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Utilizing the Knowledge of New Technological Talent: How Prior Ties Between New Talent and Current Employees Help

Vivek Tandon
National University of Singapore
Strategy and Policy
vtandon@nus.edu.sg

Gokhan Ertug
Singapore Management University
Strategy and Organisation
gokhanertug@smu.edu.sg

Abstract

The mobility of knowledge workers can be a major source of knowledge acquisition. However, hiring firms are not very good at utilizing the knowledge of their recent hires. Researchers have highlighted path dependence and technological distance as two knowledge-based problems that make it more difficult for hiring firms to use new hires? knowledge. We suggest that prior ties between the recent hires and current employees of the hiring firm can provide mechanisms to address these problems, resulting in the hiring firm?s making more use of the knowledge of recent hires. We also propose that the mechanisms through which prior ties address these two knowledge-based problems differ and have different implications for how far the hires? knowledge travels within the firm. We develop these ideas and test our hypotheses using patent data in the electronics and electrical goods industry in the US.

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The mobility of knowledge workers can be a major source of knowledge acquisition. However, hiring firms are not very good at utilizing the knowledge of their recent hires. Researchers have highlighted path dependence and technological distance as two knowledge-based problems that make it more difficult for hiring firms to use new hires' knowledge. We suggest that prior ties between the recent hires and current employees of the hiring firm can provide mechanisms to address these problems, resulting in the hiring firm's making more use of the knowledge of recent hires. We also propose that the mechanisms through which prior ties address these two knowledge-based problems differ and have different implications for how far the hires' knowledge travels within the firm. We develop these ideas and test our hypotheses using patent data in the electronics and electrical goods industry in the US.

INTRODUCTION

The mobility of knowledge workers is considered to be a major source of knowledge acquisition (Agarwal, Ganco, and Ziedonis, 2009; Almeida and Kogut, 1999). However, an emerging stream of research has shown that hiring firms are not very good at utilizing the knowledge of their recent hires (Singh and Agrawal, 2011; Song, Almeida, and Wu, 2003; Tzabbar, 2009). Even when the knowledge of recent hires is used, such use is localized. The users of the knowledge of recent hires tend to be these hires themselves or their immediate collaborators in the hiring firm. As a result, the knowledge of recent hires – which has the potential to be a major source of new knowledge for the hiring firm – ends up seeing little and localized use in the hiring firm.

Researchers have highlighted path dependence and technological distance as two knowledge-based problems that make it more difficult for the hiring firm to utilize new hires' knowledge (Cohen and Levinthal, 1990; Song et al., 2003; Tsai, 2001). However, little is known about the mechanisms that might help firms overcome these two challenges. We suggest that pre-existing ties between the recent hires and current employees of the hiring firm can provide mechanisms to address these problems. Connections between people serve as conduits of knowledge, and also facilitate coordination and the development of trust (Ahuja, 2000; Borgatti and Cross, 2003; Hansen, 1999). As a result, pre-existing ties could influence how much and how far a new hire's knowledge diffuses within and is used by employees of the hiring firm.

While connections between people can facilitate knowledge transfer in general, we propose that the specific mechanisms by which they might help address the two knowledge-based problems are different. An investigation of these mechanisms would allow us to identify the boundary conditions of the efficacy of pre-existing ties on how much and how far the knowledge of recent hires travel in the hiring firm. While research on social networks provides arguments and evidence about the mechanisms at play, how these mechanisms address the two specific knowledge transfer problems we highlight, and therefore allow a hiring firm to make more use of a recent hire's knowledge, are not as well documented.

We develop a framework based on the mechanisms through which pre-existing ties between recent hires and current employees address the problems of path dependency and lower absorptive capacity for technologically distant knowledge, thereby enabling the hiring firm to make greater and more widespread use of the recent hires' knowledge. In particular, we suggest that matching and knowledge-transfer are two mechanisms facilitated by pre-existing ties that can help address the problems of path dependency and technological distance. Matching is the process by which a recent hire is matched with and joins particular projects in the firm, whereas knowledge transfer is the propagation of the recent hire's knowledge to other employees in the firm.

We start with the baseline prediction that pre-existing ties have a positive relationship with the hiring firm's use of the recent hire's knowledge (H1). In addition, because the problems of new knowledge utilization are more acute under path dependence and technological distance (Song et al., 2003; Tsai, 2001), pre-existing ties should matter more when the hiring firm is more path-dependent and when the recent hire's knowledge is farther away from that of the hiring firm (Sorenson, Rivkin, and Fleming, 2006) (H2 and H4). Prior ties can address the problem of path dependence by improving the match between the recent hire and R&D projects and research streams in the hiring firm (Castilla, 2005). As separate from this mechanism, prior ties can help alleviate absorptive capacity constraints both by making existing scientists more aware of the recent hire's knowledge as well as by assuring the cooperation of the recent hire (Bowler and Brass, 2006; Hansen, 1999; Reagans and McEvily, 2003; Tsai, 2002). Finally, we test the further implications of these suggestions. First, since path-dependent firms are more likely to use knowledge when it is aligned well with their existing paths, the role of pre-existing ties in these firms is to match recent hires with appropriate projects in the firm (Levinthal and March, 1993; Song et al., 2003). As a result, in path-dependent firms, the role of prior ties would be most evident in projects that the recent hires themselves are a part of, since this suggests that matching has been performed (H3). Second, since lack of absorptive capacity for technologically distant knowledge is especially relevant when the recent hire is not directly available, the knowledge exchange and cooperation that are facilitated by pre-existing ties will be most evident in projects that the recent hires are not a part of (H5).

Using data pertaining to inventive activity in the Electronics and Electrical goods industry between 1985-2000, resulting in a sample of 281 firms, 27,310 patents, and 11,506 inventors who have changed firms, we find support for our predictions. We also undertake additional analysis, by distinguishing R&D projects that are undertaken in the firm soon after the hire joined the firm from later projects, to test further implications of the mechanisms we highlight. These analyses also yield results that are consistent with our framework.

THEORY & HYPOTHESES

Knowledge spillovers are an important source of new ideas that make a firm's R&D efforts more productive (Jaffe, 1986). Mobility of R&D workers from other firms has been recognized as a potentially important source of such spillovers (Almeida and Kogut, 1999; Rosenkopf and Almeida, 2003). R&D workers from other firms bring in new ideas, enabling a focal firm to mitigate its myopia. This is based on the realization that much of technological knowledge is tacit and requires face to face interaction to be transferred. Initial examinations of this idea focused on demonstrating that knowledge-spillovers were an important determinant of a firm's R&D productivity and that "learning from hiring" was indeed an important mechanism for firms to overcome their myopia and renew their organizational capabilities (Jaffe, Trajtenberg, and Henderson, 1993; Rosenkopf and Almeida, 2003).

However, a growing stream of research demonstrates that the promise of "learning through hiring" is realized only partially, because the knowledge of hired workers ends up being quite sticky and does not spread far within the hiring organization (Singh and Agrawal, 2011; Song et al., 2003; Tzabbar, 2009). A number of reasons that might be responsible for this have been suggested, both organizational and knowledge based. Our focus is on the knowledge-based causes. Two primary knowledge-based reasons prevent a firm from making greater use of a hire's knowledge: (i) the tendency to persist with current research trajectories (i.e. path dependence) (Dosi, 1988; Levinthal and March, 1993; Song et al., 2003) and (ii) the difficulties involved in making use of technologically distant (i.e. lack of absorptive capacity) (Dosi, 1988).

Path dependence is an enduring characteristic of R&D activity in firms (Dosi, 1988). Firms follow particular technological paths, where future research projects largely depend and build on past research projects (Cyert and March, 1963). Prior commitments in learning, routines, and physical assets make changing a given path costly and make continuing with the current path more profitable in the short term (Levinthal and March, 1993). The temporal interdependence in research projects also suggests that fixed investments can be better amortized over future endeavours in similar – path dependent – areas. As a result, the use of recent hires' ideas becomes more costly, difficult, and therefore unlikely, unless it is clear that their ideas do not disrupt existing trajectories (Song et al., 2003). Alignment of recent hires' knowledge with the existing technological paths of the firm is thus an important factor that influences the use of the recent hire's knowledge.

A related but distinct roadblock in making use of the knowledge of a recent hire is the distance of such knowledge from the current knowledge base of the firm's existing R&D

scientists[1], and thus the unfamiliarity of the current employees of the firm with such new knowledge (Cohen and Levinthal, 1990). Unfamiliarity implies that current scientists are less aware of the new knowledge and have a lower capacity understand that knowledge (Ahuja and Lampert, 2001; Fleming, 2001; Levinthal and March, 1993). This lack of understanding increases the risks of failure in assimilating the new knowledge, thereby inducing resistance to its use. This roadblock can be alleviated by mechanisms that ensure a good flow of knowledge and help from those who are more familiar with the new knowledge (i.e. the recent hires themselves) to current scientists. Access to and cooperation from recent hires is therefore critical (Hansen, 1999, 2002).

We now examine in depth how prior ties between the recent hire and other scientists in the firm provide mechanisms to overcome these two roadblocks.

Main Effect of Prior Ties

A recent hire's prior ties with other (i.e. currently employed) scientists in the hiring firm are likely to increase the usage of the recent hire's technological ideas, by reducing the knowledge-based obstacles (path-dependence and technological distance) we have discussed. Connections, as captured by prior ties, serve as conduits of knowledge and information that enable the recent hire and his[2] knowledge to be better known within the hiring organization (Nerkar and Paruchuri, 2005; Paruchuri, 2010). This fosters greater diffusion of the recent

[1] This roadblock differs conceptually from the one arising from path dependence. Specifically, it pertains to lack of awareness and understanding of the new technology. However, path dependence can create roadblocks for adoption even for new knowledge that the scientists understand, if the new technology is not aligned well with the firm's research streams. Consider a case where different electronic products of a firm communicate using a particular firm-specific protocol of communication. Although a new electronic component with similar technology, but following a different protocol of communication, may be easily understood by the firm's scientists, it may still not be easily incorporated without considerable modification because its protocol of communication is incompatible with the firm's past trajectory. This is not a case of the firm's scientist not understanding the new component but rather the new component not fitting well with the firm's existing research trajectory. It is true that the more distant the new technology, the less likely it is to fit with the existing research trajectories, thus making it essential to control for both path dependence and technological distance in empirical tests.

[2] "He", "him", and "his" has been used instead of "he/she", "him/her", "his/her" and "himself/herself" for reasons of brevity and not to specify any gender. These pronouns should be understood to be gender neutral.

hire's knowledge and ideas within the hiring firm, thereby mitigating the problem of lack of awareness.

Not only do prior ties increase the awareness of the hired scientist's knowledge in the firm, but they also provide mechanisms that facilitate the cooperation and active involvement of the hired scientist (Hansen, 1999; Uzzi, 1997). The presence of prior ties (i.e. relationships) are more likely to lead to deep knowledge sharing and mutual helping, through social mechanisms such as engendering social obligations, reciprocity, and trust (Bowler and Brass, 2006; Cross and Sproull, 2004; Reagans and McEvily, 2003). These mechanisms increase the hired scientist's willingness to cooperate and actively assist while also increasing the existing scientists' willingness to use the knowledge brought in by the hired scientists (since they believe that help is at hand). The advantages that prior ties bring with respect to awareness and cooperation, as we briefly outline, mitigate the problem of technological distance and thus increase the use by a hiring firm of a recent hire's knowledge.

Prior ties between the recent hire and current employees of the hiring firm also help better match the recent hire with the hiring firm's current research (Castilla, 2005). These ties help inform the hiring firm's managers about the skills and knowledge that the recent hire brings to the firm. Such prior ties also help inform the recent hire of the various research projects already underway or being started in the firm. This bidirectional information flow increases the quality of the match between the recent hire and the R&D projects within the firm (Erickson, 2001). In other words, it increases the chances that the recent hire is matched with a project that is more likely to use his skills and knowledge. Such matching mitigates the problem of path dependence in keeping a firm from using a recent hire's knowledge, since the recent hire can be made part of projects that align best with his knowledge.

Thus, we predict,

H1. The number of prior ties of the hired scientist in the hiring firm is positively associated *with the usage of the hired scientist's knowledge in the hiring firm.*

Role of Prior Ties in overcoming Path Dependence

A firm's path-dependence in its R&D implies that the firm's future research projects are likely to build on the knowledge the firm has already accumulated through its past projects. Such an inclination reduces the costs and uncertainty of conducting R&D, while also making the routines and products of path dependent firms more standardized. As such, the incentives to use new technological ideas that might disrupt or deviate from the firm's current research are likely to be lower the more path dependent a firm is (Levinthal and March, 1993; Song et al., 2003). Conversely, a recent hire's knowledge is more likely to be used in a path dependent firm when that knowledge complements and aligns well with the current research in the firm.

Prior ties between the recent hire and other employees in the hiring firm improve the quality of such alignment (Erickson, 2001) and should thereby increase the usage of the hire's knowledge. Prior ties, by improving the two way communication between recent hires and other scientists in the firm, inform both parties of possible complementarities and the match between the new hires' knowledge and the hiring firms' current research streams. The thicker and wider the communication, the greater is the probability of a better match (Hansen, 1999; Tsai, 2001). As a result, a recent hire who has more prior ties with employees in the hiring firm is more likely to be matched to projects where his knowledge is complementary to the existing knowledge in the firm, creating better alignment with the research trajectories in the firm. Because this alignment becomes more important the more path dependent a firm is, we expect prior ties to be more helpful as a firm's path dependence is higher. Thus, we predict:

H2. The greater the path dependence in R&D exhibited by the hiring firm, the stronger the positive association between the number of prior ties of the hired scientist in the hiring firm and the usage of the hired s*cientist's knowledge in the firm*.

One implication of the matching mechanism is that when path-dependence is higher, prior ties will be less important in facilitating the use of a recent hire's knowledge in projects that the recent hire is not a part of. This is because if the match between a recent hire's knowledge and research projects is good, then the alignment between his knowledge and the research projects that he is not a part will be low.

For simplicity consider two potential projects within the hiring firm, "A" and "NA" (corresponding to "aligned" and "not aligned" respectively). The "A" project aligns well with the hire's knowledge, while "NA" does not. When the matching process is good, the recent hire is made a part of "A" and not a part of "NA". The project he is not a part of is less aligned with his knowledge in this case. Conversely when the matching process is bad, the recent hire is made a part of "NA" and in this case, the project that he is not a part of, i.e. "A", is better aligned with his knowledge. In other words, the better the "matching" mechanism, the less likely that the recent hire's knowledge is aligned with research projects he is not a part of. Since prior ties are associated with better matches, a larger number of prior ties would therefore make it more likely that the recent hire's knowledge is less aligned with projects he is not a part of.

Since such alignment becomes more important for the use of his knowledge where a firm is more path-dependent, the impact of prior ties in path-dependent firms will be weaker in projects that the hired scientist is not a part of. Thus we predict:

H3. The impact of prior ties in facilitating the usage of hired scientist's knowledge in path dependent firms will be weaker when the scientist is not on the research project.

Role of Prior Ties in overcoming Technological Distance

Another reason why a recent hire's knowledge might be used less by the hiring firm is the distance of his knowledge from that of the firm (Ahuja and Lampert, 2001; Rosenkopf and Almeida, 2003). Knowledge distance creates problems based on reasons that are conceptually different from the unwillingness that is due to path dependence. Improving the match between the hire's knowledge and the firm's research trajectories is less relevant to addressing these problems. Indeed, the more distant the knowledge of a recent hire, the lower the chance that such knowledge can "fit" any research trajectory of the firm regardless of the quality of the matching mechanism. Thus distant knowledge is more likely to be used in exploratory endeavors (Ahuja and Lampert, 2001; Argyres and Silverman, 2004; Rosenkopf and Nerkar, 2001; Taylor, 2010). The primary issues that keep a firm from exploring distant knowledge are twofold: a lack of awareness about its potential applications and the risks of failure faced by the firm's employees in using it (Levinthal and March, 1993; Unsworth and Clegg, 2010).

The greater the technological distance between the recent hire's knowledge and the knowledge used by other employees in the hiring firm, the greater is the likelihood that these employees are less aware of the possibilities that the new hire's knowledge offers (Cohen and Levinthal, 1990). Given the vast and ever increasing amount of technological knowledge and their own cognitive boundaries, researchers focus most of their attention to developments close to their existing expertise (Ahuja and Lampert, 2001; Levinthal and March, 1993). Consequently, their awareness of the possibilities that distant technologies imply is inevitably limited.

Beyond this awareness problem, the technological distance of a recent hire's knowledge to the knowledge of the hiring firm also increases the uncertainty and risks of using that knowledge by others in the hiring firm (Ahuja, Lampert, and Tandon, 2014; Fleming, 2001). The lack of a complete understanding due to distance increases the likelihood of encountering obstacles while experimenting with the unfamiliar technology. These obstacles in turn increase the resistance to utilizing the new hire's knowledge in one's own work (Fleming, 2001). However, this resistance might be reduced when employees of the hiring firm have some assurance that they will be able to contact the recent hire for clarification and assistance and that the recent hire will actually co-operate when asked for help (Cross and Sproull, 2004; Hansen, 1999).

Prior ties between the recent hire and other employees of the hiring firm facilitate the use of the recent hire's knowledge by increasing awareness of his knowledge across the hiring firm and by making access to and the cooperation of the recent hire more likely. By serving as conduits of knowledge, the recent hire's prior ties to others in the hiring firm increase the awareness of his knowledge across the firm (Borgatti and Cross, 2003). In addition, prior ties also provide social mechanisms such as the possibility of social sanctions, reciprocity, and the emergence of trust (Burt and Knez, 1995; Coleman, 1988), which make the cooperation of the recent hire more likely (in helping employees of the hiring firm resolve the problems they encounter in using his knowledge).

As we have discussed, awareness of the knowledge in the first place and assurance of help become increasingly important as the recent hire's knowledge is more distant from the knowledge used in the hiring firm. Thus, we predict:

H4. The greater the technological dis*tance between the hired scientist's knowledge and the* knowledge used in the hiring firm, the stronger the positive association between the number *of prior ties of the hired scientist in the hiring firm and the usage of the hired scientist's* knowledge in the firm.

The mechanisms we discuss through which prior ties help mitigate the problem of technological distance (i.e. increasing awareness of knowledge and social mechanisms to facilitate cooperation) will be of greater importance when the recent hire himself is not on the project. If the recent hire is already a part of the project, then the impact of prior ties on increasing awareness is not as important – since the recent hire's presence ensures the awareness of his knowledge. In addition, the social mechanisms that would facilitate the recent hire's cooperation are also less relevant, since the recent hire will be directly affected by the rewards (costs) of success (failure) of the project, which incentivize his cooperation.

As a result, we expect that the impact of prior ties on overcoming technological distance would be weaker (stronger) in projects that the hired scientist is (is not) himself a part of. We therefore predict:

H5. *The impact of prior ties in facilitating the usage of hired scientist's knowledge* when the *scientist's knowledge is technologically distant from the firm's knowledge* will be stronger when the scientist is not on the research project.

While we do not hypothesize about the speed with which the recent hire's knowledge might used in the hiring firm, the mechanisms of matching and knowledge transfer we highlight are likely to differ in how fast they operate. Matching involves the inclusion of the hire into appropriate projects and is likely to take time. This is because it requires greater transfer of knowledge as well as the establishment of trust and deeper evaluation, to enable and be assured of proper matching. As a result, the impact of prior ties in facilitating a better match in path dependent firms is likely to surface after a period of time. Therefore the relationship hypothesized in H2 is likely to be stronger in later time periods after the hire's joining. On the other hand, the impact of prior direct ties in facilitating the usage of a recent hire's knowledge by mitigating technological distance is likely to occur faster, since it mainly involves increasing awareness about his knowledge and providing assurance of his cooperation should a problem surface. So we would expect little difference in the strength of the relationships hypothesized in H4 between earlier and later time periods after the hire's joining. While we do not formally hypothesize these, we do conduct additional analyses to see if this is the case.

METHODS

Data and Sample

Following previous work that studies learning by hiring we examine the inventive activity of scientists using patent data. To be able to study the use of knowledge brought in by recent hires, we need to measure the knowledge brought in by the hires, the flow of knowledge across projects, and the mobility of inventors across firms. Patent data have significant strengths in allowing us to create measures of knowledge possessed by inventors at the time of moving into a firm (by tracking their inventive activity before the move), to identify the movement of inventors across firms (by observing their inventive activity in different firms across time), and to track the flow of knowledge through citations between patents. Patent data also have limitations, which we note and acknowledge as limitations in our discussion section.

Not all inventive activity is reflected in patent data and industries differ in their proclivity to patent. To reduce this concern we limit our study to only one industry. We use COMPUSTAT data to identify public firms that list SIC 36 as their main line of business. SIC 36 corresponds to Electronics and Electric goods sector. We choose this particular sector because R&D activity, patenting, and learning from knowledge spillover are all important in this sector.

Our empirical strategy involves examining the extent to which each patent filed by each of these firms uses the knowledge brought in by each recently hired scientist, where "recently" is defined as scientists hired anytime between the year of the application of the patent to five years before this application year. Accordingly, the unit of analysis is a "patent"-"recent-hire" pair, where the patents are those filed by a firm in the years it is publicly listed and the recent-hires are those who are observed to move to the firm anytime within the five years preceding the year of application. Consider a firm that files 10 patents in year "t". Also assume that 20 inventors (i.e. movers) move to the firm in the preceding 5-year period (years t-5 to t inclusive). We examine to what extent to each of these patents build on the knowledge brought in by each of these movers who moved in recently. Thus there are 10x20 = 200 observations corresponding to these 200 unique patent-mover pairs, with the dependent variable being a measure of how much a specific patent uses the knowledge brought in by a specific mover.

We construct our measures by building a complete patenting history of these firms using the NBER patent data from 1980 to 2006. Because we need information about the inventive activity prior to our observations, we conduct our analysis on focal patents whose year of application is greater than or equal to 1985. Additionally, the lag between patent application and approval implies that the patent data at the end of the period for which NBER data are available may be curtailed. So we limit our analysis to focal patents whose year of application is less than or equal to 2000.

Mobility Events

To track the mobility of inventors between firms, we use the data provided by NBER patent project to match patents with firms. We use the data provided by Lai et al (2009) to match inventions to individual inventors. We define mobility events by identifying cases where two consecutive patents by the same inventor are filed in different firms. We follow the current literature (e.g., Singh and Agrawal, 2011) and assume the mid-point of the two dates of application (in different firms) as indicating the time of the move. This assumption is likely to lead to greater inaccuracy (as compared to the actual date of the move) as the time difference between the two patent applications increases. Accordingly, we follow Singh and Agarwal (2011) to use only those two consecutive patents that are not more than four years apart (and that are assigned to different firms, but are by the same inventor) to identify mobility events. We treat the moving inventor as affiliated with the destination firm for the entire year of the move. To minimize the possibility of identifying false moves, we also drop all cases where the inventor was observed to move more than once in the same year.

We are investigating the impact of a recent hire's prior connections with other inventors in the hiring firm on the extent to which a patent by the hiring firm uses the recent hire's knowledge. To do this, we need to affiliate inventors with firms. We used patent data to arrive at these affiliations. As before, since a patent does not connect an inventor with a firm indefinitely, we assume that an inventor is affiliated with a firm from two years before the filing of a patent in a firm to two years after this filing, unless a mobility event occurs in this interval. The four-year window is consistent with the window we use to identify mobility events, which in turn is consistent with the heuristics employed by prior literature using patents to identify moves of inventors (Singh and Agrawal, 2011). Using these heuristics for identifying the movement of inventors and their affiliation to firms, we build the career history of all inventors in our dataset.

Variables

Dependent variable. The dependent variable in our study, KnowledgeUsed, measures the extent to which a patent of the hiring firm uses the knowledge of a recently hired inventor. To arrive at this measure, we first construct a variable to proxy for the knowledge that the hire brings into the destination firm at the time of his entry into the firm. The knowledge that the inventor brings to a firm is broader than the technological ideas that he himself has invented. In particular, such knowledge also includes the set of ideas that he has used in creating his inventions, since those ideas are used in creating his inventions. Thus, we modify the firm-level measure developed by Yang et al. (2010) to define the hire's knowledge pool to be the union of two sets: (a) set of patents that have been filed by the inventor in the five years preceding the mobility event, not including the year of the move, and (b) the set of patents cited by those patents defined in (a), which are the backward patent citations of the patents filed by the inventor. Once this knowledge pool for an inventor has been defined, KnowledgeUsed is the number of citations made by a focal patent to this knowledge pool.

Independent variables. Our study's main independent variable, PriorTies, measures the number of prior ties of the recent hire in the hiring firm. To construct this measure we first identified the inventors that the hire has co-invented with during the five-year period before the move. From within this set of inventors, we then count those inventors who are affiliated with the hiring firm at the time the recent hire joins the hiring firm. In doing this, we count only those co-inventors who meet two conditions: (a) they should have been affiliated with the hiring firm before the year of the recent hire's joining and (b) they should be affiliated with the hiring firm for any year from the year of the recent hire's joining to the year of a focal patent's application. These conditions ensure that we do not count co-inventors who might have joined the firm after the focal hire and thus would not substantively correspond to our construct of prior ties. The count of the recent hire's co-inventors who meet these two conditions is the main independent variable of PriorTies.

In H2 and H4, we predicted that the impact of prior ties would be stronger in path dependent firms and when the recent hire's knowledge is more distant from that of the hiring firm, respectively. We construct the variable PathDependence to measure the path-dependence of the hiring firm. We follow Song et al (2003) to measure PathDependence as the extent to which the hiring firm depends on its own knowledge, instead of external knowledge, for its inventive activity. Specifically, the variable measures the ratio of the number of backward self-citations (backward citations to patents of the same firm) to the total number of backward patent citations used by the firm's patents in the five-year window preceding the filing year for a focal patent. The higher this ratio, the more path-dependent a firm is, as based on its citation patterns during the previous five years.

We measure the technological distance of the recent hire's knowledge from that of the firm at the time of joining, TechDistance, by comparing the technological subclasses associated with the hire's patents with the subclasses associated with the firm's patents. The USPTO associates each patent with different technological subclasses, which refer to different technologies involved in the invention. We calculate a weighted average distance between the list of technological subclasses that the hire's patents are associated with and the subclasses that the hiring firm's patents are associated with, taking the number of patents associated with each class as weights. For this purpose, we compare the patents in the hire's knowledge pool (as previously defined) with the patents filed by the firm in the five-year period preceding (but not including) the application year of a focal patent. This enables us to calculate the distance between the hire's knowledge at the time of joining and the knowledge of the hiring firm one year before the application year of a focal patent. We describe the construction of the TechDistance variable in greater detail in Appendix A.

Control variables. We control for a number of factors in our specifications. We calculate the log of the assets (one year lagged), Firmassets, to control for the size of the firm. The use of knowledge of an external source such as a recent hire could also depend on the volume and quality of the firm's own as well as the recent hire's knowledge base. Thus we control for the cumulative number of patents and the cumulative number of forward citations to the patents of the hiring firm as well as those of the recent hire (Hire cumulative patents, Hire cumulative cites, Firm cumulative patents, Firm cumulative cites). These measures are lagged by one year and logged. The firm's usage of a recent hire's knowledge can also be influenced by that individual's centrality in the network of co-inventors. We therefore control for the network size of the recent hire (as defined by the unique number of co-inventors of the recent hire in the three years before a given year, i.e. by using a three-year moving window that is lagged by one year), Hire network size. Furthermore, the time the recent hire spends in the new firm might be related to his influence in the firm. Thus we control for Years in firm, the number of years between the year of move and the year of application of a focal patent. Furthermore, because a patent might be more likely to use the knowledge of the recent hire if more of this hire's prior ties are on the patent itself, we also control for the number of the recent hire's prior ties whose names appears on a focal patent (again we use a logged value of this variable), labeled Number of ties on patent.

The hiring firm's overall tendency to build on earlier work or develop more original work can also influence a patent's use of the knowledge base of a recent hire. Similarly, the technological distance between the hiring firm's knowledge and the source firm's knowledge (i.e. the firm from which the recent hire joins the current–hiring–firm) can also influence the use of hire's knowledge. We thus account for the average tendency of the firm to build on prior knowledge by including a measure of the average number of backward citations per patent by the firm in previous five years as a control, which we label *Firm's tendency to cite* patents. We also include *Firm's distance from source firm*, a measure of technological distance between the hiring firm and the source firm (calculated in a similar manner to the individual level technological distance described previously and detailed in Appendix A) as a control.

The likelihood that a focal patent by the hiring firm uses a recent hire's knowledge might also be related to the hiring firm's desire to move into a technological area that the recent hire happens to be an expert in. This relationship might also be correlated with the decision to bring in the recent hire to the firm in the first place. It is thus important to control for this factor. Accordingly, we measure the extent to which the hiring firm's technological strategy was shifting towards the recent hire's areas of expertise at the time of joining the firm. To calculate this, we first measure the proportion of the hiring firm's patents in the technological subclasses associated with the recent hire's patents for each year in the five-year period preceding the recent hire's year of joining the firm. We then calculate the average change in this proportion over the five-year period to measure the strategic thrust of the firm with respect to the recent hire's expertise, labeled *Firm's shift to hire's expertise*.

Specification

We test our hypothesis by examining the extent to which each patent of the hiring firm cites the knowledge pool of a specific recent hire (where a recent hire is defined as one who joins the firm in the previous five years - in other words we study the degree to which each patent filed by the firm in, say, 2000 makes use of the knowledge of each inventor hired by the firm between 1995 and 2000). The analysis is done at the level of the "patent"-"recent-hire" pair (If a firm has 3 patents filed in 2000, and a total of 10 inventors joining the firm between 1995 and 2000, this would yield 30 observations for the firm in 2000 – 10 recent hires for each patent. As we note later, we incorporate patent-fixed effects in all our estimations to account for any patent-specific [i.e. research project specific] unobserved heterogeneity). We regress the main independent variable, PriorTies, on the dependent variable, KnowledgeUsed, to test our baseline hypothesis (H1). To test whether prior ties have a stronger impact in path dependent firms (H2) and when the recent hire's knowledge pool is technologically far from the hiring firm's knowledge (H4), we interact PriorTies with PathDependence and with TechDistance respectively.

To test the different implications of the two mechanisms for whether the impact is greater or smaller in projects that the recent hire is not a part of (H3 and H5), we construct a dummy variable, Hireabsent, which is 1 if the recent hire is not a part of the team of inventors for a focal patent and 0 if the recent hire is a part of that team. As expected, the sample of "patent"-"recent-hire" pairs where the recent hire is not the part of the inventing team is overwhelmingly larger than the sample where the recent hire is a part of the team. We conduct two sets of tests for H3 and H5. First, we reduce the sample to observations where the recent hire is not a part of the patent and run the same regressions as before and compare the coefficients of the two-way interactions with the full sample. Second, we also create two three-way interactions by constructing PriorTies X PathDependence X Hireabsent and PriorTies X TechDistance X Hireabsent, along with the associated two way interactions with Hireabsent, to run the regressions on the full sample. The coefficients of the three-way interactions are then interpreted to test the impact of the presence (or absence) of the recent hire from the research project (patent) in question.

Since our dependent variable is a count variable, we use Poisson regressions with robust standard errors. The Poisson model with robust standard errors is robust to misspecifications and is suitable for the non-negative and discrete nature of our dependent variable.

To control for unobserved heterogeneity associated with the nature of the research project (e.g. the importance of the project for the firm as well as any other factors that might be related to a given focal patent) we use patent fixed effects in all the specifications.

The Poisson model is of the following form: E[Y] = $e^{\beta X}$. This is a log linear form where taking logs on both sides, we get log(Y) = βX. Thus the equation becomes linear in X and the coefficients can be interpreted as semi-elasticities. Differentiating the above equation we can see that β = $\frac{dY/_Y}{dX}$. This allows us to interpret the co-efficients of interactions simply as moderators of semi-elasticities. For instance consider the equation of the form: log(Y) = $\beta_1 X_1$ + $\beta_2 X_2$ + $\beta_3 X_1 X_2$. In this case $\frac{dY/_Y}{dX_1}$ = β_1 + $\beta_3 X_2$. The β_3 thus directly represents how X_2 moderates the semi-elasticity due to X_1. In other words, the problem of non-linearity of the poisson model for interpreting interactions is eliminated by interpreting the interactions as semi-elasticities.

RESULTS

[Insert Table 1 and Table 2 here]

Table 1 presents the correlations of the main variables used in the study. Table 2 presents the results of the Poisson fixed effect regressions with the interactions of PriorTies with PathDependence and TechDistance respectively. Model 1 is the baseline model with all the controls. Model 2 introduces the main variable of interest, PriorTies. Model 3 introduces the interaction between PriorTies and PathDependence. Model 4 introduces the interaction between PriorTies and the recent hire's TechDistance with the firm. Model 5 is the full model with both of the interactions.

The coefficient of PriorTies is positive and significant in Model 2, and the in other models, providing support for H1 - that the presence of prior ties increase how much firms use the recent hire's knowledge. The positive and significant interaction between PriorTies and PathDependence in Model 3 and Model 5 provide support for H2. Prior ties are especially helpful in getting a firm to use a recent hire's knowledge when the firm is path-dependent. The positive and significant interaction between PriorTies and PathDependence in Model 4 and Model 5 provide support for H4. Prior ties are also more helpful in enabling a firm to use a recent hire's knowledge when the recent hire's knowledge is at greater technological distance from that of the firm.

[Insert Table 3 here]

Table 3 presents the results for our tests for H3 and H5, which predict different implications of the mechanisms through which prior ties help mitigate the challenges of path dependence and technological distance. In H3 we had predicted that for path-dependence, the impact of prior ties will be less evident in cases where the recent-hire is himself not on the patent. In H5, on the other hand, we had predicted the opposite for technological distance, the impact of prior ties will be more evident in cases where the recent-hire is himself not on the patent.

We first test these two hypotheses by comparing the coefficients of the interaction between the two-way interactions PriorTies X PathDependence and PriorTies X TechDistance across two sub-samples: the full sample and the reduced sample of patents which the inventor is not a part of. Model 1a tests the two way interaction between PriorTies and PathDependence in the full sample while Model 1b tests this interaction in the reduced sample. Model 2a presents the results of the full sample to test the interaction between PriorTies and TechDistance while Model 2b is the reduced sample. Model 3a is the full model for the entire sample while Model 3b is the reduced sample results.

As we can see by comparing the coefficient of PriorTies X PathDependence in Model 1b with 1a and in Model 3b with 3a, the coefficient is of greater magnitude in the full sample compared to the reduced sample. Similarly, the coefficient of PriorTies X TechDistance increases in magnitude from the full sample to the reduced sample of patents where the recent-hire is not a part of the team responsible for a focal patent.

We also conduct tests with three way interactions between PriorTies X PathDependence X Hireabsent and PriorTies X TechDistance X Hireabsent. We expect a negative coefficient for the former three-way interaction, suggesting that the effect of prior ties in path dependent firms is attenuated for patents where the recent hire is absent from the inventing team. In contrast, we expect a positive coefficient for the latter three-way interaction, suggesting that the effect of prior ties in countering technological distance is enhanced in projects where the recent hire is absent from.

[Insert Table 4 here]

Table 4 present the results of the tests with three way interactions. Model 1 introduces the three way interaction of PriorTies X PathDependence X Hireabsent, Model 2 introduces the three way interaction of PriorTies X TechDistance X Hireabsent, and Model 3 is the full model with both the three way interactions. All these models also include the relevant two way interactions with Hireabsent as controls. As predicted, the coefficient for PriorTies X PathDependence X Hireabsent is negative in Model 1 and Model 3. This provides strong support for H3. The coefficient for PriorTies X TechDistance X Hire_absent is positive in Model 2 and Model 3. This provides strong support for H5. These results as well as those in Table 3 provide strong suggestion that in path dependent firms prior ties primarily help in matching recent-hires to projects and consequently do not help in facilitating the use of recent-hire’s knowledge farther away from the recent hire. In contrast, in case of distant knowledge, prior ties increase the familiarity with the distant knowledge and also help assure others of support from the recent hire should there be obstacles in adopting the hire’s distant knowledge. Through this mechanism, the prior ties help increase the use of recent-hire’s knowledge farther away from the hire especially when the knowledge is technologically distant from what the firm is used to.

[Insert Table 5 here]

Finally we also test the suggestion regarding the speed with which the different mechanisms discussed above operated. Recall that we had suggested that since matching recent hires to projects is a more involved process that takes time, we should expect the interaction between PriorTies and PathDependence to be weak in the initial years after the recent hire joins the firm but to be stronger in the later time periods after joining. On the other hand, we would expect smaller difference in the interaction between interaction between PriorTies and TechDistance hypothesized in H4 between earlier and later time periods after the hire's joining.

To test these suggestions, we compare the main results of the two way interactions with a reduced sample of patents whose year of application is less than or equal to two years after the recent-hire's year of joining the hiring firm. We then run the regressions in each of these samples and compare the two-way interactions - PriorTies X PathDependence and PriorTies X TechDistance – between the two samples.

Table 5 presents the results of these tests. Model 1a, 2a, and 3a presents the results pertaining to the full sample patents, while Models 1b, 2b, and 3b are the results of the corresponding models pertaining to the sample of patents in the first two years. Visual inspection shows that the coefficient of PriorTies X PathDependence is smaller in the first two years (1b compared to 1a and 3b compared to 3a) while the magnitude of difference is lesser in case of PriorTies X TechDistance. These results are however only suggestive but they do provide further suggestions that are consistent with our main mechanisms of matching and knowledge-transfer.

CONCLUSION

We find that that prior ties between a recent hire and the hiring firm's current employees result in the hiring firm's making more use of this recent hire's knowledge. This is important because such hires – and more broadly the mobility of knowledge workers – have been highlighted as an important source of knowledge acquisition. However, recent research has highlighted that hiring firms do not make widespread use of the knowledge of such hires – the knowledge does not get used often by the hiring firm, and when it does it is often made use of by the hire himself or by his direct contacts. Prior ties between recent hires and the current employees of a firm can address this problem by aiding the firm's absorptive capacity and helping it reduce path dependence. We document support for the dual role of prior ties in mitigating these problems with the two- and three-way interactions which behave as predicted by our framework, and consistent with the mechanisms we assume take place. In addition, our further analysis with respect to how these effects vary over time – ideas that we briefly discuss but do not formally hypothesize – also allows us to furnish additional evidence that further corroborates why, how, and where prior ties between recent hires and the current employees of the hiring firm result in that firm's making use of the recent hire's knowledge.

Using current employees to hire talented workers is an important stratagem of high technology firms. Our study provides evidence regarding the efficacy of this stratagem regarding how well the hiring firm benefits from the hired employees knowledge. We find that prior ties help the hiring firms learn more from the hired scientists and diffuse the knowledge more broadly within the firm.

Our theoretical framework also examines how prior ties help the firm overcome two major knowledge-based roadblocks in using the hire's knowledge: path-dependence and technological distance. We argue and find that prior ties are more instrumental in facilitating the use of hire's knowledge especially in cases when the hiring firm's research is path-dependent or when the hire's knowledge pool is technologically distant from that of the firm's scientists.

Interestingly our theoretical framework suggests that prior ties help overcome these two roadblocks through different mechanisms, which in turn, have different implications regarding how far the new hire's knowledge travels within the hiring firm. We argue that prior ties help overcome path dependence primarily through a process of matching hires to relevant projects. In case of technological distance where the matching mechanism is less relevant, prior ties primarily remove obstacles to knowledge transfer from the hire to other employees of the firm. We argue that the implication of these mechanisms is that in path dependent firms the knowledge of the hire who has greater number of prior ties will largely be restricted to the projects that he is working on. On the other hand when the knowledge of the hire is quite distant from what the firm knows, prior ties facilitate greater use of the knowledge when the hire is not on the project. We test both these implications and find support for our framework.

Our study makes important contributions to the management of technology in organizations. The framework developed and tested in this study provides boundary conditions for when learning by hiring can be made more effective through the use of hiring through the firm's current employees. The framework also suggests that prior ties will in some cases have an impact after a time lag and thus might be more useful in a scenario when the velocity of change in the technological landscape is not that high. Examining this is however out of scope of this study and is perhaps a useful avenue for future research.

The use of patent data to observe mobility of scientists and the utilization of knowledge by firms imposes some limitations on our study and thus calls for some caution in interpreting the results. The data perhaps does not capture all the moves because some inventors might not have patented either in the source or in the destination firms. This reduces the generalizability of our results since less productive scientists might not be observed in the data. This however makes it more difficult for us to find results because the effect of prior ties is most likely more relevant for less active scientists. For active scientists, their reputation and larger body of knowledge is likely to independently increase the awareness of their knowledge and act as a substitute to prior ties. Controlling for prior productivity and usefulness of the mover's knowledge does reduce this concern somewhat but does not eliminate it. The second limitation of the study is that firm hires are endogenous and a firm might hire a scientists precisely because it wants to use his knowledge. To some extent patent fixed effects (which controls for firm intentions regarding a particular research project) reduce this concern. However in line with prior interpretations (Singh and Agrawal, 2011), the results should perhaps be interpreted as the "facilitating" effect of prior ties rather than as causal effects.

In this study, we examined the mechanisms through which prior social ties between a firm's current employees and its recent hires help facilitate the hiring firm's use of the hire's knowledge. We especially focused on the impact of prior ties in overcoming two prominent knowledge based roadblocks in using a new hire's knowledge: path dependence of the hiring firm and the distance of the hire's knowledge pool. We proposed that prior ties help overcome these two problems through different mechanisms and found empirical evidence consistent with our framework. This study helps advance our understanding of the conditions under which the prior ties of a firm's current employees and the scientists it hires can help facilitate knowledge use. Further, this study helps establish certain boundary conditions for the use of this strategy.

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Appendix A. Construction of TechDistance

The TechDistance measure was constructed in several steps. First, we follow Breschi et al (2003) to construct a dyadic measure of relatedness between any two technological subclasses using the entire patent data (i.e. not just the patents associated with the inventors and firms in our sample) in order to proxy for the true relationship between technologies, as revealed by the global inventive activity. For any subclass i, we created a vector $V_i = <N_{i1}, N_{i2}, \ldots. N_{ij}, \ldots. N_{im}>$ Here, N_{ij} refers to the number of patents which are associated with both the subclasses i and j, m refers to the total number of subclasses seen globally. Then for any pair of subclasses, say i and j, we calculate the relatedness between i and j by computing the normalized dot product of V_i and V_j. This calculates the cosine similarity between these two vectors, which is the measure of relatedness between the two classes and is normalized to lie between 0 and 1. Let us call this $\text{DyadicClassRel}_{ij}$.

We use $\text{DyadicClassRel}_{ij}$ to calculate the average relatedness between two vectors: one specific to the new hire and the other specific to the hiring firm. Consider $V_{hire} = < N_{h1}, N_{h2}, \ldots. N_{hP}>$. Here N_{hj} refers to the number of the recent hire's patents associated subclass j and P is the total number of subclasses associated with the hire's knowledge pool. Similarly consider another vector $V_{firm} = < N_{f1}, N_{f2}, \ldots. N_{fM}>$. Here N_{ft} refers to the number of the recent hire's patents associated subclass t and M is the total number of subclasses associated with the firm's set of patents. For each class j in Vector V_{hire}, we calculate the average relatedness of j with the firms specific vector V_{firm} using the number of patents in each of the firm's classes as weights, i.e. we calculate $\text{AvgRel\_HireClass\_Firm}_{hfj} = (\sum_t N_{ft} \text{ X } \text{DyadicClassRel}_{jt}) / \sum_t N_{ft})$. Then we calculate the average relatedness of the hire's vector of knowledge, V_{hire} with the firm vector using the number of patents in each of the hire's knowledge pool's classes as the weights. In other words we calculate, $\text{AvgRel\_Hire\_Firm}_{hf} = (\sum_j N_{hj} \text{ X } \text{AvgRel\_HireClass\_Firm}_{hfj}) / \sum_j N_{hj})$. This calculates how related a technological class of the recent hire is with that of the hiring firm on average, taking the distribution of the number of inventions in each class into account. We note that this measure of relatedness is bounded by 0 and 1. Thus, we subtract $AvgRel\_Hire\_Firm_{hf}$ from 1 to measure the technological distance between V_{hire} and V_{firm}. We call this, our final measure of distance between the knowledge of the recent hire and that of the firm – at the time of the recent hire's joining the firm, TechDistance.

Table 1. Correlations

	Mean	S.D.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) Knowledge Used	0.053	1.33	0	379	1														
(2) Priorties	0.417	0.68	0	3.64	0.04	1													
(3) PathDependence	0.072	0.04	0	0.31	-0.02	0.097	1												
(4) TechDistance	0.804	0.11	0.08	1	-0.03	-0.19	0.158	1											
(5) Hireabsent	0.996	0.06	0	1	-0.18	-0.02	0.031	0.034	1										
(6) Hirenetworksize	1.494	0.87	0	4.51	0.023	0.341	0.06	-0.08	-0.03	1									
(7) Hirecumpat	1.744	1.01	0	5.71	0.026	0.378	0.125	-0.09	-0.02	0.499	1								
(8) Hirecumcites	2.721	1.69	0	8.32	0.027	0.332	0.142	-0.19	-0.02	0.321	0.827	1							
(9) Yearsinfirm	1.76	1.57	0	5	-0.01	-0.05	0.144	0.032	0	-0.03	0.282	0.313	1						
(10) Numtiesonpat	0.004	0.06	0	3.26	0.2	0.131	-0.01	-0.06	-0.2	0.05	0.049	0.044	-0.01	1					
(11) Asset_1	9.38	1.17	0.04	10.9	-0.05	0.008	0.397	0.186	0.079	0.043	0.044	0.086	0.011	-0.08	1				
(12) Firm_cumpat	7.922	1.37	0	9.62	-0.04	0.082	0.85	0.204	0.073	0.057	0.126	0.15	0.148	-0.05	0.63	1			
(13) Firm_cumcites	9.129	2.27	0	11.9	-0.03	0.073	0.873	0.16	0.056	0.051	0.106	0.157	0.153	-0.03	0.55	0.951	1		
(14) Firm's shift to Hire's Expertise	0.001	0.01	-0.3	0.25	0.005	0.054	-0.02	-0.07	-0.01	0.035	0.046	0.04	0.059	0.024	0	-0.03	-0.02	1	
(15) Firm tendency to cite	5.745	1.95	1	54	0.041	-0.06	-0.63	-0.07	-0.03	-0.02	-0.07	-0.05	-0.14	0.015	-0.2	-0.64	-0.58	0.03	1
(16) Hiring Src firm distance	0.813	0.1	0	1	-0.02	-0.02	0.218	0.529	0.031	0	-0.01	-0.06	-0.07	-0.04	0.25	0.258	0.215	-0.08	-0.1

Table 2. Knowledge Used: Two Way Interactions

	(1)	(2)	(3)	(4)	(5)
PriorTies		0.420***	0.473***	0.544***	0.586***
		(25.393)	(28.908)	(27.922)	(30.174)
PriorTies x PathDependence			5.144***		4.901***
			(9.221)		(8.988)
PriorTies x TechDistance				1.484***	1.370***
				(8.721)	(8.548)
PathDependence	100.338	94.239	86.681	89.671	82.450
	(1.882)	(1.841)	(1.751)	(1.778)	(1.690)
TechDistance	-5.124***	-4.476***	-4.431***	-4.927***	-4.891***
	(-11.121)	(-9.712)	(-9.830)	(-12.378)	(-12.361)
Hireabsent	-2.580***	-2.678***	-2.654***	-2.642***	-2.623***
	(-38.106)	(-37.832)	(-37.432)	(-36.150)	(-36.443)
Hirenetworksize	0.285***	0.157***	0.165***	0.142***	0.149***
	(14.733)	(7.945)	(8.132)	(7.161)	(7.374)
Hire_cumpat	0.215***	0.162***	0.156***	0.164***	0.160***
	(6.491)	(4.844)	(4.688)	(4.937)	(4.832)
Hire_cumcites	0.187***	0.164***	0.167***	0.165***	0.167***
	(7.744)	(6.638)	(6.934)	(6.777)	(7.053)
Years_in_firm	-0.295***	-0.247***	-0.251***	-0.242***	-0.246***
	(-16.892)	(-12.933)	(-13.247)	(-13.357)	(-13.642)
Num_ties_onpat	2.105***	1.717***	1.817***	1.713***	1.810***
	(19.302)	(15.794)	(18.486)	(15.848)	(18.433)
Asset_1	-0.011	-0.017	-0.059	-0.048	-0.088
	(-0.034)	(-0.055)	(-0.191)	(-0.157)	(-0.288)
Firm_cumpat	3.016*	2.802*	2.714*	2.737	2.655*
	(2.059)	(1.967)	(1.969)	(1.956)	(1.962)
Firm_cumcites	-2.915*	-2.742*	-2.631*	-2.649*	-2.546*
	(-2.088)	(-2.030)	(-2.009)	(-1.992)	(-1.973)
Firm's shift to Hire's Expertise	4.042***	3.958***	4.828***	3.257***	4.129***
	(5.422)	(5.273)	(6.440)	(4.912)	(6.222)
Firm tendency to cite	3.021*	2.834*	2.715*	2.739*	2.632*
	(2.079)	(2.045)	(2.040)	(2.011)	(2.013)
Hiring Src firm distance	-0.675***	-0.827***	-0.982***	-0.737***	-0.885***
	(-4.625)	(-5.877)	(-7.011)	(-5.471)	(-6.612)
Observations	3,764,721	3,764,721	3,764,721	3,764,721	3,764,721

Robust z-statistics in parentheses *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 3. Two Way Interactions: Full Sample v. Hire Not Present

	(1a) Full Sample	(1b) Hire Absent	(2a) Full Sample	(2b) Hire Absent	(3a) Full Sample	(3b) Hire Absent
PriorTies	0.385***	0.490***	0.473***	0.611***	0.517***	0.641***
	(22.077)	(32.337)	(22.674)	(35.033)	(24.243)	(33.380)
PriorTies X PathDependence	5.580***	4.005***			5.214***	3.772***
	(10.046)	(8.203)			(9.199)	(7.456)
PriorTies X TechDistance			1.754***	1.811***	1.597***	1.743***
			(13.361)	(16.442)	(12.590)	(15.568)
PathDependence	101.376	23.647	102.866	21.731	98.280	20.276
	(1.805)	(0.451)	(1.799)	(0.420)	(1.754)	(0.391)
TechDistance	-4.070***	-4.521***	-4.572***	-5.197***	-4.576***	-5.195***
	(-9.610)	(-8.721)	(-11.686)	(-10.844)	(-11.786)	(-10.881)
Hirenetworksize	0.230***	0.184***	0.201***	0.155***	0.211***	0.162***
	(10.754)	(9.873)	(9.647)	(8.405)	(9.760)	(8.594)
Hire_cumulative_patents	0.188***	0.144***	0.194***	0.153***	0.191***	0.151***
	(5.362)	(3.860)	(5.520)	(4.158)	(5.455)	(4.116)
Hire_cumulative_cites	0.156***	0.183***	0.153***	0.178***	0.155***	0.180***
	(7.058)	(6.849)	(6.855)	(6.696)	(7.252)	(6.989)
Years_in_firm	-0.238***	-0.240***	-0.227***	-0.226***	-0.231***	-0.230***
	(-14.469)	(-12.363)	(-14.432)	(-12.278)	(-15.014)	(-12.731)
Number_of_ties_on_patent	2.625***	2.547***	2.487***	2.435***	2.570***	2.496***
	(32.008)	(24.270)	(27.985)	(22.755)	(30.747)	(23.583)
Firm_assets	0.028	-0.558	0.025	-0.577	0.006	-0.579
	(0.086)	(-1.247)	(0.077)	(-1.322)	(0.018)	(-1.320)
Firm_cumulative_patents	2.930	1.569	2.939	1.520	2.907	1.546
	(1.867)	(1.233)	(1.846)	(1.201)	(1.863)	(1.221)
Firm_cumulative_cites	-2.967*	-1.077	-2.955*	-0.997	-2.917*	-1.027
	(-2.004)	(-0.792)	(-1.966)	(-0.742)	(-1.976)	(-0.762)
Firm's shift to hire's expertise	4.572***	5.305***	2.920***	3.557***	3.792***	4.265***
	(6.497)	(6.421)	(4.441)	(4.626)	(6.017)	(5.780)
Firm's tendency to cite patents	2.964	1.498	2.967	1.430	2.908	1.431
	(1.926)	(1.293)	(1.886)	(1.248)	(1.895)	(1.244)
Firm's dist. from source firm	-1.337***	-1.299***	-1.055***	-1.020***	-1.200***	-1.142***
	(-8.552)	(-8.887)	(-7.019)	(-7.469)	(-7.771)	(-8.046)
Observations	3,764,721	3,544,232	3,764,721	3,544,232	3,764,721	3,544,232

Robust z-statistics in parentheses *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 4. Three Way Interactions

	(1)	(2)	(3)
PriorTies	-0.458***	-0.643***	-0.486***
	(-5.128)	(-7.564)	(-4.809)
PriorTies X PathDep X Hireabsent	-6.051***		-6.639***
	(-3.576)		(-3.967)
PriorTies X TechDist X Hireabsent		1.694***	2.715***
		(3.724)	(5.660)
PriorTies x PathDependence	9.468***		9.802***
	(5.526)		(5.815)
PriorTies x TechDistance		0.155	-0.926*
		(0.348)	(-1.989)
PriorTies x Hireabsent	1.009***	1.312***	1.186***
	(11.626)	(16.140)	(12.390)
PathDependence x Hireabsent	-3.718		-0.977
	(-1.756)		(-0.468)
TechDistance x Hireabsent		-5.139***	-4.947***
		(-9.371)	(-9.613)
PathDependence	101.449*	101.701	95.183
	(2.027)	(1.937)	(1.879)
TechDistance	-4.445***	-0.569*	-0.746**
	(-10.083)	(-2.367)	(-2.767)
Hireabsent	-3.228***	-3.530***	-3.474***
	(-29.229)	(-40.526)	(-26.008)
Hirenetworksize	0.136***	0.111***	0.116***
	(6.956)	(5.730)	(5.862)
Hire_cumpat	0.162***	0.179***	0.176***
	(5.159)	(6.020)	(5.781)
Hire_cumcites	0.159***	0.153***	0.154***
	(7.179)	(7.135)	(7.289)
Years_in_firm	-0.249***	-0.242***	-0.242***
	(-13.680)	(-13.830)	(-13.996)
Num_ties_onpat	2.207***	2.075***	2.152***
	(32.198)	(27.825)	(31.236)
Asset_1	0.034	0.054	0.010
	(0.111)	(0.174)	(0.033)
Firm_cumpat	2.984*	3.101*	2.976*
	(2.109)	(2.100)	(2.099)
Firm_cumcites	-2.918*	-3.010*	-2.872*
	(-2.194)	(-2.169)	(-2.144)
Firm's shift to Hire's Expertise	4.662***	3.326***	3.798***
	(6.468)	(5.324)	(6.108)
Firm tendency to cite	2.984*	3.041*	2.900*
	(2.211)	(2.127)	(2.117)
Hiring Src firm distance	-1.020***	-0.762***	-0.876***
	(-7.588)	(-6.048)	(-6.844)
Observations	3,764,721	3,764,721	3,764,721

Robust z-statistics in parentheses *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 5. Time Sensitivity

	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
	Full Sample	Years <= 2	Full Sample	Years <= 2	Full Sample	Years <= 2
PriorTies	0.473***	0.445***	0.544***	0.483***	0.586***	0.525***
	(28.908)	(24.385)	(27.922)	(20.715)	(30.174)	(23.586)
PriorTies x PathDependence	5.144***	3.944***			4.901***	3.743***
	(9.221)	(6.196)			(8.988)	(5.946)
PriorTies x TechDistance			1.484***	1.160***	1.370***	1.065***
			(8.721)	(6.882)	(8.548)	(6.613)
PathDependence	86.681	83.273	89.671	86.063	82.450	80.776
	(1.751)	(1.733)	(1.778)	(1.769)	(1.690)	(1.685)
TechDistance	-4.431***	-4.577***	-4.927***	-5.037***	-4.891***	-5.007***
	(-9.830)	(-9.026)	(-12.378)	(-10.920)	(-12.361)	(-10.919)
Hireabsent	-2.654***	-2.762***	-2.642***	-2.753***	-2.623***	-2.743***
	(-37.432)	(-25.728)	(-36.150)	(-25.120)	(-36.443)	(-25.441)
Hirenetworksize	0.165***	0.231***	0.142***	0.214***	0.149***	0.218***
	(8.132)	(8.227)	(7.161)	(7.663)	(7.374)	(7.686)
Hire_cumulative_patents	0.156***	0.232***	0.164***	0.241***	0.160***	0.235***
	(4.688)	(5.913)	(4.937)	(6.193)	(4.832)	(6.012)
Hire_cumulative_cites	0.167***	0.103***	0.165***	0.100***	0.167***	0.103***
	(6.934)	(3.676)	(6.777)	(3.544)	(7.053)	(3.721)
Years_in_firm	-0.251***	-0.106**	-0.242***	-0.094**	-0.246***	-0.104**
	(-13.247)	(-3.086)	(-13.357)	(-2.801)	(-13.642)	(-3.101)
Number_of_ties_on_patent	1.817***	1.765***	1.713***	1.688***	1.810***	1.757***
	(18.486)	(14.590)	(15.848)	(12.997)	(18.433)	(14.540)
Firm_assets	-0.059	-0.277	-0.048	-0.264	-0.088	-0.296
	(-0.191)	(-0.808)	(-0.157)	(-0.786)	(-0.288)	(-0.871)
Firm_cumulative_patents	2.714*	2.850*	2.737	2.886*	2.655*	2.825*
	(1.969)	(2.151)	(1.956)	(2.175)	(1.962)	(2.145)
Firm_cumulative_cites	-2.631*	-2.619*	-2.649*	-2.645*	-2.546*	-2.570*
	(-2.009)	(-2.094)	(-1.992)	(-2.099)	(-1.973)	(-2.059)
Firm’s shift to hire’s expertise	4.828***	6.692***	3.257***	4.873***	4.129***	5.825***
	(6.440)	(7.132)	(4.912)	(5.992)	(6.222)	(6.920)
Firm tendency to cite patents	2.715*	2.360	2.739*	2.398	2.632*	2.326
	(2.040)	(1.769)	(2.011)	(1.768)	(2.013)	(1.754)
Firm distance from source firm	-0.982***	-1.226***	-0.737***	-0.955***	-0.885***	-1.100***
	(-7.011)	(-6.907)	(-5.471)	(-5.686)	(-6.612)	(-6.527)
Observations	3,764,721	2,340,418	3,764,721	2,340,418	3,764,721	2,340,418

Robust z-statistics in parentheses *** p < 0.001, ** p < 0.01, * p < 0.05