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## **Directly or Closely Connected: Network Antecedents in the Light of Technological Impact of Inventions**

**Steffen Keijl**  
Tilburg University  
Center for Innovation Research  
S.Keijl@uvt.nl

### **Abstract**

We present a model that explains how established firms can use their network position in order to enhance the impact of their inventions. Whereas existing literature focuses on collecting knowledge for the creation of impactful inventions, our study shows how impact can be leveraged through a firm's network position after inventions are created. Besides the rather general conception of technological impact, our study differentiates between impact on direct partners and impact on non-partners. Furthermore, we differentiate between local and global network effects as a mean for firms to steer the process of impact generation. The empirical setting for this study is the biopharmaceutical industry, for which 180 patenting firms have been selected. Results indicate the importance of both local and global network characteristics for leveraging the impact of inventions. Managers are informed to consider both the number of ties their firm maintains with other firms as well as their position in the overall network structure.

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We present a model that explains how established firms can use their network position in order to enhance the impact of their inventions. Whereas existing literature focuses on collecting knowledge for the creation of impactful inventions, our study shows how impact can be leveraged *through a firm's network* position after inventions are created. Besides the rather general conception of technological impact, our study differentiates between impact on direct partners and impact on non-partners. Furthermore, we differentiate between local and global network effects as a mean for firms to steer the process of impact generation. The empirical setting for this study is the biopharmaceutical industry, for which 180 patenting firms have been selected. Results indicate the importance of both local and global network characteristics for leveraging the impact of inventions. Managers are informed to consider both the number of ties their firm maintains with other firms as well as their position in the overall network structure.

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## **1. INTRODUCTION**

Impactful inventions gain the interest of many academic scholars who are inspired by the work of Schumpeter on new combinations and creative destruction (1934; 1942). Firms gain competitive advantages from having an impactful invention, because it enhances a firms' reputation and contributes to staying ahead of competitors (Andriopoulos & Lewis, 2009). Moreover, once a certain technological invention is the base for many successive technologies, economic benefits are also likely to coincide (Trajtenberg, 1990; Harhoff et al., 1999). Many inventions are created, but only some of them will have become very impactful as technological breakthroughs. The antecedents for creating impactful inventions as well as their characteristics have often been subject to scientific inquiry in the past decade (Ahuja & Lampert, 2001; Fleming, Mingo, & Chen, 2007; Nemet & Johnson, 2012; Phene, Fladmoe-Lindquist, & Marsh, 2006; Srivastava & Gnyawali, 2011). Findings have shown how to prepare for the creation of inventions that have a higher propensity to become impactful. In this study we did not consider the creation of inventions, but we concentrate how the impact of the inventions comes about.

Besides inhouse R&D activities, the literature has repeatedly shown that external collaboration is crucial for the creation of new inventions (Ahuja, 2000; Phelps, Heidl, Wadhwa, 2012). Alliances and joint ventures are described as governance mechanisms through which organizations gain access to novel external knowledge. The attraction of non-redundant knowledge is important for the development of novel inventions that have a higher chance for impact. In contrast to earlier research which merely focused on the creation of inventions by having access to external knowledge through social capital, this study considers

the impact of inventions by dispersing knowledge and information. In terms of open innovation, this paper concentrates on the inside-out flow of knowledge and information about a firms' inventions. Therefore, this study takes two firm level characteristics derived from their position in the local and overall network structure. Specifically, the central question is how firms can configure their network position in order to enhance the impact of their inventions.

First, the size of the local network – e.g. the number of organizations with whom a firm directly collaborates – increases the chances for firms to disperse the tacit knowledge of their inventions to their partners (Sriwastawi & Gnyawali, 2012; Sampson, 2007; Lavie, 2007). That is, partnering firms share complementary knowledge with each other, which is indeed necessary for the creation of new inventions, but also an indication of the impact of firms existing inventions (Ahuja, 2000; Kogut & Zander, 1992). In short, the impact of firms inventions is likely to increase with the number of alliance partners a firm has. Besides the size of the alliance portfolio, there is the global network position of the firm to consider (Gilsing et al., 2008; Rowley et al., 2000; Granovetter, 1985). Being in a central position, i.e. being close to many other firms, helps the purposeful spread of information throughout the network. Being able to reach other actors efficiently relates to one of the structural benefits of being central. Then, having a central position increases the likelihood that a firm's inventions will be reused by other firms in subsequent creation of inventions. Hence, a central position helps to spread information to many other firms in the network, which leverages the likelihood that inventions become impactful. We will explore whether the local network or the global network is more important for leveraging technological impact, because the first is more in control of the firm than the second. Either one being more important will therefore have implications about extent to which impact can be managed by the firm.

A final contribution of our study concerns a closer look at the impact of inventions. Conventionally, studies have looked at the impact of inventions by counting the number of times firms' patents are cited. Then, the technological impact of inventions is generally defined as the extent to which inventions are adopted and reused in subsequent inventions (Ahuja & Lampert, 2001; Dahlin & Behrens, 2005). In this paper, we critically reflect this definition and create an extension by differentiating between different types of impact. First, there can be a lot of error in impact when mostly the firm itself builds upon its own inventions and other firms do not build on these inventions. Through to the exclusion of self-citations, the impact of inventions will resemble the extent to which firms inventions affect other industry players. This exclusion of so-called self-fertilization will result in a more authentic notion of impact. Second, the technological impact will be split up in influence on direct partners versus non-partners. Such a differentiation is interesting because direct partners will more likely be influenced because of knowledge flows, whereas non-partners are more likely to be affected by the excellence of the idea. This study aims to extend research on impactful inventions by questioning what truly resembles the technological impact of firms inventions?

Besides that our study contributes to the development of theory on the impact of inventions, we think our study is important for managers. Results can inform management to consider their local and global position in the overall network structure in order to leverage the impact of their inventions. This requires a strategy that reflects both the number of direct partners and the centrality of firms position in the overall network. Hence, the relative importance of being directly connected to other firms versus being closely connected to other firms will be evaluated against each other regarding their effects on the technological impact of inventions.

For this study, a dataset has been constructed based on a sample that consists of publicly traded companies that have applied for at least ten biopharmaceutical patents in one

of the years between 1990 and 2000. The dataset was created by combining publicly available data on strategic alliances, joint ventures, financial statements, and patents. The biopharmaceutical industry was selected, because it went through several technological transitions with many patent applications, alliance activities and capital investments (Rothaermel & Hess, 2007). Moreover, data on this industry have quite well been preserved over a long period in time. The longitudinal panel design enables testing which network factors contribute more to the leverage of technological impact.

The theoretical approach of combining theory on knowledge recombination and network theory will be discussed in the next section. Subsequently we test and present the results of the relative effects of different antecedents on the different impact connotations of inventions.

## **2. THEORETICAL BACKGROUND**

### **2.1 Inventions and their impact: a differentiation**

Impactful inventions are considered as important factors that drive competition, because they mark a significant change with past and current technologies (Dosi, 1982; Nelson & Winter, 1982; Tushman & Anderson, 1986). Because these inventions are often at the root of shifts in technological paradigms, impactful inventions receive increasingly scholarly attention. The creation of impactful inventions requires novel recombinations of existing but before-hand unconnected knowledge (Dahlin & Behrens, 2005; Hargadon & Sutton, 1997; Henderson & Clark, 1990; Nemet & Johnson, 2012; Phene et al., 2006; Schoenmakers & Duysters, 2011). Creators of inventions gain competitive advantages once they succeed in transforming their knowledge recombinations successfully into impactful inventions (Schumpeter, 1942; Ahuja & Lampert, 2001; McKendrick & Wade, 2009). This is especially important knowing that many inventions are created, but only some of them will eventually reach higher impact

levels. In other words, firms need to attract attention to its inventions from other firms in order to leverage their impact.

Until now, research has mainly focused on the antecedents for the creation of impactful inventions in terms of collecting and recombining diverse sources of knowledge into promising inventions (Phelps, 2010; Sampson, 2007; Srivastava & Gnyawali, 2011). Notwithstanding the antecedents for the creation of inventions, our premise is that the technological impact of firms inventions is more likely to be determined by factors after their creation. We know that in many instances there is quite some time between the creation of an invention and the moment that an invention becomes impactful. More specifically in terms of patent analysis, the creation of inventions is associated with the application date. The average amount of time between the application and grant date of the patent is two years. Then another window of five to ten years is mostly chosen to determine the impact of these inventions as the number of times their associated patents are cited by other patents. As a results, there is a gap of several years between the creation of inventions and the years in which their impact comes about. This study will therefore not concentrate on the antecedents for the creation of impactful inventions, but we will consider the factors that affect the technological impact of all firm's inventions yearly.

Although a distinction can be made between inventions that are impactful from a technological versus from a market point of view (Ahuja & Lampert, 2001), in this study we focus on the technological impact of an invention. Technological impact is defined as the extent to which the invention is a crucial basis for a sequence of subsequent technological developments around the original invention (Trajtenberg, 1990, Ahuja & Lampert, 2001). So in order for an invention to gain impact, the invention must be reused in subsequent inventions; the technological content needs to affect the content of upcoming inventions (Dahlin & Behrens, 2005). Hence, the technological impact of firm's inventions will depend

on their adoption and reuse in successive inventions. This technological impact of inventions can differ significantly from each other. Whereas some inventions stand at the basis of new technological trajectories and generate many subsequent inventions, others are merely incremental changes in existing technologies (Dosi, 1982). Besides this variation in technological impact, the question is what truly resembles the impact of inventions?

The general definition allows for impact that could solely be generated by the creator of the invention, when only the creator builds forth on the invention. We posit that the reuse of a firm's own inventions by itself erroneously increases the technological impact. Accordingly, such self-fertilization of building on a firm's own inventions should be ignored when trying to come closer to a genuine notion of technological impact. In patent analytical terms, technological impact of inventions is more closely resembled when self-citations – i.e. citations to self-owned patents – are left out of the analysis. Accordingly, the definition of technological impact is slightly adjusted as the extent to which firm's inventions are assimilated and applied in the development of inventions by other firms.

Going one step further, this study considers which other firms are affected by the inventions of a focal firm. Differentiating impact of inventions according to which firms assimilate and apply inventions for the creation of subsequent inventions contributes to a differentiation between knowledge sharing and an even more authentic notion of technological impact. Specifically, the adoption and reuse of inventions by a firm's alliance partners might resemble knowledge sharing between the firms instead of excellence on the side of the inventions. In contrast, the use of a firm's inventions by nonpartners may correspond to an even more genuine idea of technological impact, as no direct transfer of knowledge has taken place. Hence, technological impact of a firm's inventions will be split up in impact on direct partners, as a possible consequence of knowledge sharing, and impact on nonpartners, as a possible consequence of excellence of inventions. In the next section we

elaborate this and hypothesize different relationships between a firm's position in the network structure and the technological impact of firms' inventions on direct partners versus nonpartners.

### **2.3 Local network effects**

In the last decades many firms started collaborating in strategic alliances in order to increase their performance (Gulati, 1998; Hagedoorn & Schakenraad, 1994). Interfirm relationships such as alliances can be seen as conduits through which knowledge and information flows (Borgatti & Foster, 2003). Alliances allow firms to both obtain knowledge about their partners' inventions as well as to disperse knowledge and information on their own inventions. Specifically, R&D alliances are mostly agreed upon between two or multiple firms for the exploration of new technological areas. The new inventions following from alliances will be significantly affected by what is already known in terms of existing inventions from both partners (Sampson, 2007). Subsequently, the exchange, adoption and reuse of knowledge between partners play a critical role in leveraging impact of inventions. Hence, knowledge and information about inventions becomes available through alliances between partnering firms, who then will be more likely to build upon each other's inventions.

Then, the number of a firm's R&D alliance partners, which is considered as the size of the local network, plays an important role in the technological impact of a firm's inventions. Alliance partners enable a firm to disperse knowledge and information about its' inventions in the local network. The more partners become knowledgeable about a firm's inventions, the more likely it is that other firms develop inventions by building upon the focal firm's inventions (Sriwastawi & Gnyawali, 2012; Sampson, 2007; Lavie, 2007). Put differently, the more direct partners a firm has the more likely that its' inventions will impact subsequent technological developments by other firms. Accordingly, our first hypothesis is as follows:

Hypothesis 1a: There is a positive relationship between the number of direct partners (degree centrality) and the technological impact of firm's inventions.

Direct relationships between firms have proven to enable flows that consist of tacit knowledge (Ahuja, 2000; Kogut & Zander, 1992). Because of the flow of more tacit knowledge, which is a deeper understanding about the applicability of the invention, direct partners are more likely to assimilate and reuse components from a focal firm's inventions. In other words, direct partners are more likely to be impacted by the technological activities of the firm due to knowledge sharing and knowledge complementarities (Ahuja, 2000). The more direct partners a firm has, the more likely it is that firm's inventions will be adopted by its' direct partners. Specifically, these direct partners are more likely to be affected by a firm's inventions as compared to nonpartners.

In contrast, nonpartners are less likely to receive a deeper understanding of inventions that are created by firms with whom they do not collaborate, because of the absence of knowledge sharing. Only information of these inventions will eventually reach nonpartners so that they may build upon these inventions as well. This information may reach nonpartners via shared direct partners between the nonpartners and the focal firm. This is resembled through a snowballing effect of information about the invention through the network which is enhanced by the number of actors that become knowledgeable about certain inventions. Accordingly, also nonpartners will be increasingly affected by a firm's inventions when the focal firm has more direct partners. However, the magnitude of the effect of the size of the local network on the technological impact on direct partners will be larger than the effect of impact on nonpartners, because of the difference in knowledge and information. Therefore, we hypothesize:

Hypothesis 1b: The positive relationship between the number of direct partners and *the technological impact of firms' inventions is stronger* regarding the impact on direct partners as opposed to nonpartners.

## **2.4 Global network effects**

As stated above, direct partnerships are better suited for the flow of tacit knowledge and therefore the impact of inventions on direct partners and beyond is most likely to rise with the size of the local network. However, leveraging impact of inventions goes further than simply maintaining a large number of ties. For increased impact, information about inventions may actively be communicated across alliances. Firms may advance this communication by locating themselves in those network positions that enable them to control the impact of their technological inventions (Powell, Koput, & Smith-Doerr, 1996). Such communication is further enhanced by the fact that knowledge about inventions becomes increasingly codified once these inventions are created (Zander & Kogut, 1995). Whereas for the transfer of tacit knowledge, direct ties seem to be better conduits, the diffusion of codified knowledge about the new inventions takes also easily place beyond direct ties throughout the larger interfirm network as information spillovers (Ahuja, 2000). Structural network properties of interfirm collaborations may therefore become also important with regard to impact of inventions in addition to the direct relationships between firms.

The network property that will be focused upon is the structural embeddedness of a firm in the network (Granovetter, 1985; Rowley et al., 2000). Specifically, the position of a firm in the network can differentiate in terms of its centrality as the extent to which a firm is closely connected to other firms in the network. These different positions in a network of R&D alliances result in firms having divergent abilities for dispersing information about their

inventions throughout the network. Put differently, the information that flows through interorganizational networks is affected by each firm's position in the overall network structure (Powell, Koput, & Smith-Doerr, 1996). Following from this, there are several arguments in favor of central firms when it comes to triggering the impact of their inventions.

First, a centrally located firm is more visible for other firms, which shapes the central firm's reputation. Such reputation benefits can greatly enhance a firm's ability to disperse information about its' inventions to other firms in the industry. Besides affecting direct partners, visibility and reputation of the focal firm will also affect nonpartners, because the latter will generally observe the R&D activities of central players. Second, central firms are better informed about what happens in the industry (Gilsing et al., 2008). This means that central players are better positioned to exploit promising new areas of technological development and select the alliance partners needed for this. Then, centrally positioned firms have better and timelier access to novel ideas in order to create inventions, which they can thereafter better communicate throughout the network. Finally, the probability, speed, and reliability of knowledge transfer between firms is directly related to the distance between firms. The communication of information and knowledge happens more quickly by firms with a short average path length to other firms in the network (Watts, 1999). A firm that is closely connected to many other firms can disperse information concerning its inventions more easily than firms who are less centrally located (Schilling & Phelps, 2007)<sup>1</sup>. When information about inventions is more easily transferred to many other firms beyond direct ties, the likelihood increases that these inventions will generate higher levels of technological impact.

Accordingly, the second hypothesis is as follows:

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<sup>1</sup> Closeness centrality is favored over other centrality measures as it deals with the efficient reach of all other actors in a network.

Hypothesis 2a: There is a positive relationship between the level of closeness to other firms in the network and the technological impact of firm's inventions.

When concentrating on which other firms are most likely to adopt a hub firm's inventions there are different effects concerning the impact on direct partners as opposed to the impact on nonpartners. Direct partners collaborating with centrally located firms are more likely to perceive the higher status of their centrally located partners, because that might be one of the reasons for collaboration. Then the direct partners will be more likely to be affected by the firms' reputation than nonpartners. This will be enhanced by the fact that direct partners are more likely to obtain tacit knowledge about the inventions of the centrally located firm. This exchange of tacit knowledge enables partners to develop a deeper understanding of inventions created by the hub firm. Therefore, direct partners are more likely to adopt and reuse the inventions of centrally located firms as compared to nonpartners.

Subsequently, these arguments support the impact of inventions of centrally located firms, especially with regard to the impact on the direct partners of the central firm. Also regarding the impact on nonpartners, hub firms may benefit from their central position as they are better able to reach all other actors in the network. Moreover, by means of network orchestration the hub firms may control the circulation of knowledge and information and promote its' own inventions (Dhanaraj & Parkhe, 2006). Nonetheless, being too central and too close to many others may cause some nonpartners to refrain from assimilating and building upon the inventions of central players. Nonpartners may observe that they would have to compete with the hub firm and its' direct partners, although the nonpartners do not have direct access to the same knowledge. Then, nonpartners may decide not to go after the same technologies, which are exploited by the central firms and their direct partners. Instead, nonpartners may explore and develop other technologies in niche areas, or nonpartners may

somehow try to circumvent the central firms' inventions. Then the technological impact of being central in network will be less on nonpartners as compared to partners. Conclusively, we still expect a positive relationship between the network centrality and technological impact of firms' inventions on nonpartners. However, we will also test for curvilinearity in this case, because of the aforementioned reasons.

Hypothesis 2b: The positive relationship between the level of closeness to other firms *in the network and the technological impact of firms' inventions* is stronger regarding the impact on direct partners as opposed to nonpartners.

In the next section the empirical setting of this study will be discussed followed by a description of the measures and the analyses.

### **3. METHODS**

#### **3.1 Data & sample**

The data for this study comes from a large-scale data project constructed from the combination of several databases with information on alliances, firm financial statements, and patents. The empirical setting that has been chosen is the biopharmaceutical industry from 1985 until 2007. We wanted to focus on a high-tech industry in which technological development takes place at high rates, to make sure that both the level of alliance activity and the numbers of technological inventions are high. The biopharmaceutical industry is such an industry characterized by rapid technological development (Gambardella, 1995). During the 1980s and 1990s the biopharmaceutical industry demonstrates increasing numbers of patent applications in the United States, which signals the activity of technological invention creation. Furthermore, the biopharmaceutical industry characterizes itself as one in which

patents are intensively used for intellectual property protection and most inventions are indeed patented within the biopharmaceutical industry (Hall et al., 2001). Furthermore, there has been a large number of alliances in the biopharmaceutical industry since the 1980s and onwards (Hagedoorn, 1993; Schilling, 2009). The combinations of many well documented inventions and alliances made the biopharmaceutical industry very suitable to study the research question on how to leverage the impact of inventions.

In order to retrieve a sample of firms who are actively involved in the process of inventing, we identified all public firms who had applied for at least ten biopharmaceutical patents in one of the years between 1990 and 2000. The technological patent classification scheme of 2006 from the USPTO was used to assign each patent with a primary technology class, which data was drawn from the NBER patent database (Hall et al., 2001). In this technological classification scheme, the three-digit USPTO classification was used, in which the codes '424', '435', '436', '514', '530', '800', and '930' correspond with patents that are related to the biopharmaceutical industry (Phene et al., 2006; Rothaermell & Hess, 2007). In total there were 123.819 patents applied for between 1990 and 2000 in the aforementioned classes. Through the matching tables provided by NBER we identified that 37.417 patents were applied for by 896 public companies. We only wanted the companies that applied for patents intensively, because these firms signal to be actively involved in inventive processes, to whom the impact of their inventions is also more likely to be of any concern. Therefore, the condition was set that a firm should have applied for at least ten biopharmaceutical patents in one of the years between 1990 and 2000. We ended up with a sample of 180 publicly traded companies who applied for 30.168 biopharmaceutical patents between 1990 and 2000.

The next step was to match these firms with data from financial statements, which were retrieved from Compustat. After matching the patent data with the Compustat data, a triple matching procedure was used to retrieve the alliances belonging to these companies

from Thomsons' SDC Platinum. The data was matched on cusip, on their full name, and on keywords of their name<sup>2</sup>. The results from the three matching procedures were then compared by two independent researchers in order to guarantee a correct match between the firms in the sample and their alliances. SDC data have been used in numerous empirical studies on strategic alliances before (Sampson, 2007; Schilling & Phelps, 2007; Srivastava & Gnyawali, 2011). Then, alliances were collected that were announced between 1985 and 2010. However, we first started our analyses from 1990 onwards, because there is not so much information on alliances announced before 1990 in the SDC database. The duration of alliances is in general longer than one year. However, end dates of alliances are rarely mentioned in SDC. Therefore, we assumed alliances to exist for five years. Then, alliance networks were created based on five-year moving windows. Finally, we only included alliances that were concerned with research and development. Furthermore, alliances were excluded if the date on which the alliance was announced had been estimated, because sometimes alliances do not materialize although they had been announced. We ended up with 13 network structures for the biopharmaceutical industry from 1990 until 2003, which are the start and end years of the period for the analyses. The alliance data was then analyzed in R, which we used to compute the measures for our independent variables.

We used data from U.S. public firms only for three reasons. First, we wanted to include firm financial information from Compustat. Although there is a global version of Compustat, the data on non-US firms is rather rare before 2000. Furthermore, patent data from NBER was used in this study which only consists of patent that were applied for at the United States Patent Office. Finally, also the SDC data are a lot more comprehensive for U.S. firms as compared to non- U.S. firms (Schilling & Phelps, 2007). The final data set includes 179 firms involved in 591 alliances. Many of the alliances included more than two

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<sup>2</sup> For example, we matched Abbott Laboratories, but we also searched for 'Abbott' in the SDC data.

participating firms, so the number of dyads is greater, totaling 1.454. Based on these alliance data we constructed the measures of our independent variables and determined the impact of inventions on partners and nonpartners of a firm.

### **3.2 Dependent variables**

Conventional research has used citation-weighted patent counts as a measure for inventions and their quality or impact. Then, the commonly used indicator for a patent's technological impact is the number of forward citations, i.e. the number of times that a patent is cited. The main argument throughout the literature is that the more patents are cited by future patents the higher their technological impact. Forward citations have been used as a proxy for the invention's technological impact on future technological development and have been related to concepts as innovative performance (Hagedoorn & Cloudt, 2003), breakthrough inventions (Ahuja & Lampert, 2001; Phene et al., 2006), economic value of inventions (Hegde & Sampat, 2009; Trajtenberg, 1990), patent importance (Fleming, 2001; Hall, Jaffe, & Trajtenberg, 2005; Trajtenberg et al., 1997), patent value (Reitzig, 2003), and technological impact (Rosenkopf & Nerkar, 2001). The measure for technological impact in this study is also based on the number forward citations, however the time point for the analyses is not the year in which the cited patents are applied for. Instead, our measure for technological impact is measured in the year in which a firms' patents are applied for. The hypotheses refer to three differently operationalized measures for technological impact. Accordingly, the measures are as follows.

Technological impact (total cites): The technological impact of a firms' inventions in year  $t$  is determined by the number of times a firms' patents are cited in year  $t$ . For example, firm "A" applies for two patents in year  $t$  and has no patents before year  $t$ . When these two patents are five times cited in year  $t+2$ , the variable 'total cites' takes a value of '5' in year

$t+2$ . This contrasts earlier research in which ‘inventive performance’ in year  $t$  is generally measured as the number of times a firms’ patents that are applied for in year  $t$  become subsequently cited. In our example, the two patents of firm “A” get cited twenty times in total. The ‘inventive performance’ as a citation-weighted patent count would have taken a value of ‘20’ for firm “A” in year  $t$ . Our approach enables us to identify the network antecedents that occur in the year of patent citation as compared to the year of patent application.

Technological impact on direct partnering firms (cites alliance partners): The technological impact of a firms’ inventions on its’ direct partners in year  $t$  is determined by the number of times a firms’ patents are cited in year  $t$  by patents applied for in year  $t$  by the firms’ direct partners. A direct partner is a firm with whom the focal firm has been in an alliance with in year  $t$  or in year  $t-1$ . We assume that a citation is a consequence of an alliance between two firms even when the alliance between these firms ended in the year before the citation.

Technological impact on nonpartnering firms (cites alliance partners): The technological impact of a firms’ inventions on its’ nonpartners in year  $t$  is determined by the number of times a firms’ patents are cited in year  $t$  by patents applied for in year  $t$  by other firms in the sample. Nonpartners are those firms from the sample with whom the focal firm was not in an alliance with in year  $t$  or in year  $t-1$ . Citations from nonpartners are therefore assumed not to be the consequence of an R&D alliance between these firms.

### **3.3 Independent variables**

Number of direct partners (degree centrality): The measure that captures the local network effect is measured by the number of direct alliances partners a firm has in year  $t$ . This number is based on R&D alliances between sampled firms with an assumed duration of five years.

Closeness centrality: We used the measure for global network position based on the concept of closeness (Freeman, 1979), which captures the extent to which a firm is close or far positioned to all other firms in the network (Powell et al., 1996). The boundary of the network was determined by and includes only the 180 firms who are part of the sample as described in the sampling procedure. Because the networks of R&D alliances show in some of the years some disconnected components, we used a normalized closeness centrality measure. The original closeness centrality measure is computed for each firm as the inverse of the sum of the distances to all other firms. The normalized closeness centrality measure takes the sum of the inverse of each distance to all other firms in the network. Then the measure can have a range from 0 to 1. In this study, a high normalized closeness score means that a firm can reach most other firms within a small number of steps. A central firm is then not so dependent on specific other firms to disperse information about its' inventions to the wider network. We decided to use closeness centrality instead of other centrality measures such as betweenness centrality. In contrast to betweenness, closeness centrality is more about reaching other firms efficiently, which is required for the dispersion of knowledge and information for impact. Next, betweenness centrality is more concerned with being in between other pairs of firms and associated with control and information benefits in terms of obtaining all knowledge and information that is circulating in the network. Accordingly, betweenness is linked with knowledge and information throughput and the creation of inventions, whereas closeness deals with the efficient reach of other firms.

### **3.4 Control variables**

We control for 'firm size' by including the natural logarithm of the number of employees in a firm per year (Ahuja, 2000; Ahuja & Lampert, 2001; Hagedoorn & Schakenraad, 1994).

Larger firms may be more likely to be central players, have larger patent portfolios, and

therefore may be more likely to generate higher levels of technological impact. Furthermore, R&D expenditures are entered as a control variable, because firms who invest a lot in R&D may be more likely to generate impact. We also controlled for firms' operational performance by including the total sales of a firm (in millions of dollars). Controlling for sales is especially important when controlling also for the effect of R&D expenditures (Rothaermell & Hess, 2007). In order to control for unobserved heterogeneity we entered a firm fixed effect in all models as the log of the number of biotechnological patents applied for in the five years prior to the observation period. This patent experience variable serves as a control for unobserved differences in firm knowledge stocks (Ahuja & Lampert, 2001; Schilling & Phelps, 2007; Srivastava & Gnyawali, 2011). Moreover, firms with more biotechnology patents are more likely to be cited subsequently. Finally, we entered year dummies as year fixed effects. Because we investigate a 13-year time period, we need to control for time-varying factors that influence all firms, including macroeconomic circumstances. Inserting year dummies is functional, because they also control for any right truncation effect that might remain in the time series (Rothaermell & Hess, 2007).

### **3.4 Analyses**

The dependent variables in our study, technological impact measured by the number of citations *a firms' patents receive in a certain year*, is a count variable and contains only nonnegative values. A Poisson regression approach is normally suitable to predict count data, but the Poisson distribution assumes that the mean and variance of the dependent variable are equal to each other. Although the estimation of the regression coefficients is consistent, the standard errors are by and large underestimated. In our case, there is quite some overdispersion in the dependent variables, as the variances exceed the mean quite heavily. Therefore, we apply the commonly used negative binomial regression model (Schilling &

Phelps, 2007). Then, there is the choice between random effects and fixed effects modeling. Differences between both types of modeling are most of the times limited unless there is a lot of unobserved heterogeneity in the sample. We dealt with this issue both because of our sampling method as well as the inclusion of firm specific control variables, of which the individual firm patent experience is most important in our analyses. Therefore, we relied on the random effects negative binomial regression model and used the fixed effects model as a robustness check.

## **4. RESULTS**

### **4.1 Results**

The first table shows the descriptive statistics and correlations between the variables. We shortly discuss them here. On average each firm receives yearly 77,38 forward citations. Furthermore, the average number of forward citations received from direct partners or the impact on direct partners is very low with 2,34 citations yearly on average. This low average is mainly caused by the fact that not every firm in the sample engaged in alliances. Next, each firm received on average 15,50 forward citations from nonpartners, but from firms that are in the sample. Obviously, the scores of impact on direct partners and nonpartners do not add up to the total number of citations. This is due to selfcitations and citations from nonsampled firms, which are in the total citations, but subtracted in order to determine the citations from direct partners and nonpartners. The values of the bivariate correlations between the different dependent variables show that impact on nonpartners and the total technological impact are strongly correlated. The correlations with the citations from direct partners are not so high. On average, each firms is engaged in 2,63 R&D alliances yearly. As expected, degree centrality and closeness centrality do correlate strongly, although they do capture different dimensions both theoretically as well as empirically.

- - -

**Insert table: Descriptive Statistics and Correlations about here**

- - -

Then, the next table shows the results from negative binomial random effects regressions on the different dependent variables.

- - -

**Insert table: Results from negative binomial random effects regressions about here**

- - -

In all three models 1 (with the different dependent variables), we find significant positive effects from ‘firm size’, ‘R&D expenditures’, and ‘patent experience’. First, when we zoom in on the total technological impact of a firms’ patents, we see that ‘degree centrality’ has a positive effect in the second model ( $b=0,028$ ). However, when ‘closeness centrality’ is entered, the positive effect from ‘degree centrality’ becomes insignificant, whereas ‘closeness’ has a positive significant effect ( $b=1,478$ ). In the last model we checked whether curvilinear effects from ‘closeness centrality’ exist in relation to the technological impact of inventions. The linear term of ‘closeness’ is statistically significant positive ( $b=2,964$ ) and the squared term of ‘closeness’ is also statistically significant but negative ( $b=-5,483$ ), which indicates the existence of an inverted-U shaped relationship. An increase in the model fit as an increase of the  $\chi^2$  is also statistical significant when adding the squared term for ‘closeness’ centrality. Further, the effect of the number of alliance partners on impact becomes statistically significant again.

Second, we focus on the technological impact on a firms direct partners. In model 2 of the cites from direct partners, a statistically significant effect is found from ‘degree centrality’ ( $b=0,129$ ), whereas the positive effect from ‘firm size’ becomes insignificant. Adding ‘closeness centrality’ in model 3, the effect from ‘degree centrality’ becomes insignificant,

and ‘closeness’ centrality shows a strong positive effect ( $b=13,440$ ). Testing for curvilinearity of ‘closeness’ seem to reveal an inverted-U shaped relationship. However, when we computed and plotted the marginal effect of ‘closeness’ we found a diminishing positive effect<sup>3</sup>. Again, the effect of the number of alliance partners becomes marginally statistically significant again.

Third, there seems no effect from ‘degree centrality’ on the forward citations that a firm receives from nonpartners. Even more so, there appears a marginally significant negative effect ( $b=-0,015$ ) when entering ‘closeness centrality’, which shows a positive effect ( $b=1,598$ ). The model with a curvilinear effect of ‘closeness centrality’ shows that the linear term of ‘closeness’ is statistically significant positive ( $b=3,677$ ). The squared term of ‘closeness’ is also statistically significant but negative ( $b=-7,639$ ), which indicates the existence of an inverted-U shaped relationship. Also this time, we computed and plotted the marginal effect of ‘closeness centrality’ and indeed we found an inverted-U shaped relationship.

The first baseline hypothesis, suggesting a positive effect from the number of alliance partners on the technological impact of inventions is confirmed throughout the models. For testing hypothesis 1b, which suggest a stronger effect of degree centrality on the citations from direct partners, we computed the marginal effects based on the models 4 regarding the forward citations from partners and forward citations from nonpartners. There we found a total effect size of 2,06 citations from direct partners and a total effect size of 0,97 citations from nonpartners explained by degree centrality<sup>4</sup>. This confirms the hypothesis that the positive relationship between the number of direct partners and the forward citations from direct partners is stronger than the positive relationship between the number of direct partners and the forward citations from nonpartners.

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<sup>3</sup> Plots are available on request with the author.

<sup>4</sup> Effect sizes were computed based on the marginal effects by the difference between the predicted minimum and maximum values on the dependent variables. Then, we make a direct comparison as these numbers all refer to forward citations.

The second baseline hypothesis is partially confirmed. That is, for both the total technological impact of a firm's inventions as well as the impact on non-partners we find an inverted-U shaped relationship between closeness and the respective dependent variables. This is not in line with the hypothesis. However, there is a diminishing positive effect from 'closeness centrality' on the number of citations from direct partners, which is in line with hypothesis 2a and hypothesis 2b. The marginal effect shows an effect size of 5,52 forward citations from direct partners explained by a firm's network position. The marginal effect of 'closeness centrality' on citations from nonpartners is rather small. There the difference between the highest and lowest predicted value on the inverted U is only 0,44 forward citations.

#### **4.2 Robustness checks**

Several robustness checks were carried out in order to find out the robustness of the aforementioned results. First, we also used the conventional 'closeness centrality' measures instead of the normalized 'closeness centrality' measures. The results from these analyses were similar to the ones shown in the table. Secondly, a fixed effects model was carried out as well. That also did not change the results. Conclusively, the results seem to be pretty robust.

### **5. CONCLUSION & DISCUSSION**

In this study we aimed to study the antecedents for the technological impact of inventions. In contrast to many previous studies we have not considered the creation of inventions that may or may not become impactful (Ahuja, 2000; Ahuja & Lampert, 2001; Sampson, 2007; Schilling & Phelps, 2007). Instead, we focused on the antecedents for when the technological impact of inventions actually became apparent. The second goal of the study was to take a closer look at the technological impact by excluding self-fertilization. Moreover, we unfolded

the concept of technological impact by differentiating which other firms are affected by a firm's inventions. We discerned impact on direct alliance partners from impact on nonpartners. Then impact on alliance partners could be a consequence of knowledge sharing, whereas impact on nonpartners resembles a more genuine idea of technological impact. Thirdly, with this study we aimed to contribute to the development of a network theory of technological impact by separating local network effects from global network effects (Gilsing et al., 2008; Powell et al., 1996). Therefore, the number of alliance partners was concentrated upon as a proxy for the local network effect and the closeness of a firm to other firms in the network captured a firm's global network position.

Firstly, the results indicate the existence of different forms of technological impact, which are only to some extent related to each other. Citations from direct partners and citations from nonpartners represent not only theoretically but also empirically distinct notions of technological impact. On the one hand, impact on direct partners, which is seen as the extent to which partners adopt inventions, resembles knowledge sharing through interaction between the partners (Zander & Kogut, 1995). Rather trivial may be the fact that the more direct partners a firm has, the more likely it is that these direct partners are affected by the firm's inventions. Also, the more central a firm is, the more its direct partners will be affected by its inventions. Somewhat surprisingly is that the effect of closeness is larger than the effect of the number of direct ties regarding the impact on direct partners. This could mean that direct partners are particularly sensitive for the status and reputation of their central partners.

On the other hand, citations from nonpartners are stronger related to the overall number of citations of firms' inventions. This suggests that citations from nonpartners seem to be like a more valid notion of impact, which goes beyond knowledge sharing between collaborating firms. In fact, this impact on other industry firms, with whom a firm does not

collaborate, is only for a small part explained by the number of alliance partners of a firm and the position of a firm in the network. One of the conclusions is that the patents of more centrally located firms are more likely to be cited by their direct partners than by their nonpartners. Another conclusion is that true impact as determined by citations from nonpartners is less determined by network factors and perhaps more dependent on specific characteristics of the inventions.

Some general limitations to our study apply such as the fact that we used secondary data on alliances, which may not be fully complete (Schilling, 2009). Furthermore, the usual limitations of patent data apply, such as that our data represents one industry setting, in which patents serve as proxies for inventions. Specifically, the spread of information on inventions as a way to leverage impact will also largely depend on the intellectual property regime. However, the fundamental limitation of our study is the question how reliable the local and global network effects on the impact of a firm's inventions are. Specifically, we focused on characteristics of the firm whose inventions had an impact on direct partners versus nonpartners, without taking into consideration the characteristics of these partners.

As a suggestion for future research we believe that both partner characteristics may be of importance in studies on the creation of inventions as well as in studies on the impact of inventions. Then it may turn out that besides the number of ties and the position of a firm in a network, the choice of an alliance partner is also very important. A first attempt of such a study has already been conducted and we suggest further research should be done (Rothaermell & Hess, 2007). Another suggestion is to look whether different types of technological impacts also matter in terms of a firm's financial performance. Would impact on direct partners matter more or less than impact on nonpartners in terms gaining a competitive advantage.

In terms of managerial implications we find that managers should be aware of both the number of alliance partners as well as their global network position when the impact of their inventions is concerned. Managers have already been informed by numerous studies on how to create impactful inventions (Ahuja & Lampert, 2001; Phene et al., 2006; Srivastava & Gnywali, 2011), but after the creation the impact can be increased as well by purposefully dispersing information on inventions throughout the network. Our findings indicate that managers should specifically focus on maintaining a certain number of alliances, but not without considering how these alliances may affect their overall network position. So, to the extent that a firm's R&D strategy aims at high impact inventions, managers should think about and actively control their network position as a way to leverage the impact of their inventions. Partner selection may therefore be a critical condition, on which we look forward to see some interesting studies in the future.

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**Tables:**

--- Table: Descriptive Statistics and Correlations ---

Variable	Mean	STD	Min	Max	Total cites	Cites alliance partners	Cites non- partners	Firm size	R&D	Sales	Patent exp.	Degree	Closeness
Total cites	77,38	138,35	0	1382	1,00								
Cites alliance partners	2,34	9,58	0	139	0,65	1,00							
Cites non-partners	15,50	30,79	0	384	0,87	0,48	1,00						
Firm size	7,15	3,54	0	12,74	0,34	0,21	0,32	1,00					
R&D Expenditures	0,45	0,84	0	5,52	0,42	0,34	0,38	0,57	1,00				
Sales	7,64	17,91	0	195,81	0,16	0,11	0,16	0,47	0,55	1,00			
Patent experience	1,60	1,96	0	6,34	0,48	0,31	0,42	0,55	0,30	0,30	1,00		
Degree centrality	2,63	4,16	0	28	0,46	0,58	0,35	0,33	0,47	0,18	0,27	1,00	
Closeness centrality	0,19	0,17	0	0,56	0,34	0,33	0,28	0,23	0,33	0,16	0,24	0,73	1,00

N: 1733 firmyear observations in the period from 1990 - 2002

--- Table: Results from negative binomial random effects regressions <sup>a</sup> ---

	Total cites				Cites alliance partners				Cites non-partners			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Firm size	0.075*** (0.011)	0.064*** (0.011)	0.062*** (0.011)	0.064*** (0.011)	0.156*** (0.043)	0.048 (0.036)	0.058 (0.035)	0.057 (0.035)	0.091*** (0.015)	0.085*** (0.015)	0.086*** (0.015)	0.090*** (0.015)
R&D Expenditures	0.153*** (0.031)	0.143*** (0.031)	0.115*** (0.032)	0.098** (0.032)	0.281*** (0.073)	0.197** (0.065)	0.161** (0.062)	0.123 (0.065)	0.112** (0.039)	0.105** (0.039)	0.080* (0.040)	0.053 (0.041)
Sales	-0.005* (0.002)	-0.005* (0.002)	-0.006** (0.002)	-0.006** (0.002)	-0.012 (0.009)	-0.005 (0.007)	-0.016** (0.006)	-0.016** (0.006)	-0.001 (0.002)	-0.001 (0.002)	-0.002 (0.002)	-0.003 (0.002)
Patent experience	0.315*** (0.021)	0.311*** (0.021)	0.305*** (0.020)	0.305*** (0.020)	0.193*** (0.042)	0.284*** (0.040)	0.302*** (0.038)	0.298*** (0.038)	0.297*** (0.025)	0.294*** (0.025)	0.287*** (0.025)	0.282*** (0.025)
Degree centrality		0.028*** (0.005)	0.003 (0.006)	0.039** (0.014)		0.129*** (0.011)	0.003 (0.017)	0.074* (0.036)		0.012 (0.006)	-0.015* (0.007)	0.035* (0.017)
Closeness centrality			1.478*** (0.202)	2.964*** (0.556)			13.440*** (1.402)	18.816*** (3.084)			1.598*** (0.252)	3.677*** (0.696)
Closeness centrality <sup>2</sup>				-5.483** (1.910)				-14.273* (6.656)				-7.639** (2.383)
Constant	-0.535*** (0.098)	-0.426*** (0.098)	-0.456*** (0.098)	-0.537*** (0.102)	-2.924*** (0.378)	-2.404*** (0.341)	-4.716*** (0.405)	-5.330*** (0.539)	-0.955*** (0.129)	-0.904*** (0.131)	-0.961*** (0.131)	-1.070*** (0.136)
Year dummies	yes	yes	yes	yes	yes	yes	yes	yes				
chi2	1902,97	1978,23	2069,22	2092,18	207,59	409,15	540,65	518,91	1084,62	1090,49	1157,33	1174,67
N	1733	1733	1733	1733	1733	1733	1733	1733	1733	1733	1733	1733

<sup>a</sup> Standard errors in parentheses.