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KNOWLEDGE DIVERSITY, TRANSFER AND COORDINATION: THE EFFECT OF INTRAFIRM INVENTOR NETWORKS ON THE SPEED OF EXTERNAL KNOWLEDGE RECOMBINATION

Keld Laursen
Copenhagen Business School
Innovation and Organizational Economics
kl.ino@cbs.dk

Solon Moreira
University of Bath
,
sm.ino@cbs.dk

Arjan Markus
Tilburg University
Department of Organization Studies
A.Markus@uvt.nl

Abstract

We link the knowledge-based view of the firm and the social network approach to propose a theory of how intrafirm network characteristics affect the firm?s recombination speed in relation to the incorporation of technologically distant external knowledge into its production of inventions. We start from the widely accepted view that distant, externally-developed knowledge is difficult to incorporate into the focal firm?s own production. We suggest that high levels of intrafirm network diversity, tie strength, and network density are essential for a diversity of knowledge inputs, knowledge transfer, and coordinated actions which in turn, reduce the problems pertaining to the incorporation of distant knowledge. The results of an event history study of 113 pharmaceutical firms that engaged in technology in-licensing during 1986-2003 generally support our hypotheses.

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ABSTRACT. We link the knowledge-based view of the firm and the social network approach to propose a theory of how intrafirm network characteristics affect the firm's recombination speed in relation to the incorporation of technologically distant external knowledge into its production of inventions. We start from the widely accepted view that distant, externally-developed knowledge is difficult to incorporate into the focal firm's own production. We suggest that high levels of intrafirm network diversity, tie strength, and network density are essential for a diversity of knowledge inputs, knowledge transfer, and coordinated actions which in turn, reduce the problems pertaining to the incorporation of distant knowledge. The results of an event history study of 113 pharmaceutical firms that engaged in technology in-licensing during 1986-2003 generally support our hypotheses.

KEYWORDS: Recombination speed, absorptive capacity, intrafirm inventor networks, innovation, licensing.

INTRODUCTION

How do in-house informal organizational mechanisms allow firms rapidly to combine externally acquired knowledge with internal knowledge to achieve technological innovation? In turn, how does the acquired technology's distance from the focal firm's knowledge base matter in this context? This paper addresses these questions. The notion that in many industries organizational outcomes depend on firms' capabilities to recombine internal and external knowledge to create innovations, is a central tenet of work on strategy and organization (e.g., Cassiman & Veugelers, 2006; Ceccagnoli & Jiang, 2012; Hargadon & Sutton, 1997; Rosenkopf & Nerkar, 2001; Stettner & Lavie, 2013). Acquisition of external knowledge is often an attractive alternative to in-house research and development (R&D), because it allows the firm to spread the risks and costs inherent in R&D, and access a larger pool of knowledge (Ahuja, 2000; Arora & Gambardella, 1990; Kessler & Chakrabathi, 1996) which then can reduce invention development times (Leone & Reichstein, 2012; Tzabbar, Aharonson, & Amburgey, 2013).

While this prior work adds to our knowledge of how and why external knowledge is important for firm innovation processes, it does not account for the in-house organizational mechanisms that allow firms to combine externally acquired knowledge with internal knowledge to achieve innovation outcomes. Given that successful use of external knowledge may depend critically on how the focal firm is organized, achieving a better understanding of this process is an important topic in strategic management. This paper seeks to contribute theoretically and empirically to this area of work. We apply the lens of the knowledge-based view (KBV) of the firm (Grant, 1996; Kogut & Zander, 1992; Nelson & Winter, 1982) combined with a social network approach (Hansen, 1999; Obstfeld, 2005; Reagans & McEvily, 2003) to propose a theory to explain how specific configurations of intrafirm networks can speed up the recombination of in-licensed external knowledge to produce own inventions. Based on the insight that inventors find it difficult to integrate external knowledge components with which they have no prior experience, our starting point is that firms' recombination speeds decrease with the degree of unfamiliarity of the external knowledge. We posit that certain intrafirm network configurations attenuate the problems related to time-costly recombination of distant external knowledge with firm-internal knowledge. In other words, intrafirm network configurations negatively moderate the relationship between the unfamiliarity of the external knowledge and the time it takes to recombine knowledge.

Three particular KBV concepts are important in our context: internal knowledge variety, knowledge transfer, and knowledge coordination. We claim that intrafirm networks involving key knowledge workers may be a mechanism underlying all three concepts in the context of the recombination (or "integration") of external knowledge into the firm's own knowledge production. First, network diversity allows effective utilization of externally acquired knowledge; diverse internal connections provide the individual inventor with access to a *diverse set of problem-solving skills* useful for integrating external knowledge into the focal firm's own knowledge. Second, strong ties among knowledge workers facilitate *knowledge transfer* within the organization; complex knowledge is transferred best through personal interaction in a trust-based environment. Third, high network density ensures channels of communication and provides inventors with knowledge about what other inventors are doing. Thus, network density allows for *coordinated* transfer of diverse internal and external knowledge. Firm networks combining these dimensions allow better access to internal knowledge variety, and enhanced and coordinated knowledge transfer, and therefore will enable faster recombination of distant knowledge into internal knowledge production.

We examine our predictions regarding the speed of external-internal knowledge recombination in the context of 113 global pharmaceutical firms over the period 1986-2003. The analysis draws on a unique and detailed dataset which combines data on pharmaceuticals licensing agreements, inventors, and patents. We follow the idea in prior studies that co-invention and inventor networks provide advice, referrals, and knowledge for problem solving (Allen, 1977; Guler & Nerkar, 2012; Singh, 2005; Singh & Fleming, 2009). Thus, the observed co-invention ties among inventors serve as inputs to intrafirm knowledge networks in which the nodes are inventors, and the ties between nodes indicate co-inventions with colleagues. The present study utilizes event history analysis to test our hypotheses, and employs a difference-in-differences method to support our focus on licensing as a knowledge acquisition mechanism. With the exception of our prediction regarding average tie strength, the findings provide overall support for our hypotheses.

Our study constitutes an original contribution based on introducing the informal organizational dimension into the external knowledge sourcing literature. This implies identification of important informal organizational aspects of absorptive capacity in the context of external knowledge sourcing for innovation. More precisely, we advance the idea that intraorganizational networks play a very important role in allowing the rapid recombination of external knowledge into the focal firm's knowledge production. By including knowledge acquired from external parties, this work also adds to the discussion on informal organization in relation to the existence of intraorganizational networks (Carnabuci & Operti, 2013; Guler & Nerkar, 2012; Nerkar & Paruchuri, 2005) and the focus on exploiting and combining internally held knowledge. In this context, Cohen and Levinthal (1990: 128) identify absorptive capacity, defined as the "ability to identify, assimilate, and exploit knowledge from the environment," as a central determinant of process and product innovation.

However, while Cohen and Levinthal (1990: 131) maintain that internal organization may matter for the identification, assimilation, and exploitation of external knowledge, they do not spell out how and why firm-internal organization matters. Also, most subsequent work on absorptive capacity looks at knowledge-related precursors to absorptive capacity (such as R&D expenditure) with a few contributions (see e.g., Jansen, van den Bosch, & Volberda, 2005; Volberda, Foss, & Lyles, 2010) scrutinizing how absorptive capacity relates to informal within-firm organization, and even fewer examining the organizational antecedents to absorptive capacity in the context of innovation-related outcomes (see, Foss, Laursen, & Pedersen, 2011; Paruchuri, 2010). Note that Paruchuri (2010) examines the interactions between (informal) inter- and intrafirm networks and their joint effects on innovation outcomes at firm level. However, Paruchuri (2010) does not explore how externally developed technologies are recombined with the focal firm's knowledge production. Foss *et al.* (2011) look at how customer knowledge is incorporated in the focal firm's innovation production but focus on the formal organization of firms in terms of organizational practices.

Finally, we extend the KBV by identifying some of the theoretical micro mechanisms that underpin key concepts in this approach. KBV scholars have argued that firm-level variation in firms' capabilities to provide internal knowledge variety, knowledge transfer, and the coordination of knowledge-related activities, create differences in firms' abilities to orchestrate efficient knowledge recombination, and hence, variability in firm-performance. However, the core theoretical concepts of the KBV are described in fairly general terms. Here, we explain how each of these broad concepts is supported by specific micro-mechanisms underlying firms' intrafirm inventor networks.

THEORETICAL BACKGROUND

Knowledge recombination speed

Our dependent variable is external knowledge recombination speed, measured as the time taken to recombine an in-licensed technology with the focal firm's own new patents as evidenced by patent citations. There are three reasons for this choice of dependent variable. First, given that effective knowledge recombination is at the core of the KBV, knowledge recombination speed is a natural dependent variable. Second, prior research highlights that firms that are able to innovate more quickly achieve first-mover advantages and are able to capture new market opportunities (Markman, Gianiodis, Phan, & Balkin, 2005). Indeed, the (slow) generation of innovative solutions may prolong waiting times for new product introductions (Schoonhoven, Eisenhardt, and Lyman, 1990). Third, how quickly firms can internalize external knowledge is important since it is a source of competitive advantage, especially in industries where time-based competition is paramount (Kessler & Chakrabathi, 1996; Leone & Reichstein, 2012; Tzabbar et al., 2013). One of the reasons why speed is important is that it enables later entry into the product market after fundamental uncertainties have been resolved (Hawk, Pacheco-De-Almeida, &

Yeung, 2013).

For a number of reasons, recombination speed matters for our context — the global pharmaceutical industry. First, in the pharmaceutical industry time is vital for competitiveness due to the effectiveness of patent-protection in this area and exclusivity protection granted by agencies such as the Food and Drug Administration. This means that in this industry, being first can be very valuable (Roberts & Hauftman, 1987). R&D races among pharmaceutical companies emphasize the importance of speed, for instance to obtain a first-in-class drug or a so-called follow-on drug, both of which can generate substantial revenue streams (Cockburn & Henderson, 1994; DiMasi & Faden, 2011). Furthermore, given the average length of the pharmaceutical drug discovery and development process — roughly ten years from conception to market (DiMasi, Hansen, & Grabowski, 2003) — there would seem to be scope for speeding up the R&D process (see also, Cardinal, 2001).

Theoretical foundation

The KBV of the firm (Grant, 1996; Kogut & Zander, 1992; Nelson & Winter, 1982) suggests that differences in firms' combinatorial capabilities can lead to differences in firm performance which tend to persist. The KBV is based on the premise that production—including the production of knowledge—requires the "coordinated efforts of individual specialists who possess many types of knowledge" (Grant, 1996: 112).

In focusing on knowledge involving external knowledge created by individual inventors, this paper follows Grant's (1996) idea of the KBV and assumes that knowledge creation is basically an individual activity but one which, in order to be effective, requires knowledge transfer and coordination facilitated by an organization. This is consistent with our choice to focus on the effect of the intrafirm networks of individual inventors, on external knowledge recombination speed. The KBV of the firm is a general theory of production; here we examine a specific but very important type of production of knowledge, in the form of invention.

The KBV assumes that communication and learning are costly activities given the difficulties related to communicating tacit knowledge, and contends that organizations benefit from using "rules, routines and other integration mechanisms that economize on communication and knowledge transfer, and reserve problem solving and decision making by teams to unusual, complex, and important tasks" Grant (1996: 115). We posit that the production of knowledge in the form of inventions that exploit distant external inputs, involves such unusual, complex, and important tasks. We posit also that the intrafirm network of inventors can be a source of variety and can facilitate knowledge transfer and coordination.

We would acknowledge that, within a given firm, the costs related to very high levels of intrafirm tie strength and network density might outweigh their benefits as a result of the "not invented here" (NIH) syndrome (Katz & Allen, 1982). The NIH syndrome refers to the tendency among tightly-knit groups of professionals to believe that they have a monopoly on the knowledge in a particular field, resulting in new ideas from outsiders being rejected to the detriment of subsequent performance. However, given that we are exploring an issue which by definition involves a core firm-external knowledge component (licensed-in technology), the NIH problem should be less severe in our setting since the decision to work with external technology has already been taken by the managers of particular organization. There might still be some resistance from inventors to externally developed knowledge, but note that such resistance would work against our hypotheses. We return to this issue in our robustness checks.

Cohen and Levinthal (1990) suggest a useful distinction between "inward-looking" and "outward-looking" absorptive capacity. The former refers to the efficiency of the firm's internal communication, the latter refers to its points of contact with external knowledge sources (Cohen & Levinthal, 1990: 133). In order to focus on the inward-looking aspect, in the empirical design of the present paper, we take outward looking absorptive capacity as fixed since the point of contact is established through a technology licensing contract, and assume the inward-looking component in the form of informal intrafirm networks to vary across firms.[1]

The baseline: Technological distance and recombination speed

Our paper builds on a baseline proposition that is theoretically and empirically well-established in the literature. It can be stated as follows: The greater the distance between the externally acquired knowledge and the firm's knowledge base, the longer it will take the firm to recombine the external knowledge into its own inventions. From the point of view of the KBV, Kogut and Zander (1992: 392) argue that "firms learn in areas closely related to their existing practice. As the firm moves away from its knowledge base, its probability of success converges to that for a start-up operation." Indeed, a firm's knowledge stock allows the firm to make sense of the knowledge in the environment (Rosenkopf & Almeida, 2003; Zahra & George, 2002). Assimilation of external knowledge requires a common understanding, or knowledge base overlap, in order to achieve successful application of that knowledge (Cohen & Levinthal, 1990; Gilsing, Nooteboom, Vanhaverbeke, Duysters, & Vandenoord, 2008; Lane & Lubatkin, 1998; Mowery, Oxley, & Silverman, 1996). Thus, as the technological distance between the firm's knowledge base and the acquired external knowledge increases, the absorptive capacity of the firm declines which means that integration of acquired external knowledge into an invention will require more effort and time; in addition, technical problems are likely to arise in the case of unfamiliar knowledge.

[1] Of course this analytical choice might introduce a selection problem due to the possibility that acquired patents are of higher quality than non-acquired patents. We address this issue through application in the robustness checks of the difference-in-difference approach.

Our baseline has been empirically corroborated. Two recent empirical studies are particularly pertinent. Tzabbar *et al.* (2013) show that the rate of knowledge integration, among other things, depends on the degree of familiarity with the knowledge that is transferred. Leone and Reichstein (2012) show that licensing-in accelerates firms' invention speed but that this effect decreases when firms license-in unfamiliar technologies.

HYPOTHESES

Source of variety: Intrafirm network diversity

Network diversity generally refers to the diversity of the resources available in the network (Harrison & Klein, 2007; Reagans & McEvily, 2003), and in our case refers to the variety of technological experience of the collaborating inventors inside the firm. Given that knowledge recombination is at the center of the KBV, a variety of potential inputs to the knowledge generation process is essential. Grant (1996: 112) states that "efficiency in knowledge production … requires that individuals specialize in particular areas of knowledge." It is clear that if all the firm's employees possess identical knowledge, there will be no scope for knowledge recombination among them. However, among individuals with diverse knowledge, there will be many opportunities for knowledge recombination. We argue that an intrafirm network composed of a diverse group of inventors accelerates the speed of recombination of distant external knowledge and inventions, for three main reasons.

First, due to the inherent uncertainty of knowledge recombination, inventors benefit from the existence of diverse partners in their intrafirm networks. Different connections provide the individual inventor with access to diverse sets of problem-solving heuristics (Page, 2007) which support the accomplishment of complex tasks related to recombining distant knowledge (Mors, 2010; Rodan & Galunic, 2004). Moreover, potential firm-internal variety in the sources of knowledge provides opportunities for inventors to choose among different technological paths

(Katila & Ahuja, 2002; Metcalfe, 1994) as they incorporate externally acquired knowledge into their own inventions. Thus, the problem-solving ability of inventors and the possible applications for externally acquired technologies increase with diversity, and reduce the time needed to recombine complex distant knowledge acquired from outside the firm's boundaries.

Second, when inventors with different technological backgrounds collaborate, their ability to convey knowledge across distinct bodies of meta-knowledge expands (Reagans & McEvily, 2003; Tortoriello, Reagans, & McEvily, 2012). Over time, experience of interacting with dissimilar colleagues increases inventors' capability to efficiently and successfully frame their communication with other inventors which in turn, may accelerate the recombination of distant knowledge based on future interactions among heterogeneous inventors. Third, diversity within the intrafirm network increases the likelihood of overlap between the acquired external knowledge component and available relevant knowledge in the intrafirm inventor network (Cohen & Levinthal, 1990; Mowery et al., 1996). Diversity among collaborating inventors thus eases understanding of distant external knowledge and leads to shorter recombination times. However, as implied above, network diversity should have a stronger effect in the case of distant external knowledge compared to familiar knowledge. In the case of familiar knowledge, diversity is less crucial since the typical inventor working with relevant external knowledge already has experience of how to use that knowledge, and therefore will be less reliant on the problem-solving heuristics of other inventors. In sum, we state that:

> *Hypothesis 1. The higher the level of diversity of the firm's intrafirm inventor network, the faster the firm can recombine distant external knowledge into its own inventions.*

Knowledge transfer: Intrafirm average tie strength

Kogut and Zander (1992: 384) claim that "the central competitive dimension of what firms know how to do is to create and transfer knowledge efficiently within an organizational context." While a diversity of internal knowledge sources is essential for knowledge recombination, this knowledge also needs to be transferred to enable recombination (Grant, 1996; Kogut & Zander, 1992; Szulanski, 1996). We suggest that network tie strength facilitates knowledge transfer, and that the ease of knowledge transfer within an organization supports the incorporation of distant external knowledge into the focal firms' own inventions.

Tie strength refers to the intensity of the interactions between two network members, 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: 126). The characteristics of tie strength tend to increase with the increasing frequency of collaboration between inventors. Tie strength not only facilitates direct knowledge transfer through personal interaction it also facilitates indirect transfer by promoting trust between the parties (Hansen, 1999; McFadyen, Semadeni, & Cannella, 2009). While weak ties help in the search for useful knowledge, they may not benefit the exchange of complex knowledge among individuals. In the case of innovation in particular, despite the location and availability of knowledge being known to network members, it may not be shared appropriately among individuals (Hansen, 1999).

Strong ties among a firm's inventors are likely to mitigate the disadvantages related to integrating distant external knowledge for two reasons. First, knowledge that is tacit and highly complex is best transferred through personal interaction, i.e., via strong ties (Hansen, 1999; Phelps, Heidl, & Wadhwa, 2012). Distant knowledge is likely to represent complex knowledge for the inventors within a firm; strong ties increase the likelihood of this complexity being shared throughout the firm, which accelerates knowledge integration (Hansen, 1999). Second, but closely related, trust and knowledge-sharing among inventors, increase with recurring interactions (Gulati, 1995; Hansen, 1999; Reagans & McEvily, 2003). Strong (recurrent) ties allow inventors to learn about each other and develop trust based on common notions of fairness and reciprocity (Gulati, 1995, terms this "knowledge-based trust"). Accordingly, networks characterized by strong ties tend to be associated with communication, knowledge sharing, and willingness to devote time and effort to supporting peers (Rost, 2010; Sosa, 2010) because trust assures the involved parties—in our case the inventors—that the knowledge shared will not be appropriated or misused (Reagans & McEvily, 2003). This support from co-inventors may be particularly important in the context of problem-solving related to the integration of unfamiliar pieces of knowledge, given the number of problems this type of knowledge promotes for the individual inventor. This, in turn, shortens the recombination process. Based on these two points, we expect that:

> *Hypothesis 2. The higher the level of average tie strength in the firm's intrafirm inventor network, the faster the firm can recombine distant external knowledge into its own inventions.*

Coordination: Intrafirm network density

While according to the KBV, the variety of individuals' knowledge inputs and the transfer of knowledge are important for successful knowledge recombination, to be effective the recombination process needs to be coordinated. A fundamental argument of the KBV is that "If production requires the integration of many people's specialist knowledge, the key to efficiency is to achieve effective integration while *minimizing* knowledge transfer through cross-learning by organizational members" (Grant, 1996: 114, our emphasis added). Effective integration or recombination is achieved via coordination mechanisms. Effective coordination within the firm can be achieved in three ways (Srikanth & Puranam, 2011: 851): 1) by designing processes to simplify or minimize interdependence, 2) by facilitating ongoing communication between the actors, or 3) by enabling tacit coordination by leveraging/building a stock of common knowledge based on the notion that “mutually shared knowledge may economize on the need for explicit communication or plan-based coordination mechanisms” (Srikanth & Puranam, 2011: 850).

Given that the invention process involves situations characterized by complex interdependence, only 2) and 3) can be considered viable coordination mechanisms (Puranam, Singh, & Zollo, 2006). We argue that a dense intrafirm inventor network can serve as an essential coordination device that allows for easier incorporation of distant external knowledge into the focal firm’s subsequent inventions. Dense (or cohesive or closed) networks are comprised of closely inter-connected members. Central to our argument is the idea that a dense network facilitates ongoing communication for the coordination of activities. Oliver (1991: 171) states that because “highly interconnected environments provide relational channels through which institutional norms can be diffused, this tends to create more implicit coordination and collectivization in a given environment.” In our context, tacit or implicit coordination is particularly relevant, the idea being that an intrafirm network allows a focal inventor to know the specialisms of other inventors within the focal firm and what they are developing. Inventors’ ties provide information and allow observation of potentially relevant inventors with the knowledge and skills needed to recombine distant external knowledge. Inventors with this type of shared knowledge can more easily establish productive contacts and benefit from related knowledge transfer while minimizing redundant, costly, and time-consuming knowledge transfer. Thus, dense networks tend to speed up the search for relevant information within the network (Zaheer & Bell, 2005) and ease subsequent communication regarding joint problem-solving, through the incorporation of externally acquired knowledge into firm-internal production of inventions.

Closely related to the tacit coordination and coordination through communication is trust. A dense network provides a powerful means for spreading information about perceived opportunistic behavior and costly sanctions that exceed the potential benefits of the undesirable behavior (Gulati, 1995 terms this “deterrence-based trust”). Since opportunistic behavior tends to slow down knowledge recombination, inventors in dense networks will be more able to save time when recombining knowledge. However, network density should have a stronger effect in the case of distant external knowledge compared to familiar knowledge. In the latter case, coordination among individuals is less essential since individual inventors are less reliant on their networks for solving the relatively easy problems related to familiar knowledge (Fleming, King III, & Juda, 2007).

Nevertheless, sparse networks can also enable firm innovation (Burt, 2004). A sparse network, characterized by structural holes between clusters or sub-networks, can enhance firm innovation since such a network structure is likely to encompass diverse information and foster creativity (Tortoriello, 2014). Although sparse networks have been shown to be associated with high levels of heterogeneity which facilitate the creation of new knowledge, the absence of connections between network members reduces the *speed* with which individuals can share knowledge and access information (Singh, Hansen, & Podolny, 2010). Especially in relation to distant knowledge, ties are necessary to coordinate individuals and enable detection and exploitation of useful knowledge channels, and exploit the experience and knowledge held by other inventors. Thus, we hypothesize that:

> *Hypothesis 3. The higher the level of density in the firm’s intrafirm inventor network, the faster the firm can recombine distant external knowledge into its own inventions.*

DATA AND METHODS

The research sample is drawn from the global pharmaceutical industry population. Above, we argued that recombination speed matters in this industry. This and several other aspects motivated the choice of this industry as the setting for this study. First, the pharmaceutical industry is characterized as technology-driven and R&D intensive, and technological knowledge is critical for developing and sustaining competitive advantage (Roberts, 1999). Second, pharmaceutical firms routinely and systematically protect and document their inventions through patenting (Levin et al., 1987), so we can rely on patent information to identify the technological profiles of the firms in our sample (Roberts, 1999). Third, the pharmaceutical industry has been proven to be a useful context to identify and measure the effect of inventor networks on innovative output (see e.g., Paruchuri, 2010).

Four data sources were exploited for this study. First, we obtained detailed information on licensing agreements from the Deloitte Recap Database which covers licensing deals in the global pharmaceutical industry over the period 1983–2008. This database is one of the most accurate sources of information on partnerships and technology exchange in the pharmaceutical industry (Schilling, 2009). It gives access to the original licensing contracts which allowed us to extract precise information on the date of the licensing event, characteristics of the licensed technologies, contractual specifications, and information enabling identification of licensees and licensors (e.g., firm name and address, and operating segment). Second, we used patent data from the NBER project which allowed us to merge specific patent numbers connected to the traded technologies obtained from the Deloitte Recap Database, with patents registered at the US Patent and Trademark Office (USPTO). The NBER data were used also to identify the technological profiles of the firms in the sample. Third, the Harvard Patent Network Dataverse provided us with disambiguated inventor names and inventor identification numbers. This allowed us to construct intrafirm inventor networks based on co-invention, and to derive inventor-level information. Prior research has used qualitative evidence (i.e., interviews) to validate co-patenting ties as a measure of collaboration among inventors (Fleming et al., 2007). The fourth data source, the WRDS Compustat database, was exploited mainly for our control variables.

The final sample consists of 113 firms involved in the acquisition of 708 USPTO patents through licensing contracts, in the period 1986-2003.[2] This number represents approximately 47 percent of the contracts registered at Recap which initially were considered suitable to test the hypotheses. The observations excluded from the final analysis are related mainly to licensing contracts where we were unable to identify the licensee's name, or observations regarding firms that do not publish their financial information. We also excluded from the final analysis contracts where we could not identify a USPTO patent number connected to the licensed technology. To minimize the risk of selection issues, we investigate the existence of systematic differences in terms of invention speed, related to observations where a patent number was identified in the contract, and observations where the patent number was not identified. Accordingly, we conduct a *t*-test comparing number of months after licensing date to licensees' first patent. The results indicate no statistically significant differences between the two groups.

Dependent variable

Time to knowledge recombination. The time it takes firms to recombine licensed technologies is calculated on the basis of the number of months between licensing date and the *first time* the

[2] This time window is based on the fact that information on inventors' patenting activity is available only from 1981, and the explanatory variables for intrafirm networks are calculated for a 5-year period. Also, given that the firms in our sample take 26 months on average to recombine a licensed technology we stop the sample in 2003 to minimize right censoring concerns.

licensee incorporates the licensed technology as a backward citation in a *new patent*. In order to get as close as possible to the date when the licensed technology was successfully recombined, and to avoid noise introduced by differences in patent office procedures, we use as a reference the application date rather than the date the *new patent* was granted. Consequently, the date of external knowledge acquisition is defined on the basis of the licensing date specified in the Recap database, while the recombination date comes from the Patent Network Dataverse. This variable is intended to capture how fast firms are able to recombine a body of new, externally acquired knowledge with existing knowledge. Leone and Reichstein (2012) apply this dependent variable in a similar context, as a robustness check to capture how inward licensing can shorten the time firms take to invent a new technology. Here, we consider that citing the licensed technology in a new patent as an indication that the licensee has assimilated and successfully applied the in-licensed knowledge. To reduce the likelihood that the knowledge connected to a licensed technology is not related to new recombination opportunities for the licensee, we examine only patents cited by the licensee for the first time after the licensing agreement.

Explanatory variables

We measure *technology distance* using the "focal index" proposed by Ziedonis (2007). Then the technology distance between a licensed technology and a firm's knowledge base is measured on the basis of the patent class connected to the licensed technology and the technology classes in which the licensee has been active prior to the licensing event. The measure is computed as:

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

where $\left(\sum_{t-5}^{t}\sum_{j}\tilde{C}_i \cdot \rho_i\right)_c$ represents the citation-weighted sum of firm *i*'s patents applied for within five years of the time of the license agreement *t* and which belong to the same primary patent class *c* as 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 firm *j* that were applied for by date *t* during the same five-year time window. The use of weighted citations offers the possibility to capture the relative importance of each patent in the firm's portfolio (Griliches, 1990).

The *network diversity* measure aims at capturing the level of knowledge heterogeneity among the active inventors *within* the focal firm (Rodan & Galunic, 2004). Therefore, rather than capturing firm-level diversity, we focus on network level diversity among active inventors. The first step to compute this measure is to identify which inventors are active at the time the technology is acquired; we considered as active those inventors with at least one patent during the five years prior to the focal year. Also, we only examine diversity among inventors with at least one active intrafirm tie, which means that inventors that patent only in collaboration with other individuals outside the firm, and single inventors on all patents, are excluded from the analysis. In order to calculate the diversity measure we use a Herfindahl index based on the International Patent Classification (IPC) 2-digit codes of the patents produced by firm's inventors. We define the level of network diversity in firm *i*'s intra inventor network in year *t* as:

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

We consider that the main IPC code attributed to a patent reflects a distinct technology field *j* = *1*, *2*, *3…th.* Therefore, if the inventors within the *i*th firm have accumulated N_i patents within the five years prior to the licensing contract, each of the patents can be assigned to one technology field. Accordingly, N_{it} represents the total number of patents produced by the active inventors within firm *i* in the past five years, and N_{jit} is the number of patents assigned to technology class *j* among the total number of patents produced by firm *i's* inventors. The final measure is calculated by subtracting 1 from the value reflecting the concentration of patent classes across different technology domains.

Average tie strength captures the average intensity of collaboration among inventors *within* the firm. We measure tie strength between each observed pair of inventors based on the number of patented co-inventions. We average this across the number of inventors in the firm. We again apply a five-year moving window. We measure network density 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 (Guler & Nerkar, 2012; Marsden, 1990). Network density for firm *i* in year *t* is computed as follows:

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

We define *observed ties* as the number of unique ties existing between two inventors that co-patent, and the number of *possible ties* for the total number of inventors ($\frac{N \times (N-1)}{2}$) listed in the firm's patents.

Control variables

In order to isolate the effects of the explanatory variables, we include several firm-, technology-, and contract-level control variables which might affect the time it takes to recombine knowledge. We apply moving windows of different time lengths to compute these control variables. Window time length ranges from four to seven years, and differs according to the specific control variable; the control variables for intrafirm network are calculated for the same time length as the explanatory variables (5 years). In relation to intrafirm inventor network characteristics, we control for *clustering* (Guler & Nerkar, 2012) and *average path length* (Fleming et al., 2007), two structural characteristics that we would expect to affect knowledge flow across inventors by speeding up the time taken to transfer knowledge between two points in the network. Our clustering measure is scaled by degree of clustering expected in a random bipartite network of the same size and density. Additionally, we include a dummy variable that takes the value 1 if the firm has *co-patented* at least once prior to the licensing date (Laursen, Leone, & Torrisi, 2010). This variable captures the external ties allowing inventors to acquire relevant knowledge.

We control also for several firm characteristics. First, to control for *firm size* we include the logarithm of number of employees in the year of the licensing deal. Second, we control for firm *R&D intensity* as total R&D expenditure divided by total sales at year *t*. We control also for the amount of unabsorbed resources using licensee *slack*, calculated as the ratio of number of employees to sales (Mellahi & Wilkinson, 2010). Another characteristic that might influence the rate at which the licensee is able to recombine external knowledge and to speed it up, is related to familiarity with the licensor's technologies *other than the licensed technology*. Therefore, we control for total number of the licensee's *prior citations* to other of the licensor's patents during the four years prior to the licensing contract. In order to capture fast-paced knowledge recombination driven by industry competition (Ferrier, Smith, & Grimm, 1999) we generate a dummy variable that takes the value 1 if both firms operate in the same segment, and 0 otherwise. We include a dummy variable that takes the value 1 if the firm produced a patent during the 12 months previous to the licensing date, to control for technologies licensed at different stages in the invention process. Finally, we include a dummy variable that takes the value 1 if the licensee is headquartered in the United States.

We also use dummy variables to control for licensing deal contractual specifications. The inclusion of a technology flow-back provision clause (i.e., a grant-back clause) gives the licensor rights to any improvements developed by the licensee to the licensed technology (Choi, 2002). A *technological furnishing* clause commits the licensor to supplying know-how about the licensed technology to support its understanding and application by the licensee, thus mitigating some of the problems related to distance. Finally, we control for a *milestone* payment clause in the licensing contract. Among technology related characteristics, we control for *technology value* using total number of forward citations received by the licensed technology, and for total number of *scientific references* in the backward citations to the licensed technology to capture cross-technology differences in terms of the scientific knowledge that the patent draws on. It is important also to account for the effect that the stage of development when the technology is licensed has on the speed of knowledge recombination. Based on Recap information, we create a dummy variable that takes the value 1 if the drugs have been licensed before the *clinical stage*, and zero otherwise (Banerjee, 2012). Finally, the contracts in our sample can be associated with different therapeutic classes; we rely on the classification proposed by the World Health Organization and the description provided in Recap, to create dummy variables that account for differences in terms of 12 main therapeutic classes plus miscellaneous, observed across the licensing deals (see Table 2 for a description of the therapeutic areas).

Finally we control for licensor's characteristics. First, we control for the number of successful patent applications filed by the licensor in the seven years prior to the licensing contract, to account for differences in licensor's size and technological capabilities. Second, we control for differences between firms and universities as licensors by adding a dummy variable for contracts where the licensor is a university. Third, based on the Recap database we classify the firms in the final sample based on three main sectors: *Biotech*, *Pharmaceutical,* and *Medical devices*. In order to capture cross-sector differences in terms of innovation speed, we used sector fixed effects based on dummy variables for the licensees' main operating segment.

Model specification and estimation

Our hypotheses refer to the time taken to recombine knowledge so we generate a dependent variable based on an event history analysis structure. Using event history analysis to investigate the effect of the explanatory variables on the time it takes to recombine knowledge has at least two major advantages. First, it allows time to be modeled directly as the dependent variable without the need to transform it into a discrete outcome. Second, it allows us to model observations that do not experience the transition (recombination) during the time frame covered by the data, by dealing with right-censoring issues as a non-random process (Blossfeld, Golsch, & Rohwer, 2007), and to include observations for which we only have partial information on the time they entered the sample (licensing date) to the last date that patent data on backward citations are available. Following previous studies (e.g., Leone & Reichstein, 2012), we employ a log-logistic specification to accommodate the time-dependence shape of the transition rate for the observations in the sample. Additonally, to take account of firm-specific unobserved heterogeneity, we use a shared frailty model with gamma mixture specification (Blossfeld *et al.*, 2007).

Descriptive statistics and correlations

Table 1 reports the means, standard deviations, and Pearson correlation coefficients of the variables used in the analysis. With the exception of the correlations between *average path length* and *network density,* and *clustering* and *average tie strength*, these results raise no concerns about collinear variables. The correlations between *average path length* and *network density,* and *clustering* and *average tie strength* are in line with the theoretical expectations but in order to check for potential bias, we enter the variables stepwise. We also find a moderate negative correlation between *network diversity* and *network density* which is in line with the network analysis literature. The results for the main explanatory variables do not change as the variables enter the model. Also, the maximum variance inflation factor (VIF) associated with any of the independent variables is 4.34 (mean VIF=2.15), which is well below the rule-of-thumb value of 10 (Gujarati, 1995).

[Insert Table 1 around here]

We are able to track the patenting behavior of the firms in our sample up to December 2006; therefore, our analysis is censored at the latest dates available in the patent citations data. Considering knowledge recombination speed from a descriptive perspective, the longest time to transition for the firms in our sample is 168 months. Among 708 firm-technology observations, a total of 116 firms cite the licensed technology in a new patent (i.e., recombination achieved) during the time frame of our analysis. For the observations that experienced transition, the average time for knowledge recombination is 25 months. This compares with the average time of 74 months at risk for all the firms in the sample (including censored observations). Among the 592 firm-technology observations that did not experience transition during the time window of our analysis, 129 observations exited the sample before December 2006. These observations are subject to a different type of right-censoring. In our empirical setting, they exit the sample early because they disappear from Compustat (through bankruptcy or acquisition) and end earlier than the latest information available in the patent data. We model those observations setting exit time as date of the latest Compustat record.

We plot the cumulative hazard function after estimating the log-logistic model, to visualize the pattern of the hazard function in relation to its non-monotonic shape. The results for the observations in our sample (see Figure 1) indicate an initial increase in the hazard rate followed by a decrease. Additionally, in order to visualize the shape of the hazard rate for observations with high and low levels of technological distance we generate two groups on the basis of the mean values for distance. As suggested by Figure 1, firms dealing with lower distance values have a higher probability of experiencing earlier transition compared to those firms coping with high distance levels.

[Insert Figure 1 around here]

RESULTS

Table 2 reports the results for the log-logistic model with the shared gamma mixture specification. The dependent variable across the six models reported in Table 2 reflects the time between licensing date and first citing of the licensed technology in a new patent. Model I reports the estimations for the controls and the variables underlying the interaction terms. In models II-VI the interaction terms capturing the relationships described in the hypotheses enter one at a time with the controls. For simplicity, discussion of the results focuses on the full model in column VI.

[Insert Table 2 around here]

Based on the positive and significant coefficient of the variable for technological distance, we find support for our baseline proposition concerning the effect of increasing levels of distance (unfamiliarity) for prolonging the time it takes for the firm to recombine external knowledge. This result is in line with the findings in Tzabbar *et al.* (2013) and Leone and Reichstein (2012), who also develop the idea that distance is an important predictor of the firm's capacity to recombine external knowledge rapidly.

Hypothesis 1 states that *the higher the level of diversity of the firm's intrafirm inventor network, the faster the firm can recombine distant external knowledge into its own inventions.* The coefficient of the interaction between technological distance and network diversity is significant and negative, supporting the idea that network diversity negatively moderates the relationship between distance and the time it takes to recombine knowledge, i.e., accelerates the recombination of distant knowledge. Hypothesis 2, that *the higher the level of average tie strength in the firm's intrafirm inventor network, the faster the firm can recombine distant external knowledge into its own inventions* is not supported by our results. The coefficient of the interaction between technological distance and tie strength is not significant at any conventional level. The insignificant coefficient of this interaction term indicates that distance is positively related to knowledge recombination regardless of the strength of the ties among the firm's inventors.

Finally, we find support for the moderation effect predicted in Hypothesis 3 that *the higher the level of density in the firm's intrafirm inventor network, the faster the firm can recombine distant external knowledge into its own inventions*. The coefficient of the interaction term between technological distance and network density is negative and significant, indicating that the positive effect of distance on the time it takes to recombine knowledge becomes less positive (or more negative) when interacted with network density.

ALTERNATIVE EXPLANATIONS AND ROBUSTNESS CHECKS

While our empirical setup rules out time invariant endogeneity due to firm-level heterogeneity, time variant endogeneity might be an issue. First, it could be argued that the licensing firm is more likely to cite a relatively higher quality or more relevant technology regardless of whether or not it has licensed the technology. Such technologies also may be more frequently commercialized in the markets for technology, which creates a selection problem and means that backward citations may not reflect the true effect of licensing and subsequent recombination. Second, a licensee might be more likely to license a technology that is in a domain where it is planning to expand technological activities. Licensing efforts might be associated with other measures aimed at improving access to a specific technological area. However, we do not consider this potential problem to be of huge concern since our independent informal organizational variables can only be very indirectly and slowly influenced by the firm's top management team. To deal with the first issue, we performed a robustness check to evaluate the number of citations received by a technology after and before the licensing date, using a conditional difference-in-differences design (Singh & Agrawal, 2011).

The first step in the difference-in-differences analysis is using patent numbers connected to each of the licensed technologies in our sample to identify a corresponding non-licensed technology. We conduct the matching process considering the following characteristics: application year, grant year, main technological class, and number of forward citations to a patent within the first three years after the licensing event. After identifying comparable patents, we computed the total number of citations made by the focal firm to both groups of technologies (licensed and non-licensed) after and before the licensing date. The results (see Table 3) indicate a significant increase in the number of citations received by a licensed technology relative to the number of citations received by the technologies in the control group. When looking at the baseline period, we observe that the patents in the control group received an average number of citations of *0.0042,* while the treatment group was not cited. Using the difference-in-differences approach to examine changes in citation patterns after the licensing date, we see that the average number of citations for the licensed technologies increased to *0.1553* while the control increased to *0.0058*. This result indicates an average net increase of *0.1453* in the number of citations to the licensed technologies.

[Insert Table 3 around here]

We conducted two additional robustness checks (results not reported here for reasons of space). The network literature points to the potential downsides of very high levels of network diversity, tie strength, and density. This suggests that diversity, tie strength, and density curvilinearly moderate the effect of distance on time to knowledge recombination. We investigated this empirically by adding to Model VI (Table 2) the squared values of our measures for network density, average tie strength, and network diversity, and their respective interactions with technological distance. The parameters of the relevant squared variables were statistically insignificant. An alternative explanation for the effect of distance on time to knowledge recombination is related to the fact that distant technologies are perhaps not licensed with the intention of application in a new invention. To address this, we conducted a *t*-test comparing the distance between those observations that experience transition and are cited in a new in-house patent during the time window of our analysis, and those that are not. We found no statistically significant difference between the two groups.

DISCUSSION AND CONCLUSION

We began this study by noting that the theoretical and empirical literature suggests that firms' internal-external recombination speed decreases with the degree of unfamiliarity of the external knowledge. We employed a KBV of the firm lens to propose a theory predicting that firms can develop their capabilities to achieve faster recombination of distant externally developed technologies into their own technology production. We explored several novel mechanisms underlying the KBV's core concepts, distinguishing among their effects on the speed of internal-external knowledge recombination.

This study has important theoretical implications. A key contribution is that it adds an (informal) organizational dimension to the external knowledge sourcing literature. This body of work tends to focus on the relations between the firm and its external sources of innovation and ignore how intrafirm organizational factors support exploitation of external knowledge for innovation. We contribute by explicitly considering the informal organizational structure. Since Burns and Stalker (1961) it has been recognized that the firm's internal organization matters for innovation outcomes. However, Burns and Stalker's study and subsequent work on innovation and strategic management (e.g., Carnabuci & Operti, 2013; Guler & Nerkar, 2012) tend to focus on how internal organization affects the recombination of in-house knowledge for the purposes of innovation but do not consider how it might positively influence the exploitation of external knowledge.

This paper shows that the firm's informal organization affects its ability to exploit externally acquired distant knowledge. We demonstrate the importance of Cohen and Levinthal's (1990) concept of inward-looking absorptive capacity: our arguments and results support the idea that variety of internal knowledge, and coordination of knowledge recombination activities by the firm's inventors are imperative. These aspects of inventors' knowledge networks can be said to constitute the micro-foundations of the firm's inward-looking absorptive capacity. This resonates with recent studies claiming that inventors and their knowledge networks constitute the micro-foundations of the firm's R&D capabilities (Guler & Nerkar, 2012; Nerkar & Paruchuri, 2005; Paruchuri, Nerkar, & Hambrick, 2006).

This study also adds to work on the KBV of the firm by specifying a set of micro mechanisms that underlie its core concepts including firm-internal sources of knowledge variety, ease of knowledge transfer, and coordination of knowledge-intensive activities to avoid wasteful action. We have proposed a set of theoretical mechanisms to explain how intrafirm inventor networks fulfill those three tasks roles and ensure rapid recombination of distant external knowledge into the focal firms' inventions. These mechanisms explain also why diversity provides the *variety* of knowledge need for innovation, why tie strength enables ease of *knowledge transfer*; and why network density serves as the necessary *coordination* device. This increases theoretical understanding of the process of knowledge recombination, and operationalizes the KBV empirically in the important context of invention.

We found empirical support for most of our predictions: intrafirm network diversity and network density positively moderate the relationship between degree of distance between the focal firm's knowledge base and externally acquired knowledge, and speed of recombination of external knowledge into the focal firm's knowledge production for invention output. However, we found the moderating effect of average intrafirm ties among inventors to be insignificant. We have established theoretically that the primary effect of tie strength in the context of invention is to facilitate knowledge transfer, and this insignificance result could be due to Grant's (1996: 114) assertion that "*transferring* knowledge is not an efficient approach to integrating knowledge" (original emphasis). In Grant's view, knowledge transfer *per se* is often redundant and what is important is how to achieve fast recombination through effective coordination of the knowledge transferred (Grant, 1996). In addition, recurring interactions among pairs of inventors might lead to relationships characterized by supportive behavior and extensive bilateral knowledge sharing. However, these relationships are costly, and inventors are generally able to maintain only a few of strong ties. In addition, such ties can induce myopic search behavior (cf. Uzzi, 1997). Thus, the aggregate effect of tie strength may not show a clear direction.

The findings in this paper have implications for managerial practice. They point to the indirect influence of intrafirm network structure on the ability of firms to quickly integrate external knowledge. Thus, managers should pay attention to the collaborative behavior of their employees. Although managers cannot directly control their employees' social interactions, they can assign inventors to temporary projects to foster collaboration between otherwise unconnected employees. Managers need to support inventor network structures in R&D departments to encourage a culture of continuous *effective* knowledge sharing and transfer among inventors and research units.

This paper has some limitations. First, although we took care over the empirical research design, endogeneity problems might still be an issue; however, we hope that the empirical strategy employed reduces concerns over unobserved heterogeneity and omitted variables bias. We employed a frailty estimator in our hazard models, which captures unobserved heterogeneity through the inclusion of a shared gamma mixture specification. We applied a difference-in-differences approach to the relationship between licensing-in and citation patterns to strengthen our claim that licensing is a mechanism that allows firms to acquire external knowledge, and which promotes inventive performance provided the focal firm has an appropriate informal organization.

Although our findings should be generalizable to other high-technology, sectors such as telecommunications, consumer electronics, and computers, industries where invention is complex, future research would confirm whether our proposed theory is transferable to other industries. We focus specifically on the role of intrafirm inventor ties as underlying internal-external recombination speed. However, individual inventors' ties across firm boundaries may also have an impact on the firm's ability to recombine external and internal knowledge (Tortoriello & Krackhardt, 2010; Tushman & Scanlan, 1981). Future research could investigate these external individual ties. In line with the literature, we utilize co-patenting to capture collaboration and knowledge networks (Fleming et al., 2007; Paruchuri, 2010; Singh, 2005). We acknowledge that patent collaborations capture only a subset of the interpersonal ties within a firm, although our focus on inventor networks appears particularly relevant in the context of knowledge recombination and invention. Future work could examine other types of interpersonal ties that go beyond the informal organization. The literature on organization as a determinant of knowledge recombination investigates either the formal (Foss et al., 2011; Jansen et al., 2005) or the informal organization (e.g., the present paper, Carnabuci & Operti, 2013; Guler & Nerkar, 2012). However, informal and formal organization may be complementary in terms of their impact on effective knowledge recombination. For example, it might be that (formal) cross-functional teams complement (informal) network density in relation to the impact on speedy knowledge recombination. We hope that the present paper provides a first step towards exploring this research agenda.

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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	0.823	0.236	1.00										
[2]	Network Diversity	0.637	0.219	0.12	1.00									
[3]	Average Tie Strength	1.723	1.116	-0.03	0.12	1.00								
[4]	Network Density	0.155	0.189	-0.16	-0.52	-0.17	1.00							
[5]	Clustering	2.347	0.873	-0.09	0.09	0.79	0.02	1.00						
[6]	Average Path Length	0.53	1.634	0.20	0.41	0.17	-0.66	0.01	1.00					
[7]	Same Sector	0.388	0.488	0.02	0.02	0.09	0.12	-0.05	-0.23	1.00				
[8]	Co Patent	0.989	0.106	-0.07	0.05	0.05	0.00	0.07	0.02	-0.08	1.00			
[9]	Prior Citations	0.667	3.296	-0.06	-0.01	-0.04	0.16	0.03	-0.12	0.00	0.02	1.00		
[10]	Scientific References	31.487	54.479	-0.04	0.00	0.12	-0.06	0.11	0.05	0.09	0.04	-0.02	1.00	
[11]	Technology Value	54.767	135.985	0.04	0.09	0.02	0.05	0.07	-0.03	0.07	0.03	0.03	-0.02	1.00
[12]	Technological Furnishing	0.627	0.484	0.05	0.14	-0.07	-0.22	-0.08	0.26	0.00	-0.08	-0.07	-0.05	-0.13
[13]	Grant-back Clause	0.253	0.435	0.06	0.03	-0.07	-0.13	-0.19	0.12	0.16	-0.15	-0.04	-0.14	-0.07
[14]	Milestone	0.629	0.484	-0.10	-0.21	0.12	-0.03	0.15	0.08	-0.13	-0.05	-0.04	-0.01	-0.01
[15]	R&D Intensity	119.466	113.908	-0.22	-0.19	-0.02	0.40	0.05	-0.38	0.21	0.10	-0.03	0.08	-0.09
[16]	Slack	188.629	132.908	0.10	0.22	0.36	-0.47	0.21	0.44	-0.06	-0.02	-0.15	0.14	-0.02
[17]	Previous Year Patent	0.962	0.192	0.05	0.40	0.06	-0.29	0.05	0.17	0.07	0.54	0.04	0.05	0.04
[18]	Licensor University	0.105	0.306	-0.04	-0.32	-0.07	0.34	-0.01	-0.28	-0.27	0.04	0.13	-0.04	-0.04
[19]	Licensor Number of Patents	197.154	540.838	-0.22	-0.18	-0.05	0.34	0.00	-0.27	-0.07	0.03	0.05	-0.11	-0.08
[20]	US Firm	0.871	0.335	-0.01	-0.09	0.00	0.19	-0.05	-0.14	0.18	0.04	0.08	-0.11	0.00
[21]	Log(Number Employees)	7.46	2.716	0.22	0.28	0.13	-0.62	0.00	0.68	-0.25	-0.05	-0.15	0.01	0.03
[22]	Early Stage Technology	0.278	0.448	-0.02	-0.12	-0.12	-0.03	-0.20	0.04	-0.04	0.07	0.08	0.04	-0.02

	Variable	Mean	S.D.	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]	[21]	[22]
[12]	Technological Furnishing	0.627	0.484	1.00										
[13]	Grant-back Clause	0.253	0.435	0.13	1.00									
[14]	Milestone	0.629	0.484	-0.01	0.02	1.00								
[15]	R&D Intensity	119.466	113.908	-0.04	-0.20	0.11	1.00							
[16]	Slack	188.629	132.908	0.13	0.11	0.18	-0.28	1.00						
[17]	Previous Year Patent	0.962	0.192	0.11	0.00	-0.06	-0.02	0.12	1.00					
[18]	Licensor University	0.105	0.306	-0.31	-0.17	0.04	0.16	-0.31	-0.32	1.00				
[19]	Licensor Number of Patents	197.154	540.838	-0.06	0.21	0.13	0.03	-0.19	-0.14	0.07	1.00			
[20]	US Firm	0.871	0.335	-0.14	-0.05	-0.07	0.08	-0.20	-0.03	0.03	0.12	1.00		
[21]	Log(Number Employees)	7.46	2.716	0.09	0.15	0.10	-0.67	0.60	0.10	-0.29	-0.18	-0.21	1.00	
[22]	Early Stage Technology	0.278	0.448	-0.11	0.03	0.20	0.14	-0.06	-0.11	0.26	0.00	0.01	-0.06	1

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
Technological Distance		1.723***	1.904***	1.749***	1.275**	1.666***
		(0.604)	(0.527)	(0.600)	(0.528)	(0.493)
Technological Distance x Network Diversity			-15.552***			-9.684***
			(4.987)			(3.083)
Technological Distance x Avg. Tie Strength				0.799		0.647
				(1.366)		(1.051)
Technological Distance x Network Density					-6.849***	-8.056**
					(2.536)	(3.378)
Network Diversity	-3.125	-4.066**	-3.684***	-4.431**	-2.584*	-4.018**
	(2.389)	(1.933)	(1.423)	(1.906)	(1.482)	(1.783)
Average Tie Strength	0.268	-0.001	-0.308	-0.034	0.827**	0.713*
	(0.479)	(0.553)	(0.422)	(0.604)	(0.380)	(0.384)
Network Density	-4.727**	-5.915***	-8.020***	-6.061***	-2.795*	-5.555***
	(2.312)	(2.292)	(1.851)	(2.264)	(1.497)	(1.971)
Clustering	-0.377	0.029	0.601	0.149	-1.265***	-0.136
	(0.629)	(0.764)	(0.610)	(0.852)	(0.490)	(0.541)
Average Path Length	-0.720***	-0.941***	-1.112***	-0.958***	-0.578***	-0.726***
	(0.279)	(0.244)	(0.213)	(0.240)	(0.204)	(0.162)
Same Sector	-0.317	-0.120	0.379	-0.144	-0.273	0.238
	(0.566)	(0.546)	(0.484)	(0.561)	(0.594)	(0.439)
Co Patent	4.630*	7.671***	19.001***	8.957**	5.325*	11.393**
	(2.373)	(2.468)	(4.747)	(3.715)	(2.946)	(5.084)
Prior Citations	-0.005	0.019	0.053	0.017	0.077***	0.027
	(0.050)	(0.045)	(0.043)	(0.045)	(0.028)	(0.028)
Scientific References	0.005	0.005	0.002	0.005	0.002	-0.003
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.008)
Technology Value	-0.010***	-0.009***	-0.009***	-0.009***	-0.010***	-0.012***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Technological Furnishing	-0.094	-0.255	0.058	-0.173	-0.107	0.440
	(0.522)	(0.550)	(0.494)	(0.556)	(0.512)	(0.587)
Grant-back Clause	0.067	0.279	0.578	0.298	0.780*	1.110**
	(0.451)	(0.413)	(0.415)	(0.418)	(0.445)	(0.444)
Milestone	0.966**	1.311***	1.382***	1.329***	0.760*	0.949**
	(0.458)	(0.403)	(0.353)	(0.400)	(0.412)	(0.369)
R&D Intensity	0.007**	0.007***	0.007***	0.006***	0.005***	0.005***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Slack	-0.001	-0.002	-0.003	-0.002	0.001	-0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Previous Year Patent	-4.600**	-5.758***	-15.160***	-6.970**	-3.299	-6.558
	(1.976)	(1.813)	(3.852)	(3.271)	(2.066)	(4.458)
Licensor University	-2.003*	-2.624***	-2.699***	-2.777***	-1.630**	-1.740**
	(1.077)	(0.895)	(0.726)	(0.943)	(0.664)	(0.696)
Licensor Number of Patents	0.001**	0.001***	0.001**	0.001***	0.001**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
US Firm	-1.488	-1.204	-0.137	-1.112	-1.803	2.150***
	(1.206)	(1.138)	(1.082)	(1.184)	(2.178)	(0.794)
Log(Number Employees)	0.792***	0.982***	1.020***	1.000***	0.522***	0.618***
	(0.280)	(0.239)	(0.226)	(0.239)	(0.184)	(0.156)
Early Stage Technology	0.457	0.579	1.085*	0.640	1.219**	2.277***
	(0.530)	(0.512)	(0.577)	(0.507)	(0.562)	(0.708)
Therapeutic areas						
Alimentary tract and metabolism (baseline)						

Blood and Blood Forming Organs	2.003	0.858	-0.461	0.779	1.655	-0.192
	(1.230)	(1.229)	(1.345)	(1.282)	(1.313)	(0.879)
Cardiovascular System	4.315***	3.857***	3.163**	3.910***	1.448	1.237**
	(1.164)	(1.050)	(1.287)	(1.041)	(0.942)	(0.624)
Dermatologicals	2.436*	2.422*	2.291*	2.495*	0.976	1.125
	(1.307)	(1.320)	(1.324)	(1.356)	(1.051)	(0.967)
Genito Urinary System and Sex Hormones	2.885**	2.252*	2.215*	2.283*	3.010***	2.478***
	(1.269)	(1.258)	(1.244)	(1.256)	(1.121)	(0.797)
Systemic Hormonal Preparations	1.890*	1.117	0.911	1.069	0.077	-0.667
	(1.035)	(1.043)	(1.178)	(1.030)	(1.043)	(0.750)
Anti-infectives for Systemic Use	0.215	-0.558	-0.710	-0.547	-1.796**	-1.583**
	(1.167)	(1.013)	(1.115)	(1.000)	(0.761)	(0.640)
Antineoplastic and Immunomodulating Agents	3.212***	2.576***	1.899*	2.589***	1.145	0.331
	(1.080)	(0.972)	(1.137)	(0.956)	(0.976)	(0.672)
Musculoskeletal System	0.702	-0.410	-1.108	-0.445	0.542	-0.526
	(1.545)	(1.599)	(1.671)	(1.561)	(1.397)	(1.312)
Nervous System	4.221***	3.835***	3.371***	3.870***	1.611	1.142
	(1.223)	(1.174)	(1.232)	(1.207)	(1.008)	(0.968)
Respiratory System	2.177*	1.135	0.004	1.061	-0.873	-2.591**
	(1.205)	(1.130)	(1.381)	(1.120)	(1.391)	(1.090)
Sensory Organs	1.102	-0.265	-1.502	-0.327	-0.441	-3.242***
	(1.306)	(1.322)	(1.577)	(1.316)	(1.621)	(1.242)
Miscellaneous	1.584	1.007	0.280	1.124	-0.798	-1.791***
	(1.008)	(0.992)	(1.384)	(1.006)	(1.210)	(0.664)
Firm Sector						
Biotech (baseline)						
Pharmaceutical	-0.447	-0.602	-0.193	-0.543	-0.227	0.433
	(0.672)	(0.653)	(0.688)	(0.687)	(0.704)	(0.593)
Medical Devices	11.267**	9.775**	11.015**	9.684*	14.589***	17.674***
	(5.419)	(4.929)	(4.966)	(5.019)	(4.103)	(4.107)
Constant	-2.121	-5.940	-10.776***	-6.461	0.592	-7.900**
	(4.305)	(4.478)	(3.221)	(4.604)	(3.939)	(3.316)
log(G) constant	-0.560***	-0.589***	-0.762***	-0.596***	-0.939***	-1.237***
	(0.178)	(0.147)	(0.169)	(0.154)	(0.193)	(0.268)
log ((-)) constant	1.589***	1.645***	1.834***	1.652***	1.931***	2.139***
	(0.248)	(0.223)	(0.234)	(0.225)	(0.225)	(0.204)
Number of observations	708.000	708.000	708.000	708.000	708.000	708.000
Log-likelihood	-370.332	-366.031	-360.525	-365.836	-364.185	-357.795
Chi2	112.778***	121.380***	132.392***	121.770***	125.071***	137.852***
Likelihood ratio comparison		8.602***	19.614***	8.992***	12.293***	25.074***

*p<0.10, ** p<0.05, *** p<0.01

Table 3. Difference-in-Differences Estimators (N=708)

	Average number of citations received from the licensee		
	Base line	Follow up	
	Subsample mean:	Subsample mean:	First difference (row):
Focal Patents	All cites= *0*	All cites=*0.1553*	All cites=*0.1553*
Control Patents	Subsample mean:	Subsample mean:	First difference (row):
	All cites=*0.0042*	All cites=*0.0058*	All cites=*0.0016*
	First difference (column):	First difference (column):	Difference in differences:
	All cites=-*0.0042*	All cites=*0.1495******	All cites=*0.1453******

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

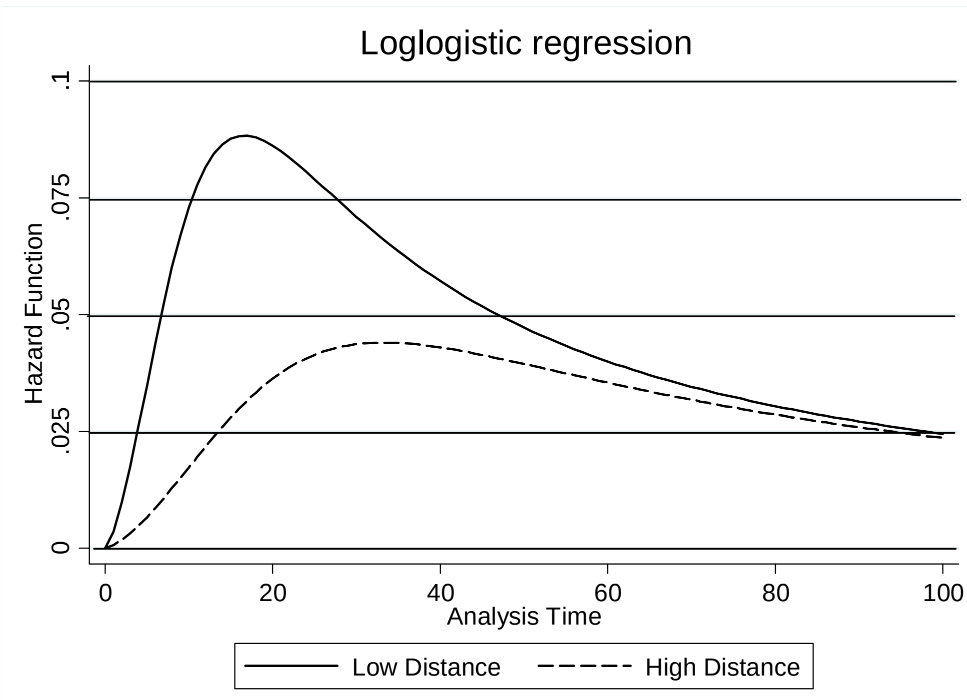

Figure 1. Estimated Hazard Functions of Small versus Large Distance Licensed Technologies