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How Do Prior Ties Affect Learning by Hiring?

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Research has shown that hiring R&D scientists from competitors fosters organizational learning. We examine whether hiring scientists who have many collaborative ties with the hiring firm prior to the mobility event produces different learning outcomes than hiring scientists who have few or no such ties. We theorize that prior ties reduce explorative learning and increase exploitative learning. Namely, we posit that prior ties lead the hiring firm to focus on that part of a new hire's knowledge with which they are already familiar and that they help appropriate the new hire's newly generated knowledge. At the same time, prior ties induce new hires to search locally within the hiring firm's knowledge base and to produce more incremental, lower-impact innovations. Using data on R&D scientists' mobility in the Electronics and Electrical Goods industry, we find broad support for our hypotheses. Our results extend our theoretical understanding of learning-by-hiring processes and bear practical managerial implications.

Keywords: *innovation management; knowledge management; knowledge transfer/replication; organizational learning*

Introduction

A sizeable stream of literature has shown that hiring R&D scientists from other firms is a primary mechanism to capture knowledge spillovers from competitors and boost innovative performance (Almeida & Kogut, 1999; Filatotchev, Liu, Lu, & Wright, 2011; Jain, 2016; Kaiser, Kongsted, & Rønde, 2015; Parrotta & Pozzoli, 2012; Rosenkopf & Almeida, 2003; Singh & Agrawal, 2011; Slavova, Fosfuri, & De Castro, 2016). Newly hired R&D scientists

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bring ideas, methods, and experience they have developed in other firms, enabling the hiring firm to learn new ways of doing things and thereby counter tendencies towards “learning myopia” (Levinthal & March, 1993). Hiring is an especially important learning mechanism for R&D-intensive organizations because technological knowledge is largely tacit and, therefore, most effectively transferred through joint problem solving and face-to-face interaction (Carnabuci & Operti, 2013; Song, Almeida, & Wu, 2003). In light of these considerations, learning-by-hiring processes have gained center stage in recent debates on the productivity of R&D-based organizations, as well as in organizational learning and knowledge-based theories of the firm (Groysberg & Lee, 2009; Groysberg, Lee, & Nanda, 2008).

Whereas initial work in this area focused on establishing the phenomenon of learning by hiring and its beneficial effects (Almeida & Kogut, 1999; Rosenkopf & Almeida, 2003; Song, Almeida, & Wu, 2001), more recent studies have looked at factors affecting the relative efficacy of the learning-by-hiring process, such as knowledge distance of the hire from the hiring firm, path dependence of the hiring firm (Song et al., 2003), whether the hiring firm is dominated by a few stars (Tzabbar, 2009), and age of the firm (Jain, 2016). Our study advances this stream of research by examining whether hiring R&D scientists who have many preexisting collaborative ties with the hiring firm may produce different learning outcomes than hiring scientists who have few or no such ties.

The overarching contention of our study is that the presence of preexisting collaborative ties influences *what* firms learn from their new hires and, specifically, whether hiring new scientists will lead to exploitative versus explorative learning (March, 1991). To probe this argument, we examine a set of related questions. We begin by asking: *What part of a new hire’s knowledge* do prior collaborative ties help transfer and use? We distinguish between two kinds of knowledge that a new hire may carry to the hiring firm. On one hand, a new hire may possess knowledge that the hiring firm is already familiar with and has used before—what we label “shared knowledge.” On the other hand, the new hire may carry knowledge that the hiring firm has never used before and, hence, is genuinely new to it—what we call “unique knowledge.” We hypothesize that prior ties increase the likelihood that the hiring firm will focus on new hires’ shared knowledge (which facilitates exploiting the firm’s existing knowledge base), whereas hiring scientists with few or no prior ties leads firms to focus on new hires’ unique knowledge (and, hence, to explore beyond the firm’s existing knowledge base).

To further substantiate the argument that hiring scientists with many prior collaboration ties facilitates exploitative learning, while hiring scientists with few or no such ties conduces to exploratory learning, we derive a set of additional hypotheses. In particular, we posit that prior ties affect the extent to which, first, the new hire will search knowledge within the hiring firm’s knowledge base as opposed to engaging in distant search outside of the firm’s knowledge boundaries (Rosenkopf & Nerkar, 2001); second, the new hire will generate high-versus low-impact knowledge after joining the firm (Fleming, 2001); and, finally, the hiring firm will be able to appropriate the hire’s newly generated knowledge by using it as “a source of future development and exploitation by the firm itself” (Belderbos, Cassiman, Faems, Leten, & Van Looy, 2014: 845; Belenzon, 2012).

To examine our hypotheses, we follow previous work and use patent data to obtain micro-level information on the learning-by-hiring process (Almeida & Kogut, 1999; Rosenkopf & Almeida, 2003; Singh & Agrawal, 2011; Song et al., 2003; Tzabbar, 2009). We identify all

R&D scientists in the field of Electronics and Electrical Goods whose names appear on more than one patent between 1985 and 2000. Among these scientists, we identify those who moved across firms and we trace, for each of them, which part of their knowledge was "unique" versus "shared" at the time of hiring. We then examine these scientists' prior collaboration ties using information on their copatenting relationships prior to the mobility event. Specifically, whenever a newly hired scientist has copatented an invention with a scientist from the hiring firm prior to the hiring event, we count that as a prior collaboration tie. In addition to being a widely validated approach to measuring R&D-based collaboration (e.g., Fleming, Mingo, & Chen, 2007; Nerkar & Paruchuri, 2005), our focus on copatenting ties enables us to directly capture the type of collaborative relationship that is central to our theoretical argument: unlike other kinds of relationships, such as friendship or advice, copatenting ties indicate strong, work-related collaborations that involve a significant amount of joint problem solving and tacit knowledge exchange (Carnabuci & Operti, 2013).

Our empirical analyses provide broad support for our hypotheses and yield several novel insights into how the presence of preexisting collaboration ties between a new hire and a hiring firm affects the learning-by-hiring process. First, we find that if a scientist has many prior collaboration ties with the hiring firm, the hiring firm is systematically less likely to use that scientist's unique knowledge compared to his or her shared knowledge. Second, we show that the likelihood that a new hire will draw from the hiring firm's existing knowledge base, as opposed to engaging in distant search outside of it, increases with the number of preexisting collaboration ties between the new hire and the hiring firm. Third, we find that the number of prior collaboration ties increases the likelihood that the hiring firm will appropriate the knowledge generated by the new hire after joining. Finally, we find partial support for the hypothesis that having collaborative ties with the hiring firm prior to being hired leads newly hired scientists to produce lower-impact knowledge.

Taken together, our findings suggest that the learning outcomes generated by hiring R&D scientists from other firms vary markedly depending on how many collaboration ties the new hire has had with the hiring firm prior to being hired. By showing that hiring scientists with many prior collaboration ties tends to facilitate exploitative learning, whereas hiring scientists with few or no prior ties is conducive to exploratory learning, this study extends our theoretical understanding of the learning-by-hiring process and bears important managerial implications concerning the link between a firm's hiring and learning strategies.

Theory and Hypotheses

Do Prior Ties Affect Which Type of Knowledge the Hiring Firm Uses?

Organizational scholars have long argued that a primary way in which organizations acquire new knowledge is by hiring new employees (Lee & Allen, 1982). However, not all new hires carry the same amount of novel knowledge. March's (1991) seminal model, for example, posits that the extent to which hiring new employees leads to exploring knowledge that is new to the firm, as opposed to exploiting the firm's existing knowledge, depends on the ease with which new employees' knowledge gets assimilated into the organization. From the perspective of the present study, this argument is important because research has shown that prior ties are instrumental in integrating newcomers into the new firm (Castilla, 2005; Sterling, 2014) and in helping them develop shared mental models with incumbent employees (Vera, Nemanich, Vélez-Castrillón, & Werner, 2016). When combined with March's model, these findings suggest that if the new hire has many prior ties with the hiring firm, he or she will more quickly be integrated into the hiring firm and incumbent employees will more readily identify a common ground between the new hire's knowledge and theirs. This suggests that the hiring firm will tend to assimilate the new hire's shared knowledge into its existing knowledge, as opposed to learning from the new hire's unique knowledge. By contrast, when new hires have few or no prior ties, assimilating them into the firm will tend to be more difficult and require more time; therefore, it is more likely that new hires will retain more of their unique knowledge and contribute ideas that are new to the firm and different from its existing knowledge.

March's (1991) organizational learning model emphasizes the role of the hiring firm in assimilating newcomers. However, the claim that prior ties increase the use of newcomers' shared knowledge but decrease the use of newcomers' unique knowledge dovetails with other streams of research. Examining organizational socialization processes from the perspective of newcomers, for example, Castilla (2005) shows that employees joining a new firm face a pressing need to demonstrate their worth and integrate quickly into the organization. Because both of these objectives are harder to achieve in the absence of a common knowledge base, newcomers have a strong motivation to focus on areas of shared knowledge in order to develop shared understandings, engage in productive conversations, and learn from their new colleagues. Whereas for newcomers it is generally difficult to know who knows what within their new firm (Ren & Argote, 2011), prior ties can inform them about where knowledge overlaps lie, thereby facilitating their attempts at focusing on shared knowledge areas as a basis for conversations and collaborative work with their new colleagues (Castilla, 2005; Morrison, 2002; Sterling, 2014). We therefore propose that relative to newcomers who have few or no prior ties, newcomers who can count on many prior ties are more likely to contribute knowledge that their colleagues find easy to understand and use (shared knowledge) while deemphasizing knowledge with which their colleagues may be unfamiliar (unique knowledge).

Literature on knowledge exchange in small work groups both enriches and provides initial evidence supporting this argument. Thomas-Hunt, Ogden, and Neale (2003), for example, showed through a series of experiments that individuals who have no social ties to other group members tend to emphasize their unique knowledge more than do individuals who have such ties. Furthermore, emphasizing one's unique knowledge and contributing ideas that stem from that knowledge improves other members' perceptions of the individual if he or she has no social ties with those members, which might reinforce that particular behavior. However, the opposite is true if the individual does have social ties to other group members. In these cases, emphasizing one's *shared* knowledge tends to improve group members' perceptions of the individual. Finally, Thomas-Hunt et al. show that group members are more likely to pay attention to the unique knowledge contributions of members who have no connections to them than to the unique knowledge contributions put forward by members who have social ties to them. Applied to the context of our study, these results suggest that a newcomer's unique knowledge is more likely to remain unspoken or pass unnoticed if that person has prior connections with incumbent employees. On the flip side, the unique knowledge of individuals who are not previously connected is more likely to be discussed, emphasized, and appreciated (Thomas-Hunt et al., 2003).

In sum, the above arguments suggest that the larger the number of ties between a new hire and the hiring firm prior to joining the firm, the greater should be the chances that the hiring firm will use that hire's shared knowledge. Conversely, the fewer the prior ties linking a new hire to the hiring firm, the greater the chances that the hiring firm will use knowledge that is unique to that hire and, therefore, new to the firm. This leads to the following hypothesis:

Hypothesis 1: The more prior ties a new hire has to the hiring firm, the less the hiring firm will use that part of a hire's knowledge that had not been previously used by the hiring firm (i.e., unique knowledge) compared to that part of a hire's knowledge that had been previously used by the hiring firm (i.e., shared knowledge).

Do Prior Ties Affect Which Type of Knowledge the Hired Scientist Uses?

Our first hypothesis is about which part of a newly hired scientist's knowledge the hiring firm is more likely to utilize. The arguments we have advanced to build this hypothesis also help us illuminate a complementary question—Which part of a firm's knowledge base are newly hired scientists more likely to use?

Prior ties not only channel information about who knows what (Borgatti & Cross, 2003) but also help assimilate newly hired employees into the firm by conveying tacit knowledge about the firm's knowledge landscape, routines, research trajectories, and current opportunities (Allen, James, & Gamlen, 2007; Castilla, 2005; Fernandez, Castilla, & Moore, 2000). Hence, we propose that the more connections new hires have before joining the firm, the easier it should be for them to search and filter ideas within the firm's existing knowledge base and develop an understanding of how they can use and build upon that knowledge (Carnabuci & Operti, 2013; Morrison, 2002). Conversely, newcomers who have few or no prior ties will generally have more limited access to such tacit information and will therefore develop a more superficial understanding of the firm's knowledge landscape and ongoing projects. Accordingly, the likelihood that they will locate suitable ideas within the firm's existing knowledge base and find useful ways to build upon and extend it should be lower, when compared to newcomers who have more prior ties. These arguments lead to the following hypothesis:

Hypothesis 2: The more prior ties a new hire has to the hiring firm, the more the new hire will use the firm's existing knowledge base after joining the firm.

Do Prior Ties Affect Which Type of Knowledge the Hired Scientist Produces?

The above arguments also have implications for the type of knowledge a newly hired scientist is more likely to produce upon joining the firm. We have argued that new hires with many prior ties to the firm are more likely to contribute through their shared knowledge relative to their unique knowledge. Furthermore, we posited that having many prior ties also induces new hires to draw knowledge from the firm's existing knowledge base, as opposed to searching outside the firm's knowledge boundaries. These arguments suggest that in addition to facilitating a smooth assimilation of the new hire within the firm, having many prior ties is likely to direct the hire's search process towards "local" rather than "distant" knowledge areas. This observation is relevant because an important line of theory posits that combining distant knowledge inputs is crucial in order to produce high-impact, radically new knowledge (Ahuja & Katila 2004; Ahuja & Lampert, 2001; Rosenkopf & Nerkar, 2001). According to this argument, when scientists search locally, they tend to combine closely related knowledge inputs. Consequently, the knowledge they produce is more likely to be incremental and of low impact. We therefore advance the following hypothesis:

Hypothesis 3: The more prior ties a new hire has to the hiring firm, the lower is the impact of the knowledge generated by the new hire after joining the firm.

Do Prior Ties Affect the Appropriability of the Knowledge Produced by the Hired Scientist?

Lastly, the number of prior ties of a new hire is likely to affect a firm's ability to appropriate the hire's new knowledge. A key objective when hiring scientists from other firms is to internalize these scientists' knowledge within the hiring firm's boundaries (e.g., Tzabbar, 2009). Nevertheless, appropriating the full value of a scientist's knowledge output is impossible because (patented) knowledge is a public good (Operti & Carnabuci, 2014). Thus, whereas some of the new hire's knowledge may fuel the firm's internal research trajectories, a nonnegligible portion may end up benefitting other firms' knowledge production trajectories, possibly even more than they benefit the hiring firm itself (Ahuja, Lampert, & Novelli, 2013; Belenzon, 2012; Operti & Carnabuci, 2014).

The theory we have advanced so far suggests that the extent to which firms are able to appropriate new hires' knowledge should be comparatively high in the case of newly hired scientists who had many ties to the firm prior to joining, whereas it should be lower for those who joined the firm with few or no prior ties. As we articulate below, this is because the knowledge produced by new hires who have more prior ties to the hiring firm is more likely to be specific to the firm; firm specificity, in turn, reduces the usefulness of knowledge to other firms and increases its appropriability by the hiring firm (Zhao, 2006).

As we have mentioned, prior ties channel information about the firm's current research trajectories and ongoing projects (Castilla, 2005; Fernandez et al., 2000). Furthermore, new hires' desire to prove their worth and integrate quickly within the firm provides a strong incentive to leverage this information and use their shared knowledge to contribute to such projects. Additionally, when there are many prior ties between the new hire and incumbent scientists, the latter are familiar with the new hire's knowledge and can therefore identify opportunities for collaboration in ongoing projects to which the new hire could contribute (Ren & Argote, 2011). Such opportunities, however, are less apparent when a new hire has no or few prior ties because incumbent scientists have a less accurate understanding of the new hire's knowledge.

The information flow facilitated by the new hire's prior ties is also likely to help the new hire create innovations that are more complementary to the hiring firm's existing assets, such as marketing and manufacturing capabilities (Teece, 1986). These firm-specific capabilities are a product of firm-specific routines that develop through a process of continued development within the firm (Dierickx & Cool, 1989; Dosi, Teece, & Winter, 1992). The knowledge regarding these routines and their relative strengths are typically tacit (Helfat, 1994), and prior ties within the hiring firm are likely to be effective for the transfer of such tacit knowledge (Carnabuci & Operti, 2013; Hansen, 2002). As a result, new hires with prior ties to the hiring firm should be better informed about complementary assets or capabilities within the firm and can thus tailor their work more toward capitalizing on such assets. These complementarities, being a product of firm-specific routines, are less likely to be present outside of the firm, making the new hire's knowledge production more specific to the firm's idiosyncratic capabilities and therefore more appropriable by the firm (Zhao, 2006). These arguments lead to our fourth hypothesis:

> *Hypothesis 4*: The more prior ties a new hire has to the hiring firm, the greater is the extent to which the hiring firm will appropriate the knowledge generated by the new hire after joining the firm.

Method

Data and Sample

To test our hypotheses, we follow previous work and use U.S. Patent and Trademark Office (USPTO) patent data to obtain microlevel information on the learning-by-hiring process (Almeida & Kogut, 1999; Rosenkopf & Almeida, 2003; Singh & Agrawal, 2011; Song et al. 2003; Tzabbar, 2009). We identify all R&D scientists employed by the firms active in the Electronics and Electrical Goods sector whose names appear on more than one patent between 1985 and 2000. As we detail below in this section, we use the information contained in the patents applied for by each of these individuals or by their hiring firms in order to (a) identify the mobility of scientists across firms, (b) assess which part of a new hire's knowledge is used by the hiring firm, (c) trace where the new hire draws knowledge from after joining the firm, (d) quantify the impact of the knowledge generated by the new hire, and (e) measure the degree to which the new hire's knowledge is appropriated by the hiring firm. Before we explain our measures in detail, we describe what patents are and why they provide useful information for our study.

The USPTO statute states that anyone who "invents or discovers any new and useful process, machine, manufacture, or composition of matter, or any new and useful improvement thereof, may obtain a [utility] patent" (35 U.S.C. § 101). When a patent is granted, the patent assignee obtains property rights (i.e., a temporary legal monopoly) over the patented knowledge and may trade those rights at will. Patent documents are a primary source of codified knowledge because for an invention or discovery to be granted patent, it must be explicated

> in such full, clear, concise and exact terms as to enable any person skilled in the art or science to which the invention or discovery to which it pertains or with which it is most nearly connected, to make and use the same. (35 U.S.C. § 112)

Incentives to patent vary across sectors (Mansfield, 1986). In sectors where incentives to patent are high, such as electrical and electronics, patents have been shown to provide reasonably detailed, comprehensive and reliable information on several key aspects of the knowledge production process (Almeida & Phene, 2004; Jaffe, Trajtenberg, & Henderson, 1993; Tzabbar, 2009).

In our study, we use several sources of patent-based data. Although the rights to any knowledge produced within a firm are generally held by that firm, the names of all the inventors (in the context of our study, R&D scientists) who collaborated on a patent must be included in the patent application. This information enables us to trace scientists' knowledge production activity and organizational affiliation over time. Furthermore, any time that more than one scientist is listed on a given patent, this information can be used to infer the existence of a collaboration tie among those scientists. Unlike survey-based approaches designed to infer other kinds of relations, such as friendship and advice, copatenting ties capture specifically scientists' R&D-based collaboration ties. Prior studies have considered copatenting ties to represent "strong" collaborative ties because the collaboration projects leading to a patent typically extend over several years and require extensive face-to-face interaction and exchange of technological knowledge and problem-solving routines (Carnabuci & Operti, 2013). It should also be noted that copatenting ties capture *successful* collaboration ties, since it is possible that two scientists collaborated but failed to obtain a patent for their invention or discovery. Such cases would not be captured by our data. As we elaborate in the discussion section, this feature of our data is in line with the theoretical focus of this study: we are interested in the role of prior ties in facilitating trust and knowledge exchange between a newly hired scientist and the hiring firm; whereas there are relatively unambiguous theoretical reasons to expect those mechanisms to be at work in the case of successful collaboration ties, this is not necessarily the case for unsuccessful collaborations (e.g., unsuccessful collaborations may in some cases *reduce* rather than enhance trust). More generally, copatenting ties have been used extensively by prior studies as a measure of R&D-based collaboration ties and have been further validated by qualitative interviews and fieldwork (Carnabuci & Operti, 2013). Therefore, we use copatenting ties to identify any prior R&D-based collaboration ties existing between a new hire and scientists working in the hiring firm.

The USPTO categorizes patents into technological subclasses. Scholars have used these subclasses to characterize the areas of technological knowledge possessed by firms and individual scientists (Carnabuci & Operti, 2013; Fleming et al., 2007). Similarly, we use this information to relate the firm's knowledge base to that of newly hired scientists and, specifically, to identify which portion of a newly hired scientist's knowledge is shared versus unique. On this basis, as we explain below, we construct our variables of theoretical interest, as well as several control variables that enable us to account for important confounding factors.

Patent applicants have a legal obligation to cite so-called *prior art*, that is, all public knowledge that the patented invention uses as an input. As Jaffe et al. explain:

> The granting of the patent is a legal statement that the idea embodied in the patent represents a novel and useful contribution over and above the previous state of knowledge, as represented by the citations. Thus, in principle, a citation of Patent X by Patent Y means that X represents a piece of previously existing knowledge upon which Y builds. (1993: 580)

Whereas it is possible that some prior art may not be duly reported in the patent document, both legal and economic incentives ensure that patent citations provide reasonably complete and accurate information. Over the past few decades, a large body of literature has used citations to prior patents, also known as "backward citations," to identify which pieces of technological knowledge scientists and firms use as an input for their inventive activity (e.g., Ahuja & Lampert, 2001; Jaffe et al., 1993; Song et al., 2003).

In sum, by providing validated, longitudinal, and fine-grained measures of scientists' and firms' knowledge, patent data allow us to model the empirical processes under investigation in considerable detail while accounting for a large number of potentially confounding factors. Furthermore, being time stamped, patent data allow us to meaningfully compare firms' and scientists' inventive activity before and after each hiring event. As different from this approach, comparisons based on self-reporting, for example, could be less reliable because of idiosyncratic differences between subjects and their perceptions, which would be difficult to eliminate as a result of the challenges in objectively quantifying concepts such as knowledge flows. Using patent data also allows us to build on and contribute to prior findings in the learning-by-hiring literature, in which the use of patent data is widespread.

Of course, patent data also have limitations, and in the discussion section we elaborate on how those limitations might influence our findings. For now, it is important to reiterate that proclivities to patent vary across sectors. This poses two potential problems. First, in sectors that are less R&D intensive, incentives to patent could be low, and not all inventive activity would be reflected in patent data. Second, it is hard to make meaningful comparisons across sectors with different proclivities to patent. To reduce these concerns, we limit our study to a single sector characterized by a high proclivity to patent. We use COMPUSTAT data to identify all public firms that list Standard Industrial Classification Code 36, which corresponds to the Electronics and Electrical Goods sector, as their main line of business. We chose this particular sector because R&D activity, patenting, and learning by hiring are all important in this sector (Mansfield, 1986; Sorensen & Stuart, 2000).

For all the hypotheses, our unit of analysis is the "firm–new hire" pair, where each observation in our estimations is a particular "firm–new hire–year" triplet, with one observation per "firm–new hire" pair that is indexed by the year of the move. This yields an estimation sample of 6,399 mobility events. We construct our measures by building a complete patenting history of each firm, using National Bureau of Economic Research (NBER) patent data from 1980 onwards. Because we also need information about the inventive activity of the scientists and firms that occur before the observations we use in our estimation models (for the construction of relevant variables for both the new hire and the hiring firm), we conduct our analysis on focal patents whose year of application is 1985 or later. In addition, 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 right truncated. Therefore, we limit our analysis to focal patents whose year of application is 2000 or earlier.

Mobility Events

To track the mobility of scientists between firms, we use data provided by the NBER patent project to match patents with firms. To match patents to inventors, we use the data provided by Li et al. (2014). These data use an algorithm to match patents with individual inventors, combining information from multiple sources including the USPTO and NBER. We define mobility events by identifying cases in which two consecutive patents by the same scientist are filed in different firms. We follow previous work (e.g., Singh & Agrawal, 2011) and assume that the midpoint of the two dates of application (in different firms) provides a proxy for the year of the move. This assumption is likely to cause greater inaccuracy as the time difference between the two patent applications increases. Accordingly, we again follow Singh and Agrawal (2011) and use only those two consecutive patents that are not more than 4 years apart (and are assigned to different firms but are by the same scientist) to identify mobility events. We treat the moving scientist (i.e., the new hire) as affiliated with the destination firm for the entire year of the move. To minimize the possibility of identifying false moves, we drop cases in which the scientist would have been marked to move more than once in the same year as well as those who are not observed to move again from the hiring firm in a 3-year period.

Because we are investigating the impact of new hires' prior ties with other scientists in the hiring firm, we need to affiliate scientists with firms. Because a patent does not connect a scientist with a firm indefinitely, we assume that a scientist is affiliated with a firm from 2 years before the filing of a patent to 2 years after this filing, unless a mobility event occurs during this interval. This 5-year window is consistent with the window we use to identify mobility events and with the heuristics employed by prior literature using patents to identify the mobility of scientists (e.g., Singh & Agrawal, 2011). Using these heuristics to identify the mobility of scientists and their affiliation to firms, we build the career history (i.e., affiliations to firms and moves between firms) of all scientists in our data set.

Variables

Our objective is to provide robust tests across a broad variety of empirical operationalizations of the theoretical constructs. In what follows, we describe each variable used to test our four hypotheses and its various empirical operationalizations. Since the number of variables used is large, we provide an overview of all variables in Appendix 1.

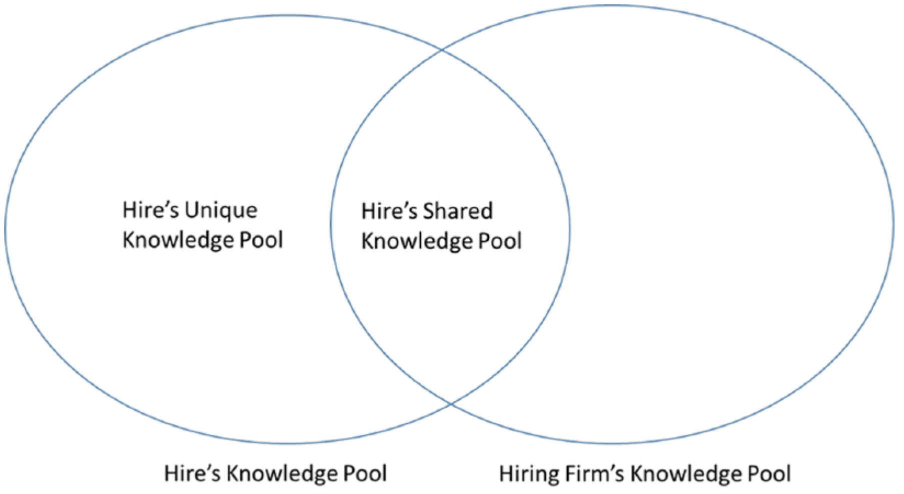
Dependent variables. We use two sets of dependent variables: the first set corresponds to patents of the entire hiring firm (to test Hypothesis 1), and the second set corresponds to patents of the new hire only (to test Hypotheses 2 through 4).

To derive the measures for Hypothesis 1, we first construct a variable to proxy for the overall knowledge that the new hire brings to the hiring firm at the time of entry. This knowledge encompasses the technological inventions that the new hire has invented as well as the set of technological ideas that the new hire has used in creating his or her inventions. Thus, we modify the firm-level measure developed by Yang, Phelps, and Steensma (2010) to define new hires' knowledge pool as the union of two sets: (1) the set of patents filed by this scientist in the 5 years preceding the mobility event, not including the year of the move; and (2) the set of patents cited by the patents defined in the first set, which are the backward patent citations of the patents filed by this scientist.

After computing each scientist's overall knowledge pool, we split it into two parts: "shared knowledge pool" and "unique knowledge pool" (see Figure 1). The new hire's unique knowledge pool consists of those patents in his or her knowledge pool that are neither filed by the hiring firm nor cited by any patents filed by the hiring firm prior to the hire's move into this firm. The hire's shared knowledge pool, then, consists of those patents in the hire's knowledge pool that do not belong to his or her unique knowledge pool.[1]

Thus, we compute *Unique Knowledge Used by Hiring Firm* as the total number of citations made by the hiring firm's patents to the new hire's unique knowledge pool in the 3-year period after the move (including the year of the move). *Shared Knowledge Used by Hiring Firm* similarly measures the total number of citations by the hiring firm's patents to the new hire's shared knowledge pool. Hence, by construction, the sum of these two counts gives us *Overall Knowledge Used by Hiring Firm*. We then construct a variable to measure the proportional use of a new hire's unique knowledge by the hiring firm, which we obtain by dividing *Unique Knowledge Used by Hiring Firm* by *Overall Knowledge Used by Hiring Firm*.

Figure 1
Distinguishing Between Hire's Knowledge Pools



Hypothesis 1 posits that prior ties increase the extent to which the hiring firm will focus on that portion of a new hire's knowledge that it has used before (shared knowledge), compared to that portion of a new hire's knowledge that is new to the firm (unique knowledge). Testing this hypothesis requires separating the effect of prior ties on *what* knowledge (shared vs. unique) the hiring firm uses from the effect prior ties may have on *how much* of a new hire's knowledge the hiring firm uses. To this end, we adopt two different approaches. First, we analyze the effect of prior ties on *Unique Knowledge Used by Hiring Firm* after controlling for *Overall Knowledge Used by Hiring Firm*. The logic of this test is to test whether prior ties reduce the use of a new hire's unique knowledge pool holding constant the hiring firm's overall use of the new hire's knowledge. Second, we directly test how prior ties affect the proportion of unique knowledge used by the hiring firm.[2] A larger value in this proportion (labeled *Unique Knowledge Proportion Used by Hiring Firm*) indicates that the hiring firm uses more of the new hire's unique knowledge and, consequently, less of the new hire's shared knowledge.

Hypothesis 2 examines the extent to which the new hire uses the hiring firm's knowledge in his or her inventions during the 3-year period after moving. Again, we test this hypothesis through two different operationalizations. First, we regress the count of the total number of citations made *to* the hiring firm's patents by the new hire's patents after moving (*Hire's Use of Hiring Firm's Knowledge*), controlling for the total number of patents by the new hire after moving (*Hire's Number of Patents Postmove*). Second, we use an alternative dependent variable (*Hiring Firm Knowledge Used Average*), which is calculated by dividing *Hire's Use of Hiring Firm's Knowledge* by *Hire's Number of Patents Postmove*. As we have mentioned, for these calculations, we use the new hire's patents that are applied for within 3 years after the move.

Hypothesis 3 and Hypothesis 4 are concerned with the future impact of the inventions produced by the new hire. Hypothesis 3 examines the degree to which the new hire's patents are used by other patents in the future, that is, the impact of the new hire's patents. Hypothesis 4 examines the degree to which the new hire's knowledge is used within the hiring firm itself, compared to spilling over to other firms. To test these hypotheses, we use information about the patents that cite the new hire's patents (i.e., the "forward citations"). Since patents that are observed earlier in our sample have a longer period over which they can garner forward citations, they are likely to have more forward citations than patents observed later in the sample period (simply on the basis of this fact, rather than as a result of any substantive differences between the patents). To enable meaningful comparison, we therefore follow a standard practice and consider forward citations by only those patents that are applied for within 5 years of the application of the new hire's patents.

We test Hypothesis 3 through two approaches. First, we use the total number of citations made *to* the new hire's patents overall (i.e., by any patent), which we label *Overall Citations to New Hire's Patents*, as the dependent variable. In conducting this analysis, we control for *Hire's Number of Patents Postmove*. Second, we also use the corresponding ratio-based dependent variable, *Average Impact*, which we construct by dividing *Overall Citations to New Hire's Patents* by *Hire's Number of Patents Postmove*.

To test Hypothesis 4, we follow Park and Lee (2006), who argue that the returns to inventions are appropriated through "follow-up" inventions. Therefore, the extent to which follow-up inventions are made within the hiring firm, compared to outside this firm, captures the degree to which the hiring firm appropriates the new hire's knowledge (Park & Lee, 2006). These arguments are supported by the findings in Hall, Jaffe, and Trajtenberg (2005), who report that self-citations received by a firm's patents are more positively associated with a firm's market value than are external citations. Our strategy in testing Hypothesis 4 is therefore to examine the effect of prior ties on the extent to which follow-up inventions from the hire's patents belong to the hiring firm itself, while controlling for overall number of follow-up inventions. To ensure our results are robust, we again use two approaches to test our hypothesis. First, we estimate the effect of prior ties on *Citations to New Hire's Patents by Hiring Firm* (i.e., the total number of citations made to the new hire's patents by the hiring firm's patents only) while controlling for *Overall Citations to New Hire's Patents*. When we use it as a control variable, we scale *Overall Citations to New Hire's Patents* by dividing it by 100. Second, consistent with Park and Lee, we construct another ratio-based dependent variable, labeled *Appropriation by Hiring Firm*, which is *Citations to New Hire's Patents by Hiring Firm* divided by *Overall Citations to New Hire's Patents*. As before, we use the hired scientist's patents that are applied for within 3 years after the move, and for the forward citations, we use those made by patents that are applied for within 5 years of the application year of a particular patent by the hire.

Independent variables. Our key explanatory variable, *Prior Ties*, measures the number of prior ties between a new hire and the hiring firm. We use prior copatenting to construct this measure.[3] The literature has noted how copatenting ties represent strong collaborative relationships involving a substantial amount of (tacit) knowledge exchange and joint problem solving. Scientists involved in such relationships typically collaborate on an R&D project for several years and, therefore, have ample opportunities to build trust and partner-specific collaboration routines (Carnabuci & Operti, 2013). Even though prior employment in the same firm can also constitute a form of prior ties, we took the more conservative approach of considering only copatenting because in large firms such as those in our sample, it is not clear that simply being in the same firm is evidence of being connected.

We first identified the scientists with whom a new hire has copatented during the 5-year period before the move. Within this set of scientists, we count those who were affiliated with the hiring firm at the time the new hire joins the firm. In doing so, we include in our measure of prior ties only those copatenting scientists who meet two conditions: (1) they were affiliated with the hiring firm before the year of the new hire's joining, and (2) they were affiliated with the hiring firm within 5 years from the year of the new hire's joining. These conditions ensure that we count only those copatenting scientists who were present in the hiring firm both before and after the new hire joined the firm, thus substantively corresponding to our construct of prior ties. The count of the copatenting scientists who meet these two conditions is our main independent variable, *Prior Ties*.

Control variables. We control for the size of the firm by including *Firm Assets* in our specification. As a result of the skewness of this variable, we use the log of assets (lagged by a year) and scale it by 10. The use of knowledge of an external source, such as a new hire, might depend on the volume and quality of the firm's own knowledge base. Thus, we control for the cumulative number of patents of the hiring firm (*Firm Cumulative Patents*). This measure is lagged by 1 year and logged to reduce the skewness of this variable. We control for the impact of the patents invented by the new hire, *Hire's Impact Before Move*, by calculating the cumulative number of forward citations of the new hire's patents (number of patents that cite these patents) up to the year before the move. We then log this, count it to reduce the high levels of skewness, and divide it by 100 to scale it. A firm's use of a new hire's knowledge can also be influenced by that individual's centrality in his or her collaboration network. We therefore control for the network size of the new hire. We measure a *Hire's Network Size* by taking the natural logarithm of the number of unique scientists with whom the new hire has copatented in the 3 years before the year of the move. We use the natural logs for all the logged variables.[4] We control for the hiring firm's technological breadth, *Firm's Breadth of Knowledge*, by calculating the Herfindahl index of the distribution of firm's patents in different subclasses in the 5-year period before the move and subtracting it from 1. We control for the new hire's technological breadth, *Hire's Breadth of Expertise*, by calculating the Herfindahl index of the distribution of the new hire's patents in different subclasses in the 5-year period before the move and subtracting it from 1.

We account for unobserved factors that might influence the magnitude of a hiring firm's use of a new hire's knowledge overall by controlling for the hiring firm's overall knowledge use, *Overall Knowledge Use by Hiring Firm*, calculated as we have previously described. We divide the raw variable by 1,000 to present meaningful two-decimal coefficient information. Since the firm's use of a new hire's knowledge of a particular type might depend on the size of the new hire's knowledge pool, we control for the size of the new hire's shared knowledge pool, *Shared Knowledge Pool Size* (the number of patents in the shared knowledge pool), and the size of the new hire's unique knowledge pool, *Unique Knowledge Pool Size* (the number of patents in the unique knowledge pool). We scale these two variables by dividing them by 1,000. We control for the technological distance of a new hire's knowledge from that of the hiring firm at the time of joining, *Hire's Technological Distance*, by comparing the technological subclasses associated with the new 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 new 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 new hire's knowledge pool (as previously defined) with the patents filed by the hiring firm in the 5-year period before (but not including) the new hire's move. This allows us to calculate the distance between the new hire's knowledge at the time of joining and the knowledge of the hiring firm 1 year before the move. The construction of this variable is detailed in Appendix 2.

A firm's overall tendency to build on earlier work or to develop more original work can also influence a hiring firm's use of a new recent hire's knowledge base. We account for the average tendency of firms to build on their prior knowledge by including a measure of the average number of backward citations per patent by the hiring firms in the previous 5 years (divided by 100 to scale) as a control, which we label *Firm's Tendency to Cite*. In addition, we control for the hiring firm's interest in the new hire's technological area by measuring the extent to which a hiring firm's technological strategy was shifting toward a new hire's areas of expertise at the time he or she joined the firm. To calculate this, we measure the proportion of the hiring firm's patents in the technological subclasses associated with the new hire's knowledge pool for each year in the 5-year period before the year he or she joined the firm. We then calculate the average change in this proportion over the 5-year period to measure the firm's strategic thrust with respect to a new hire's areas of expertise, which we label *Firm's Shift to Hire's Expertise*.

Finally, firms might have a firm-specific strategy to use prior ties of current employees to hire new employees because of idiosyncratic firm-specific unobserved factors (e.g., firm culture). This firm-specific heterogeneity can also influence the use of new hires' knowledge (e.g., through better cultural fit). We address this concern by employing firm fixed effects in our estimations.

Specifications

Our analyses are at the level of the hiring firm–new hire pair. We have one observation for each "hiring firm–new hire" pair in our estimation models, corresponding to the year when a new hire joins a particular firm. We incorporate firm fixed effects in all our estimations. Our primary dependent variables are count variables that display overdispersion. Therefore, we use negative binomial models for these analyses (Cameron & Trivedi, 2009). We use the Stata command "xtsum" to examine the degree of within and between variances. Nearly 90% of variance in our primary dependent variables and independent variable is "within" firm variance rather than "between" firm variance. This indicates that we do not lose much variance by using fixed-effects models.

As discussed, we also estimated models using ratio dependent variables. For example, the regressions using the count dependent variable *Unique Knowledge Used by Hiring Firm* control for *Overall Knowledge Used by Hiring Firm* and, thus, indirectly examine the impact of *Prior Ties* on the use of hire's unique knowledge in proportion to the use of hire's overall knowledge. Using the ratio dependent variable, labeled *Unique Knowledge Proportion Used* *by Hiring Firm*, provides a different and arguably more direct test of this effect. The ratio variables are bounded below by 0 and above by 1 (and in the case of *Hiring Firm Knowledge Used Average* and of *Average Impact*, bounded below by 0): since ordinary least squares assumes unbounded dependent variables, we use panel Tobit regressions for these analyses. Since Tobit does not support conditional fixed-effects models, we use random-effect models in our tests.

In our estimations, we account for endogeneity as we describe below.

Addressing Endogeneity

It is possible that hiring firms use prior ties in order to hire employees with certain types of knowledge (e.g., knowledge that is shared with that of the hiring firm). Similarly, hiring firms may use prior ties to hire employees who are more inclined to produce knowledge of a particular kind (such as building on the hiring firm's knowledge or producing more firm-specific knowledge). These possibilities raise the concern that prior ties may be endogenously related to our outcome variables. We address this concern in two ways. First, as we described earlier, we account for the hiring firm's intention to use a new hire's knowledge by controlling for the firm's tendency to shift toward the new hire's technological area of expertise. Such intentions can lead to greater use of the new hire's knowledge as well as to the use of prior ties to bring the hire into the firm. These control variables and the firm fixed effects that account for time-invariant firm-level confounding factors reduce endogeneity concerns.

We additionally employ a "two-stage residual inclusion" (2SRI) technique (Cameron & Trivedi, 2009; Chen, Hong, Jiang, & Kubik, 2013; Terza, Basu, & Rathouz, 2008). This technique is similar to and reduces to the two-stage least squares (2SLS) technique in linear models. Like 2SLS, the first step involves regressing the potentially endogenous variable to all the right-hand side exogenous variables and instruments. Unlike 2SLS, however, the second-stage regression includes the residuals (rather than predicted values) from the first-stage regression, along with the endogenous variable. The inclusion of first-stage residuals leads to consistent estimates in nonlinear models, whereas the traditional 2SLS technique yields inconsistent estimates in nonlinear models (Terza et al., 2008).

For our study, we employ two instruments. First, we leverage the fact that firms frequently resort to using prior ties to hire when the supply of employees is scarce in the labor market. Firms even offer their current employees incentives such as bonuses to bring their contacts into the firm (Van Hoye, 2013). We therefore instrument *Prior Ties* by a variable that measures changes in the labor-market supply of potential hires who are similar to the focal hire, as indicated by the number of R&D scientists who are knowledgeable in the same technological area as the focal hire. Specifically, we measure increases in the number of scientists who patented in the same technological areas (subclasses) as the new hire over the preceding 3-year period (i.e., the number of scientists in the area in the previous year minus the same number 4 years before). We call this variable *Change in Potential Hires* and scale it by dividing it by 1,000. The intuition here is that when the number of potential hires in the areas of a focal hire's technical expertise increases, the firm will have a greater choice of people in the new hire's technological area and will therefore be less likely to use the prior ties of their current employees to hire new employees in that area. The negative sign of this variable in our first-stage regressions (see Table 2, Model 1) confirms the expectation that an increase of scientists in the hire's area is negatively associated with the use of prior ties. Second, we use the technological distance between the hiring firm and the hire's previous employer at the time of joining, *Hiring and Source Firm Distance*, as another instrument. This measure is constructed in a manner similar to *Hire's Technological Distance*. The intuition is that the greater the distance between the hiring firm and the hire's previous employer, the greater the ex ante uncertainty facing the hiring firm about the "true quality" of the hire and, in turn, the greater the value of *Prior Ties* as a source of information and uncertainty reduction. The positive coefficient of the first-stage regression (see Table 2, Model 1) confirms this intuition. The F statistic of these two variables in the first stage is 9.93, thereby suggesting that these are not likely to be weak instruments.[5]

Results

Table 1 presents a correlations matrix among the variables used in our study. As can be seen in the table, on average, a hire has about one prior tie with the hiring firm ($M = 0.93$). The hiring firm's average patent cites about seven patents from the hire's unique knowledge pool, and on average, the hire's patents within 3 years after joining cite about four patents from the hiring firm. Table 2 presents the results of the first-stage regression, which we use to construct our endogeneity correction variable for the tests of our hypotheses. Table 3 presents the results for our tests of Hypothesis 1. Models 1 and 2 use *Unique Knowledge Used by Hiring Firm* as the dependent variable. Model 1 introduces the other control variables, and Model 2 is the full model that we interpret here. Model 2 shows that the coefficient of *Prior Ties* is negative (−1.60) and significant ($p < .001$). We use the *margins* command in Stata 13 to assess the magnitude of these effects. We kept all the variables at their means in conducting these analyses. We find that an increase of 1 unit of *Prior Ties* from 0 to 1 is associated with a decrease in the use of unique knowledge by about 10.3% of the mean. Models 3 and 4 use *Shared Knowledge Used by Hiring Firm* as the dependent variable. As we can see from Model 4, the coefficient of *Prior Ties* is positive (0.19) but not significant ($p = .242$). The negative coefficient in the case of *Unique Knowledge Used by Hiring Firm* and the nonsignificant but positive coefficient in the case of *Shared Knowledge Used by Hiring Firm* together suggest that a greater number of *Prior Ties* reduces the use of unique knowledge relative to shared knowledge. This is also borne out in the regressions with the proportional dependent variable, as we discuss below. We also note that although the direct zero-order correlation between *Prior Ties* and *Unique Knowledge Used by Hiring Firm* (see Table 1) suggests a positive association between the two variables, this association is confounded by the positive relationship between *Prior Ties* and *Overall Knowledge Used by Hiring Firm*. We see that when the use of overall knowledge of the hire is held constant, *Prior Ties* are indeed negatively associated with the use of hire's unique knowledge. Consistent with this finding, *Prior Ties* are negatively associated with the use of hire's unique knowledge as a proportion of overall knowledge of hire used by the firm. This can be seen most vividly in the Tobit models in which *Unique Knowledge Proportion Used by Hiring Firm* is regressed on *Prior Ties*. Models 5 and 6 of Table 3 report the results of this regression. Model 6 is the complete model and shows that the coefficient of *Prior Ties* is negative (–0.88) and significant ($p < .001$). The margins analyses show that an increase of

Table 1
Correlations and Descriptive Statistics

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	M	SD
1. Unique Knowledge Used by Hiring Firm	1																											7.08	32.63
2. Shared Knowledge Used by Hiring Firm	.07	1																										7.37	38.88
3. Unique Knowledge Proportion Used	.14	−.27	1																									0.63	0.41
4. Hire's Use of Hiring Firm's Knowledge	.01	.17	−.15	1																								3.84	17.66
5. Hiring Firm Knowledge Used Average	−.02	.17	−.28	.56	1																							0.68	1.57
6. Hiring Firm Knowledge Used Proportion	−.07	.06	−.34	.24	.60	1																						0.07	0.14
7. Overall Citations to New Hire's Patents	.04	.09	−.08	.55	.18	.12	1																					19.63	51.4
8. Average Impact	.03	.01	−.06	.07	.11	.08	.44	1																				4.86	6.69
9. Citations to New Hire's Patents by Hiring Firm	.02	.08	−.08	.59	.20	.11	.80	.20	1																			4.33	23.48
10. Appropriation by Hiring Firm	.02	.05	−.06	.21	.19	.17	.13	−.04	.26	1																		0.15	0.23
11. Prior Ties	.06	.33	−.41	.15	.16	.14	.09	.01	.06	.04	1																	0.93	2.18
12. Hire's Number of Patents Postmove	.04	.13	−.07	.61	.16	.10	.73	.06	.57	.19	.17	1																3.59	5.56

(continued)

Table 1 (continued)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	M	SD
13. Hire's Use of Overall Knowledge	.15	.33	−.08	.74	.34	.04	.48	.06	.48	.17	.12	.6	1															43.3	131.3
14. Hire Impact Before Move	.15	.16	−.18	.07	.07	.04	.05	−.01	.03	.02	.27	.09	.11	1														0.02	0.02
15. Hire's Network Size	.17	.15	−.19	.08	.08	.07	.05	−.01	.04	.04	.44	.12	.1	.36	1													1.38	0.76
16. Hire's Breadth of Expertise	.06	.09	−.17	.05	.02	.02	.05	−.02	.04	.03	.19	.09	.07	.51	.27	1												0.85	0.17
17. Hire's Technological Distance	.01	−.05	.12	−.03	−.05	−.01	−.03	−.04	−.03	.01	−.09	−.02	−.03	−.05	−.03	.02	1											0.77	0.12
18. Firm Assets	.03	.01	−.09	.01	.03	.08	−.05	−.11	−.03	.04	.06	.01	−.04	.03	.07	.01	.35	1										0.82	0.19
19. Firm Cumulative Patents	−.10	.07	−.34	.09	.17	.24	.04	.01	.03	.04	.09	.04	.01	.02	.03	.01	.28	.71	1									6.21	2.14
20. Firm Breadth of Knowledge	−.01	.02	−.14	.03	.05	.08	.02	.01	.02	.01	.06	.02	.01	−.02	−.01	.00	.12	.34	.54	1								0.99	0.03
21. Shared Knowledge Pool Size	.03	.71	−.44	.17	.20	.13	.09	.02	.07	.03	.59	.16	.22	.31	.29	.18	−.11	.04	.15	.05	1							0.01	0.03
22. Unique Knowledge Pool Size	.64	.06	.12	.01	−.02	−.07	.03	.01	.01	.01	.08	.08	.13	.40	.35	.22	.02	−.03	−.11	−.04	.10	1						0.03	0.05
23. Overall Knowledge Use	.67	.78	−.12	.13	.11	.01	.09	.02	.08	.05	.28	.12	.34	.22	.22	.10	−.03	.02	−.01	.01	.54	.44	1					0.01	0.05
24. Firm's Tendency to Cite	.18	.02	.25	−.06	−.10	−.21	−.09	−.11	−.05	.02	−.03	−.03	.04	.06	.04	.01	−.07	−.17	−.47	−.05	−.03	.20	.12	1				0.07	0.03
25. Firm's Shift to Hire's Expertise	.01	.02	−.04	−.01	−.02	.01	.02	.02	.01	−.02	.06	.02	.01	.01	.02	.02	−.03	−.04	−.02	.01	.02	.03	.03	.01	1			0.00	0.01
26. Change in Potential Hires	.08	.24	−.18	.08	.06	.01	.03	−.02	.03	.01	.25	.10	.12	.32	.32	.24	−.12	.04	.08	.03	.39	.33	.23	.01	.05	1		0.26	0.45
27. Hiring and Source Firm Distance	−.01	.01	−.05	.01	.03	.06	−.01	−.02	−.03	.03	.01	.02	−.01	.01	.04	.02	.65	.28	.27	.13	−.01	.01	.01	−.07	−.03	−.07	1	0.08	0.11

Table 2
First-Stage Ordinary Least Squares Regression

	(1)
	Prior Ties
Hire's Impact Before Move	3.30* (1.58)
Hire's Network Size	0.88*** (0.03)
Hire's Breadth of Expertise	0.31* (0.14)
Hire's Technological Distance	−1.04*** (0.24)
Firm Assets	0.73*** (0.17)
Firm Cumulative Patents	−0.09*** (0.02)
Firm Breadth of Knowledge	4.79*** (0.96)
Shared Knowledge Pool Size	46.14*** (1.15)
Unique Knowledge Pool Size	−2.64*** (0.61)
Overall Knowledge Used by Hiring Firm	−2.00*** (0.54)
Firm's Tendency to Cite	−2.72** (0.92)
Firm's Shift to Hire's Expertise	6.68*** (1.47)
Hiring and Source Firm Distance	0.60* (0.26)
Change in Potential Hires	−0.21*** (0.06)
Year Dummies	Yes
Constant	−4.81*** (0.94)
Observations	6,399
R^2	.44

Note: Standard errors are shown in parentheses. All tests are two-tailed.
*$p < .05$.
**$p < .01$.
***$p < .001$.

1 unit of *Prior Ties* from 0 to 1 is associated with a decrease in the use of hire's unique knowledge by 19% of the mean. These results provide support for Hypothesis 1.

Table 4 presents the results for the first test of Hypothesis 2, which predicts that *Prior Ties* increase the extent to which the hired scientist builds on the knowledge base of the hiring firm after joining. We use two different approaches to test this hypothesis. For the first, we use negative binomial fixed-effects regressions to predict *Hire's Use of Hiring Firm's Knowledge* while controlling for *Hire's Number of Patents Postmove*. Model 2 of Table 4 shows that the coefficient of *Prior Ties* is positive (1.20, $p < .001$). Increasing the value of *Prior Ties* from 0 to 1 is associated with an increase in backward citations made by the hire's patents to the hiring firm's patents by 0.22 citations, which is 5.7% of the mean of this dependent variable (the mean number of backward citations made by hire's patents to the hiring firm patents). As before, we also estimate a random-effects Tobit specification with *Hiring Firm Knowledge Used Average* as the dependent variable. The coefficient in the Tobit specification is 2.05 ($p < .001$), as can be seen in Model 4 of Table 4. The margins analysis shows that the per patent use of firm's knowledge increased by 0.53, which is 78% of the mean.

Table 5 presents the results for Hypothesis 3, which we test by using *Overall Citations to New Hire's Patents* as the primary dependent variable. Model 2 of Table 6 shows the

Table 3
Firm's Use of Hire's Knowledge

	(1)	(2)	(3)	(4)	(5)	(6)
	Unique knowledge used: Count	Unique knowledge used: Count	Shared knowledge used: Count	Shared knowledge used: Count	Unique knowledge used: Proportion	Unique knowledge used: Proportion
	Controls only	Prior ties and controls	Controls only	Prior ties and controls	Controls only	Prior ties and controls
Hire's Impact Before Move	8.14*** (1.21)	12.84*** (1.25)	7.96*** (1.46)	7.38*** (1.54)	−0.69 (0.90)	2.58* (1.03)
Hire's Network Size	0.25*** (0.02)	1.63*** (0.11)	0.34*** (0.03)	0.18 (0.14)	−0.10*** (0.02)	0.67*** (0.12)
Hire's Breadth of Expertise	0.67*** (0.14)	1.10*** (0.14)	2.59*** (0.24)	2.53*** (0.24)	−0.81*** (0.11)	−0.58*** (0.11)
Hire's Technological Distance	−3.66*** (0.16)	−4.86*** (0.18)	−6.69*** (0.21)	−6.56*** (0.24)	1.45*** (0.15)	0.84*** (0.17)
Firm Assets	2.02*** (0.19)	3.28*** (0.22)	−0.31 (0.26)	−0.47 (0.29)	0.84*** (0.21)	1.43*** (0.22)
Firm Cumulative Patents	−0.12*** (0.02)	−0.27*** (0.02)	0.35*** (0.03)	0.37*** (0.03)	−0.20*** (0.02)	−0.28*** (0.02)
Firm Breadth of Knowledge	2.88** (0.90)	10.01*** (1.05)	3.35 (2.15)	2.50 (2.27)	−1.06 (0.92)	3.00** (1.10)
Shared Knowledge Pool Size	−7.69*** (0.88)	63.26*** (5.45)	6.00*** (0.41)	−2.65 (7.41)	−8.13*** (0.47)	29.74*** (5.87)
Unique Knowledge Pool Size	0.52† (0.27)	−4.48*** (0.49)	−0.90** (0.34)	−0.33 (0.59)	1.70*** (0.26)	−1.92** (0.61)
Overall Knowledge Used by Hiring Firm	4.29*** (0.29)	1.71*** (0.32)	3.01*** (0.20)	3.41*** (0.39)		
Firm's Tendency to Cite	−0.53 (0.86)	−4.16*** (0.90)	−0.66 (1.44)	−0.22 (1.49)	−0.54 (0.88)	−2.91** (0.95)
Firm's Shift to Hire's Expertise	0.72 (1.10)	10.97*** (1.38)	0.08 (1.21)	−0.99 (1.51)	−1.57* (0.76)	4.05*** (1.15)
Endogeneity Correction	−0.06*** (0.01)	1.55*** (0.12)	0.04*** (0.00)	−0.15 (0.16)	−0.08*** (0.01)	0.80*** (0.14)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Prior Ties		−1.60*** (0.12)		0.19 (0.16)		−0.88*** (0.14)
Constant	−3.23*** (0.88)	−9.92*** (1.02)	−4.84* (2.09)	−4.02† (2.20)	2.19* (0.89)	−1.67 (1.05)
Observations	6,399	6,399	6,177	6,177	4,298	4,298
Log likelihood	−13,243	−13,173	−9,956	−9,955	−3,473	−3,452

Note: Standard errors are shown in parentheses. All tests are two-tailed.
†$p < .10$.
*$p < .05$.
**$p < .01$.
***$p < .001$.

Table 4
Hire's Use of Firm's Knowledge: Averaged Over Hire's Patents

	(1)	(2)	(3)	(4)
	Count	Count	Average per patent	Average per patent
	Controls only	Prior ties and controls	Controls only	Prior ties and controls
Hire's Impact Before Move	4.48** (1.38)	0.53 (1.54)	6.45* (2.75)	−0.02 (3.03)
Hire's Network Size	0.17*** (0.03)	−0.85*** (0.18)	0.31*** (0.05)	−1.47*** (0.36)
Hire's Breadth of Expertise	−0.03 (0.14)	−0.29* (0.14)	−0.25 (0.25)	−0.77** (0.27)
Hire's Technological Distance	−1.46*** (0.19)	−0.68** (0.23)	−1.84*** (0.36)	−0.45 (0.45)
Firm Assets	−0.35 (0.24)	−1.28*** (0.29)	−1.53* (0.70)	−3.01*** (0.76)
Firm Cumulative Patents	0.09** (0.03)	0.20*** (0.03)	0.40*** (0.07)	0.59*** (0.08)
Firm Breadth of Knowledge	2.85† (1.51)	−2.54 (1.77)	2.55 (2.40)	−7.06* (3.04)
Shared Knowledge Pool Size	2.66*** (0.66)	−50.69*** (9.18)	8.53*** (1.75)	−83.69*** (18.25)
Unique Knowledge Pool Size	0.32 (0.43)	4.30*** (0.77)	−1.03 (1.00)	5.70** (1.65)
Overall Knowledge Used by Hiring Firm	−0.14 (0.36)	2.28*** (0.56)	0.94 (0.89)	4.58*** (1.15)
Firm's Tendency to Cite	−0.85 (1.30)	1.59 (1.36)	5.51† (2.88)	11.04*** (3.07)
Firm's Shift to Hire's Expertise	−1.93 (1.26)	−9.13*** (1.73)	−3.84 (2.46)	−16.84*** (3.54)
Hire's Number of Patents Postmove	0.03*** (0.00)	0.01 (0.00)		
Endogeneity Correction	0.03*** (0.01)	−1.16*** (0.20)	0.11*** (0.02)	−1.94*** (0.40)
Year Dummies	Yes	Yes	Yes	Yes
Prior Ties		1.20*** (0.21)		2.05*** (0.40)
Constant	−3.74* (1.47)	1.47 (1.71)	−3.91† (2.30)	5.20† (2.91)
Observations	6,240	6,240	6,399	6,399
Log likelihood	−10,497	−10,479	−8,590	−8,577

Note: Standard errors are shown in parentheses. All tests are two-tailed.
†$p < .10$.
*$p < .05$.
**$p < .01$.
***$p < .001$.

Table 5
Overall Impact of Hire's Patents

	(1)	(2)	(3)	(4)
	Count	Count	Averaged over hire's patents	Averaged over hire's patents
	Controls only	Prior ties and controls	Controls only	Prior ties and controls
Hire's Impact Before Move	4.36*** (0.91)	4.18*** (1.00)	12.13† (6.51)	20.21** (7.16)
Hire's Network Size	0.09*** (0.02)	0.04 (0.11)	0.42** (0.13)	2.67** (0.84)
Hire's Breadth of Expertise	−0.11 (0.08)	−0.13 (0.09)	−0.82 (0.59)	−0.15 (0.64)
Hire's Technological Distance	−0.51*** (0.12)	−0.47** (0.15)	−1.50† (0.85)	−3.26** (1.06)
Firm Assets	0.27† (0.15)	0.22 (0.18)	−4.08** (1.52)	−2.23 (1.66)
Firm Cumulative Patents	−0.11*** (0.02)	−0.10*** (0.02)	0.01 (0.16)	−0.22 (0.18)
Firm Breadth of Knowledge	1.74* (0.73)	1.47 (0.94)	2.05 (4.73)	14.06* (6.47)
Shared Knowledge Pool Size	1.50** (0.54)	−1.09 (5.83)	4.84 (4.48)	120.98** (43.01)
Unique Knowledge Pool Size	0.89*** (0.25)	1.08* (0.49)	1.18 (2.38)	−7.36† (3.95)
Overall Knowledge Used by Hiring Firm	0.62* (0.26)	0.73* (0.36)	1.41 (2.24)	−3.16 (2.80)
Firm's Tendency to Cite	−0.59 (0.77)	−0.46 (0.82)	5.26 (6.23)	−1.77 (6.73)
Firm's Shift to Hire's Expertise	−0.55 (0.77)	−0.92 (1.14)	2.09 (5.97)	18.57* (8.51)
Hire's Number of Patents Postmove	0.03*** (0.00)	0.03*** (0.00)		
Endogeneity Correction	0.03*** (0.01)	−0.03 (0.13)	0.11* (0.05)	2.69** (0.95)
Year Dummies	Yes	Yes	Yes	Yes
Prior Ties		0.06 (0.13)		−2.58** (0.95)
Constant	−1.43* (0.71)	−1.17 (0.91)	5.20 (4.54)	−6.22 (6.18)
Observations	6,385	6,385	6,399	6,399
Log likelihood	−21,296	−21,296	−18,879	−18,875

Note: Standard errors are shown in parentheses. All tests are two-tailed.
†$p < .10$.
*$p < .05$.
**$p < .01$.
***$p < .001$.

results. The coefficient for *Prior Ties* is 0.06 but not significant (p = .655). We do not find support for Hypotheses 3 with this dependent variable. As an additional analysis, similar to our other predictions, we ran a random-effects Tobit specification with random firm effects with *Average Impact* as the dependent variable. This model yields a negative and significant coefficient of *Prior Ties* (−2.58, p = .007). Increasing the value of *Prior Ties* from 0 to 1 decreases the average number of citations by 1.79, which is 36.8% of the mean of this dependent variable. Overall, we find only partial support for Hypothesis 3.

Hypothesis 4 is about the relationship between the number of prior ties of a hire and the extent of appropriability of the knowledge produced by the hire after the move. Model 2 of

Table 6
Appropriability of Hire's Knowledge

	(1)	(2)	(3)	(4)
	Count	Count	Proportion	Proportion
	Controls only	Prior ties and controls	Controls only	Prior ties and controls
Hire's Impact Before Move	1.81 (1.36)	0.17 (1.51)	−0.06 (0.44)	−0.55 (0.48)
Hire's Network Size	0.11*** (0.03)	−0.33† (0.18)	0.02** (0.01)	−0.11* (0.06)
Hire's Breadth of Expertise	−0.10 (0.13)	−0.22 (0.14)	0.00 (0.04)	−0.04 (0.04)
Hire's Technological Distance	−0.88*** (0.19)	−0.53* (0.23)	−0.18** (0.06)	−0.07 (0.07)
Firm Assets	0.38 (0.23)	−0.04 (0.29)	0.22† (0.12)	0.10 (0.13)
Firm Cumulative Patents	−0.04† (0.03)	0.00 (0.03)	0.00 (0.01)	0.02 (0.01)
Firm Breadth of Knowledge	−0.37 (1.14)	−2.75† (1.49)	−0.24 (0.33)	−0.98* (0.45)
Shared Knowledge Pool Size	1.87* (0.82)	−21.18* (9.39)	−0.15 (0.29)	−7.29* (2.95)
Unique Knowledge Pool Size	1.27*** (0.36)	2.83*** (0.72)	0.27† (0.15)	0.78** (0.26)
Overall Knowledge Used by Hiring Firm	0.41 (0.38)	1.42* (0.56)	−0.02 (0.15)	0.26 (0.19)
Firm's Tendency to Cite	1.99 (1.22)	3.23* (1.32)	1.72*** (0.45)	2.17*** (0.49)
Firm's Shift to Hire's Expertise	−2.60* (1.25)	−5.80** (1.79)	0.11 (0.39)	−0.90 (0.57)
Overall Citations to Hire's Patents	0.38*** (0.01)	0.31*** (0.03)		
Endogeneity Correction	0.03*** (0.01)	−0.48* (0.21)	0.01** (0.00)	−0.15* (0.07)
Year Dummies	Yes	Yes	Yes	Yes
Prior Ties		0.51* (0.21)		0.16* (0.07)
Constant	−0.38 (1.11)	1.90 (1.44)	0.06 (0.32)	0.76† (0.43)
Observations	6,210	6,210	5,508	5,508
Log likelihood	−10,363	−10,360	−3,182	−3,179

Note: Standard errors are shown in parentheses. All tests are two-tailed.
†$p < .10$.
*$p < .05$.
**$p < .01$.
***$p < .001$.

Table 6 tests Hypothesis 4 using *Citations to New Hire's Patents by Hiring Firm* as the dependent variable. The coefficient of *Prior Ties* is positive and significant (0.51, $p = .014$). Increasing the value of *Prior Ties* from 0 to 1 is associated with an increase in forward citations by the firm patents by 0.27 citations, which is 6.23% of the mean of forward citations by the firm's patents. We also ran supplementary analyses using Tobit specifications with firm random effects using *Appropriation by Hiring Firm* as the dependent variable. In this model the coefficient of *Prior Ties* is positive (0.16, $p = .015$). Increasing the value of *Prior Ties* by 1 unit from 0 to 1 is associated with an increase in the average impact of a new hire's patents by 0.05, which is about 33% of its mean. These results provide support for Hypothesis 4. A hire with more ties to the hiring firm produces knowledge that is more specific to the firm and that is used more within the firm than outside.

Robustness Analyses

We also conducted robustness tests by analyzing the hiring firm's (for Hypothesis 1) and the hire's (for Hypotheses 2 through 4) patents in different year windows after the mobility of the new hire. In particular, we constructed the count dependent variables using three additional time windows: 2 years after the move, 4 years after the move, and 5 years after the move. The coefficient of *Prior Ties* in the specifications for *Unique Knowledge Used by Hiring Firm* for the 2-year window is −1.57 ($p < .001$), for the 4-year window is −1.64 ($p < .001$), and for the 5-year window is −1.58 ($p < .001$). This shows that the support for Hypothesis 1 is robust across different window specifications.

The coefficients of *Prior Ties* in the specifications for *Hire's Use of Hiring Firm's Knowledge* for the 2-year window is 1.20 ($p < .001$), for the 4-year window is 1.15 ($p < .001$), and for the 5-year window is 1.12 ($p < .001$). These results follow the same pattern as for the 3-year window described in our main results and provide support for the intuition behind Hypothesis 2—that new hires with more prior ties are more likely to use the hiring firm's own knowledge, rather than outside knowledge, in their knowledge production.

The coefficients of *Prior Ties* for the impact of a new hire's patents as measured by *Overall Citations to New Hire's Patents* for the 2-year window is 0.03 ($p = .843$), for the 4-year window is 0.06 ($p = .627$), and for the 5-year window is 0.05 ($p = .694$). The coefficients of *Prior Ties* for the average overall forward citations per patent (Tobit specification) for the 2-year window is −2.80 ($p = .008$), for the 4-year window it is −2.77 ($p = .002$), and for the 5-year window is −2.95 ($p = .001$). This shows that the pattern of results for Hypothesis 3 is robust to examining the impact of a new hire's patents across different time windows. The coefficients of *Prior Ties* for appropriability (*Citations to New Hire's Patents by Hiring Firm*) of a new hire's patents for the 2-year window is 0.40 ($p = .051$), for the 4-year window is 0.61 ($p = .004$), and for the 5-year window is 0.50 ($p = .016$). Thus, the results follow the same pattern as for the 3-year window in our main analysis and provide support for Hypothesis 4, suggesting that new hires with more prior ties are more likely to produce inventions that are more firm specific and appropriable by the firm.

We conducted additional robustness tests by also investigating Hypothesis 2 in an alternative manner. Even though the tests discussed above test the extent to which the hire's patents used the hiring firm's knowledge, they do not provide an intuitive sense of how much the hire used the hiring firm's knowledge in proportion to knowledge from other sources. As in our main analyses, we use two approaches to test this. First, we regress the *Hire's Use of Hiring Firm's Knowledge* while controlling for the total number of citations made by the new hire's patents to any patent (*Hire's Use of Overall Knowledge*). When we use it as a control variable, we scale *Hire's Use of Overall Knowledge* by dividing it by 100. Second, we also construct an alternative dependent variable, labeled *Hiring Firm Knowledge Used Proportion*, which is calculated by dividing *Hire's Use of Hiring Firm's Knowledge* by *Hire's Use of Overall Knowledge*. This variable measures a new hire's use of the hiring firm's own knowledge in proportion to the new hire's use of prior knowledge overall.

Table 7 presents the results of these tests. Model 2 shows that the coefficient of *Prior Ties* is positive (1.11, $p < .001$). An increase in the value of *Prior Ties* from 0 to 1 is associated with an increase in backward citations to firm patents by 0.21 citations, which is 5.5% of the mean value of backward citations to the firm. We also ran a random-effects Tobit specification with *Hiring Firm Knowledge Used Proportion* as the dependent variable. As Model 4 of

Table 7
Hire's Use of Firm's Knowledge: Proportional to Overall Knowledge Use

	(1)	(2)	(3)	(4)
	Count	Count	Proportion	Proportion
	Controls only	Prior ties and controls	Controls only	Prior ties and controls
Hire's Impact Before Move	1.22 (1.32)	−2.45† (1.47)	0.28 (0.24)	−0.34 (0.27)
Hire's Network Size	0.18*** (0.03)	−0.78*** (0.17)	0.03*** (0.00)	−0.14*** (0.03)
Hire's Breadth of Expertise	0.08 (0.14)	−0.21 (0.15)	−0.02 (0.02)	−0.07** (0.02)
Hire's Technological Distance	−1.68*** (0.18)	−0.95*** (0.23)	−0.15*** (0.03)	−0.02 (0.04)
Firm Assets	−0.17 (0.24)	−1.01*** (0.28)	−0.16** (0.06)	−0.30*** (0.06)
Firm Cumulative Patents	0.08** (0.03)	0.18*** (0.03)	0.04*** (0.01)	0.06*** (0.01)
Firm Breadth of Knowledge	3.12* (1.49)	−1.94 (1.74)	0.16 (0.20)	−0.75** (0.26)
Shared Knowledge Pool Size	4.50*** (0.65)	−45.37*** (8.98)	0.71*** (0.16)	−8.08*** (1.61)
Unique Knowledge Pool Size	1.11** (0.42)	4.90*** (0.76)	−0.07 (0.09)	0.58*** (0.15)
Overall Knowledge Used by Hiring Firm	−2.28*** (0.36)	−0.13 (0.53)	−0.13 (0.08)	0.22* (0.10)
Firm's Tendency to Cite	−1.94 (1.30)	0.46 (1.37)	0.28 (0.25)	0.80** (0.26)
Firm's Shift to Hire's Expertise	−0.64 (1.26)	−7.36*** (1.72)	−0.02 (0.22)	−1.26*** (0.31)
Hire's Use of Overall Knowledge	0.17*** (0.00)	0.17*** (0.00)		
Firm's Shift to Hire's Expertise	0.04*** (0.01)	−1.07*** (0.20)	0.01*** (0.00)	−0.19*** (0.04)
Year Dummies	Yes	Yes	Yes	Yes
Prior Ties		1.11*** (0.20)		0.20*** (0.04)
Constant	−3.91** (1.45)	0.95 (1.69)	−0.16 (0.20)	0.71** (0.25)
Observations	6,240	6,240	6,345	6,345
Log likelihood	−10,484	−10,467	−1,666	−1,651

Note: Standard errors are shown in parentheses. All tests are two-tailed.
†$p < .10$.
*$p < .05$.
**$p < .01$.
***$p < .001$.

Table 7 shows, the coefficient in the Tobit specification is 0.20 ($p < .001$). An increase in the value of *Prior Ties* from 0 to 1 increases the proportion of the use of the hiring firm's knowledge to the use of knowledge from any source by .06, which is 85% of the mean of this dependent variable. These results provide additional support for Hypothesis 2 and suggest that when the new hire has more prior ties with the hiring firm, he or she is more likely to build on the firm's knowledge base instead of using outside knowledge.

Discussion

This study contributes to the learning-by-hiring literature by illuminating how the presence of prior ties between a hiring firm and its newly hired R&D scientists affects the learning-by-hiring process. Our results indicate that hiring scientists with many prior collaboration ties tends to facilitate exploitative learning, while hiring scientists with few or no such ties conduces to exploratory learning. To substantiate this claim, we examined how prior ties affect several related aspects of the learning-by-hiring process. First, we showed that hiring R&D scientists who have many preexisting collaboration ties increases the likelihood that the hiring firm will use those scientists' shared (i.e., familiar) knowledge, as opposed to their unique (i.e., novel) knowledge. Second, we found that the presence of prior collaborative ties affects the new hires' search strategies, leading them to search knowledge locally within the hiring firm's existing knowledge base, as opposed to engaging in distant search outside of it (Rosenkopf & Nerkar, 2001). Third, we found partial support for the hypothesis that having collaborative ties with the hiring firm prior to being hired leads newly hired scientists to produce more marginal, lower-impact knowledge. And, finally, we showed that prior ties help firms appropriate their hires' newly generated knowledge (Belderbos et al., 2014: 845; Belenzon, 2012).

These findings are important because extant studies have emphasized how hiring R&D scientists from other firms helps firms *explore* new knowledge and reduce the inherent tendency towards learning myopia (Rosenkopf & Almeida, 2003; Song et al., 2003; Tzabbar, 2009). Whereas our findings do not contradict this argument, they caution against overly simplistic imageries of the learning-by-hiring process and provide a more articulated and nuanced view that includes both explorative and exploitative learning outcomes. For example, prior studies have tended to assume that if a scientist holds unique knowledge that is new to the hiring firm, hiring that scientist will necessarily yield exploratory learning. By contrast, we showed that even though a newly hired scientist may hold valuable knowledge that falls outside of the hiring firm's scope, the likelihood that the hiring firm will actually use and learn from that knowledge decreases if the new hire had many collaboration ties with the hiring firm prior to joining.

Recognizing that prior collaboration ties affect what part of a new hire's knowledge the hiring firm is more likely to use not only deepens our theoretical understanding of the learning-by-hiring process but also enables us to propose hiring strategies that align with a firm's contingent learning objectives and needs. It is well understood that firms may be successful in the long run only if they combine and dynamically balance two distinct forms of organizational learning—exploitation and exploration. However, we know far less about how, in practice, managers might favor each learning strategy or switch between the two as needed. The present study highlights hiring as an actionable and flexible lever that managers can use not just to enhance organizational learning in a broad and general sense but, rather, to carry out specifically an exploitative or explorative learning strategy depending on the contingent needs and opportunities of the firm. Specifically, we showed that hiring scientists who had many prior ties with the firm favors exploitative learning, yielding speedier and more certain results. This hiring strategy is likely to be especially beneficial when the manager aims to integrate new hires quickly into the firm's existing knowledge trajectories, which in turn is crucial in order to deepen the firm's existing knowledge base (Katila & Ahuja, 2002). Furthermore, our results suggest that hiring scientists who have prior collaboration ties with the firm results in new hires' producing knowledge that is more firm specific and, therefore, more easily appropriable. On the other hand, hiring scientists with few or no prior collaboration ties may be more effective when the manager's strategy is to enhance the firm's explorative learning. Our results indicate that socializing scientists with no prior ties may take longer and that the returns of such a hiring strategy are more uncertain. However, if the manager's strategic priority is indeed to broaden—rather than deepen—the firm's knowledge base, or to prioritize the pursuit of high-impact innovations, hiring scientists who have never collaborated with the firm is more likely to pay off.

In line with March's (1991) seminal model, our findings emphasize the inherent trade-off between maximizing exploitation by quickly assimilating newcomers into the firm versus maximizing exploratory learning by hiring newcomers who are hard to assimilate. Specifically, our results suggest that hiring knowledge workers with many prior ties facilitates their smooth integration within the firm, but because newcomers ignite exploratory learning only as long as they preserve their knowledge diversity, it reduces a firm's ability to learn from those new hires' unique knowledge. Similarly, our results dovetail with research on hiring through referrals (Breaugh, 2008; Castilla, 2005). This literature highlights how referrals produce a double benefit. On one hand, they reduce information asymmetry and help firms hire workers who are more likely to fit in with the firm and match its needs (Breaugh, 2008). On the other hand, they provide valued insider information to the new hires, thereby helping them integrate within the firm and enhance the likelihood of a future successful performance (Castilla, 2005). Whereas we do not directly observe referrals in our study, the finding that prior ties affect learning by hiring suggests a possible and thus far unexplored link between the referral and learning literatures. Might hiring through referrals reduce the firms' exploratory learning? Given the theoretical and practical implications associated with this question, we hope our research will spur research in this direction.

Our study also contributes to the literature on networks and knowledge transfer (e.g., Hansen, 1999; Levin & Cross, 2004; Uzzi, 1997). Work in this area has examined in remarkable depth how the task-oriented, collaboration-based ties that people build in the workplace shape the flow of knowledge across individuals and firms (Tortoriello, Reagans, & McEvily, 2012). A particularly fecund line of inquiry has expanded on the seminal work by Nahapiet and Ghoshal (1998) and examined the role of structural, relational, and cognitive dimensions of social capital in organizations, as reflected in the network of relationships connecting individuals to one another within and across organizations (Inkpen & Tsang, 2005). One key finding of this literature is that strong, long-lasting collaboration ties—akin to the ones examined in the present study—are crucial channels for knowledge transfer because sharing a history of past collaboration helps individuals build competence-based and benevolence-based trust and develop more effective communication and collaboration routines (Levin & Cross, 2004). Indeed, the presence of such strong ties has been shown to be especially important for the transfer of complex, tacit knowledge of the kind that R&D scientists use and exchange (Hansen, 1999; Tortoriello et al., 2012). Despite its notable progress in illuminating how collaboration ties channel knowledge within and across organizations, this line of research has not examined the role of prior ties in the context of worker mobility. By integrating insights from the knowledge transfer and learning-by-hiring literatures, our study establishes a fruitful point of connection between these two lines of research and shows how insights accumulated about the role of prior ties can help illuminate important learning-by-hiring outcomes.

Limitations

Our study builds on other studies that use patent data to examine learning by hiring. 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 caution in interpreting the results.

For example, these data do not capture all the actual moves because some scientists might not have patented in either the source firm or the destination firm. This reduces the generalizability of our results because the moves of less productive scientists might not appear in the data. However, we conjecture that this would also make it more difficult to find support for our predictions because the effect of prior ties might be more relevant for less active scientists. For active scientists, their reputation and larger body of knowledge might be sufficient to independently increase the awareness of their knowledge and act as a substitute to prior ties, a conjecture that we do find support for in our additional analyses. Controlling for prior productivity and the usefulness of the mover's knowledge might reduce this concern, but it does not eliminate it.

Using patent data to trace knowledge flows has considerable advantages. These include providing an objective and longitudinal window of observation into knowledge production and mobility activity, enabling us to control for many confounding factors. However, one limitation is that the perspective these data afford is more distant than what can be gleaned by primary observation. Consequently, while we can discover average associations and tendencies between concepts in the data, we cannot observe the interactions between scientists directly and offer a rich detailed observation of the knowledge exchange processes, such as those about firm-specific routines, between them. Thus, large-sample studies, like ours, that can uncover statistical associations and relationships should be complemented with in-depth process studies such as Arthur, DeFillippi, and Jones (2001), who build a theoretical framework about how firms and workers learn from individual projects, in order to enrich our knowledge about the concrete mechanisms of knowledge dissemination posthiring. This complementary value of large-sample studies with more in-depth process studies should help the literature build more robust theories about how organizations learn by hiring.

Another issue with our study is that firms might hire scientists through the contacts of their current employees because they plan to use those scientists' knowledge. To some extent, firm fixed effects and some of our other control variables reduce this concern. Furthermore, we employ the 2SRI technique to explicitly address this issue. However, in line with prior interpretations (Singh & Agrawal, 2011), our results should more cautiously be interpreted as correlational or associational effects of prior ties and not as causal effects. We are not able to leverage a clear exogenous shock or perform random assignment. Therefore, we document a relationship but not necessarily the direction of causality. A related concern is that prior ties might be correlated with shared knowledge, thereby leading to a positive relationship between prior ties and shared knowledge use. However, as we noted earlier, the positive relationship is not a mechanical artifact of variable construction since the correlations between shared knowledge and prior ties are such that prior ties explain only 9% of shared knowledge, assuming a linear univariate relationship.

These limitations notwithstanding, our study has important and broad implications for both scholars and practitioners. In brief, and essentially, we highlight a trade-off of central relevance to the learning-by-hiring literature: hiring scientists with prior ties increases a firm's ability to exploit and appropriate both the new hire's base of shared knowledge and the firm's own knowledge and deepen its research capabilities; however, this comes at the cost of reducing the firm's ability to explore new directions, thereby possibly reducing their dynamic capabilities.

Appendix 1

Variable Descriptions

Variable	Description
Dependent	
Unique Knowledge Proportion Used by Hiring Firm	(Number of citations by the hiring firm to the unique knowledge pool of the new hire) / (Number of citations to the entire knowledge pool of the new hire)
Unique Knowledge Used by Hiring Firm	Number of citations by the hiring firm to the unique knowledge pool of the new hire
Hire's Use of Hiring Firm's Knowledge	Number of citations made to the hiring firm's patents by the new hire's patents after joining the hiring firm
Hiring Firm Knowledge Used Average	(Number of citations made *to the hiring firm's patents* by the new hire's patents after joining the hiring firm) / (Number of patents by the new hire after joining the hiring firm)
Hiring Firm Knowledge Used Proportion	(Number of citations made *by* new hire's patents after joining the firm *to* the hiring firm's patents) / (Number of citations made *by* the new hire's patents after joining the firm *to* any patent by any firm)
Overall Citations to New Hire's Patents	Number of citations made *to* the new hire's patents after joining the hiring firm by any patent at any firm
Average Impact	(Number of citations made *to* the new hire's patents after joining the hiring firm) / (Number of patents by the new hire after joining the hiring firm)
Citations to New Hire's Patents by Hiring Firm	Number of citations made to the new hire's patents by only the patents of the hiring firm
Appropriation by Hiring Firm	(Number of forward citations made *to* the new hire's patents after joining the hiring firm *by* the hiring firm's patents) / (Number of citations made *to* the new hire's patents after joining the firm by any patent at any firm)
Independent	
Prior Ties	Number of scientists *currently in the hiring firm* with whom the new hire has copatented during the 5-year period before the move
Control	
Hire's Use of Overall Knowledge	Number of citations made *by* the new hire's patents after joining the firm *to* any patent by any firm
Hire's Number of Patents Postmove	Number of patents by the new hire after joining the hiring firm
Hire's Impact Before Move	Cumulative number of citations to the new hire's patents until 1 year before the move (logged)
Hire's Breadth of Expertise	(1 – the Herfindahl index of the distribution of the new hire's patents in different U.S. Patent and Trademark Office subclasses in the 5-year period before the move)
Hire's Network Size	Number of scientists with whom the new hire has copatented in the 3 years before the year of move (logged)
Hire's Technological Distance	Distance between the vector of subclasses in the new hire's patent portfolio before the move and the vector of subclasses in the hiring firm's patent portfolio before the move
Firm Assets	Log of the hiring firm's assets
Firm Cumulative Patents	Cumulative number of the hiring firm's patents
Firm Breadth of Knowledge	(1 – the Herfindahl index of the distribution of hiring firm's patents in different technological subclasses in the 5-year period before the move)
Shared Knowledge Pool Size	Number of patents in the new hire's knowledge pool that the hiring firm has invented itself or has cited in its inventions

(continued)

Appendix 1. (continued)

Variable	Description
Unique Knowledge Pool Size	Number of patents in the new hire's knowledge pool that the hiring firm has neither invented itself nor cited in its inventions
Overall Knowledge Used by Hiring Firm	Number of citations by the hiring firm to the entire knowledge pool of the new hire
Firm's Tendency to Cite	Average number of backward citations per patent by the hiring firm in the previous 5 years
Firm's Shift to Hire's Expertise	Average change in the proportion of the hiring firm's patents in the technological subclasses of the new hire's knowledge pool in the previous 5 years

Appendix 2

Construction of Hire's Technological Distance

We constructed the *Hire's Technological Distance* measure in several steps. First, we follow Breschi, Lissoni, and Malerba (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 scientists and firms in our sample) to proxy for the true relationship between technologies, as revealed by the global inventive activity. For any subclass *i*, we created a vector $V_i = \langle N_{i1}, N_{i2}, \ldots, N_{ij}, \ldots, N_{im} \rangle$, where N_{ij} refers to the number of patents associated with both the subclasses *i* and *j* and *m* refers to the total number of subclasses seen globally. Second, for any pair of subclasses, for example, *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. We call this $DyadicClassRel_{ij}$.

We use $DyadicClassRel_{ij}$ to calculate the average relatedness between two vectors: one specific to the new hire and the other specific to the hiring firm. Consider $V_{hire} = \langle N_{h1}, N_{h2}, \ldots, N_{hj}, \ldots, N_{hP} \rangle$, where N_{hj} refers to the number of the recent hire's patents associated with subclass *j* and *P* is the total number of subclasses associated with the hire's knowledge pool. Similarly, consider the vector $V_{firm} = \langle N_{f1}, N_{f2}, \ldots, N_{ft}, \ldots, N_{fM} \rangle$, where N_{ft} refers to the number of hiring firm's patents associated with 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 firm's specific vector V_{firm} using the number of patents in each of the firm's classes as weights; that is, we calculate $AvgRel\_HireClass\_Firm_{hfj} = (\Sigma_t N_{ft} \times DyadicClassRel_{jt}) / \Sigma_t N_{ft}$. 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 weights. In other words, we calculate, $AvgRel\_Hire\_Firm_{hf} = (\Sigma_j N_{hj} \times AvgRel\_HireClass\_Firm_{hfj}) / \Sigma_j N_{hj}$. This calculates how related a technological class of the recent hire is to 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 the hire joins the firm—as *Hire's Technological Distance*.

Notes

1. As we note here, by "unique knowledge" we mean knowledge that the scientist possesses but that the hiring firm has not used before. We do not claim that this knowledge makes the scientist "unique" in the field in general. Our suggestion and focus is simply that when considered in the context of knowledge used by a given firm, the knowledge that the scientist possesses but that the firm has not used previously is this scientist's "unique knowledge." If it is preferable for the reader, one might think of "nonshared" as an alternative label for this pool of a scientist's knowledge for a given "scientist–hiring firm" pair.

2. While this second operationalization provides a more direct test of our hypothesis, some authors have raised concerns about using proportional dependent variables and, indeed, there is some disagreement concerning the most appropriate modeling specification for such dependent variables (Wiseman, 2009). By operationalizing our dependent variables as both a count and a proportion, our goal is to ensure our results are robust across modeling choices. We thank an anonymous reviewer for pointing us towards this direction.

3. There are other kinds of connections than those measured by prior patenting activity. However, for the setting that we are studying (R&D activity in the Electronics and Electrical Goods sector) and our interest in observing the differential effect of prior ties on the use of shared and unique knowledge (which patent data allow us to measure with reasonable proxies), using previous copatenting activity to measure prior ties is a reasonable option. If purely social interactions (which we are not able to measure in our study) are positively correlated with prior ties as we measure them, the arguments we review and posit on the way to deriving our predictions still apply (and our findings and results remain informative). If social interactions are negatively correlated (a possible but unlikely situation) with prior ties as we measure them, then the arguments we posit apply much more strongly to work interactions (as captured by prior copatenting) over social interactions, based on any nonnull results we get from our estimations. If social interactions are unrelated to (i.e., not correlated with) prior ties as we measure them, then they are generally making our measure of prior ties noisier and the estimates less precise. For our investigation and the testing of our hypotheses, these above cases do not present a fundamental problem. If our claim was that prior patenting activity was fully or solely capturing social interactions, rather than prior ties that are mainly work and task related, or if our arguments were exclusively reliant on these ties being "social," or if "social" ties would be tied to some arguments that are alternative to the ones that we posit for deriving our predictions (and yet yielding the very same predictions), the case would have been more problematic. However, as we summarize in this note, our assessment is that for this setting and our investigation, our approach to measuring prior ties is appropriate and reasonable.

4. We also test our primary models of count dependent variables with the raw (nonlogged) version of the control variables. For these robustness tests, we drop *Firm Assets* since this was required for the models to converge. These tests yielded results that are qualitatively similar to the main results we present. The coefficient of *Prior Ties* in the specifications for *Unique Knowledge Used by Hiring Firm* is −1.02 ($p < .001$); for Hypothesis 2, the coefficient of *Prior Ties* is 0.68 ($p < .001$); for Hypothesis 3, the coefficient of *Prior Ties* is positive but not significant (0.06, $p = .464$), whereas the coefficient of *Prior Ties* for the average overall forward citations per patent (Tobit specification) is −1.62 ($p = .006$); and for Hypothesis 4, we find that the coefficient of *Prior Ties* is positive and significant (0.35, $p = .004$).

5. We also conducted a test that might provide some information about the validity of our instruments. For this test, we ran instrumental variable Poisson regressions for Hypothesis 1 and tested for overidentification. The Hansen's J test was not significant ($p = .236$), thereby indicating that the null of correct model specification and valid overidentifying restrictions cannot be rejected. This provides some support for the use of our instruments.

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