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# All for One and One for All: How Intrafirm Networks Affect the Speed of Knowledge Recombination

**Solon Moreira**
Copenhagen Business School
Innovation and Organizational Economics
sm.ino@cbs.dk

**Arjan Markus**
Copenhagen Business School
Department of Innovation and Organizational Economics
am.ino@cbs.dk

## Abstract

Drawing on absorptive capacity and social network theory, we examine the effect of intrafirm network closure, tie strength, and diversity on firms? recombination speed of technologically distant external knowledge. Results from an event history study of 113 pharmaceutical firms, which engage in technology licensing in the period 1986-2003, reveal that the time to recombine external knowledge into own invention increases with technological distance. However, intrafirm co-invention network closure and diversity shorten the time to recombine distant external knowledge. These results mark the importance of inventors? knowledge networks as antecedent of the speed with which firms can absorb external knowledge.

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ABSTRACT. Drawing on absorptive capacity and social network theory, we examine the effect of intrafirm network closure, tie strength, and diversity on firms' recombination speed of technologically distant external knowledge. Results from an event history study of 113 pharmaceutical firms, which engage in technology licensing in the period 1986-2003, reveal that the time to recombine external knowledge into own invention increases with technological distance. However, intrafirm co-invention network closure and diversity shorten the time to recombine distant external knowledge. These results mark the importance of inventors' knowledge networks as antecedent of the speed with which firms can absorb external knowledge.

**KEYWORDS:** recombination speed, absorptive capacity, intrafirm inventor networks, innovation, licensing

## INTRODUCTION

Nowadays firms increasingly rely on a combination of internal and external resources to create inventions which can be subsequently commercialized into innovations (Laursen & Salter, 2006). Particularly in high-tech and fast-pace industries, external partners play a critical part in a firm's R&D process as firms gain access to complementary assets (Dyer & Singh, 1998). Acquisition of external knowledge is an attractive alternative to in-house R&D, because firms spread the risk and cost inherent to R&D and may shorten the development of inventions (Ahuja, 2000). A plethora of studies has emerged over the past two decades showing that firms differ in the ability to draw on external sources of knowledge (Volberda, Foss, & Lyles, 2010). Cohen & Levinthal (1989, 1990) named this ability "absorptive capacity" and refers to a firm's "ability to identify, assimilate and exploit knowledge from the environment" (Cohen & Levinthal, 1990, p. 128). Despite our growing understanding of the ability to harness external knowledge for own invention, the current absorptive capacity literature is limited with regard to at least four important aspects.

First, the role of individuals in developing firm-level absorptive capacity has been largely overlooked (Volberda et al., 2010). In their seminal article, Cohen & Levinthal (1990) metaphorically refer to the development of individuals' absorptive capacity and how it constitutes an organization's absorptive capacity. The idea that individuals play an important role for a firm's ability to draw on external knowledge goes back to earlier work by Allen & Cohen (1969) and Tushman (1977) arguing that a single staff member may act as a gatekeeper and boundary-spanner. Yet, the emergence of absorptive capacity through individual cognition and action has been subject to little rigorous research and may provide insight into the origin of firm-level absorptive capacity. In particular individuals active in the firm's R&D process, inventors, are likely to play a key role in the assimilation and integration of external knowledge.

Second, related to the previous limitation, research on absorptive capacity has ignored the role of interaction patterns between individuals within the firm. Again, Cohen & Levinthal (1990) refer several times to interactions and links across individuals as they affect communication and knowledge-sharing processes within the firm. As a result, ties between a firm's employees may alter the way external knowledge is absorbed into the firm. Surprisingly, very few studies exist on interactions between employees and how it affects integration of external knowledge (see for an exception Paruchuri, 2009), even though employee networks have been claimed to constitute the microfoundation of firm absorptive capacity (Volberda et al., 2010).

A third limitation of research on absorptive capacity concerns the rather static perspective on the ability to utilize external knowledge. Absorbing knowledge from the environment takes time and the velocity with which a firm identifies, assimilates and commercializes external knowledge influences a firm's innovation speed, which in turn is a source of competitive advantage (Kessler & Chakrabathi, 1996). The speed of learning from external knowledge has been subject to scarce prior theoretical work (Kessler & Chakrabathi, 1996; Zahra & George, 2002) and few recent empirical studies (Leone & Reichstein, 2012; Tzabbar, Aharonson, & Amburgey, 2012). Yet, examination of how and under what conditions firms are able to quickly capture rents from externally acquired knowledge would increase our understanding of a largely neglected dimension of absorptive capacity.

Fourth, most empirical contributions in the absorptive capacity literature are limited to traditional measures of absorptive capacity, such as firm-level R&D spending (Cohen & Levinthal, 1990; Tsai, 2001). Although those measures provide an insightful point of view on the overall firm capacity to absorb external knowledge, they do not capture how specific external knowledge components, acquired through particular mechanisms, eventually result in new inventions. In other words, knowledge input from the environment has not been linked to specific firm output.

This paper addresses these limitations by investigating how the configuration of inventor networks within the firm affect the speed of recombination of external knowledge with internal knowledge. Our focus is on the agents of recombination, inventors, because they rely on their skills and knowledge to carry out inventive search and subsequently propose and implement solutions to problems faced in the process of external knowledge integration (Fleming, 2001). We take a social network perspective because inventors generally do not operate in isolation, but depend on a web of colleagues through which he or she searches for advice, obtains referrals and acquires useful knowledge for problem-solving (Nerkar & Paruchuri, 2005; Tsai & Ghoshal, 1998). In this paper, we theoretically and empirically develop the concept of external knowledge recombination speed, which is defined as the time between external knowledge acquisition and the moment this knowledge is successfully recombined into an own invention.

We draw on the search literature, absorptive capacity literature and social network theory to make four predictions. First, we predict that the speed of external knowledge recombination is dependent on the distance (unfamiliarity) between the acquired external knowledge and a firm's knowledge base. This effect, we argue, is contingent upon structural and compositional characteristics of the intrafirm inventor network. First, we posit that network closure shortens the time of distant external knowledge recombination, because closed networks promote knowledge-sharing and network search advantages which in turn fosters quick problem-solving. Second, tie strength between inventors facilitates transfer of complex knowledge and we expect accordingly that an intrafirm inventor network characterized by high average tie strength accelerates recombination of distant external knowledge. Third, we predict that inventor network diversity shortens the time it takes to recombine distant external knowledge, because inventors who are part of a diverse intrafirm network are able to quickly reach a diverse set of problem-solving heuristics.

We examine these predictions in the context of 113 US pharmaceutical firms in the period 1986-2003. Pharmaceutical firms are particularly suitable for our study, since they commonly conduct R&D, engage in external knowledge acquisition in their search for invention and document their innovative activity (Arora & Gambardella, 1990). For our analysis we draw on a unique and detailed dataset that combines the licensing agreements of pharmaceutical firms, the inventors active in those firms and the patents produced by the firms. We rely on 708 licensed technologies which serve as instances of external knowledge acquisition. Also, we follow prior studies with the idea that co-invention or collaboration between inventors represents non-directional communication and information channels (Allen, 1977; Singh, 2005). The observed co-invention ties between inventors then serve as input to construct our intrafirm knowledge networks where inventors are represented by nodes and ties indicate co-invention with colleagues. The speed of external knowledge recombination is measured as the number of months between a licensing agreement and the first time the licensed technology is cited in a firm's new patent.

Our findings provide support for all hypotheses except our prediction regarding average tie strength. First, we find that the larger the distance between external knowledge and a firm's knowledge base, the more time a firm requires to recombine external knowledge into own invention. Subsequently, we find support for our predictions that intrafirm network closure and network diversity shorten the time of distant external knowledge recombination. We do not find support for the idea that average tie strength moderates the relationship between technological distance and external knowledge recombination speed.

Our main contribution to theory lies in postulating the role of individuals' collaboration networks in the process of integrating external knowledge. We address this by examining how collaboration patterns of inventors affect sharing and transfer of external knowledge. In this way, we advance our understanding of the micro-level antecedents of firm-level absorptive capacity (Volberda et al., 2010). We show that collective actions of inventors are an integral part of a firm's capacity to absorb knowledge and effectively exploit future inventive opportunities. In addition to our multi-level view on absorptive capacity, we also complement the notion of learning in the absorptive capacity literature (Zahra & George, 2002) with the speed of learning, a yet unexplored but important dimension of absorptive capacity.

This paper is organized as follows. The next section discusses theory and motivates the hypotheses. Subsequently, the methods section introduces the data and event history technique used in this study. The next section reports the empirical findings, which is followed by a discussion of our findings. The final section concludes.

## THEORY AND HYPOTHESES

An invention is the outcome of a search process that involves problem-solving by inventors and eventually recombination of existing knowledge components in a novel manner (Fleming, 2001; Hargadon & Sutton, 1997). The invention process has shifted from taking place solely within the firm to a more open model in which firms acquire knowledge from a variety of sources (Chesbrough, Vanhaverbeke, & West, 2006). Acquisition of external knowledge facilitates firm invention, because external knowledge and internal R&D are complementary (Cassiman & Veugelers, 2006). Firms do not have all relevant knowledge in-house and therefore engage in alliances, licensing and hiring to update their R&D process (Levin et al., 1987). The process of knowledge recombination thus increasingly relies on recombination of both internal and external knowledge components. In this respect, Cohen & Levinthal (1990) argue that firms vary in the ability to draw on external knowledge. The absorptive capacity of firms refers to the ability to recognize, assimilate and exploit external knowledge and "is largely a function of the level of prior related knowledge" (Cohen & Levinthal, 1990, p. 128).

According to the knowledge-based theory of the firm knowledge is collectively stored among employees and firms can be seen as social communities (Kogut & Zander, 1996). Social communities are the origin of knowledge creation and knowledge transfer within the firm (Tsai, 2001). In similar manner, the literature on organizational learning asserts that learning involves knowledge transfer among individuals and business units within the firm (Linda Argote, Mcevily, & Reagans, 2003). Organizations can thus be understood as network arrangements (Tsai, 2001). Networks among employees, and especially those individuals that are active in a firm's R&D process, inventors, influence the extent to which technological knowledge is diffused and generated within a firm (Nerkar & Paruchuri, 2005).

Intrafirm social networks can be seen as an antecedent of a firm's absorptive capacity (Volberda et al., 2010), because intrafirm networks shape knowledge flows among individuals and determine the efficiency of communication between them. Relevant knowledge for problem-solving is distributed among individuals within the firm (Lenox & King, 2004) and can be detected and shared through networks (Turner & Makhija, 2012). To illustrate this, Nerkar & Paruchuri (2005) argue that "bounded rational inventors search across the internal knowledge network on the basis of incomplete information about which knowledge should be recombined" (Nerkar & Paruchuri, 2005, p. 773). Networks among inventors also constitute communication patterns. The efficiency of communication (Cohen & Levinthal, 1990) refers to inward-looking absorptive capacity and determines the effectiveness of internal sharing of external knowledge. In this sense, intrafirm inventor networks influence firm innovation through sharing, development and recombination of external knowledge, and interpersonal networks can be seen as an antecedent of a firm's recombination capacity, constituting the microfoundations of a firm's inventive capabilities (Allen & Cohen, 1969; Brown & Duguid, 2001).

Shortening the time of the invention process is crucial to consolidate the competitive position of firms (Kessler & Chakrabathi, 1996). Recent evidence suggests that the use of external knowledge shortens a firm's invention process (Leone & Reichstein, 2012), yet the effect depends on the channel through which external knowledge is acquired (Lee & Allen, 1982; Tzabbar, Aharonson, & Amburgey, 2012) and a firm's absorptive capacity (Cohen & Levinthal, 1990). In this paper we specifically examine the influence of specific intrafirm network configurations of inventors on the speed with which a firm integrates and recombines externally acquired knowledge. We define external knowledge recombination speed as the time to recombination of externally acquired technological knowledge into own invention. In the next sections we develop hypotheses on how structural and compositional features of intrafirm networks among inventors affect recombination speed of external knowledge.

Technological distance and recombination speed. The ease with which firms recombine external knowledge hinges upon having related prior experience with the acquired knowledge (Cohen & Levinthal, 1990). Prior experience becomes the natural starting point for subsequent searches of new knowledge, and a firm's knowledge stock, which is accumulated over time, is used as a lens through which firms make sense of knowledge from the environment (Rosenkopf & Almeida, 2003). The technological development of a firm over time thus affects the technological distance between a firm's knowledge base and external knowledge. Assimilation of external knowledge requires a common base of understanding, or overlap in technological knowledge base, in order to achieve successful application of this piece of knowledge (Cohen & Levinthal, 1990). As a result, when the technological distance between the firm's technological base and acquired external knowledge increases, the absorptive capacity of a firm declines (Gilsing, Nooteboom, Vanhaverbeke, Duysters, & Vandenoord, 2008; Lane & Lubatkin, 1998). This means that cost and effort to recombine external knowledge increases with distance (Leone & Reichstein, 2012). To illustrate this, integration of distant external knowledge will require more effort and time as inventors in the firm are likely to encounter problems when they deal with unfamiliar knowledge. The solution generation process will subsequently prolong the time to recombine distant external knowledge into an invention. Consequently, a firm requires more time to understand distant knowledge and may need more time to invest in its absorption, and this will slow down the process of external knowledge recombination. Our baseline hypothesis therefore states:

Hypothesis 1. *The larger the distance between the externally acquired knowledge and the firm's* knowledge base, the longer it takes the firm to recombine external knowledge

Intrafirm network closure and recombination speed of distant external knowledge. Closed networks (also called cohesive or dense networks) are networks where the members are well-connected to each other. From an innovation perspective, network closure may either be beneficial or harmful for firm innovation (Burt, 1992; Coleman, 1988). On the one hand, network closure leads to knowledge-sharing among members of the network and fosters information flow through the network (Reagans & McEvily, 2003). Furthermore, closed networks are likely to have effective norms and promote trust (Coleman, 1988) and facilitate the exchange of tacit and complex knowledge (Hansen, 1999). On the other hand, the opposite of a closed network, a disconnected network, may also be effective for firm innovation (Burt, 2004). A disconnected network, which features structural holes between clusters or sub-networks, enhances firm innovation through the likelihood that such a network structure exhibits diverse information and fosters creativity.

We claim that intrafirm network closure benefits the speed of learning from external sources of innovation. More specifically, we argue that inventor network closure within the firm ameliorates a firm's ability to quickly recombine and eventually integrate distant external knowledge. Intrafirm inventor network closure shortens the time to recombine distant external knowledge for at least four reasons. First, closed networks ease the search and detection of relevant knowledge available in the network of inventors. Through their ties, inventors may hear and observe about potentially relevant inventors with knowledge and skills needed for the recombination of distant external knowledge. Thus, closed networks tend to lower costs related to monitoring the network and speed up the search time for relevant information within the network (Zaheer & Bell, 2005). The presence of such network search advantages in closed networks shortens the time inventors need to recombine distant knowledge. Second, closed inventor networks tend to feature knowledge sharing and the willingness to devote time and effort to support their peers (Reagans & McEvily, 2003). Such cooperative behavior is likely to be present due to cooperative norms and fosters knowledge transfer between inventors in the firm. For this reason, one may expect that the prolonged recombination time inherent to distant knowledge tends to be shorter in dense networks as a result of a mutually supportive environment. Third, network closure promotes the formation of norms, which, in turn, enhance mutual understanding between inventors and lower the possibility of misinterpretation and loss of relevant information (Reagans & McEvily, 2003; Zaheer & Bell, 2005). Inventors in closed networks thus tend to save time due to the formation of successful communication routines. Fourth, closure leads to better information flow within the network and this spurs idea sharing and feedback among the inventors (Fleming, Mingo, & Chen, 2007). In line with our predictions we claim that firms with a closed intrafirm co-invention network experience shorter recombination time of distant external knowledge. Our second hypothesis thus states the following:

Hypothesis 2. Firms with an intrafirm inventor network that has a high level of network closure recombine distant knowledge faster than firms with an intrafirm inventor network that has a low level of network closure

Intrafirm average tie strength and recombination speed of distant external knowledge. Tie strength refers to the intensity of interaction between two members of the network and is "a combination of the amount of time, the emotional intensity, the intimacy (mutual confounding) and the reciprocal services which characterize the tie" (Granovetter, 1973, p. 1361). Tie strength characteristics tend to increase with increasing frequency of collaboration between inventors. Tie strength promotes trust and facilitates knowledge transfer, especially knowledge that is complex and tacit (Hansen, 1999). Previous studies have also suggested that increasing tie strength favors knowledge creation, creativity and exploratory learning (Sosa, 2010). Tie strength has been coined as one of the factors that aid the absorption of knowledge developed outside the network (Bower & Hilgard, 1981). Strong ties among inventors within a firm are likely to mitigate disadvantages related to integrating distant external knowledge according to two main arguments. First, trust and knowledge-sharing among inventors increases with recurring interaction (Reagans & McEvily, 2003). This in turn increases the willingness of inventors to spent more time and effort on supporting each other (Seibert, Kraimer, & Liden, 2001; Sosa, 2010), for example on problem-solving. Second, knowledge that is tacit and highly complex is better transferred through strong ties (Phelps, Heidl, & Wadhwa, 2012). Distant knowledge is likely to be a complex matter for inventors within the firm, and therefore tie strength increase the likelihood that such complexity is shared throughout the firm which accelerates the integration process (Hansen, 1999). Taken together, we expect that high average tie strength shortens the recombination process of distant knowledge and we therefore posit the following hypothesis:

Hypothesis 3. Firms with an intrafirm inventor network that has high average tie strength recombine distant knowledge faster than firms with an intrafirm inventor network that has low average tie strength

Intrafirm network diversity and recombination speed of distant external knowledge. Network diversity refers to the diversity of resources available in the network[1]. Or in other words, the extent to which network connections span boundaries (Reagans & McEvily, 2003). In the context of this paper, network diversity refers to variety in technological experience among the collaborating inventors inside the firm (Harrison & Klein, 2007), or the extent to which inventor ties span technological boundaries. Network diversity or range increases knowledge sharing among members of the network (Reagans & McEvily, 2003), and promotes the problem-solving ability of members through access to diverse resources available in the network (Phelps, 2010). An intrafirm network composed of a diverse group of inventors will accelerate the time to recombination of distant external knowledge for at least three reasons. First, due to the inherent uncertainty of knowledge recombination, inventors benefit from having diverse partners in their intrafirm network. Diverse connections provide a single inventor with access to a diverse set of problem-solving heuristics (Page, 2007), and are better able to accomplish complex tasks related to recombining distant knowledge (Rodan & Galunic, 2004). Thus, the collective problem-solving ability of inventors increases with diversity and shortens the time it takes to recombine complex distant knowledge acquired from outside the boundaries of the firm. Second, co-

[1] We specifically disentangle network composition from network structure. Prior studies argued that network structure is correlated with information diversity embedded in the network. For example, dense networks tend to exhibit low diversity, because interaction between individuals leads to knowledge overlap (Burt, 2004; Granovetter, 1973; McFadyen et al., 2009). Yet, this need not be the case, and recent calls have been made in favor of disentangling network structure and composition (e.g. Kilduff & Brass, 2010; Phelps, 2010; Zaheer & Soda, 2009).

invention between inventors with different technological background expands their ability to convey complex knowledge across distinct bodies of knowledge (Tortoriello, Reagans, & McEvily, 2012). Over time interaction among diverse inventors thus positively affects the ability of inventors to efficiently frame their communication with different partners, which, in turn, may accelerate recombination of distant knowledge in the future. Third, diversity within the intrafirm network increases the likelihood of overlap between the acquired external knowledge component and available relevant knowledge already existent in the intrafirm co-inventor network (Cohen & Levinthal, 1990). Diversity among collaborating inventors thus eases the comprehensibility of distant external knowledge and leads to shorter recombination time. Our final hypothesis therefore states:

Hypothesis 4. Firms with an intrafirm inventor network that has a high level of network diversity recombine distant knowledge faster than firms with an intrafirm inventor network that has a low level of network diversity

## DATA AND METHODS

We test the aforementioned hypotheses in the context of the global pharmaceutical industry. Firms in this industry develop and commercialize drugs, chemical components and biological products. The focus on pharmaceutical firms provides a good research context for at least four reasons. First, the pharmaceutical industry is characterized as technology driven and R&D intensive, which makes technological knowledge a critical component to develop and sustain competitive advantages (Roberts, 1999). Second, firms in this industry routinely and systematically protect and document their inventions (Hagedoorn & Cloodt, 2003). Third, R&D collaboration with other firms and universities represent an important driver of technology development (Arora & Gambardella, 1990). Finally, the pharmaceutical industry has proven to be a valuable context to identify and measure the effect of inventor networks on innovative output (Paruchuri, 2009).

The data used in this study relies on four data sources. First, we used detailed information on licensing agreements from the Deloitte Recap Database, which covers licensing deals in the global pharmaceutical industry for the period 1983 – 2008. This database is one of the most accurate sources of information regarding partnerships and technology exchange in the pharmaceutical industry (Schilling, 2009), allowing us to retrieve information directly from the original licensing contracts. Second, we drew on the NBER patent project to merge the specific patent numbers connected to the traded technologies from the Deloitte Recap Database with patents registered at the United States Patent and Trademark Office (USPTO). Third, we relied on the Harvard Patent Network Dataverse which provided us with the disambiguated inventor names and inventor identification number. This allowed us to construct intrafirm inventor networks based on co-invention as well as derive inventor-level information. Finally, we utilized the WRDS Compustat database mainly for control variables.

The four datasets were matched in the following manner. We started with a set of 1510 contracts in which we were able to observe a patent number. We required licensing contracts to have patent numbers, because this allowed us to unambiguously connect the traded technologies with the USPTO information. In this way we were able to exactly identify when a technology was licensed and when the technology was recombined by the licensee. Then we matched the licensing database with WRDS Compustat using information of the licensee. Since the Compustat database only consists of publicly traded firms, we were left with 973 firms-technology observations after this initial merging process. Then we subsequently matched the remaining contracts with NBER patent data to be able to construct the patenting histories of both licensee and licensors. In addition to this, we matched individual technologies with the NBER database to extract information regarding each individual technology in the licensing contracts. In the next and final step we connected the Harvard Patent Network Dataverse with the remaining contracts based on both patent number and licensee names. The Dataverse database provided us with the exact application date of each patent applied for at the USPTO. On the firm level, the Dataverse database offers the possibility to identify individual inventors and connect them to individual technologies and licensees. In turn, this allowed us to construct inventor networks within the licensing firms based on co-invention ties (e.g. Fleming, King III, & Juda, 2007).

The final sample consists of 113 firms involved in the acquisition of 708 USPTO patents using licensing contracts. Given that the information regarding inventors patenting activity is only available from 1981 and explanatory variables regarding intrafirm networks are calculated based on 5 year moving window, the first licensing contract in the sample is observed in 1986. Furthermore, we ended the sample in 2003[2] to allow sufficient time to observe if the patents produced by the licensee indicate that the licensed technology was successfully recombined. The number of observations used to run the econometric analysis corresponds to approximately 47% of the number of contracts registered at RECAP that was initially considered to be used to test the hypotheses. The number of observation used to run the econometric analysis corresponds to approximately 47% of the number of contracts registered at RECAP that was initially considered to be used to test the hypotheses.

### The Dependent Variable

[2] The patent data covers the period 1976 – 2006, but the decision to end the licensing observations 3 years before the latest record of patent data was based on the fact, that on average, firms in our sample take 26 months (2.2 years) to recombine the licensed technology. Alternatively, we also run the models using a 5 year gap, instead of 3, and the results remained identical.

Time to knowledge recombination. The time it takes firms to recombine licensed technologies is calculated based on the number of months between the licensing date (onset risk) and the first time that the licensee cites the licensed technology, as a backward citation, in a new patent (transition date). Using the dates of the patent application, instead of the grant dates, we avoid noise introduced by differences in patent office procedures (Leone and Reichstein, 2012). To avoid potential issues regarding bias originating from the use of the same data source to calculate the onset risk and the transition time, the dependent variable was calculated based on information from two different (independent) databases. The onset risk is defined based on the licensing date specified at the RECAP database, while the transition date comes from the Patent Network Dataverse. This variable is intended to capture how fast firms are able to recombine a new externally acquired body of knowledge with existing ones. Prior studies have applied backward citations as an indication of the knowledge sources used to generate a new patent (Hall, Jaffe, & Trajtenberg, 2001). Following this perspective, we consider the citation of the licensed technology in a new patent an indication that the licensee was able to assimilate and successfully apply the licensed knowledge[3].

**Explanatory variables**

Technological distance. The distance between the licensed technology and the knowledge base of the licensee is calculated using the patenting behavior of the acquiring firm prior to the licensing agreement. We measure technological distance with the focal index proposed by Ziedonis (2007) as a way to capture the extent to which a firm is able to realize value from a licensed patent. Our measure relies on the assumption that patenting behavior is a good indication of a firm's overall

[3] One could argue firms may cite a technology without having to license it. In our sample 8 cases were observed in which the licensed technology was referred in the backward citation of a patent applied to the licensee before the licensing date. This low number can be attributed to the fact that in the pharmaceutical industry firms can easily identify if a patent has been infringed (Ziedonis, 2004). These observations are excluded from the main analysis.

technological activities. The technological distance between a licensed technology and a firm's knowledge base is then measured on basis of the patent class connected to the licensed technology and the technology classes the licensee has been active in prior to the licensing event. The measure is computed as follows:

$$Technological\ distance = 1 - \left[\frac{\left(\sum_{t-5}^{t}\sum_{j}\tilde{C}_i \cdot \rho_i\right)_c}{\left(\sum_{t-5}^{t}\sum_{j}\tilde{C}_i \cdot \rho_i\right)}\right]$$

In which $\left(\sum_{t-5}^{t}\sum_{j}\tilde{C}_i \cdot \rho_i\right)_c$ represents the citation-weighted sum of firm i's patents that were applied for within five years at the time of the license agreement t and belong to the same primary patent class c as the one of the licensed patent; and $\left(\sum_{t-5}^{t}\sum_{j}\tilde{C}_i \cdot \rho_i\right)$ is the sum of all citation-weighted patents issued to the firm j that were applied for by date t also considering a 5 years window.

Network density. We measure network closure by calculating the overall density of the intrafirm network (Ahuja, Soda, & Zaheer, 2011; Obstfeld, 2005). Density captures the extent to which potential linkages are realized within a network, and is a commonly used measure of network structure (Marsden, 1990). We calculated our density measure for five-year windows. Network density for firm i in year t is computed as follows:

$$Network\ density = \frac{Observed\ N\ inventor\ ties_{it}}{Possible\ N\ inventor\ ties_{it}}$$

The observed or actual ties are defined as the number of times two inventors co-patent, and the number of possible or potential ties follow the number of inventors (N) active in the firm ($\frac{N \times (N-1)}{2}$).

Average tie strength. Average tie strength captures the average intensity of collaboration between inventors within the firm. We measured tie strength between each observed pair of inventors based on the number of patents they have co-invented with each other. We then averaged this across the number of inventors.

Network diversity. The diversity measure aims to capture the level of technological diversity among the active inventors within the focal firm. To operationalize this measure we take into account that the inventors may have also accumulated knowledge from research activities developed prior to joining the focal firm. Therefore, rather than capturing firm-level diversity we focus on network level diversity formed by the active inventors at the year of the licensing contract. Furthermore, we only look into diversity among the inventors that have at least one intrafirm active tie, which means that inventors that produced no patent, or patented only in collaboration with other individuals outside the firm, or were a single inventor in all patents are not included in the analysis. The diversity measure is calculated using a herfindahl index of the IPC codes (2 digits) of the patents produced by the firm's inventors with at least one patent, connected to the licensing firm, within the 5 years prior to the licensing contract. We define network diversity present in firm i's intra inventor network in year t as:

$$Network\ diversity = 1 - \sum_{j=1} \left(\frac{N_{ij}}{N_i}\right)^2$$

Following previous studies (e.g. Griliches, 1990) we consider that the main IPC code attributed to a patent reflects a distinct technological field j = 1, 2, *3…th.* Therefore, if the inventors within the ith firm have accumulated $N_i$ patents within the 5 years prior to the licensing contract, each of the patents can be assigned to one technological field.

**Control Variables**

We include a variety of network, firm, technology and contract level control variables that may also affect the speed of knowledge recombination. In the case of the control variables regarding the intrafirm network, all the measures were calculated on the same time length as the explanatory variables (5 years). Regarding intrafirm inventors network characteristics, we control for clustering and average path length. We expect that those two structural characteristics will affect the knowledge flow across inventors by speeding up the time knowledge takes to be transferred from one point to the other within the network. Additionally, we included a dummy variable that takes value 1 if the firm has co-patented at least once prior to the licensing date. This variable is intended to capture the availability of external ties through which inventors can acquire relevant knowledge.

We also control for several firm characteristics. First, we included the logarithm of the number of employees at the year of the licensing deal to control for firm size. Second, we control for cross firm differences in terms of R&D intensity adding the total R&D expenditures divided by total sales. We also control for the amount of unabsorbed resources using licensee slack, which is calculated based on the ratio between sales and number of employees. Another characteristic that can also influence the speed with which the licensee is able to recombine the external knowledge in a faster way regards the familiarity that it has with other licensor's technologies. Therefore, we controlled for the total number of prior citations within 4 years prior to the licensing contract that the licensee has made to any of the licensor's patents. Based on the industry specifications described in the licensing contracts we generated a dummy variable that takes value 1 when both firms operate in the same segment and 0 otherwise. We also control for the general licensee's invention speed by calculating the average time between the patents produced before acquiring the licensed technology. We included a dummy variable taking value 1 if the firm has produced a patent within the 12 months that precede the licensing date. By adding this variable we expect to control for the fact that certain technologies may be licensed in different stages of the invention process. Finally, we add a dummy variable taking value 1 if the licensee has a U.S. headquarter.

We also control for contractual specifications of the licensing deal using dummy variables. The inclusion of the technology-flow back provision clause (i.e. grant-back) indicates that the licensor has rights over any improvement that the licensee develops with regard to the licensed technology. Therefore, we expect that signing a contract with a grant-back clause reduce the incentives that licensees have further development of the licensed technology (Choi, 2002). Contracts that include the technology furnishing clause indicate that the licensor commits to supply know-how on the licensed technology to support the licensee on understanding and applying it, mitigating part of the problems originating from distance. Finally, the inclusion of milestone payments in a licensing contract offers the possibility for the licensee to receive monetary compensations for further developing the licensed technology.

Looking into technology related characteristics, we control for technology value using the total number of forward citations received by the licensed technology. We expect that more valuable technologies are also more likely to be recombined in a faster way. Additionally, we also control for the total number of scientific references listed in the backward citations of the licensed technology as a way to capture cross-technology differences in terms of development stage. The final set of control variables regard the licensor's characteristics. First, we control for the number of successfully applied patents that the licensor filed in the 7 years prior to the licensing contract as the licensor's size and technological capabilities may also affect the licensee's willingness to quickly invent using the licensed technology. Second, in order to control for differences between firms and universities as licensors we added a dummy variable to identify the contracts in which the licensor is a university. Finally, following the convention in this literature, we added sector dummies indicating the segment within the pharmaceutical firm in which the licensee operates and year dummies.

### Model Specification and Estimation

Given that the hypotheses refer to the time to knowledge recombination we generated the dependent variable following an event history analysis structure. Accordingly, we apply event history analysis technique to model the time taken, T, between the licensing date and the first time the licensing technology is cited by the licensee in a new patent. Among the potential methods within event history analysis umbrella we first considered the Cox Proportional Hazard model to test the proposed hypotheses. However, while no distribution assumption is made about the dependent variable, the Cox model assumes proportionality in the effects of the explanatory variables over time (Mills, 2011). The assumption of proportional hazard was checked using the scaled Schoenfeld residuals regressed against the log of survival time and the results for the global test indicated a violation of the proportionality assumption, suggesting the use of a parametric model (Schoenfeld, 1982). After ruling out the possibility to use a Cox Proportional Hazard model we were left to choose among a potential set of parametric models. In order to decide among the possible models we considered the underlying mechanisms driving the hazard to knowledge recombination. We expect that firms that license-in technologies with low distance will be able to recombine the new knowledge with existing components in a rapid pace, which increases the hazard to knowledge recombination as the time increases. However, as the time elapses the technologies with lower distance exit the sample, leaving in the sample technologies that take more time to be recombined. This effect is expected to become dominant and lowers the hazard rate until a point in which the hazard function starts to decline. Taking into account the mechanism underlying the hazard rate of knowledge recombination we expect a nonmonotonic hazard function (Leone & Reichstein, 2012). Accordingly, we decided to employ a log-logistic model as a way to accommodate the expected process of an initial increase followed by decreasing rate (Mills, 2011).

Considering that the capacity to deal with distant knowledge is likely to be also determined by firm characteristics that are not captured by the explanatory variables used in the econometric model, we correct for potential endogeneity issues originating from the presence of unobserved heterogeneity across the firms. Prior studies using a similar setting to the one presented in this paper have dealt with unobserved firm-level differences affecting duration dependence by employing frailty estimators (e.g., Pennings & Wezel, 2009). Following the recommendation by Blossfeld et al. (2007), we model the unobserved heterogeneity using a shared gamma mixture specification associated with the log-logistic model.

**Descriptive Statistics and Correlations**

Table 1 reports the means, standard deviations and Pearson correlation coefficients of the variables used in the analysis. The results raised no concerns regarding collinear variables, except for the correlations between Average path length with Network density and Clustering with Average Tie Strength. The moderate correlations between those variables are in line with theoretical expectations, but in order to check for potential bias we entered the variables in a stepwise manner and the results for the main explanatory do not change as the variables enter the model. Additionally, the maximum variance inflation factor (VIF) associated with any of the independent variables was 4.34 (mean VIF = 2.15), which is well below the rule-of-thumb value of ten (Gujarati, 1995). Finally, the likelihood ratio comparison test at the bottom of Table 2 indicate models II – V provide significant improvement relative to the baseline model (for model 5, likelihood ratio: 35, df: 4, $p<0.001$).

[Insert Table 1 around here]

We were able to track the patenting behavior of the firms in our sample until December 2006, therefore our analysis is censored at the latest dates available in the patent citation data. Looking into the knowledge recombination speed, the longest time to transition for the firms in our sample was 168 months. Out of 708 firm-technology observations a total of 116 firms cited the licensed technology in a new patent (made the transition) during the time frame of our analysis. For the observations that experienced the transition the average time for knowledge recombination was 25 months. In contrast, the average time of at risk months for all the firms in the sample (including censored observations) was 74 months. Among the 592 firm-technology observations that did not experience the transition during the time window of our analysis 129 observations exit the sample earlier than December 2006, those observation were subject to a different type of right-censoring. In the empirical setting used in this paper these observations exit the sample earlier because their latest records on COMPUSTAT ended earlier than the latest information available in the patent data. We modeled those observations differently by setting the exit time at the date of the latest Compustat record, implying that although these observations exit the sample, they do not experience the transition. The fact that the financial records for a given firm are discontinued is likely to be due to bankruptcy or an M&A process, which eliminate the possibility of a firm being observed in the patent citation data[4].

**RESULTS**

Table 2 reports the results for the log-logistic model with shared gamma mixture. The dependent variable across the six models reported in this table reflects the time gap between the licensing date and the first time the licensed technology was cited in a new patent (for the non-censored

[4] If we consider those firms exiting the sample earlier, approximately 20% of the observations experience the transition within the time frame of the event history analysis

observations). Model I reports the estimators for controls and main effects of the interaction terms. Additionally, we included year dummies to control for period effects, such as overall differences in patenting behavior in the pharmaceutical industry. In models II – VI the interaction terms capturing the relationships described in the hypotheses were entered one-by-one along with all the controls. For the sake of simplicity we will focus the discussion of the results on the full model in column VI.

[Insert Table 2 around here]

Hypothesis 1 predicted that the higher the distance between the licensed technology *and the firm's knowledge base, the longer the time to knowledge recombination*. The coefficient for the technological distance variable is positive and significant at 1% level when all controls are included in the equation, providing strong evidences in favor of our first hypothesis. The result lends support for the fundamental idea developed in this paper that distance (unfamiliarity) is an important predictor for firm capacity to recombine external knowledge in a faster pace. This finding is similar to the results obtained by Leone & Reichstein (2012) regarding the joint effect of unfamiliarity and contractual specifications (the use of grant back clause) on the time a licensee takes to produce its first invention after a licensing contract.

Hypothesis 2 stated that firms with an intrafirm inventor network that has a high degree of network closure recombine distant knowledge faster compared to firms with an intrafirm inventor network which has a low degree of network closure. Accordingly, the interaction term between technological distance and network density exhibits a negative and significant coefficient, indicating that the positive effect of distance on time to knowledge recombination becomes less positive (or more negative) when interacted with network density. This results support the expected effect described at hypothesis 2. Thus, the negative and significant of the interaction term indicates that firms with a densely connected intra inventor network are better able to deal with technological distance in a faster way.

Hypothesis 3 did not find support in the results. We predicted that firms characterized by an intrafirm inventor network with high tie strength recombine distant knowledge faster compared to firms with a low tie strength intrafirm inventor network. The interaction between technological distance and tie strength did not produce significant coefficients at conventional level. Hence, the insignificant coefficient for this interaction term indicates that distance is positively related to knowledge recombination regardless of the tie strength among the inventors within the firm.

Finally, the results offered support to the moderation effect predicted at hypothesis 4 regarding the fact that firms with an intrafirm inventor network that has a high degree of network diversity recombine distant knowledge faster compared to firms with an intrafirm inventor network that has a low degree of network diversity. Accordingly, the interaction between technological distance and network diversity produced a significant and negative coefficient. This finding supports the idea that network diversity negatively moderates the relationship between distance and time to knowledge recombination.

## ALTERNATIVE EXPLANATIONS AND ROBUSTNESS CHECKS

Despite prior research indicating that technology licensing leads to knowledge transfer (Arora, 1996; Ceccagnoli & Jiang, 2012), we acknowledge that the link between licensing-in and patent citations has not yet been established in the literature. Therefore, we performed a robustness check to evaluate the number of citations received by a technology after and before the licensing date using a conditional differences-in-differences design (Singh & Agrawal, 2011). By doing so, we expect to strengthen the confidence in the main results by focusing on two important aspects.

First, it could be argued that the licensing firm is more likely to cite a technology of relatively higher quality or relevance independently from licensing it or not. Accordingly, technologies with such characteristics may also more likely to be commercialized in the markets for technology, which creates a selection problem in which backward citations do not reflect the true effect of licensing. Second, a licensee may be more susceptible to license a technology in a domain in which the firm is intending to expand its technological activities. So, it is likely that the licensing efforts would also be associated with other measures aiming to improve a firm's access to a specific technological area.

To perform the differences-in-differences we followed the steps as in the study by Singh & Agrawal (2011). First, each licensed technology in our sample was matched based on propensity scores using application year, patent class and subclass to the closest technology in the entire technological space (USPTO patents). Second, we certified that no observation in the control group was in fact licensed by the focal firm in the sample. Third, we computed the total number of citations that the focal firm made to both groups of technologies, the treatment and control, after and before the licensing date. There were only eight observations in which the licensed technology had been cited by the licensee before the licensing contract, those observations were removed from the event history analysis but were used to estimate the difference-in-differences model. Based on this matching sample between licensed and non-licensed technologies sharing similar characteristics, we evaluated the change in the number of citations. The results indicate (Table 3) a significant and substantial increase in the number of citations received by a licensed technology when accounting for the number of citations received by the technologies in the control group. Considering the baseline period, the patents in the control group received an average number of citations of 0.054, while the licensed technologies had on average 0.030 citations. However, in the year after the licensing event the average number of citations for the licensed technologies increases to 1.483 while the control group remains the same. Therefore, taking into account the pre-licensing and post-licensing differences between the average number of citations received by the treatment and control group we observe that a focal technology is, indeed, significantly more likely to be cited after the license event.

[Insert Table 3 around here]

Finally, an alternative explanation to the effect of distance on time to knowledge recombination is related to the fact that the distant technologies may not be licensed with the intention to be applied in a new invention. Therefore, it could also be suggested that our results regarding the effect of technological distance on time to knowledge recombination comes from the censored observations for which we only have partial information. To address this concern and check the plausibility of this argument we conducted a t-test (Table 4) comparing the distance level between those observations that experience and those that don't experience the transition during the time window of our analysis. The results indicate that the difference between the two groups is not statistically significant.

[Insert Table 4 around here]

**DISCUSSION**

The present study was motivated by the fact that the absorptive capacity literature has neglected the actions and interactions of individuals within the organization in the process of knowledge absorption. Moreover, research on absorptive capacity has overlooked how fast firms recombine knowledge from the environment with internal knowledge. In this paper we address these shortcomings and examine the influence of intrafirm inventor networks on firm's absorptive capacity or ability to integrate external knowledge. We specifically investigated how network structure, tie characteristics and network composition within the firm affect the absorption speed of distant external knowledge. We made the argument that firms take longer to absorb and recombine distant knowledge. Yet, by drawing on social network theory and literature on search within organizations we subsequently claimed that certain characteristics of the intrafirm inventor network influence the absorption of distant external knowledge. First, network closure tends to aid inventors in their search for relevant knowledge for recombination, through monitoring and knowledge-sharing benefits. Thus, closed networks foster fast recombination of complex knowledge. Second, repeated interaction between inventors enhances their ability to convey complex issues from one another. Moreover, inventors with strong ties build trust between each other and this increases supportive behavior. Thus we expected that high average tie strength speeds-up distant external knowledge recombination. Our final prediction focused on network diversity, since access to a diverse network allows inventors to draw on a diverse set of problem-solving heuristics. Thus, firms that contain intrafirm networks with inventor ties that span technological boundaries experience shorter cycles of distant knowledge recombination.

The empirical results indeed showed that technologically distant external knowledge prolongs the time of external knowledge recombination compared to close knowledge. More importantly, the results showed that intrafirm network closure and diversity shorten the time with which firms assimilate distant external knowledge. This is in line with our predictions. Yet, our results did not support our prediction that tie strength moderates the relationship between technological distance and speed of external knowledge recombination. We discuss our results in light of the absorptive capacity and external knowledge sources literatures.

Our finding that strong average intrafirm ties among inventors do not accelerate the recombination of distant knowledge is in contrast to what we expected, based on the literature on knowledge-sharing within firms (e.g. McFadyen & Cannella, 2004). Two explanations can be put forward why this is the case. First, in addition to its benefits, tie strength can also impair the inventors' ability to develop distant external knowledge. Recurring interaction between a pair of inventors may lead to a trustworthy relationship characterized by supportive behavior (Granovetter, 1973). Yet, inventors with a limited number of partners with whom they collaborate can become myopic and focus on a limited set of colleagues. As a result, the effect of tie strength may not have a clear direction.

The results and contributions of this paper should be considered in the light of its limitations. First, the findings in this study may be specific to the pharmaceutical context. The pharmaceutical industry is characterized by a mature market for technology, in which patent protection and licensing is rather the norm than exception. Related to this, despite ample evidence that firms acquire external knowledge to foster own R&D (e.g. Laursen, Leone, & Torrisi, 2010) firms may license for a variety of reasons. Future research could therefore examine how fast firms learn from other external sourcing mechanisms such as hiring, alliances and firm acquisition (See Tzabbar et al., 2012, for a recent example).

Second, we utilize co-patenting to capture collaboration and knowledge networks, following recent literature (Paruchuri, 2009; Singh, 2005). Although our focus on co-invention is particularly relevant in the context of knowledge recombination, we acknowledge the fact that patent collaborations only capture a subset of the present interpersonal ties within a firm. Future research could advance our understanding of intrafirm networks and recombination speed by focusing on different types of interpersonal networks, including friendship networks.

Finally, we believe our econometric methods have sufficiently dealt with endogeneity issues as a result of unobserved heterogeneity and omitted variable bias. First, we employed a frailty estimator in our hazard models which captures unobserved heterogeneity through the inclusion of a shared gamma mixture specification. In addition to this, our difference-in-difference approach towards the relationship between licensing-in and citation patterns strengthens our believe that licensing represents a mechanism through which firms acquire external knowledge, which in turn fuels firms' inventive performance.

## CONCLUSION

Overall, our study provides insight in how individual-level network formation affects a firm's ability to quickly recombine and integrate external knowledge. In particular, our study has theoretically and empirically substantiated the idea that intraorganizational inventor networks affect the prior unexplored speed dimension of a firms' absorptive capacity. Our study reinforces recent calls for consideration of intrafirm social networks as antecedent of absorptive capacity and organizational learning. We encourage future research to further explore the role of multi-level networks, both internal and external, on the speed of external knowledge recombination.

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**Table 1. Descriptive Statistics and Correlations Coefficients (N = 708)**

| Variable | Mean | S.D. | [1] | [2] | [3] | [4] | [5] | [6] | [7] | [8] | [9] | [10] | [11] |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| [1] Technological Distance | 0.824 | 0.280 | 1.00 | | | | | | | | | | |
| [2] Network Density | 0.259 | 0.285 | -0.19 | 1.00 | | | | | | | | | |
| [3] Average Tie Strength | 1.581 | 1.007 | -0.01 | -0.21 | 1.00 | | | | | | | | |
| [4] Network Diversity | 0.622 | 0.228 | 0.15 | -0.57 | 0.13 | 1.00 | | | | | | | |
| [5] Clustering | 2.246 | 0.854 | -0.07 | -0.05 | 0.77 | 0.09 | 1.00 | | | | | | |
| [6] Average Path Length | 2.557 | 1.632 | 0.20 | -0.64 | 0.25 | 0.43 | 0.10 | 1.00 | | | | | |
| [7] Same Sector | 0.357 | 0.479 | 0.01 | 0.07 | 0.10 | 0.06 | -0.07 | -0.18 | 1.00 | | | | |
| [8] Co Patent | 0.892 | 0.310 | -0.18 | -0.08 | 0.05 | 0.07 | 0.07 | 0.04 | -0.04 | 1.00 | | | |
| [9] Prior Citations | 1.261 | 7.847 | -0.04 | 0.12 | -0.06 | 0.01 | 0.03 | -0.12 | -0.05 | 0.04 | 1.00 | | |
| [10] Scientific References | 30.381 | 52.714 | -0.01 | -0.06 | 0.11 | 0.02 | 0.10 | 0.07 | 0.05 | 0.07 | -0.01 | 1.00 | |
| [11] Technology Value | 60.671 | 155.548 | -0.11 | 0.14 | -0.03 | 0.00 | 0.02 | -0.08 | -0.01 | 0.07 | 0.07 | 0.00 | 1.00 |
| [12] Technological Furnishing | 0.559 | 0.497 | 0.08 | -0.29 | -0.01 | 0.15 | -0.06 | 0.26 | 0.15 | 0.05 | -0.10 | -0.05 | -0.11 |
| [13] Grant-back Clause | 0.242 | 0.429 | 0.02 | -0.03 | -0.05 | 0.04 | -0.13 | 0.08 | 0.17 | -0.08 | -0.07 | -0.07 | 0.00 |
| [14] Milestone | 0.613 | 0.487 | -0.00 | -0.05 | 0.12 | -0.15 | 0.13 | 0.07 | -0.01 | -0.03 | 0.08 | -0.04 | -0.08 |
| [15] R&D Intensity | 124.633 | 132.409 | -0.21 | 0.26 | -0.02 | -0.20 | 0.05 | -0.32 | 0.13 | 0.00 | -0.01 | 0.01 | -0.10 |
| [16] Licensor University | 0.177 | 0.381 | -0.12 | 0.21 | -0.11 | -0.34 | -0.04 | -0.27 | -0.35 | -0.18 | 0.03 | -0.07 | -0.06 |
| [17] Licensor Number of Patents | 334.927 | 1.451.046 | -0.05 | 0.16 | -0.07 | -0.11 | 0.00 | -0.17 | -0.11 | 0.00 | 0.77 | -0.04 | 0.03 |
| [18] US Firm | 0.898 | 0.303 | 0.01 | 0.12 | -0.00 | -0.06 | -0.05 | -0.09 | 0.08 | -0.09 | 0.05 | -0.06 | -0.04 |
| [19] Log(Number Employees) | 7.129 | 2.844 | 0.24 | -0.52 | 0.16 | 0.32 | 0.08 | 0.68 | -0.25 | 0.25 | -0.08 | 0.10 | 0.06 |
| [20] Average Patenting Time | 4.091 | 5.165 | -0.05 | 0.39 | -0.24 | -0.38 | -0.31 | -0.51 | 0.11 | -0.39 | -0.07 | -0.13 | -0.04 |
| [21] Previous Year Patent | 0.766 | 0.423 | 0.09 | -0.27 | 0.13 | 0.34 | 0.13 | 0.33 | -0.01 | 0.63 | 0.03 | 0.09 | 0.06 |
| [22] Slack | 165.471 | 149.181 | 0.09 | -0.37 | 0.35 | 0.28 | 0.21 | 0.42 | -0.01 | 0.24 | -0.11 | 0.14 | -0.09 |

| Variable | Mean | S.D. | [12] | [13] | [14] | [15] | [16] | [17] | [18] | [19] | [20] | [21] | [22] |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| [12] Technological Furnishing | 0.559 | 0.497 | 1.00 | | | | | | | | | | |
| [13] Grant-back Clause | 0.242 | 0.429 | 0.18 | 1.00 | | | | | | | | | |
| [14] Milestone | 0.613 | 0.487 | 0.17 | 0.04 | 1.00 | | | | | | | | |
| [15] R&D Intensity | 124.633 | 132.409 | -0.06 | -0.07 | 0.15 | 1.00 | | | | | | | |
| [16] Licensor University | 0.177 | 0.381 | -0.32 | -0.23 | 0.08 | 0.28 | 1.00 | | | | | | |
| [17] Licensor Number of Patents | 334.927 | 1.451.046 | -0.13 | -0.02 | 0.12 | 0.21 | 0.06 | 1.00 | | | | | |
| [18] US Firm | 0.898 | 0.303 | -0.14 | -0.05 | -0.10 | 0.08 | 0.09 | 0.07 | 1.00 | | | | |
| [19] Log(Number Employees) | 7.129 | 2.844 | 0.07 | 0.08 | -0.01 | -0.60 | -0.37 | -0.22 | -0.20 | 1.00 | | | |
| [20] Average Patenting Time | 4.091 | 5.165 | -0.07 | -0.02 | -0.02 | 0.13 | 0.22 | 0.03 | 0.11 | -0.49 | 1.00 | | |
| [21] Previous Year Patent | 0.766 | 0.423 | 0.08 | 0.03 | -0.02 | -0.08 | -0.36 | 0.01 | -0.09 | 0.40 | -0.55 | 1.00 | |
| [22] Slack | 165.471 | 149.181 | 0.14 | -0.03 | 0.12 | -0.25 | -0.32 | -0.16 | -0.08 | 0.54 | -0.26 | 0.25 | 1.00 |

**Table 2. Results of Log-Logistic Hazard Models with Gamma Frailty Predicting the Time to Knowledge Recombination**

| Variable | Model I | Model II | Model III | Model IV | Model V | Model VI | Model VII |
|---|---|---|---|---|---|---|---|
| Technological Distance | | 2.439*** | 2.339*** | 2.446*** | 2.019*** | 1.915*** | 1.573** |
| | | (0.614) | (0.555) | (0.605) | (0.530) | (0.460) | (0.533) |
| Technological Distance x Network Density | | | -6.418** | | | -12.107*** | -13.087*** |
| | | | (2.191) | | | (3.433) | (3.207) |
| Technological Distance x Avg. Tie Strength | | | | 1.368 | | 0.959 | 2.128** |
| | | | | (1.629) | | (0.972) | (0.801) |
| Technological Distance x Network Diversity | | | | | -9.815** | -10.860** | -7.552*** |
| | | | | | (3.234) | (4.008) | (2.176) |
| Network Density | -2.561+ | -1.309 | -1.160 | -1.014 | -1.238 | -1.097 | 1.545 |
| | (1.484) | (2.132) | (1.325) | (2.075) | (1.779) | (1.219) | (0.963) |
| Average Tie Strength | 0.184 | 0.374 | 0.504+ | 0.424 | 0.535+ | 0.617+ | 0.385 |
| | (0.312) | (0.395) | (0.295) | (0.419) | (0.296) | (0.349) | (0.282) |
| Network Diversity | -1.083 | 0.332 | -0.282 | 0.123 | 1.828 | 0.227 | -1.974* |
| | (1.255) | (1.684) | (1.070) | (1.838) | (1.404) | (1.330) | (0.846) |
| Clustering | -0.428 | -0.677 | -0.933** | -0.649 | -0.930** | -0.867* | |
| | (0.371) | (0.526) | (0.326) | (0.569) | (0.326) | (0.380) | |
| Average Path Length | -0.499* | -0.633*** | -0.688*** | -0.584** | -0.745*** | -0.713*** | |
| | (0.197) | (0.177) | (0.168) | (0.178) | (0.163) | (0.156) | |
| Same Sector | 0.235 | -0.190 | -0.103 | -0.238 | -0.020 | -0.198 | |
| | (0.457) | (0.546) | (0.449) | (0.581) | (0.398) | (0.394) | |
| Co Patent | 7.060** | 6.449* | 3.483 | 8.458+ | 13.465*** | 6.821 | |
| | (2.401) | (3.045) | (2.291) | (4.779) | (3.323) | (5.064) | |
| Prior Citations | 0.060* | 0.038 | 0.024 | 0.032 | 0.040+ | 0.020 | |
| | (0.029) | (0.037) | (0.037) | (0.040) | (0.023) | (0.023) | |
| Scientific References | 0.003 | 0.005 | 0.006 | 0.006 | 0.004 | 0.006 | |
| | (0.004) | (0.005) | (0.005) | (0.005) | (0.005) | (0.004) | |
| Technology Value | -0.011*** | -0.010** | -0.011*** | -0.010** | -0.008* | -0.010*** | |
| | (0.003) | (0.003) | (0.002) | (0.003) | (0.003) | (0.003) | |
| Technological Furnishing | -0.078 | -0.360 | -0.154 | -0.331 | -0.323 | -0.374 | |
| | (0.454) | (0.412) | (0.383) | (0.419) | (0.453) | (0.397) | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Grant-back Clause | -1.186** | -1.116** | -1.225*** | -1.152** | -0.823* | -1.020** | |
| | (0.429) | (0.385) | (0.353) | (0.394) | (0.362) | (0.341) | |
| Milestone | 1.405*** | 1.129** | 1.353*** | 1.073* | 1.151*** | 1.288*** | |
| | (0.374) | (0.430) | (0.345) | (0.432) | (0.329) | (0.297) | |
| R&D Intensity | 0.004* | 0.007** | 0.006*** | 0.007** | 0.008*** | 0.007*** | |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | |
| Licensor University | -1.309* | -1.413* | -1.119* | -1.426* | -1.048+ | -1.034* | |
| | (0.613) | (0.703) | (0.521) | (0.710) | (0.557) | (0.515) | |
| Licensor Number of Patents | 0.000 | 0.000 | 0.000+ | 0.000 | 0.000 | 0.000 | |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | |
| US Firm | -0.880 | -1.490* | -1.323* | -1.440* | -1.978*** | -1.356* | |
| | (0.697) | (0.709) | (0.583) | (0.733) | (0.584) | (0.646) | |
| Log(Number Employees) | 0.574** | 0.461* | 0.474** | 0.448* | 0.500*** | 0.544*** | |
| | (0.213) | (0.183) | (0.149) | (0.186) | (0.144) | (0.141) | |
| Average Patenting Time | 0.084 | 0.002 | -0.012 | -0.003 | 0.018 | -0.020 | |
| | (0.107) | (0.088) | (0.081) | (0.097) | (0.061) | (0.077) | |
| Previous Year Patent | -4.202** | -5.654** | -2.385+ | -7.873* | -11.820*** | -5.386 | |
| | (1.462) | (1.877) | (1.331) | (3.892) | (2.457) | (4.381) | |
| Slack | -0.001 | 0.001 | 0.001 | 0.000 | 0.002 | 0.000 | |
| | (0.002) | (0.003) | (0.002) | (0.003) | (0.002) | (0.002) | |
| Sector Dummies | YES | YES | YES | YES | YES | YES | YES |
| Year Dummies | YES | YES | YES | YES | YES | YES | YES |
| Constant | -1.818 | 3.108 | 3.013 | 3.405 | 2.093 | 1.964 | 3.834*** |
| | (4.452) | (4.422) | (3.139) | (4.840) | (2.838) | (3.054) | (0.775) |
| log(G) constant | -0.532*** | -0.746*** | -0.835*** | -0.760*** | -0.938*** | -1.006*** | -0.709*** |
| | (0.154) | (0.168) | (0.148) | (0.165) | (0.220) | (0.175) | (0.150) |
| log ((-)) constant | 1.648*** | 1.818*** | 1.869*** | 1.826*** | 1.902*** | 1.960*** | 2.003*** |
| | (0.245) | (0.219) | (0.207) | (0.218) | (0.232) | (0.203) | (0.190) |
| Number of observations | 708 | 708 | 708 | 708 | 708 | 708 | 772 |
| Log-likelihood | -383.459 | -375.553 | -372.579 | -374.985 | -371.680 | -365.758 | -451.999 |
| Chi2 | 86.523*** | 102.335*** | 108.284*** | 103.472*** | 110.081*** | 121.926*** | 62.194*** |
| Likelihood ratio comparison | | 15.812*** | 21.761*** | 16.949*** | 23.559*** | 35.403*** | |

+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

**Table 3. Differences-in-differences Estimators (N=745)**

| | Base Line | | | Follow Up | | | |
|---|---|---|---|---|---|---|---|
| Outcome Variable | Control | Treated | Diffeference | Control | Treated | Difference | Difference-in-Differences |
| Number of Citations | 0.054 | 0.030 | -0.024 | 0.054 | 1.483 | 1.430 | 1.454 |
| Standard Deviation | 0.090 | 0.090 | 0.127 | 0.090 | 0.090 | 0.127 | 0.180 |
| T | 0.60 | -0.22 | -0.19 | 0.05 | 16.20 | 11.41 | 8.09 |
| P>\|t\| | 0.550 | 0.743 | 0.849 | 0.550 | 0.000 | 0.000*** | 0.000*** |

*<0.10, **p<0.05, ***<0.001

**Table 4. Results of t-tests on mean values for recombined and not-recombined technologies (N=745)**

| | Recombined | Not-Recombined | Difference |
|---|---|---|---|
| Technological Distance | 0.8015 | 0.8270 | 0.0255 |
| Patent Value | 90.8176 | 47.7027 | -43.1149*** |
| Scientific References | 21.4913 | 33.4459 | 11.9545*** |

*<0.10, **p<0.05, ***<0.001