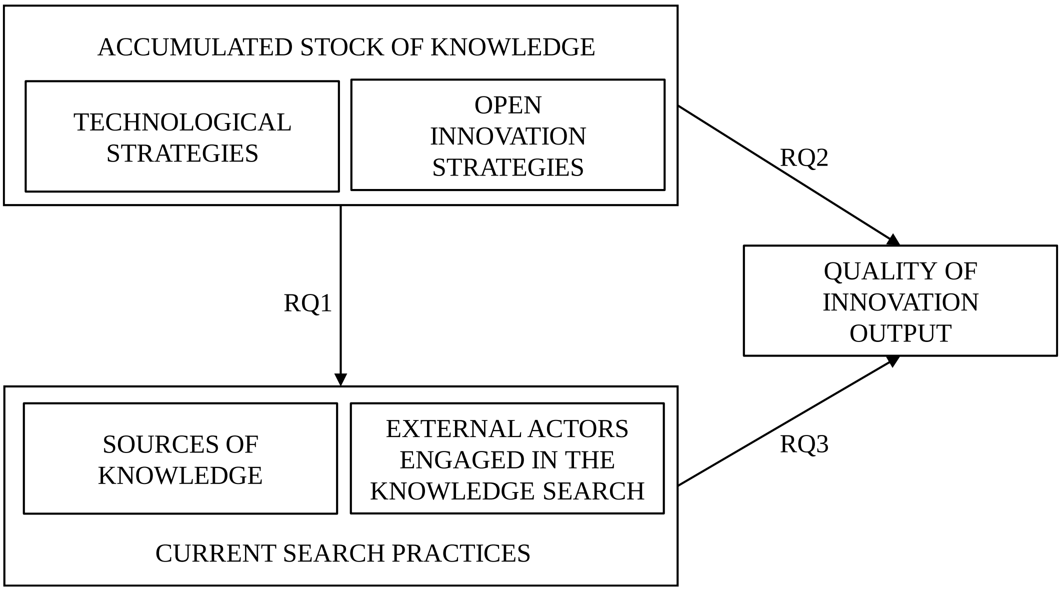

Figure 1. Theoretical framework and research questions

The **stock of knowledge** summarizes the professional background and experience accumulated by the firm and potentially available as a starting point for future R&D efforts. It is described by both technological strategies carried out by companies and open innovation (OI) practices previously adopted to achieve experience. This dimension answers the questions on *where* to search and *how* to accumulate knowledge. Actually, the spatial dimension of the search is defined by technological strategies, where exploitation vs. exploration reflects local vs. distant knowledge search. In addition, OI strategies delineate the different modalities through which knowledge is developed, transferred and absorbed for future applications.

The **search practices** refer to the opportunities and the sources that firms directly employ in the specific R&D effort under investigation. They are defined by both the sources of information stimulating new developments and the external actors directly engaged in the KS. This dimension answers the questions on *how* to search - i.e. starting from which sources of inspiration - and *who* is involved in the search process.

The **quality of innovation output** is characterized in terms of:

- marketability, as the ability of the patented invention to reach the market and contribute to firm's competitive advantage;
- originality of the technological combination, suggesting the focal firm's capability to generate new architectures and recombine knowledge;
- technological acknowledgement, signaling the technical value of the patented technology;
- internal value, as a proxy of the private value attributed by the patent assignee to the invention.

3. LITERATURE REVIEW

3.1 Accumulated stock of knowledge

3.1.1 Technological strategies

As uncovered by Laursen and Salter (2006), KS helps firms to find sources of variety and create new combinations of technologies and knowledge. Literature focused on KS strategies by investigating their breadth and depth (Katila, 2002; Katila and Ahuja, 2002). The first refers to the extent of external sources or channels (e.g. suppliers, users, universities and firms) monitored by companies, whilst the latter concerns the search intensity within each channel.

The company's capability to monitor, process, integrate and employ external flows of knowledge will depend on the ability to link this knowledge to its existing knowledge base (Denicolai *et al.*, 2016; Shenkar and Li, 1999). As suggested by Cohen and Levinthal (1990), "*prior related knowledge confers an ability to recognize the value of new information,* *assimilate it, and apply it to commercial ends. These abilities collectively constitute what we call a firm's absorptive capacity*". More specifically, Lane *et al.* (2006) defined absorptive capacity as the "*firm's ability to utilize externally held knowledge through three sequential processes: recognizing and understanding potentially valuable new knowledge outside the firm through exploratory learning, assimilating valuable new knowledge through transformative learning, and using the assimilated knowledge to create new knowledge and commercial outputs through exploitative learning*".

Actually, among the various classifications of KS strategies, one of the most used is **exploitation vs. exploration**. Indeed, they represent two distinct KS activities that differently impact on companies' innovation performance (Belderbos *et al.*, 2010; Benner and Tushman, 2002; He and Wong, 2004; March, 1991; Miller *et al.*, 2007; Miner *et al.*, 2001; Schulz, 2001; Simon, 1991). With exploitation, firms perform local search by using knowledge that is closely related to their pre-existing knowledge bases and leveraging existing capabilities, while exploratory search aims at moving away from current knowledge bases (i.e. distant search) and accessing to new knowledge domains. Conceptually speaking, higher search breadth is associated with exploration strategies (Katila and Ahuia, 2002), which improves the possibilities for finding new useful combinations. It was widely discussed that companies need to simultaneously pursue both types of search strategies. As remarked by Benner and Tushman (2003), "*organizations that must meet current requirements and new customer demands do not have the luxury of choice. They must deal simultaneously with the inconsistent demands of exploitation and exploration*". While exploration and exploitation are mutually exclusive within a single technological field, they are orthogonal across different domains; hence, high levels of exploitation in a specific area may coexist with high levels of exploration in other ones (Gupta *et al.*, 2006).

Another important issue regards the different levels of exploitation of existing knowledge. Indeed, the differences in search depth lead to varying degrees of familiarity with the knowledge. Therefore, companies may restructure their stock of knowledge by pursuing specialization vs. diversification choice (Campbell, 1990; Santalo and Becerra, 2008). For instance, with **specialization** strategies companies focus on a narrow area of knowledge, skills or activities (Brusoni *et al.*, 2001; Duysters and Hagedoorn, 2000), reducing the likelihood of errors and false starts. Specialization makes search more reliable and allows companies to better identify valuable knowledge elements and develop connections among them (Katila and Ahuia, 2002).

On the other hand, companies may diversify in order to extend business activities into disparate fields (Argyres, 1996; Granstrand *et al.*, 1997), searching and accumulating knowledge with potential application in multiple product-market domains (Miller, 2006). Technology portfolios in which knowledge is spread over many technical fields are considered as signaling higher levels of technological diversification (Leten *et al.*, 2007).

3.1.2 Open innovation strategies

The OI paradigm (Chesbrough, 2003) has found audience amongst scholars, business people and policy makers who identify new opportunities to innovate in the access to external sources of knowledge and technology. In contrast to the closed model - which is only focused on internal R&D activities to achieve competitive advantage - OI searches and employs external sources to improve profits (Chesbrough *et al.*, 2006; Garriga *et al.*, 2013; Reed *et al.*, 2012). Indeed, Chesbrough (2006) defines OI as “*the use of purposive inflows and outflows of knowledge to accelerate internal innovation, and expand the markets for external use of innovation, respectively*”. Therefore, firms can search for new knowledge and information, as well as update their stock of knowledge, not only through internal efforts, but also by opening up their R&D processes. The effects of OI on firms’ stock of knowledge were widely investigated by scientific literature (Belderbos *et al.*, 2004; Perez *et al.*, 2013; Prahalad and Ramaswamy, 2004).

In a **closed system**, new products and services are entirely developed within the boundaries of the innovating firm and exploited to enter the market first and win (Chandler, 1990). Even though firms rely on closed strategies, they still need to access to external information and be able to assimilate, absorb, assess and use new knowledge (Cohen and Levinthal, 1990). For instance, they geographically decentralize their R&D efforts and involve their subsidiaries in the search for new solutions and technological ideas (Lahiri, 2010), thus sourcing knowledge from distant units (Venaik *et al.*, 2005) in addition to local inputs. With decentralization, firms distribute their R&D activities in order to share and allocate specific technical fields (Nayyar and Kazanjian, 1993; Nerkar and Roberts, 2004). Further, additional inputs comprise new knowledge sourced externally by both local and distant units. For instance, firms' members may attend conferences and fairs, browse patents, read trade journals or reverse-engineer competing products. Otherwise, companies may hire new skilled personnel in order to acquire their competencies in specific technical areas. Therefore, even though firms perform R&D internally, they require external sources of information to stimulate it (Dzikovski, 2015; Gomes *et al.*, 2011; Mothe and Nguyen-Thi, 2013).

On the contrary, when a company decides to adopt OI, many business models can be outlined (Michelino *et al*., 2015a). This work takes into account four OI practices for accessing external knowledge: outsourcing of R&D activities, joint development, purchase of external technology and incorporation of knowledge through mergers and acquisitions (M&As). Actually, in all these practices it is possible to detect a formal use of external knowledge (i.e. source of innovation), since a third party directly contributes to the R&D effort necessary to develop new solutions and technologies.

Companies can **outsource R&D** and involve third parties for the search and development of a new technology, even by externalizing only a part of the R&D effort (van de Vrande *et al.*, 2009). In outsourcing there is an evident one-way transfer of knowledge from the external actor to the focal firm (Teirlinck and Spithoven, 2008). Hence, in order to access to external knowledge and information (Ebersberger *et al.*, 2012; van de Vrande *et al.*, 2009), the outsourcer organization hires the services of an external actor to support its R&D efforts and engage in technical dialogue and direct assistance. In this way, it absorbs available and specialized knowledge within specific technical areas (Foss *et al.*, 2013; Santamaria *et al.*, 2010), which is neither available inside the firm nor can be created internally in a cost-effective way (Teirlinck and Poelmans, 2012).

As to **joint development**, it is based on a deliberate two-way exchange of knowledge between the focal firm and third parties (Teirlinck and Spithoven, 2008). By collaborating with external actors, companies absorb codified knowledge residing in partners and tacit knowledge and know-how, which cannot be easily contracted through market transactions (Spithoven *et al.*, 2010). As a matter of fact, for firms operating in dynamic environments - featured by rapid development and increasing technical complexity - it is very difficult to possess and capitalize on all the necessary knowledge. Therefore, companies specialize and employ R&D collaborations to complement their knowledge (Perez *et al.*, 2013). This leads to the creation of complex networks of relationships with customers, suppliers and other industrial and scientific organizations, in which firms search and develop new products, technologies and knowledge (Dittrich and Duysters, 2007). Indeed, companies may potentially learn from such interactions, which open up opportunities for joint value creation and innovation (Prahalad and Ramaswamy, 2004). Therefore, R&D collaboration can be a source of competitive advantage, since it gives access to external sources and information (Belderbos *et al.*, 2004).

Instead of performing R&D activities in house, companies may also **purchase external technologies** (Huang and Rice, 2009) and acquire intellectual property rights - such as trademarks and patents - or non-patented inventions, such as know-how and other types of knowledge (Acha, 2008). By acquiring already available information and technologies, firms can rapidly integrate external knowledge and know-how (Schroll and Mild, 2011), especially when they do not have enough expertise for developing them (Lee *et al.*, 2010).

Finally, **M&A strategies** are employed to extend firms' resources by acquiring new knowledge and technologies from a third entity, thus allowing them to achieve higher innovation performance by combining technological knowledge residing in two companies (Ensign *et al.*, 2013). To obtain effective M&As, such technological resources need to deviate from the firm's core competencies - and, thus, be difficult for companies' members to directly assimilate and subsequently exploit (Miller *et al.*, 2007). Additionally, M&As are preferred when the knowledge residing in the acquired/merged entity is stored in tacit form, since this impedes the transmission and the codification of knowledge once it is identified (Miller *et al.*, 2007). Therefore, M&As are more effective when the technical knowledge of both entities is similar enough to facilitate learning, but different enough to provide new opportunities and the incentives to explore it (Makri *et al.*, 2010). At the same time, also efficiency gains can be reached with the diffusion of know-how within the acquired/merged actor, the reallocation of knowledge to more promising technological solutions and synergies resulting from the M&A (Stiebale, 2013).

3.2 Current search practices

3.2.1 Sources of knowledge

The recourse to external sources of innovation depends on their features and internal factors, such as firms' R&D capabilities and the need for complementary assets (West and Bogers, 2014). These sources add or complement firms' internal knowledge base (Chuma, 2006;

Laursen and Salter, 2006; Witzeman *et al.*, 2006) and may enhance the creation and the combination of new technologies (Ferreras-Mendez *et al.*, 2015), fostering firms' innovation performance (Martini *et al.*, 2015). In addition, they are also useful for recognizing opportunities of all kinds, including not just product and process innovation, but also new markets and organizational structures, contractual designs, arbitrage opportunities, suppliers, buyers, complementors and management processes (Foss *et al.*, 2013). Obviously, external search alone can be ineffective to support firm's R&D effort when it is not able to capitalize and apply the knowledge assimilated outside and combine it with internal mechanisms, thus the search process will be inconclusive in expanding its stock of knowledge (Martini *et al.*, 2015).

Through interviews conducted with Belgian inventors, Callaert *et al.* (2014) investigated the relevance of the sources of inspiration for the development of patented technologies, uncovering that more than one-half of R&D efforts employed information from scientific literature and prior art. Indeed, **scientific and non-patent literature** are sources of relevant background information, e.g. deriving from public research, and contribute to elements of the invention (Ogawa and Kajikawa, 2015; Roach and Cohen, 2013; Tijssen *et al.*, 2000). Therefore, the citation of scientific literature in patent documents reflects the existence of knowledge flows between scientific and technological actors and industry-science relations (Cassiman *et al.*, 2010; Van Looy *et al.*, 2007).

On the other side, **citations to prior patented technologies** reflect spillovers and pathways of innovative trajectories, where downstream documents cite those upstream technologies on which they build (No *et al.*, 2015; Trajtenberg, 1990). Indeed, the cited patent represents a piece of previously existing knowledge upon which the citing patent builds. A significant contribution regarding the use of patent citations derives from Jaffe *et al.* (2000): conducting a survey on the determinants of citation selection, they discovered that the nature of the technological relationship between two patents can be different. For instance, the citing patent can be seen as an alternative way of doing something that the cited patent did before (i.e. similarity of application); otherwise, the citing patent can do something different than the cited patent, but utilizes a similar method, even though the purpose is different (similarity of technology).

A last consideration concerns the use of **self vs. external citations**. As argued by Belenzon (2011), knowledge recombination is the ability of a company to combine its past inventions with external ideas, which are cited in its applications (i.e. spillovers), or perform cumulative innovation by employing and citing its already patented technologies.

3.2.2 External actors engaged in the knowledge search

Since no company possesses all technological resources internally, firms need to assimilate knowledge located outside their boundaries by finding channels for accessing and sharing valuable information and resources (Zhao, 2015). Thus, they need to interact with a range of actors, such as clients, customers, crowd, citizens, users, suppliers, competitors, other companies, inventors, consultants, intermediaries, universities, foundations and research centers (Afuah and Tucci, 2012; Belderbos *et al.*, 2004; Dittrich and Duysters, 2007; Faems *et al.*, 2005; Laut *et al.*, 2015; Martini *et al.*, 2013; Mina *et al.*, 2014). Therefore, the knowledge generated during the inventive process derives from both internal and external actors engaged.

As suggested by Poot *et al.* (2009), companies may establish collaboration agreements with industrial partners (e.g. competitors, suppliers and consultancies) or scientific entities, such as universities, research institutes, government labs and hospitals.

Firms enter into **cooperation with industrial partners** for many reasons, since they give access to new knowledge bases, ideas and possibilities through the interaction (Granovetter, 1973). Furthermore, they are a source of complementary expertise for companies operating in industries typified by technological complexity, where no single firm possesses all the knowledge, skills and techniques required (Powell *et al.*, 1996; Rausser, 1999). These complementary assets are critical to successful develop and commercialize new solutions, technologies and products. In addition, they include information, capabilities and knowledge about market access, marketing and distribution channels, production processes, expertise in managing R&D and development processes, experience in evaluating payoffs far in the future, experience on how to operate and grow a firm in the same industry, and strategic and operational know-how (Arora and Gambardella, 1990; Pisano, 1990; Teece, 1992).

Regarding **partnerships with scientific entities**, they are a source of up-to-date information and knowledge, which is too tacit to be transferred through licensing or acquisition (Liebeskind *et al.*, 1996). The collaboration with universities gives access to international knowledge networks (Okubo and Sjöberg, 2000) and, consequently, to international markets. In addition, universities and scientific partners can be involved in developing prototypes and handling patents and licenses (Cyert and Goodman, 1997). The engagement of scientific actors provides interaction opportunities, which generate new concepts, business ideas, emerging knowledge and technological know-how that enterprises can translate into new products (Powell *et al.*, 1996). Moreover, by partnering with scientific entities, companies may access to public resources and funds (Bayona Saez *et al.*, 2002). In fact, collaboration is stimulated by public programs promoting research and partnerships between public and private entities. R&D partners can give an answer to the demand for both basic knowledge and pre-competitive research (Arora and Gambardella, 1994) and more specific knowledge, which focuses on problem solving and product design and development, i.e. applied research (Bayona Saez *et al.*, 2002). Finally, partnerships with universities and research centers allow companies to keep up-to-date in industrial standards and to access to government information useful to find out on what other firms in the sector are investing (Sakakibara, 1997). R&D

cooperation with scientific actors is usually characterized by long-term activities because of the basic and complex nature of the joint research, which requires larger learning processes (Hall *et al.*, 2000). In such partnerships, companies need to be particularly able to absorb the knowledge transferred by scientific authorities and have a strong internal capacity for R&D (Bayona Saez *et al.*, 2002). Yet, in many cases, the results obtained from scientific partnerships are not directly exploitable for business applications.

4. METHODOLOGY

The suggested framework consists of three conceptual blocks, i.e. accumulated stock knowledge, current search practices and quality of innovation output (Figure 1). Indeed, the stock of knowledge summarizes the professional background and experience accumulated by the firm and potentially available as a starting point for future R&D efforts, while the search practices refer to the opportunities and the sources that firms directly employ in the specific R&D effort under investigation. Callaert *et al.* (2014) defined various sources of knowledge, inspiration and information on which build future R&D efforts, among which: a) professional background/expertise, b) scientific literature, c) patents, d) firm contacts, and e) contacts with knowledge generating institutes. In this work, we underline the relationship between the previous experience on specific knowledge domains and the selected search practices for the development of new technologies. Therefore, having knowledge management and KS strategies a significant impact on the result of the R&D efforts, it is possible to assume a direct relationship with the quality of innovation output, also considering that they contribute to the improvement and transformation of firm's knowledge stock.

4.1 Patents sample definition

For the study of the aforementioned elements, we designed a framework that employs information deriving from patent documents. Specifically, data are extracted from PATSTAT database through a PHP based software that we developed for detecting, collecting and analyzing data. We confined our analysis to filings recorded in EPO, USPTO or WIPO, since the documents registered in national offices may lack of some data. We decided to investigate all the priority filings - i.e. the first granted patent applications filed to protect an invention - potentially claimable. Indeed, if we had analyzed only priorities actually claimed, we would have considered only the high-value applications (Harhoff *et al.*, 2003; Johnstone *et al.*, 2012), neglecting the remaining R&D efforts that led to less valuable results but have, however, an impact on the firm's stock of knowledge.

The first step regards the linkage between the firms within the sample and the PATSTAT applicant table. For each patent we searched both the name of the parent company and its subsidiaries in the assignee field, also taking into account the names of the units previously acquired or merged. Further, we searched for patent applications held by the focal firm, in order to collect:

1. documents filed in year *t*, from which we extracted information about the current search practices employed and the patent quality;
2. patented technologies owned by the focal firm in year *t* but filed before *t*, i.e. constituting its accumulated stock of knowledge.

The first group consists of documents filed by the focal company, i.e. for which the focal firm is the applicant, even in co-ownership with third parties. Therefore, these patents delineate the R&D efforts carried out by companies to develop new technologies.

Since KS practices are presumed to be affected by firms' existing stock of knowledge, the second group of patent documents encloses all the technologies owned by the firm before the period under investigation. From these technologies we detected the implicitly and explicitly related knowledge that companies may have employed in the investigated R&D process and, specifically, that may have influenced the KS practice selection and the results of the R&D effort. This implies the building of a methodology to explore the information disclosed in patent applications and operationalize knowledge. In literature, knowledge domains and technological strategies are investigated by studying patent classification codes (Cammarano *et al.*, 2017; Graff, 2003; Nakamura *et al.*, 2015; Sakata *et al.*, 2009), such as International Patent Classification and Cooperative Patent Classification (CPC) codes. Indeed, such nomenclatures identify the technical fields affected by the invention and, consequently, the knowledge areas required and the competencies involved for the development of the patented technologies. Being the CPC taxonomy more detailed, for our purposes we preferred such classification. Indeed, each CPC code consists of a hierarchical symbol denoting 1) section, 2) class, 3) sub-class, 4) main group and 5) sub-group. By employing the entire code (i.e. CPC at level 5), innovation can be studied at the product level, or rather at the maximum level of disaggregation. Yet, in order to study knowledge domains, the fourth-level code (i.e. until the main group) has to be preferred, since the same knowledge may be used to develop different products or components.

Then, the information regarding knowledge resides in previous patent applications and it is operationalized through CPC codes. Since knowledge evolves rapidly and companies lose most of their technical experience if they abandon a technological field for some years (Ahuja and Lampert, 2001; Argote, 1999; Fleming, 2001; Hall *et al.*, 2005; Leten *et al.*, 2007), competencies previously accumulated, and not further employed, may result obsolete and not available in *t*. Therefore, from a knowledge-based perspective, the number of patents effectively contributing to the stock of knowledge is lower than the real patent portfolio owned by the focal firm at the beginning of the year *t*, since the term of the legal patent protection is higher. Indeed, the period for which the experience accumulated by the firm in a specific knowledge field is further employable is smaller. For instance, the aforementioned studies confine to 5 years the experience period (t_{EXPER}). In this work, we define industry-specific experience periods to take into account the peculiarities of the sectors under investigation.

4.2 Accumulated stock of knowledge

As to the stock of knowledge deriving from the technical background and expertise, we focused our attention on both technological strategies previously carried out by companies and OI practices adopted to accumulate experience (Figure 2). Recovering the literature on KS (Katila, 2002; Katila and Ahuja, 2002; Lakemond and Detterfelt, 2013; Lane *et al.*, 2006), for technological strategies we considered exploitation vs. exploration and the level of specialization on the knowledge fields involved in the new technologies. As to OI, we considered the weight of each practice on the accumulation of experience, in order to understand how firms have achieved the actual level of professional background. Among the various practices, we included internal development, involvement of external inventors in the development of owned technologies, joint development with third entities, purchase of single technologies and incorporation of other companies.

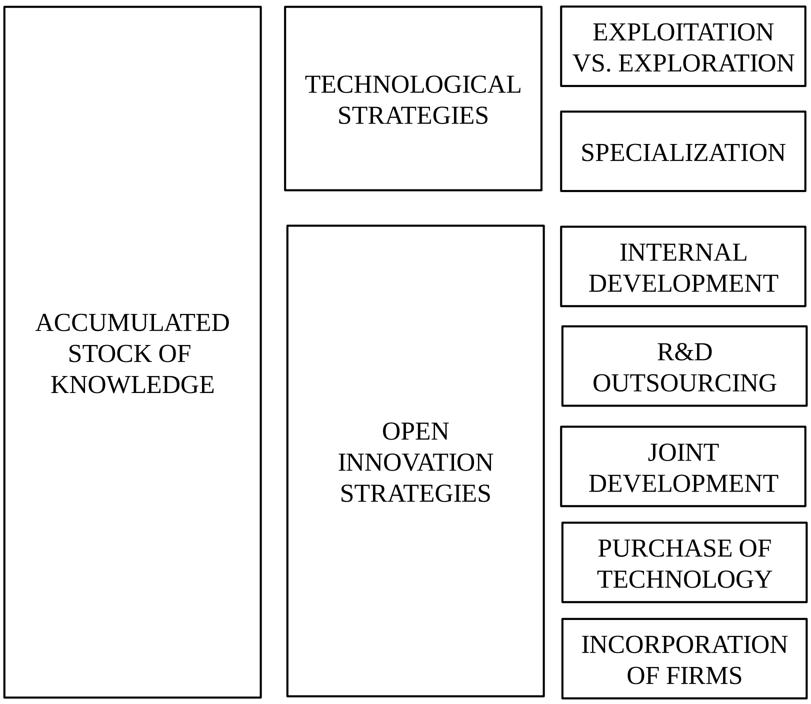

Figure 2. Accumulated stock of knowledge

Therefore, the stock of knowledge before *t* is defined by both patents filed from t – 1 to t – t_{EXPER}, reporting the focal firm as the assignee, and technologies applied by third parties within the same period but owned by the focal company in *t*, after the transfer of rights or the incorporation of the previous holder. Indeed, we assume that also technologies developed by third parties but further acquired by the focal firm contribute to its current stock of knowledge and to the definition of the technological strategy to be adopted in *t* within a specific knowledge area.

4.2.1 Technological strategies

In order to analyze exploitation vs. exploration strategy at the knowledge domain level, it is necessary to define the exploitation and exploration phases. Indeed, when a firm starts to explore a technological field, it is required an exploration period (t_{EXPLOR}) to master the technology before it becomes really exploitable (Michelino *et al.*, 2015b). For instance, Belderbos *et al.* (2010) set this period equal to 3 years.

Therefore, in year *t* each CPC code disclosed within the stock of knowledge can be labeled as (Figure 3):

- exploitative, if at least a patent application reporting the same field was deposited from t – t_{EXPER} to t – t_{EXPLOR}. Indeed, knowledge deriving from technologies filed before t – t_{EXPER} is considered as obsolete and excluded by the stock of knowledge, while that generated after t – t_{EXPLOR} is still in the exploration phase in year *t*;
- explorative, otherwise.

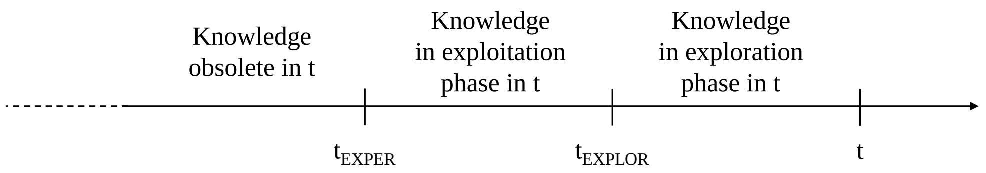

Figure 3. Time periods

Once analyzed the strategy pursued within each knowledge domain involved in each patent, the ratio of CPC codes in exploration phase on the total number of codes in the document is calculated. Therefore, the percentage variable XPLR is defined, ranging from 0% - if all the CPC codes declared in the document are in the exploitation phase - to 100%, if all of them are explorative:

$$XPLR = \frac{no.of\ CPC\ codes\ recorded\ in\ the\ focal\ patent\ in\ exploration\ phase}{total\ no.of\ CPC\ codes\ recorded\ in\ the\ focal\ patent} * 100$$

As to specialization, although scientific literature takes into account the frequency with which companies operate within a specific technological field, no operationalization employing patent data was uncovered about the weight of such technological field on the overall innovation strategy carried out. As a matter of fact, not all the domains are equally relevant for the company: only some knowledge areas are strongly stressed and mostly contribute to the development of the core technology of current business activities. Therefore, a different technological specialization may be detected in each technological field. All in all, companies concentrating their R&D efforts on few relevant fields are carrying out a specialization strategy. Conversely, working on a larger body of knowledge can be seen as a proxy of diversification strategies. In literature on patent data, a similar concept is expressed by the so called technological familiarity: a component is familiar to the firm when it has been recently and frequently used (Arts and Veugelers, 2012; Fleming, 2001).

For each knowledge domain, specialization is estimated by dividing the number of patents disclosing the CPC code by the total amount of patent applications within the stock of knowledge. Technological specialization (SPEC) of a patent filed in *t* is then calculated as the average value of the specialization of the different CPC codes it declares. It is a percentage variable ranging from 0% - if no code declared in the document was found in any patent in the stock of knowledge - to 100%, if all the technological fields in the focal patent are already disclosed in all the documents of the stock of knowledge:

$$SPEC = \frac{\sum_{CPC} no.\,of\ patents\ within\ the\ stock\ of\ knowledge\ (CPC_i)}{\sum_{CPC} total\ no.\,of\ patents\ within\ the\ stock\ of\ knowledge} * 100$$

4.2.2 Open innovation strategies

For the analysis of the knowledge stock, we also focused on the practices adopted to achieve innovation, introducing five categories according to the OI paradigm:

- patents developed with the use of only internal resources, which can be considered as deriving from a closed process;
- patents developed also with the use of external resources: when the focal firm is found as the only assignee, but some inventors do not belong to it, it is reasonable to suppose that a part of the development process was outsourced to third parties;
- co-patents, jointly developed by the focal company with one or more organizations/coassignees, after a collaborative perspective;
- patents developed by external organizations and subsequently transferred to the focal company by the means of a separate acquisition;
- patents developed by firms that were afterwards incorporated in the focal company through M&As.

In order to define such categories, different steps were followed. Before starting the analysis, any inventor disclosed in the assignee field was removed, so that only organizations were reported as assignees. After this intervention, all the patent applications disclosing the focal company in the assignee field were analyzed. If two or more owners were found in the assignee field, the patent was labelled as joint, according to many literature contributions (Al-Ashaab *et al.*, 2011; Kim and Song, 2007). Otherwise, the inventors' affiliation was detected (see section 4.3.2 for more details). Therefore, if all the inventors found in an application belong to the focal firm, the patent was labelled as internally developed, outsourced otherwise.

In addition, from the analysis of the legal status of the documents, the transfers of patent rights toward the focal company were detected, and such patents were defined as purchased. Finally, in order to detect patents deriving from M&As, each subsidiary belonging to the focal firm was further investigated to understand whether it was previously acquired/merged or not. For acquired and merged units the patent portfolio prior to the acquisition/merge date was identified and all the patents labelled as incorporated.

Therefore, for each patent filed in year *t*, we extracted the list of CPC codes and for each code we searched for previous documents - within the stock of knowledge - that report it. By analyzing these applications, we estimated the contribution of each OI practice to the improvement of the prior experience within the focal CPC code. Indeed, for the prior patent applications containing the CPC codes we defined the weight of the five practices within the accumulated stock of knowledge. Then, five ratios were estimated (INTERNAL, OUTSOUR, JOINT, PURCH, INCORP) to delineate how professional background was accumulated within the technical fields useful for the development of the focal patent filed in *t*. For instance, JOINT is computed as the ratio of joint patents filed in the experience period, which disclose at least one of the CPC codes reported in the focal patent, on the total number of patented technologies within the stock of knowledge that were developed in at least a technical field mentioned in the focal document:

$$JOINT = \frac{\sum_{CPC} no.of\ joint\ patents\ within\ the\ stock\ of\ knowledge\ (CPC_i)}{\sum_{CPC}\ total\ no.of\ patents\ within\ the\ stock\ of\ knowledge\ (CPC_i)}$$

4.3 Current search practices

Regarding the KS practices, we focused on the sources of knowledge employed and the actors engaged (Figure 4).

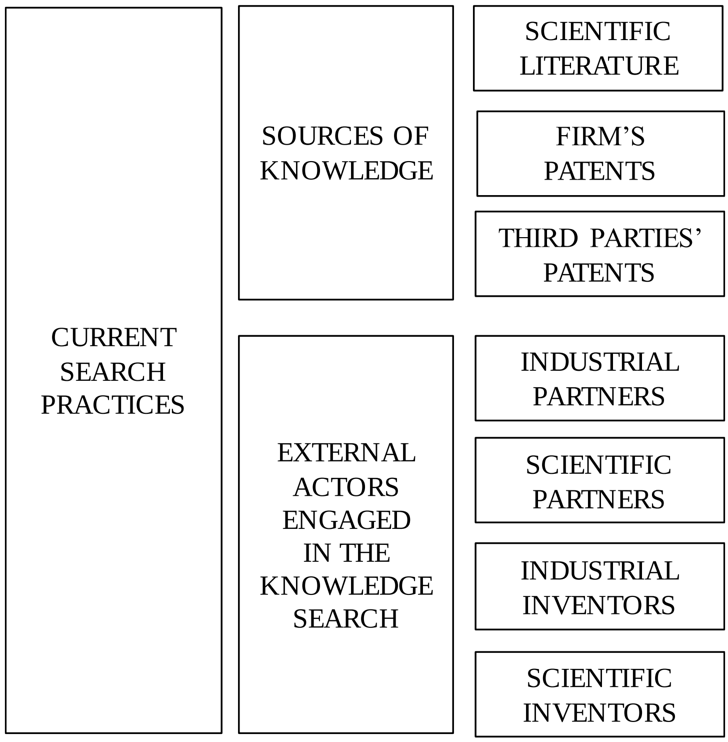

Figure 4. Current search practices

4.3.1 Sources of knowledge

Regarding the recourse to external sources of knowledge, information and inspiration, we followed the interpretation and the operationalization acknowledged by literature, i.e. employing citations to previous patent applications and scientific documents. Hence, three dummies were considered:

- NPL_CIT, equal to 1 when non-patent literature (NPL) was cited in the focal patent and the focal firm built its patented technology on relevant scientific research;
- SELF_CIT, with value 1 when prior knowledge owned by the focal firm was further recombined in order to achieve new technical development and, then, cited within the focal patent;

- XTR_CIT, assuming value 1 when at least an external patent application has been cited within the focal patent, signaling that a piece of previously existing external knowledge has inspired the development of new technology applications.

4.3.2 External actors engaged in the knowledge search

As to the actors involved in the R&D effort, we focused on both the assignees and the inventors recorded in patent documents.

The former are used to find information about the collaboration with external partners, from which firms gathered knowledge. Particularly, if two or more organizations were found in the assignee field, we registered the existence of a partner that can be either an industrial company or a scientific organization. Therefore, two dummies can be defined for each patent:

- IND_PART, equal to 1 if at least an industrial partner is detected for the focal patent;
- SCI_PART, signaling the occurrence of scientific organizations within the focal patent.

Similarly, by investigating the inventor field, we uncovered whether companies absorb information from external inventors for the development of the focal patent. Therefore, for each inventor disclosed in the inventor field it is necessary to detect its affiliation. A two-step procedure was developed for this purpose. First, we analyzed the person's address field: if the record contains words related to scientific organizations (the list contains about 100 keywords, such as "university", "medical center" and "research center") the PHP software suggests to consider it as a scientific inventor, also allowing a web search to support the interpretation. Otherwise, the list of all the distinct assignees disclosed in the patent applications reporting the focal person was extracted. Indeed, we assumed that the inventor belongs to the organization mostly occurring in such documents, inheriting the partner typology from such entity. In some cases, no automatic association was possible, e.g.:

- when the software suggests the affiliation to an industrial organization but, among the less recurring organizations, scientific entities where uncovered, since it is possible that a scientific inventor (i.e. a professor) patented preponderantly with companies that engaged his/her research group;
- when no organization prevails on the others, i.e. when the most recurring entity covers less than 50% of the patent applications in which the focal inventor has been recorded.

If no automatic association is possible, the software provides a customized search to find information from websites and platforms like Linkedin, Academia, Research Gate, Google Scholar, Xing, Zoominfo etc. Therefore, the user can manually label the inventor as industrial or scientific and define his/her affiliation. Hence, for the focal patent two dummy variables related to the access to external available and specialized knowledge were considered:

- IND_INV, assuming value 1 when at least an inventor belonging to external companies has been recorded in the inventor field;
- SCI_INV, equal to 1 when at least an external scientific inventor has been engaged in the R&D effort.

4.4 Quality of innovation output

For the analysis of the quality of innovation output, we employed information already acknowledged by scientific literature. Specifically, four elements were taken into account: marketability, originality of the technological combination, technological acknowledgment and internal value (Figure 5). Indeed, the quality of the R&D effort has to be seen from different perspectives, in order to detect both its market potential and its technological features.

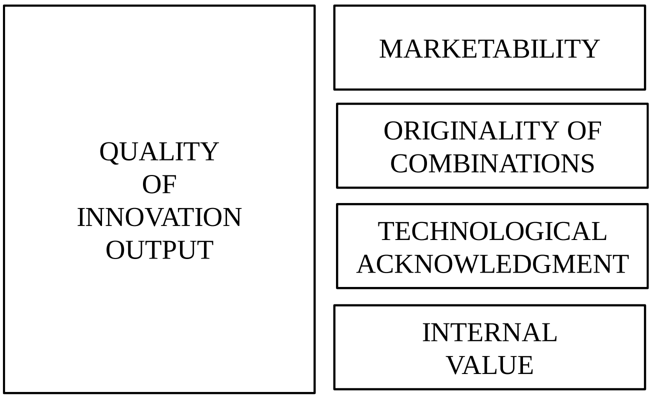

Figure 5. Quality of innovation output

Regarding marketability, we considered the existence of a patent family. Indeed, the number of family patents has been considered as indicating the level of R&D activity relevant to international diffusion (Breitzman and Mogee, 2002; Harhoff *et al.*, 2003), thus implying marketability (Geum *et al.*, 2013). Ernst (2003) used the average number of family patents granted by the organization in the technology areas of interest compared to the industry mean for evaluating the firm's products marketability. The family size increases when inventions are applied for protection in multiple countries (Johnstone *et al.*, 2012), claiming the priority patent. Hence, for each patent we defined the dummy MRKT, assuming value 1 if the focal patent generates a family and is followed by further documents claiming it within five years from its application.

As to the originality of the technological combination, innovation can be achieved by recombining already established knowledge elements (Fleming, 2001) or introducing an established element into a new setting (Hargadon and Sutton, 1997). Fleming (2001) suggested to proxy components with patent technological classes. Multiple classification codes are usually assigned to a patent and they can be used to observe indirectly the process of recombinant search and learning. Thus, the CPC code at level 5 (i.e. the entire code) was used to operationalize the knowledge elements and understand whether the combination is "new to the world", by verifying if the same combination occurs in the experience period in all the patent applications recorded in PATSTAT database. The variable COMBO assumes value 1 for new combinations, 0 otherwise.

The third patent quality indicator is technological acknowledgment, evaluated through the analysis of forward citations. When a patent is cited within future applications, a higher technical importance can be presumed: patents that are cited are more relevant, influent and innovative than disregarded ones (Albert *et al.*, 1991; Alcácer and Gittelman, 2006; Dahlin and Behrens, 2005; Lahiri, 2010; Mazzucato and Tancioni, 2012; Messeni Petruzzelli *et al.*, 2015; Miller *et al.*, 2007; Rosenkopf and Nerkar, 2001). Fleming and Sorenson (2004) argued that the number of forward citations of a patent highly correlates with its technological importance. Thus, we added the dummy TECH, with value 1 if at least a forward citation was received by the focal patent within the following five years from its publication.

The last indicator we considered is the internal value attributed by the firm, operationalized through the renewal fees payment status (Gittelman, 2008; Pakes and Simpson, 1989), since the focal firm is interested in keeping a patent active only if it is perceived as an opportunity, also taking into account that it is expensive for owners to renew patent protection for additional years. Therefore, we labelled as lapsed patents whose fees are unpaid within the eighth year from their application, active otherwise. Consequently, the variable INT_VAL assumes value 1 for active patents, 0 for lapsed ones.

Table 1 summarizes the 18 variables considered in the study.

Dimension			Variable	Operational definition
accumulated stock of knowledge	technological strategies	exploitation vs. exploration	XPLR	percentage of CPC codes of the focal patent in exploration phase
accumulated stock of knowledge	technological strategies	specialization	SPEC	average occurrence of CPC codes of the focal patent in the patents within the stock of knowledge
accumulated stock of knowledge	open innovation strategies	internal development	INTERNAL	share of patents within the stock of knowledge containing the CPC codes of the focal patent that are internally developed
accumulated stock of knowledge	open innovation strategies	R&D outsourcing	OUTSOUR	share of patents within the stock of knowledge containing the CPC codes of the focal patent for which external inventors are involved
accumulated stock of knowledge	open innovation strategies	joint development	JOINT	share of patents within the stock of knowledge containing the CPC codes of the focal patent that are jointly developed with external partners
accumulated stock of knowledge	open innovation strategies	purchase of technology	PURCH	share of patents within the stock of knowledge containing the CPC codes of the focal patent that are purchased from external companies
accumulated stock of knowledge	open innovation strategies	incorporation of firms	INCORP	share of patents within the stock of knowledge containing the CPC codes of the focal patent that are inherited by merged or acquired companies
current search practices	sources of knowledge	scientific literature	NPL_CIT	dummy: the focal patent reports NPL citations
current search practices	sources of knowledge	firm's patents	SELF_CIT	dummy: the focal patent reports self-citations
current search practices	sources of knowledge	third parties' patents	XTR_CIT	dummy: the focal patent reports external citations
current search practices	external actors engaged in the knowledge search	industrial inventors	IND_INV	dummy: external industrial actors are disclosed in the inventor field of the focal patent
current search practices	external actors engaged in the knowledge search	scientific inventors	SCI_INV	dummy: scientists and researchers are disclosed in the inventor field of the focal patent
current search practices	external actors engaged in the knowledge search	industrial partners	IND_PART	dummy: industrial organizations are disclosed in the assignee field of the focal patent
current search practices	external actors engaged in the knowledge search	scientific partners	SCI_PART	dummy: scientific organizations are disclosed in the assignee field of the focal patent
quality of innovation output		marketability	MRKT	dummy: the focal patent generates a patent family in five years
quality of innovation output		originality of combinations	COMBO	dummy: the combination of CPC codes within the focal patent is new
quality of innovation output		technological acknowledgment	TECH	dummy: the focal patent has five-year forward citations
quality of innovation output		internal value	INT_VAL	dummy: the focal patent fees result as paid at the eighth year

Table 1. Summary of the variables

5. FRAMEWORK APPLICATION

The devised framework was tested on patents filed in 2005 by 157 R&D intense companies from bio-pharmaceutical and technology hardware & equipment industries. The choice of the year of analysis depends on the need of evaluating *ex-post* patent quality indicators, being 2005 the latest period for which information is available in our PATSTAT version. The selection of the sectors derives from their antithetical peculiarities, being characterized by different R&D issues related to product life cycles, development pace, product complexity and nature of innovation. Indeed, we aim at uncovering generalizable relationships among the variables under investigation and contributing to the current debate on KS by providing evidences of the correlations between accumulated knowledge stock, current search practices and quality of innovation output.

In detail, the sample consists of 58 bio-pharmaceutical companies and 99 technology hardware & equipment firms. For the year 2005, 1,069 and 9,895 patents were detected for the two industries respectively. Since a study of the stock of knowledge accumulated within the experience period is required, we also downloaded 11,653 patents filed by bio-pharmaceutical companies and 38,425 applied by technology hardware & equipment firms before 2005.

As mentioned in the previous section, both the experience period and the exploration phase depend on the features of the investigated industries. Table 2 displays the values assigned to each variable for the two sectors, also providing explanations to support our assumptions.

Industry	Variable	Years	Notes
Bio-pharmaceutical	t_{EXPER}	7	Firms file patents covering new drugs within seven years from the beginning of the project. The experience interval should consider the high time-to-prototype, since the lack of patent applications in a specific technological domain in the previous years may not imply the loss of knowledge, since an invention may be in the development phase.
	t_{EXPLOR}	4	Firms require more time to make a technological field exploitable because of the product complexity and the integral nature of innovation.
Tech. HW & equipment	t_{EXPER}	3	The shorter product life cycles force companies to continuously adapt their technical competencies, which may be considered obsolete in few years.
	t_{EXPLOR}	2	Firms are forced to speed up the process of familiarization with a new knowledge domain because of the faster development pace.

Table 2. Time periods by industry

Hence, in the bio-pharmaceutical industry the stock of knowledge in 2005 is defined by patents filed from 1998 to 2004, while only knowledge fields already explored before 2001 are in the exploitation phase in 2005. As to the technology hardware & equipment sector, the previous experience is investigated by analyzing documents applied from 2002 to 2004, while only CPC codes disclosed in patents filed in 2002 can be considered as exploitative in 2005.

Each industry-level analysis is performed cumulating the patents owned by each company within the belonging sector. Table 3 exhibits the descriptive statistics by industry, also including the statistical significant differences between the two sectors.

Variable	Tech. HW & equip.			Bio-pharmaceutical			Total			Mann-Whitney U	Asymp. Sig.
	Mean	N	S.D.	Mean	N	S.D.	Mean	N	S.D.		
XPLR	20.1%	9,895	0.351	20.4%	1,069	0.342	20.2%	10,964	0.350	5.2E+06	0.135
SPEC	8.9%	9,895	0.130	10.5%	1,069	0.110	9.0%	10,964	0.128	4.6E+06	0.000
INTERNAL	72.2%	9,895	0.225	60.8%	1,069	0.228	71.1%	10,964	0.227	3.3E+06	0.000
OUTSOUR	14.1%	9,895	0.138	17.1%	1,069	0.144	14.3%	10,964	0.139	4.3E+06	0.000
JOINT	1.1%	9,895	0.043	7.8%	1,069	0.111	1.7%	10,964	0.057	1.8E+06	0.000
PURCH	8.6%	9,895	0.116	7.6%	1,069	0.101	8.5%	10,964	0.114	5.2E+06	0.189
INCORP	0.2%	9,895	0.017	2.1%	1,069	0.048	0.4%	10,964	0.023	2.8E+06	0.000
NPL_CIT	44.0%	9,895	0.497	67.0%	1,069	0.472	46.0%	10,964	0.499	4.1E+06	0.000
SELF_CIT	45.0%	9,895	0.498	43.0%	1,069	0.495	45.0%	10,964	0.497	5.2E+06	0.139
XTR_CIT	83.0%	9,895	0.375	66.0%	1,069	0.473	81.0%	10,964	0.389	4.4E+06	0.000
IND_INV	11.0%	9,895	0.313	13.0%	1,069	0.339	11.0%	10,964	0.316	5.2E+06	0.033
SCI_INV	4.0%	9,895	0.189	9.0%	1,069	0.286	4.0%	10,964	0.202	5.0E+06	0.000
IND_PART	1.0%	9,895	0.116	2.0%	1,069	0.148	1.0%	10,964	0.119	5.2E+06	0.020
SCI_PART	0.0%	9,895	0.041	1.0%	1,069	0.091	0.0%	10,964	0.049	5.3E+06	0.000
MRKT	58.0%	9,895	0.494	89.0%	1,069	0.312	61.0%	10,964	0.488	3.6E+06	0.000
COMBO	45.0%	9,895	0.498	52.0%	1,069	0.500	46.0%	10,964	0.498	4.9E+06	0.000
TECH	84.0%	9,895	0.369	66.0%	1,069	0.475	82.0%	10,964	0.384	4.3E+06	0.000
INT_VAL	96.0%	9,895	0.185	83.0%	1,069	0.378	95.0%	10,964	0.216	4.6E+06	0.000

Table 3. Descriptive statistics and Mann-Whitney test

On average, bio-pharmaceutical companies own stocks of knowledge more focused and specialized on technical fields that they employ for further developments. Indeed, the technological background required for developing new molecules is confined to biochemical sciences, whereas a wider range of disciplines is involved in the realization of hardware devices. In addition, the integral nature of innovation, the uncertainty of the R&D process and the relevance of the basic search forces bio-pharmaceutical firms to specialize within few technical areas. Contrarily, because of modularity of IT design and component-based products, technology hardware & equipment companies search for new solutions in wider technological fields and base their research on application sciences and engineering.

Furthermore, bio-pharmaceutical firms are characterized by a more open behavior, both in how their stock of knowledge was constituted and in the current involvement of external actors in the KS. Actually, the drug discovery and development process is expensive and time-consuming, requiring the involvement of third parties, since no company holds all the tangible and intangible resources needed. This is in line with many scientific contributions, signaling that the bio-pharmaceutical industry shows a great propensity in OI adoption

(Chesbrough and Crowther, 2006; Cooke, 2005; Fetterhoff and Voelkel, 2006; Gassmann *et al.*, 2008; Kleyn *et al.*, 2007; Michelino *et al.*, 2015c).

Regarding the use of external sources of information, technology hardware & equipment firms exhibit higher shares of external citations, while within the bio-pharmaceutical industry we uncovered a higher propensity to cite non-patent literature, signaling the scientific nature of the inventions.

As to the quality of innovation output, bio-pharmaceutical companies show higher patent marketability and originality of combinations, but patents in the technology hardware & equipment sector have higher technological acknowledgment and internal value. The larger number of patent families in the bio-pharmaceutical industry is related to the longer life cycle of products and the organic nature of molecules explains the higher variation of architectures of drugs. Yet, since patents are applied at the beginning of the pre-clinical phase, only the applications that pass the required experimentations are renewed. Finally, within the technology hardware & equipment industry the prevalence of competence-enhancing innovations explains the higher relevance of forward citations.

In what follows, the research questions are investigated through correlation analysis.

5.1 How accumulated stock of knowledge is related to current search practices

Tables 4 and 5 show the correlation coefficients in the two industries. A number of similarities emerges in the linkages between variables within the two sectors.

		technological strategies		OI strategies				
		XPLR	SPEC	INTERNAL	OUTSOUR	JOINT	PURCH	INCORP
sources of knowledge	NPL_CIT	.057	-.074*	.025	.029	-.070*	-.123**	-.130**
	SELF_CIT	-.192**	.211**	.117**	.046	.121**	.160**	.160**
	XTR_CIT	-.040	.066*	.094**	-0.04	.089**	.080**	.055
external actors engaged in the KS	IND_INV	.044	-.108**	-.062*	.078*	-.010	-.046	-.081**
	SCI_INV	.045	-.043	-.135**	.116**	-.010	-.003	.005
	IND_PART	.114**	-.057	-.083**	-.034	.087**	-.051	-.044
	SCI_PART	-.013	.046	-.063*	.002	.019	.064*	.025

* correlation is significant at .050 level; ** correlation is significant at .010 level

Table 4. Spearman's correlations between accumulated stock of knowledge and current search practices in the bio-pharmaceutical industry

		technological strategies		OI strategies				
		XPLR	SPEC	INTERNAL	OUTSOUR	JOINT	PURCH	INCORP
sources of knowledge	NPL_CIT	.003	.060**	.016	.046**	.019	-.045**	.039**
	SELF_CIT	-.153**	.223**	.096**	.060**	.104**	.008	-.024*
	XTR_CIT	.009	.047**	.050**	.055**	.032**	-.122**	.027**
external actors engaged in the KS	IND_INV	.025*	-.036**	-.121**	.106**	.006	-.019	.025*
	SCI_INV	.011	-.010	-.062**	.077**	-.039**	.001	-.021*
	IND_PART	.021*	-.032**	-.035**	-0.017	.087**	-.024*	-.001
	SCI_PART	.019	-.021*	-.001	-.020*	.025*	-.014	-.005

* correlation is significant at .050 level; ** correlation is significant at .010 level

Table 5. Spearman's correlations between accumulated stock of knowledge and current search practices in the technology hardware & equipment industry

As to technological strategies, exploration is negatively linked to the recourse to self-citations and positively related to the joint development with industrial partners. On the contrary, specialization is positively related to the use of self- and external citations and negatively linked to the involvement of industrial inventors. In fact, if a firm is exploring new domains, it lacks of expertise on such fields and needs external players to conduct its research activities. In addition, if a company is already specialized on a technological domain, it tends to cite its previous knowledge or absorb external information in the current development, but there is no need to directly engage external inventors.

Regarding openness, the prevalence of internally developed patents within the stock of knowledge is positively associated with the recourse to self- and external citations and negatively related to the involvement of external actors in the current KS. Indeed, firms internally develop technologies when all the necessary knowledge can be drawn within their boundaries and they possess sufficient capacity to absorb information useful for the development of new technologies from external sources - i.e. prior art. Conversely, different open models adopted in the past for developing the stock of knowledge are positively related to the employment of external players in the present KS. For instance, the engagement of external actors in new R&D efforts is more likely when previous experience has been achieved mainly through outsourcing practices. This demonstrates that the past behavior tends to be replicated in the present, with companies relying on either open or closed strategies over time.

The main differences between the two industries regard the relationship between the past use of incorporation and the search practice selection. Indeed, in the bio-pharmaceutical industry, incorporation replaces the need to access to scientific information and collaborate with external actors, also fostering the recombination of previous internal knowledge. Conversely, for technology hardware & equipment companies, previous incorporations improve the use of R&D outsourcing and external information, such as non-patent literature and patented technologies developed by third parties.

Another interesting difference regards the effect of specialization on the access to external scientific information. While non-patent literature is necessary to bio-pharmaceutical firms when they are less specialized in the knowledge fields involved in the invention, among technology hardware & equipment companies the higher the specialization the higher the scientific nature of the patented technology.

5.2 How stock of knowledge is related to quality of innovation output

Tables 6 and 7 show the correlation coefficients in the two industries. In what follows, similar behaviors in the two sectors are presented.

		technological strategies		OI strategies				
		XPLR	SPEC	INTERNAL	OUTSOUR	JOINT	PURCH	INCORP
quality of innovation output	MRKT	-.022	.019	.055	.059	-.029	.027	.007
	COMBO	.022	.085**	.098**	.034	.197**	.117**	.155**
	TECH	-.073*	.105**	.029	-.035	.160**	.187**	.176**
	INT_VAL	-.004	.089**	.006	-.088**	.064*	.121**	.034

* correlation is significant at .050 level; ** correlation is significant at .010 level

Table 6. Spearman's correlations between accumulated stock of knowledge and quality of innovation output in the bio-pharmaceutical industry

		technological strategies		OI strategies				
		XPLR	SPEC	INTERNAL	OUTSOUR	JOINT	PURCH	INCORP
quality of innovation output	MRKT	.002	.049**	.038**	.005	.119**	-.001	-.034**
	COMBO	.060**	.020*	-.004	.063**	.120**	.069**	.043**
	TECH	-.046**	.080**	.006	.043**	.016	.038**	.003
	INT_VAL	-.084**	.011	-.096**	.048**	-.031**	.048**	.025*

* correlation is significant at .050 level; ** correlation is significant at .010 level

Table 7. Spearman's correlations between accumulated stock of knowledge and quality of innovation output in the technology hardware & equipment industry

As of technological strategies, exploration is negatively linked to the occurrence of forward citations. Differently, specialization is positively correlated to originality of combinations and technological acknowledgment. Actually, the previous knowledge on specific domains enables higher quality, as to both the capacity of generating new architectures - i.e. combining pieces of knowledge - and the relevance of the results for the current state of the art. *Vice versa*, exploration *per se* implies high risky R&D efforts and, then, higher failure rates, resulting in lower quality outputs.

Regarding openness, when companies included external contributions in the accumulation of their own stock of knowledge, a better quality is obtained in current development. In particular, both joint development and incorporation imply more originality of combinations, while technology purchase allows a more diversified quality, also enclosing technological and internal value. Thus, companies that strongly carried out OI strategies in the past are more likely to better recombine knowledge by employing the competencies absorbed by their R&D partners, the technical value inherent in the acquired technology and the complementary capabilities possessed by acquired or merged units.

No notable differences were uncovered between the two industries.

5.3 How search practices are related to quality of innovation output

Tables 8 and 9 show the correlation coefficients in the two industries. A number of similarities emerges in the linkages between variables within the two sectors.

		sources of knowledge			external actors engaged in the KS			
		NPL_CIT	SELF_CIT	XTR_CIT	IND_INV	SCI_INV	IND_PART	SCI_PART
quality of innovation output	MRKT	.152**	.060*	.092**	-.049	.016	-.109**	.032
	COMBO	.001	.203**	.239**	-.077*	-.055	-.020	-.076*
	TECH	-.242**	.362**	.453**	-.009	-.069*	-.090**	-.063*
	INT_VAL	-.193**	.295**	.353**	.010	-.081**	.019	.015

* correlation is significant at .050 level; ** correlation is significant at .010 level

Table 8. Spearman's correlations between current search practices and quality of innovation output in the bio-pharmaceutical industry

		sources of knowledge			external actors engaged in the KS			
		NPL_CIT	SELF_CIT	XTR_CIT	IND_INV	SCI_INV	IND_PART	SCI_PART
quality of innovation output	MRKT	.205**	.074**	.139**	.006	.003	-.049**	-.014
	COMBO	.047**	.064**	.055**	.018	.013	-.047**	-.018
	TECH	.127**	.176**	.163**	-.010	.012	-.150**	-.068**
	INT_VAL	.013	.086**	-.063**	.019	.018	-.034**	.008

* correlation is significant at .050 level; ** correlation is significant at .010 level

Table 9. Spearman's correlations between current search practices and quality of innovation output in the technology hardware & equipment industry

In general, the recourse to all sources of knowledge implies a better quality, whereas the direct involvement of external partners in the KS diminishes it. Indeed, when new technologies are developed starting from knowledge and information already available either internally or from external sources, it is more likely to achieve market results and technological value. Conversely, no result is ensured if firms involve external actors in their R&D efforts, since the direct engagement of third parties is mainly necessary in explorative activities, for which it is more difficult to obtain high quality.

No notable differences were uncovered between the two industries.

6. DISCUSSIONS AND CONCLUSIONS

The paper provides a multidimensional patent-based framework that investigates the relationships among accumulated stock of knowledge, current KS practices and quality of innovation output. Indeed, multiple perspectives are necessary to uncover *where* and *how* to search for knowledge and information, *who* is engaged in the KS process and *how* previous experience accumulated within the stock of knowledge affects the patent quality.

The methodology has been tested on a sample of R&D intense bio-pharmaceutical and technology hardware & equipment companies, with the aim of uncovering generalizable findings and contributing to the current research on KS. Results confirm the relationship between previous experience accumulated within stock of knowledge, KS practice selection and patent quality.

High specialization implies the use of external sources of information and inspiration without directly involving external actors, whereas when firms lack of previous experience on specific fields they explore them by engaging industrial partners. Consequently, specialization leads to high value technologies and more immediate results, while exploration more often than not generates lower quality outputs. In addition, when accumulated knowledge derives mainly from internal development, firms' future R&D efforts are inspired by their prior inventions or by external patented technologies, demonstrating a significant absorptive capacity. Frequently, the use of such information and sources of inspiration leads to high quality inventions.

Results regarding the effect of OI practices justify the need to investigate how firms accumulate knowledge and the impact of different activities on the KS practice selection. Indeed, we demonstrate a path dependency regarding OI adoption: the higher the knowledge accumulated with a specific OI practice, the higher the recourse to the same practice for further developments. This is true both for outsourcing and R&D collaboration. The use of OI practices to improve, expand and update the stock of knowledge generates positive effects on the output of the current R&D effort. This finding is not in contrast with the negative correlation between the engagement of external organizations in current search activities and the quality of innovation output. Indeed, we demonstrate that OI adoption generates positive effects in the medium/long term, since more time is required to directly exploit the knowledge accumulated from such interactions. Therefore, previous experience deriving from OI practices valorizes the stock of knowledge and, consequently, the results of further R&D efforts on the same technical fields. On the contrary, current OI activities are mainly carried out to explore new technological areas, thus positive results may be achieved only later, when the knowledge captured by external partners and actors will be exploited.

The aforementioned relationships were uncovered in both industries, even though they are featured by extremely different characteristics, e.g. regarding development pace, time-to-prototype, product complexity, nature of innovation and product life cycles. The results of such explorative analysis suggest to distinguish between generalizable and industry-specific KS behaviors. Indeed, some issues are clearly affected by the characteristics of the investigated sectors, such as the impact of purchased technologies and M&As, the role of scientific research and literature as source of inspiration and the effect of the engagement of industrial vs. scientific actors in the KS.

In our opinion, a significant contribution regards the employment of patent data to build each element of the multidimensional framework. This provides a consistence to the whole methodology, being patent data objective, standardized, processed and validated by patent examiners, and useful for analyzing all the industries in which they are a means of appropriation of innovation (Pavitt, 1984). Specifically, some methodological contributions can be delineated. Firstly, in this work we suggest an instrument to operationalize the stock of knowledge, based on information disclosed in technology classification codes within patent documents. Secondly, we provide evidence that OI practices - such as R&D collaboration, outsourcing, purchase of technology and M&As - can be captured from patent statistics. Thirdly, we developed a complex procedure for finding the inventors' affiliation, which is one of the most discussed and problematic issues in scientific literature about patents. Actually, our research methodology may be employed for a wide range of applications within many research topics.

As the paper demonstrates, the quality of innovation output is affected by both accumulated stock of knowledge and current KS practices. Therefore, this study provides evidence that KS is fundamental for improving the effectiveness of the R&D effort, also stimulating managers in adopting OI strategies to improve their knowledge stock and employing external sources or actors to absorb knowledge and information. In addition, the results exhort decision-makers, managers and researchers to approach KS after a multidimensional perspective and deepen the multiple effects of the conceptual blocks we defined.

Some limitations can be outlined for the work. Firstly, the methodology has been tested on companies belonging to two R&D intense industries, therefore our hypotheses of generalization have to be tested on other sectors, although the two investigated industries are featured by many differences and our explorative analysis has still found common elements. Secondly, the research is confined to top R&D spending companies; hence, the findings may not provide a general overview of the examined industries as a whole, even though the sample under investigation covers a relevant share of patenting activities within the belonging sectors. Thirdly, the use of patent data for analyzing OI adoption could be questionable, since not all R&D collaborations can be captured by co-patenting activities (Hagedoorn et al., 2003); this may lead to the underestimation of OI activities. Lastly, not all technological inventions are patented or technically patentable (Archibugi and Pianta, 1996), and patent propensities vary across firms and industries. This leads to the consideration that our framework may not be useful for analyzing knowledge in all sectors.

Future research will be addressed to examining other industries, since the analysis of new sectors is required in order to better distinguish between generalizable findings and industry-specific ones. Finally, it is possible to extend the analysis to multiple subsequent years, in order to uncover how companies modify their KS strategies and recombine, integrate and expand their stock of knowledge over time.

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APPENDIX: LIST OF COMPANIES

Company	Industry
4SC	Bio-pharmaceutical
Abbott	Bio-pharmaceutical
Actelion Pharmaceuticals	Bio-pharmaceutical
Active Biotech	Bio-pharmaceutical
Adtran	Technology hardware & equipment
Advanced Digital Broadcast	Technology hardware & equipment
Advanced Semiconductor Engineering	Technology hardware & equipment
Advantest	Technology hardware & equipment
Affymetrix	Bio-pharmaceutical
Alexion Pharmaceuticals	Bio-pharmaceutical
Allergan	Bio-pharmaceutical
Almirall	Bio-pharmaceutical
Altera	Technology hardware & equipment
Amgen	Bio-pharmaceutical
Analog Devices	Technology hardware & equipment
Apple	Technology hardware & equipment
Arena Pharmaceuticals	Bio-pharmaceutical
ARM Holdings	Technology hardware & equipment
Arris	Technology hardware & equipment
Aruba Networks	Technology hardware & equipment
ASML Holding	Technology hardware & equipment
Atmel	Technology hardware & equipment
Austriamicrosystems	Technology hardware & equipment
Avago Technologies	Technology hardware & equipment
Avaya	Technology hardware & equipment
Axis Communications	Technology hardware & equipment
Bavarian Nordic	Bio-pharmaceutical
Biomarin Pharmaceuticals	Bio-pharmaceutical
Boehringer Ingelheim	Bio-pharmaceutical
Broadcom	Technology hardware & equipment
Brocade Communications Systems	Technology hardware & equipment
BTG	Bio-pharmaceutical
Bull	Technology hardware & equipment
Calix	Technology hardware & equipment
Cavium Networks	Technology hardware & equipment
Celgene	Bio-pharmaceutical
Ciena	Technology hardware & equipment
Corning	Technology hardware & equipment
Cosmo Pharmaceuticals	Bio-pharmaceutical
Cree	Technology hardware & equipment
CSR UK	Technology hardware & equipment
Cypress Semiconductor	Technology hardware & equipment
Dell	Technology hardware & equipment
Delta Electronics	Technology hardware & equipment
Dialog Semiconductor	Technology hardware & equipment
Egis Pharmaceuticals	Bio-pharmaceutical
Elan	Bio-pharmaceutical
Electronics for imaging	Technology hardware & equipment
Eli Lilly	Bio-pharmaceutical
ELMOS Semiconductor	Technology hardware & equipment
Emulex	Technology hardware & equipment
Epigenomics	Bio-pharmaceutical
Ericsson	Technology hardware & equipment
Evotec	Bio-pharmaceutical
Fairchild Semiconductor	Technology hardware & equipment
FEI	Technology hardware & equipment
Finisar	Technology hardware & equipment
Forest Laboratories	Bio-pharmaceutical
Gedeon Richter	Bio-pharmaceutical
Gilead Sciences	Bio-pharmaceutical
GW Pharmaceuticals	Bio-pharmaceutical
Harmonic	Technology hardware & equipment
Harris	Technology hardware & equipment
Hikma Pharmaceuticals	Bio-pharmaceutical
HTC	Technology hardware & equipment

Illumina	Bio-pharmaceutical
Infineon Technologies	Technology hardware & equipment
Integrated Device Technology	Technology hardware & equipment
Intermec	Technology hardware & equipment
International Rectifier	Technology hardware & equipment
Intersil	Technology hardware & equipment
Ipsen	Bio-pharmaceutical
Isis Pharmaceuticals	Bio-pharmaceutical
JDS Uniphase	Technology hardware & equipment
Johnson & Johnson	Bio-pharmaceutical
Juniper Networks	Technology hardware & equipment
Kla-Tencor	Technology hardware & equipment
Krka	Bio-pharmaceutical
Kulicke & Soffa	Technology hardware & equipment
Lam Research	Technology hardware & equipment
Lattice Semiconductor	Technology hardware & equipment
Lexmark	Technology hardware & equipment
Linear Technology	Technology hardware & equipment
Logitech international	Technology hardware & equipment
LSI Corp	Technology hardware & equipment
Lundbeck Pharmaceuticals	Bio-pharmaceutical
Marvell Technology	Technology hardware & equipment
Maxim Integrated Products	Technology hardware & equipment
MediaTek	Technology hardware & equipment
Medivir	Bio-pharmaceutical
Mellanox Technologies	Technology hardware & equipment
MEMC Electronics Materials	Technology hardware & equipment
Merck DE	Bio-pharmaceutical
Merck US	Bio-pharmaceutical
Merz Pharma	Bio-pharmaceutical
Microchip Technology	Technology hardware & equipment
Micron Technology	Technology hardware & equipment
Micronic Mydata	Technology hardware & equipment
Microsemi	Technology hardware & equipment
MorphoSys	Bio-pharmaceutical
Mylan	Bio-pharmaceutical
NCR	Technology hardware & equipment
Neopost	Technology hardware & equipment
NetApp	Technology hardware & equipment
NicOx	Bio-pharmaceutical
Nokia	Technology hardware & equipment
Novartis	Bio-pharmaceutical
Novo Nordisk	Bio-pharmaceutical
NPS	Bio-pharmaceutical
NVIDIA	Technology hardware & equipment
OmniVision Technologies	Technology hardware & equipment
ON Semiconductor	Technology hardware & equipment
Onyx Pharmaceuticals	Bio-pharmaceutical
Perrigo	Bio-pharmaceutical
Pfizer	Bio-pharmaceutical
Pitney Bowes	Technology hardware & equipment
Plantronics	Technology hardware & equipment
PMC-Sierra	Technology hardware & equipment
Polycom	Technology hardware & equipment
Qiagen	Bio-pharmaceutical
Qlogic	Technology hardware & equipment
Qualcomm	Technology hardware & equipment
Quantum	Technology hardware & equipment
Radiall	Technology hardware & equipment
Rambus	Technology hardware & equipment
Regeneron	Bio-pharmaceutical
Research in motion	Technology hardware & equipment
RF Micro Devices	Technology hardware & equipment
Roche	Bio-pharmaceutical
SanDisk	Technology hardware & equipment
Shire	Bio-pharmaceutical
Sierra Wireless	Technology hardware & equipment

Silicon Image	Technology hardware & equipment
Silicon Laboratories	Technology hardware & equipment
Spirent Communications	Technology hardware & equipment
Stada Arzneimittel	Bio-pharmaceutical
STMicroelectronics	Technology hardware & equipment
Suss MicroTec	Technology hardware & equipment
Synaptics	Technology hardware & equipment
Telit Communications	Technology hardware & equipment
Tellabs	Technology hardware & equipment
Teradyne	Technology hardware & equipment
Teva Pharmaceutical Industries	Bio-pharmaceutical
Texas Instruments	Technology hardware & equipment
Theravance Biopharma	Bio-pharmaceutical
Triquint Semiconductor	Technology hardware & equipment
UCB Pharma	Bio-pharmaceutical
United Therapeutics	Bio-pharmaceutical
Vectura	Bio-pharmaceutical
VeriFone Systems	Technology hardware & equipment
Vertex Pharmaceuticals	Bio-pharmaceutical
Warner Chilcott	Bio-pharmaceutical
Western Digital	Technology hardware & equipment
Xerox	Technology hardware & equipment
Xilinx	Technology hardware & equipment
Xyratex	Technology hardware & equipment
Zeltia	Bio-pharmaceutical