Learning-by-Hiring: When Is Mobility More Likely to Facilitate Interfirm Knowledge Transfer?

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To investigate the conditions under which learning-by-hiring (or the acquisition of knowledge through the hiring of experts from other firms) is more likely, we study the patenting activities of engineers who moved from United States (U.S.) firms to non-U.S. firms. Statistical findings from negative binomial regressions show that mobility is more likely to result in interfirm knowledge transfer when (1) the hiring firm is less path dependent, (2) the hired engineers possess technological expertise distant from that of the hiring firm, and (3) the hired engineers work in noncore technological areas in their new firm. In addition, the results support the idea that domestic mobility and international mobility are similarly conducive to learning-by-hiring. Thus, our paper suggests that learning-by-hiring can be useful when hired engineers are used for exploring technologically distant knowledge (rather than for reinforcing existing firm expertise) and also for extending the hiring firm's geographic reach.
(*Learning-by-Hiring; Engineer Mobility; Knowledge Transfer*)

Introduction

Few organizations internally generate all the knowledge required for continuous technological development. Firms must, therefore, often turn to external sources such as suppliers, buyers, universities, consultants, and competitors. However, given the tacit and complex nature of most valuable knowledge, its acquisition can be difficult (Kogut and Zander 1992). A significant portion of the knowledge that organizations seek to acquire is embedded in individuals. When these individuals move between organizations, they can apply this knowledge to new contexts, thereby effectively transferring the knowledge across firms (Argote and Ingram 2000). Thus, human mobility can play an important role in a hiring firm's knowledge-building processes, especially when knowledge tends to be "sticky" and remains localized within firms, regions, and countries (Szulanski 1996, Jaffe et al. 1993). This paper suggests that human mobility can serve as a mechanism for the acquisition of externally developed knowledge, and examines the conditions under which the mobility of R&D engineers is most likely to facilitate interfirm knowledge transfer.

Previous research suggests that the mobility of engineers (within and between firms) can significantly influence how knowledge and capabilities are transferred. In his pioneering work on the sociology of inventions, Gilfillan (1935) suggested that labor mobility, especially among engineers, erodes the differential level of knowledge among firms. Building upon Arrow's (1962) seminal work on the link between labor mobility and knowledge spillovers, economists have also considered labor mobility as

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an important spillover channel (Moen 2000). However, the use of mobility as an interfirm learning mechanism has received little formal attention or rigorous analysis (Ettlie 1985).[1] In a recent exception, Almeida and Kogut (1999) tracked the movements of over 400 engineers and showed their patterns of mobility influenced the inter- and intraregional patterns of knowledge flow. Recently, Argote and Ingram (2000) argued that because people play a critical role in the success of technology transfer, further research is needed to assess how they do so; one fundamental issue involves identifying the conditions under which human mobility is most likely to result in knowledge transfer.

In this paper, we attempt to examine these conditions. To do so, we use evolutionary economics, which highlights the localized, path-dependent nature of search behavior in firms (Nelson and Winter 1982). We propose that the dual conditions of technologically localized search and geographically localized knowledge present a challenge to firms that seek to learn from technological or geographic distances. We argue that learning-by-hiring (defined as the acquisition of knowledge from other firms through the hiring of experts) is useful for innovation beyond the firm's current technological and geographic boundaries.[2]

This paper studies the mobility of engineers in the global semiconductor industry, specifically the movement from U.S. companies (firms headquartered in the U.S.) to non-U.S. companies (firms headquartered in foreign countries) located either in the U.S. or abroad. We use patent data to track mobility and patent citation data to trace interfirm knowledge flows. We then employ negative binomial regressions to investigate the most useful conditions for learning-by-hiring.

[1] Much of the existing research on human mobility treats mobility as a dependent variable and focuses on investigating the factors influencing mobility (Lee and Mitchell 1994).

[2] In this study, we focus only on the role of mobility as a mechanism for acquiring knowledge from other firms to enhance innovation. Of course, hiring can be useful to innovation in other ways. For instance, engineers can use their skills to enhance their organization's capabilities, without building on their previous employer's knowledge.

Theory and Hypotheses

The Nature of Knowledge and Learning-by-Hiring

March and Simon (1958) suggested that innovation often results from borrowing rather than invention. In a classic study of major product and process innovations at DuPont between 1920 and 1950, Mueller (1966) observed that the original sources of most inventions come from outside the firm. Firms often find it less costly and faster to source externally available knowledge than to develop competencies internally (Mansfield 1988).

The extent to which firms can source external knowledge is determined, in part, by the nature of the knowledge to be sourced (Zander and Kogut 1995) and by firm-specific capabilities (Cohen and Levinthal 1990). State-of-the-art technologies are often tacit knowledge (Winter 1987), and this knowledge is built internally through experience (Cohen and Levinthal 1990, Song 2002) or learning-by-doing (Teece 1982). Because it is often embodied in individuals and cannot easily be transferred across firms, organizational boundaries serve as knowledge envelopes. Thus, valuable knowledge is much more likely to be diffused within the organization than outside it (Zucker et al. 1996). For example, Almeida et al. (2002) show that multinational firms transfer knowledge across countries more effectively than do alliances or markets because they not only have more internal mechanisms for knowledge transfer at their disposal, but can also use these mechanisms flexibly. Even within a firm, however, tacit knowledge is "sticky" and does not necessarily flow easily unless the individuals possessing the tacit knowledge also move (Szulanski 1996). If the movement of tacit knowledge within firms is difficult, its transfer across firms is likely to be even more challenging.

There are, however, several mechanisms that firms use to access external knowledge. Mowery et al. (1996) pointed to the use of alliances in acquiring knowledge. Almeida (1996) highlighted the advantages of co-location in technology-intensive regions. Similarly, Shan and Song (1997) showed that foreign direct investments are also used to source external knowledge embedded in foreign countries. Licensing agreements also represent formal methods that require firms possessing key knowledge to permit its transfer. However, firms that hold state-of-the-art technology are often reluctant to allow such transfer to other firms because the tacit nature of this knowledge can provide an important source of competitive advantage (Kogut and Zander 1996).

Leonard-Barton (1995) argued that at low levels of codifiability, knowledge transfer might not be easy. Because knowledge may sometimes be difficult to separate from those who possess it, Dosi (1988) suggested that hiring people away from a rival firm is a way of transferring knowledge that is otherwise immobile. Previous literature (Teece 1982, Winter 1987) suggests that human mobility provides a way for firms to access knowledge developed at other firms without their approval. In a case study investigating Samsung's entry into the semiconductor industry, Kim (1997) cited Samsung's deliberate and successful strategy of hiring scientists and engineers from U.S. firms as a platform for acquiring critical knowledge. The mobility of experienced experts does not simply provide a one-time transfer of information, as is often the case in technology licensing, but may also facilitate the transfer of capabilities, permitting further knowledge building (Kim 1997). Song et al. (2001) empirically test this idea and show that learning-by-hiring can be employed to access and build on external knowledge. This study looks beyond the question of whether mobility is useful for interfirm learning, by investigating the conditions under which mobility best facilitates interfirm knowledge transfer.

Learning-by-Hiring and Firm Path Dependence

Although the hiring of engineers could bring new knowledge into the firm, the extent to which mobile engineers leverage their previous firms' knowledge bases may vary substantially according to the attributes of both the hiring firms and the mobile engineers. Regarding firm characteristics, evolutionary economics proposes that the search for new knowledge is often localized or path dependent; i.e., it is influenced by a firm's past experiences (Nelson and Winter 1982). When firms perform well, they may be satisfied with their current programs of innovation (Sorensen and Stuart 2000) and may thus be less motivated to access other firms' expertise to improve their own performance. As organizations experience success, their routines and products become more standardized, and it may become more difficult and costly for them to integrate capabilities from other firms. Moreover, under the conditions of uncertainty that often characterize innovation, the results of past searches become the natural starting points for new innovative searches, and firms continue to build on their own established knowledge (Nelson and Winter 1982, Dosi 1982, Stuart and Podolny 1996). Hence, this path dependence impedes a firm's receptivity to external knowledge by reducing the motivation and ability to seek, recognize, and assimilate knowledge that may be distant from its current practice. We suggest that the hiring of outside experts could mitigate this tendency towards local search by exposing the organization to new ideas, practices, and areas of expertise. However, even for a newly hired expert, effectively transferring knowledge from the outside may not be easy. Self-reinforcing feedback helps perpetuate an organization's existing capabilities but tends to increasingly isolate that organization from new or externally available resources and capabilities. Path-dependent firms will value knowledge close to existing technological and market conditions very highly and myopically devalue more distant knowledge available outside the firm. Thus, firms that exhibit strong path dependence are less likely to be open to new knowledge brought in by mobile engineers. Therefore, we hypothesize:

HYPOTHESIS 1. *The level of knowledge sourced from a hired engineer's previous firm is lower when the hiring firm exhibits greater path dependence.*

Mobile Engineer Characteristics and Learning-by-Hiring. The relationship between a mobile engineer's expertise and the hiring firm's existing technological trajectory may also influence the likelihood of learning from the engineer's previous firm. Hired engineers, too, exhibit local search behaviors and attempt to innovate in their new firms in technological areas close to their existing knowledge (developed in part at previous firms). As mentioned above, a firm's technological areas, especially those that are core, are likely to have established trajectories that affect their receptivity to externally generated knowledge. Core areas, in which innovative activity proceeds along well-trodden paths, are less likely to be receptive to a new hire's influence and will offer fewer opportunities to incorporate external knowledge (than are less-established or peripheral technological areas).

The technological area in which the mobile engineer is employed depends, in part, on his area of expertise. If the hired engineer's area of expertise matches the hiring firm's core technological area, the engineer is likely to work within this core area. The engineer is likely to pursue innovative activities along the hiring firm's existing technological trajectory, with the accompanying restraints of standardized routines and established practices and procedures that reflect the "myopia of learning" (Levinthal and March 1993). Thus, we suggest that when the hired engineer's area of expertise matches the hiring firm's core technological area, the hiring firm's openness to knowledge from the engineer's previous firm is likely to be low.

Hypothesis 2a. *The level of knowledge sourced from a hired engineer's previous firm is lower when the engineer's area of technological expertise matches the hiring firm's area of technological expertise.*

Similarly, the particular technological areas within hiring firms in which a hired engineer pursues innovative activities can affect the extent to which he builds on the knowledge of his previous firm. When a hired engineer pursues innovative activities in the core areas of a hiring firm's technical expertise, then he is less likely to build knowledge from the previous firm than when he works in peripheral areas. Hence, we hypothesize:

Hypothesis 2b. *The level of knowledge sourced from a hired engineer's previous firm is lower when the engineer pursues innovative activities in the hiring firm's core area of technological expertise* (*rather than a peripheral area*).

Domestic vs. International Mobility. Our hypotheses suggest that the mobility of experts can be used to extend the technological boundaries of a hiring firm. We suggest that mobility can also be used to extend geographical boundaries of interfirm knowledge transfer. Building on Jaffe et al.'s (1993) work on the geographic localization of knowledge, several subsequent studies have suggested that the mobility patterns of experts influence the patterns of knowledge flow. For example, Zucker et al. (1998) found that localized knowledge spillovers in the biotechnology industry stem from the immobility of star scientists, or the "intellectual human capital" tied to particular locations. Almeida and Kogut (1999) showed that in the semiconductor industry, knowledge tends to be localized only in certain regions characterized by high internal mobility and low cross-regional mobility. Regions with high cross-regional mobility exhibit no knowledge localization. These articles suggest that the lack of cross-regional mobility influences the localization of knowledge spillovers. Other studies suggest that if there is substantial cross-regional, interfirm mobility of key personnel, knowledge can diffuse quickly across firms. Zander and Kogut (1995) reported that the turnover of key personnel significantly increases involuntary knowledge spillovers in the form of imitative technologies. Although learning-by-hiring is not directly tested, these studies collectively indicate that knowledge may migrate from region to region, or even across national borders, quickly if highly capable and experienced engineers are mobile. Though the cost of hiring may be high and the likelihood of international mobility may be less than that of domestic mobility, the richness of mobility as a knowledge transfer mode makes it likely that hiring these individuals is useful in moving knowledge across firms domestically or internationally. Thus, this paper also examines whether the level of knowledge sourced from a hired engineer's firm differs for domestic and international mobility.

Controls. Technological distance between the hiring firm and the hired engineer's previous firm (or the dissimilarity of their technological profiles) may also influence the level of interfirm knowledge transfer. Some prior studies have supported the idea that firms may be more able and willing to learn from each other when they are technologically closer. Lane and Lubatkin (1998), for instance, show that firms with greater technological overlap have greater relative absorptive capacity and hence are more likely to learn from each other. On the other hand, Mowery et al. (1998) suggest that mobility can be even more useful when firms are technologically distant because a high degree of overlap between two firms may indicate that neither firm has much to learn from the other. Given that mobility is often used not only to transfer knowledge, but also to interpret and apply this knowledge in a new context, the need for similarity may be mitigated when this rich mechanism is employed for the transfer of knowledge. Thus, these contrasting arguments suggest that there may be a trade-off, as regards the technological distance between two firms, between the motivation to learn (higher when firms are technologically distant) and the ability to learn (higher when firms are close). These arguments highlight the possibility of an inverted U-shaped effect, with the level of interfirm knowledge flow first increasing and then decreasing with increasingly distant technological profiles between the two firms. We therefore control for the effect of technological distance by also adding a quadratic term in our regression models.

Mobile engineers with stronger innovative capabilities are likely to have more knowledge to transfer than do those with weaker abilities. As argued by Ibarra (1993), the expertise stemming from individual attributes such as experience is an important source of power. Bringing about a change in the status quo (as technological learning often entails) requires an individual to use power and influence. We therefore control for the strength of the mobile engineer's innovative ability as measured by the total number of patents filed by the engineer in his previous firm. We also control for whether the engineer's area of expertise matches the core technological areas of his previous employer. In the absence of such a match, the engineer may not possess substantial knowledge about the previous firm's core technology areas and may be a less useful source of knowledge.

The technological capabilities of hiring firms may influence the level of knowledge sourced from previous firms in opposing ways (Song and Shin 2002). On one hand, technological capabilities can serve as "absorptive capacity," which enhances a firm's ability to identify, assimilate, and integrate external knowledge (Cohen and Levinthal 1990). Alternatively, firms with strong technological capabilities may be less inclined to source external knowledge because they may have already developed competitively valuable capabilities along established technological trajectories. Because the strength of the hiring firm's technological capabilities may influence the level of knowledge sourced through learning-by-hiring, we control for this factor.

Data and Methods

We use U.S. patent and patent citation data from the global semiconductor industry to test the hypotheses over a 20-year period (1980–1999). We focus on engineers who have moved within the semiconductor industry from U.S. firms to non-U.S. firms (including moves to both U.S.-based and foreign R&D labs), and examine their subsequent innovative activities in the hiring firms. This focus enables us to provide a fair contrast between the knowledge flows resulting from domestic and international mobility, because in both cases the movement of experts is from U.S. to non-U.S. firms. We focus on mobile engineers hired from U.S. firms, given the fact that the United States is the technology leader in many segments of the global semiconductor industry and foreign firms often attempt to source semiconductor technology developed in the United States (Almeida 1996). Using a matched-pair t-test, we first examine whether the movement of engineers in our sample was associated with significant knowledge transfer from the previous firm to the hiring firm. We then use negative binomial regressions to examine the effects of hiring firm characteristics and hired engineer attributes on the extent to which hired engineers source knowledge developed at their previous firms.

Data

Over the last decade, patents have become increasingly popular as indicators of technological output and innovative capabilities (Hall et al. 2000). Patent data have received so much attention because they are systematically compiled, have detailed information, and are available continuously across time. We use patent data extensively to shed light on the knowledge-building patterns of semiconductor firms.

A patent document contains a host of information, including citations to other patents. The list of citations for each patent is arrived at through a uniform and rigorous process applied by the patent examiner as a representative of the patent office. The patent applicant and her lawyer are obliged by law to specify in the application any and all of "the prior art" of which she is aware. The list of patent citations so compiled is available on the patent document, along with information on the patenting firm, inventor, geographic location, and technology types. In principle, a citation of *Patent X* by *Patent Y* indicates that *Patent Y* builds upon previously existing knowledge embodied in *Patent X*. Based on this premise, a series of recent articles have used patent citation data to track knowledge flows (Jaffe et al. 1993, Almeida 1996, Almeida et al. 2002). Thus, through patent documents one can infer both organizational and technological influences on a particular invention and thus track knowledge building across people, firms, geographic regions and countries, and time. This study uses data on all patents granted in the United States from January 1, 1980 through December 31, 1999. The U.S. Patent and Trademark Office patent database is useful in examining international knowledge flows because (a) every major player (U.S. or international) in the semiconductor industry patents extensively under this system for both inventions created in the United States and abroad, and (b) the system of citations is applied uniformly across firms regardless of the national origin of the multinational corporation.

As indicators of domestic or international knowledge transfer, patent citations suffer from some limitations. First, much knowledge building does not result in patenting. However, in semiconductors the incentives for patenting innovations are strong, and semiconductor manufacturers are prominent among the ranks of the most prolific filers of patents. IBM, Toshiba, Texas Instruments, AT&T, Samsung, Hitachi, Motorola, Mitsubishi, NEC, and Fujitsu were each granted over 1,000 patents during 1980–1999, and each one received more than 100 patents during 1999 alone. Additionally, the interfirm mobility of engineers has been recognized as an important driver in the rapid growth of the semiconductor industry in the United States (Rogers and Larson 1984, Holbrook et al. 2000), as well as a key component in the ability of non-U.S. firms to "catch up" (Kim 1997, Song et al. 2001).

Second, the argument can be made that patents represent explicit technological knowledge rather than tacit knowledge. We suggest that while patent documents may themselves represent codified knowledge, patent citations allow us to observe the patterns and end points of the knowledge transfer process, regardless of the type of knowledge (codified and/or tacit) involved in the process. Descriptive and empirical studies of innovation in semiconductor firms support the idea that tacit knowledge plays an important role in industry innovations (Saxenian 1990). Almeida and Kogut (1999) show that patent citations by firms within a region are closely related to the underlying pattern of knowledge flows facilitated via personnel transfer. Hence, we expect that the transfer and application of tacit knowledge, in part, create innovations that lead to patents. Further, Mowery et al. (1996) point out that codified knowledge flows and tacit knowledge flows are closely linked and complementary. Hence, while our arguments deal with tacit knowledge, we use patent citation data to indicate the beginning and end points of knowledge transfer.

Finally, not all patent citations represent knowledge building. Some citations may be introduced to distinguish the invention from dissimilar ones, or to protect the firm from litigation. We recognize that such motives introduce noise into our data, but we have no reason to believe that it produces systematic bias in our results. Thus, despite some limitations associated with the use of patent citation data, the uniformity and availability of the data has led to their increasing use in strategic management research to capture knowledge and its flows (Rosenkopf and Nerkar 2001, Jaffe et al. 1993).

We use data on inventors' locations to identify the geographic location of the patent, and firms' locations to identify the R&D lab in which the inventor works. To identify the sample of engineers who moved from U.S. to non-U.S. firms (and patented in both), we began by retrieving data for every semiconductor patent filed in the United States between 1975 and 1999. Based on the advice of patent examiners in the U.S. Patent Office, we identified 11 patent (technology) classes at the three-digit level that constituted semiconductor-related technology. Patents with their primary technology classes falling into one of these 11 classes were considered semiconductor patents.

Next, we tracked the patenting activities of each engineer listed in this sample of semiconductor patents, looking for instances where an engineer located in the United States filed a patent for a U.S. firm, and then subsequently filed a patent for a non-U.S. firm.[3] In these cases, we concluded that interfirm mobility occurred from a U.S. firm to a non-U.S. firm. We attempted to carefully identify and screen mobile engineers by collecting the complete patenting history of every likely engineer (including dates of patenting, firms, geographic locations, and technological areas of innovation). To maximize the probability that we were observing actual movements, we (a) compared the first and last names and middle initial for exact matches, and (b) checked that the temporal, geographic, and technological patterns of the patenting records revealed no contradictions or inconsistencies. We identified 180 mobile engineers, including 86 cases of cross-border mobility. Finally, as the basis for the main data set for this paper, we listed characteristics of all the patents filed by each mobile engineer at the firm that hired him or her. Our data collection resulted in a sample containing all 534 patents filed by the mobile engineers at their hiring firms (i.e., after moving), with one observation per patent. For each observation, we compiled the corresponding hiring firm characteristics, mobile-engineer characteristics, and details of their patents. Given the potential bias due to the nonindependence among observations in the cases when a particular mobile engineer filed multiple patents, we also constructed a separate data set that included only the first patents filed by these mobile engineers at their hiring firms. Thus, we have 534 observations in the "all patent" data set and 180 observations in the "first-patent-only" data set. We call each patent in our data set a "Hiring Firm Patent."

Methods

To test our hypotheses at the patent level, we used negative binomial regressions on patent citation counts. As an extension of the Poisson regression, a negative binomial regression is used to estimate models of occurrences (counts) of an event when the event has extra-Poisson variation in the form of overdispersion. In our negative binomial models, the probability that the number of patent citations will occur n times (with $n = 0, 1, 2, \ldots$) is as follows:[4]

$$\mathrm{Prob}(Y = yj) = e^{-\lambda j} \lambda_j^{Yj} / Y_j!,$$

where $\lambda_j = \exp(\sum B_i X_{ij}) \exp(\mu_j)$ and $e^{\mu j} \sim \mathrm{Gamma}(1/\alpha, 1/\alpha)$ for observed counts of patent citations Y_j with covariates X_i for the jth patent of the mobile engineer i.

Dependent Variable

Knowledge Sourced. The dependent variable, measured at the patent level, represents the extent of knowledge sourced from the hired engineer's previous firm. The variable is operationalized as the number of citations each hiring firm patent makes to any patent from the mobile engineer's previous firm. An increase in this measure indicates an increase in the degree to which a patent builds upon knowledge from the mobile engineer's previous firm.[5]

[3] The method that we employ to identify mobile engineers can pinpoint mobility only when an inventor patents in a firm before and after the interfirm mobility. We are not able to observe mobility when the inventor patents in only one firm (either before or after moving) and when the inventor does not patent in either firm—thus these mobile engineers are not included in our sample. However, though our sample represents a subset of all hired engineers, we believe our findings are still valid and important, because the mobile engineers in our sample who filed patents in both companies can be viewed as experienced "intellectual capital" (similar to the sampling scheme of Zucker et al. 1998). Thus, the paper focuses on external knowledge sourced and the resultant innovations that are directly attributable to the activities of these observed experienced mobile engineers.

[4] In the negative binomial model that we specify above, μ_j is an unobserved, omitted variable and $e^{\mu j}$ follows a gamma distribution with mean 1 and variance α as the overdispersion parameter. The larger α is, the greater the overdispersion.

[5] For ease of exposition, we framed the hypotheses in terms of hiring firm and mobile-engineer characteristics, though the hypotheses are tested at the patent level.

Independent Variables

Path Dependence. To measure path dependence (Hypothesis 1) of the hiring firm, we use self-citations. Self-citing occurs when a patent filed by a firm cites another patent from the same firm. Sorensen and Stuart (2000) and Rosenkopf and Nerkar (2001) used self-citations in a similar way to evaluate the extent of exploitative innovation or path dependence. Thus, we operationalize path dependence as the ratio of the number of self-citations to the number of total citations made by a hiring firm in each patent technology class (to which a hiring firm patent belongs).

Expertise Fit. We assess an engineer's key area of technological expertise by the technology class of the highest percentage of the engineer's total patents filed at the previous firm. Similarly, a firm's core technology area is assessed through the technology classes that account for the highest percentage of the firm's patents. We operationalize the fit between a hiring firm's core technology and the mobile engineer's expertise (Expertise Fit) by constructing a dummy variable, which takes on a value of one if the mobile engineer's prior area of expertise and the hiring firm's core technology are identical, and a value of zero otherwise (Hypothesis 2a).

For this measure, the core technology area of a hiring firm is determined by the number of patents filed in the five-year window preceding the specific hiring firm patent's date of application. Large hiring firms, such as Siemens, NEC, or Samsung, have filed a large number of patents in multiple technology classes and may thus have multiple core technology areas. Therefore, we identified core technology classes (1) with a more than 10% patent share in the five-year, window, and (2) in which the hiring firm has filed patents for the five consecutive years preceding the specific hiring firm patent's date of application.[6]

[6] Instead of multiple core technology areas, we also identified the primary technology area of a hiring firm with the largest number of patents filed and ran the regression models. The results were generally consistent with models using multiple core technology areas. Thus, we decided to use multiple core technology areas that are more realistic for large corporations.

Innovation Area. This variable indicates whether the hired engineer innovates in the new firm's core technology area or in a peripheral technology area. Using the same definition of the hiring firm's area of core technology, we introduce a dummy variable indicating whether the mobile engineer filed a hiring firm patent in a technology class included in the core technology area or not (Hypothesis 2b). The variable takes on a value of one if the technology class of the specific hiring firm patent is identical to the firm's core technology areas and a value of zero otherwise.

Domestic Mobility. To examine whether there is a significant difference between domestic and international mobility in the extent to which a hiring firm sources external knowledge, we introduce a dummy for domestic mobility. Mobility from a U.S. firm to a U.S.-based R&D lab of a non-U.S. firm is coded as one and mobility to a non-U.S.-based operation of a non-U.S. firm is coded as zero.

Controls. The degree of technological overlap between the hiring firm and the hired engineer's previous firm is measured in terms of the extent to which the two firms are patenting in the same technological areas. Following Jaffe (1986), we use the distribution of the firms' patents over 11 semiconductor-related patent classes to characterize their technological positions. We aggregate the set of patents filed by each firm and summarize the percentage of assignments in each of the 11 patent classes. The Euclidean distance between the hiring firm and the previous firm is then calculated:

$$\text{DISTANCE}_{ph} = \sqrt{\sum_{n=1}^{11} (P_{np} - P_{nh})^2},$$

where P_{np} is the percentage of patents in class n in the previous firm and P_{nh} is the percentage of patents in class n in the hiring firm.

The strength of a hiring firm's technological capabilities is operationalized as the total number of patents filed by the firm over the five-year period. A mobile engineer's prior research productivity is operationalized as the total number of patents filed by the engineer in his previous firm. In addition, we control for the number of patents belonging to a mobile engineer's previous firm and the number of citations made by a hiring firm patent because these may influence the extent of citations to the previous firm. Following the same method that we used to construct the "Expertise Fit" variable, we create a dummy variable indicating the fit between the mobile engineer's area of expertise and his previous firm's core technology areas.

The time at which each independent variable would be measured varies according to the specific patent's date of application. An appropriate window of time for defining the state of an engineer's or a firm's innovative activities appears to be five years, because this period approximately matches product life cycles in the semiconductor industry. Thus, we measure our independent variables using patent or patent citation data over the five-year window preceding the specific patent's application date. Because patent data are available from 1975 through 1999, the analysis is performed over the period 1980–1999.

Results

Before we tested our main hypotheses, we first examined the idea of learning-by-hiring in our sample. We investigated whether the movement of an engineer was associated with knowledge transfer from the previous firm over and above the knowledge the hiring firm typically sourced from the other firm before the engineer moved. To conduct this test, we first developed a control sample of patents belonging to the hiring firm (corresponding to each patent in the "first patent" sample). For each "first patent," we identified a randomly selected control patent that was granted to the hiring firm before the earliest possible date of movement and belonging to the same technology area (semiconductors). (Because we did not have precise dates of mobility, we estimated the earliest possible date of mobility by the date of the last patent of the mobile engineer in the previous firm.) Thus, the control patents comprised a matched premobility sample. Of the 180 patents (in the first patent sample), 29 cases did not have comparison patents because no patents were granted to the hiring firm in the given year in the semiconductor industry. Thus, we had 151 cases of matched pairs. For each patent in the two samples, we then calculated the ratio of citations to the mobile engineer's previous firm (i.e., the number of citations made by the patent to the mobile engineer's previous firm divided by the total number of citations made by that patent). We thus followed the matched-pair comparison method used in Almeida et al. (2002) and used t-tests to evaluate difference in sample means. The results showed that the first patents granted to mobile engineers in the hiring firms are much more likely (about seven times) to cite their previous firms' patents than randomly selected controls from the time period before mobility. We found a statistically significant difference in sample means at the 0.01 level. Thus, these results support the idea of learning-by-hiring in our sample.

Using negative binomial regressions, we tested our main hypotheses regarding the conditions under which the mobility of engineers is more likely to facilitate interfirm knowledge transfer. Table 1 presents the descriptive statistics. The correlation matrix does not show any troubling collinearity among the variables, except for the two "fit" variables—expertise fit with the hiring firm and innovation area fit variables. Table 2 summarizes the statistical findings from the negative binomial regressions. The first three equations represent the analysis from the "first-patent-only" data set with 180 observations, and the last three equations from the "all-patents" data set with 534 observations. Given the potential bias due to non-independence among observations, we use the first three equations as primary models and confirm the results using the last three equations. To check the robustness of our findings in the presence of potential multicollinearity, we ran nested equations by adding the two "fit" variables sequentially. We Estimated Equations (1) and (2) ((5) and (6) in the full patent sample) without "innovation area fit" and "expertise fit," respectively. Equation (3) ((6) in the full patent sample) is a full model with both "fit" variables. In addition, to evaluate the magnitude of the estimated effects from the negative binomial regressions, we computed the percentage change in the dependent variable associated with a one standard deviation change in each independent variable, evaluated at the mean of the data, as shown in the Appendix.

Consistent with Hypothesis 1, the Path Dependence variable is significant and negative in the first three

Table 1 Summary Statistics and Correlations

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11
1. Knowledge sourced	0.27	0.71											
2. Path dependence	0.04	0.08	−0.08										
3. Expertise fit with hiring firm	0.66	0.48	−0.16	−0.06									
4. Innovation area fit	0.72	0.45	−0.17	0.12	0.33								
5. Domestic dummy	0.52	0.50	0.03	0.09	−0.04	−0.05							
6. Technological distance	0.45	0.18	0.14	−0.01	−0.08	−0.03	−0.12						
7. (Technological distance)^2	0.24	0.19	0.14	−0.03	−0.10	−0.05	−0.09	0.97					
8. Hiring firm's total patent #	109.32	169.61	−0.02	0.22	0.16	0.29	0.16	−0.05	−0.07				
9. Hired engineer's patent #	3.11	4.38	0.10	−0.01	0.05	−0.05	0.04	−0.01	0.01	−0.02			
10. Previous firm's total patent #	830.58	1287.9	0.26	0.01	−0.03	0.03	−0.08	0.23	0.21	−0.01	0.03		
11. Number of total citations for each hiring firm patent	6.12	5.16	0.25	−0.04	0.06	0.06	0.19	−0.03	−0.05	0.29	0.10	−0.02	
12. Expertise fit with previous firm	0.69	0.46	0.12	0.05	0.07	−0.01	−0.04	0.01	−0.01	0.02	−0.02	−0.04	−0.01

Note. "First-patent-only" data set; $N = 180$.

equations. The results suggest that when a firm has stronger path dependence, mobile engineers are less likely to build upon the knowledge of their previous firms. It is interesting to note that the Path Dependence variable was significant for the "first-patent" models but not for the "all-patent" models. The "first-patent" models cover patents created relatively soon after the engineer joins the hiring firm. The "all-patent" models include patents developed over a longer period of time, including those developed after

Table 2 Learning-by-Hiring and Interfirm Knowledge Transfer: Statistical Findings from Negative Binomial Regressions

	First patent model ($N = 180$)			All patent model ($N = 534$)		
Equation	1: Expertise fit	2: Innovation area fit	3: Both	4: Expertise fit	5: Innovation fit	6: Both
Path dependence (H1)	−14.297	−11.520	−13.207	−5.741	−4.823	−5.296
	(6.764)**	(6.357)*	(6.597)**	(3.590)	(3.446)	(3.503)
Expertise fit (with hiring firm) (H2a)	−0.953	—	−0.76	−0.766	—	−0.653
	(0.417)**	—	(0.436)*	(0.290)***	—	(0.304)**
Innovation area (H2b)	—	−0.844	−0.594	—	−0.621	−0.398
	—	(0.415)**	(0.423)	—	(0.319)*	(0.332)
Domestic mobility	−0.011	0.129	0.000	0.008	0.109	0.004
	(0.398)	(0.395)	(0.396)	(0.287)	(0.283)	(0.287)
Technology distance (control)	0.693	0.124	0.878	−2.649	−2.761	−2.507
	(4.309)	(4.372)	(4.312)	(3.314)	(3.324)	(3.303)
(Technology distance)^2 (control)	0.425	0.977	0.122	2.806	2.909	2.570
	(3.745)	(3.774)	(3.733)	(3.067)	(3.079)	(3.059)
# of hiring firm patents (control)	0.0013	0.0010	0.0009	0.0005	0.0007	0.0008
	(0.0013)	(0.0013)	(0.0013)	(0.0009)	(0.0009)	(0.0009)
# of mobile engineer patents (control)	0.056	0.034	0.052	0.012	0.006	0.010
	0.056	0.034	0.052	0.012	0.006	0.010
# of previous firm's patents (control)	0.0003	0.0004	0.0003	0.0003	0.0003	0.0003
	(0.0001)***	(0.0001)***	(0.0001)***	(0.0001)***	(0.0001)***	(0.0001)***
# of citations by patent (control)	0.055	0.055	0.051	0.084	0.079	0.081
	(0.035)	(0.035)	(0.035)	(0.023)***	(0.024)***	(0.026)***
Expertise fit with previous firm (control)	1.165	0.922	1.085	0.616	0.539	0.608
	(0.486)**	(0.477)*	(0.484)**	(0.340)*	(0.335)	(0.338)*
Likelihood ratio chi-square	6.79	8.24	5.74	23.10	25.45	22.16
Prob > chi-square	0.009	0.004	0.016	0.0001	0.0001	0.0001

Note. *Significant at $p = 0.1$; **significant at $p = 0.05$; ***significant at $p = 0.01$. Standard errors in parentheses.

the mobile engineer had established herself and presumably gained more power and influence within the firm. These results may suggest that the firm's path dependence is a greater constraint to an engineer utilizing external knowledge when the engineer first joins a firm (and this is reflected in the nature of her early patent citations). Path dependence may matter less when the engineer grows more established, develops power and influence within the new organization, and is therefore more able to decide her own research direction, incorporating knowledge drawn from her previous firm.

Regressions run on both data sets show that Expertise Fit was negative and significant. This result supports Hypothesis 2a and suggests that when a hired engineer's key area of expertise lies outside the core technology areas of the hiring firm, the engineer is more likely to build upon the knowledge base of his previous firm. Similarly, Innovation Area was also significant and negative in Equations (2) and (5), supporting Hypothesis 2b, although the variable became insignificant in Equations (3) and (6) with the expertise fit variable added. This finding lends some support to the idea that a mobile engineer is more likely to cite the previous firm's patents when the engineer pursues innovative activities in the hiring firm's noncore areas.

Finally, the dummy variable for Domestic Mobility was not significant. This lack of significance indicates that the data do not support the idea that domestic mobility is more conducive to learning-by-hiring than is international mobility. Moreover, as shown in the Appendix, the percentage change in the dependent variable with a one standard deviation change in the domestic dummy variable was only 0.1%, indicating support for the idea that domestic mobility and international mobility are similarly conducive to learning-by-hiring.

Among the control variables, both the previous firm's number of patents and the mobile engineer's expertise fit with the previous firm were generally positive and significant, as expected. In addition, the number of citations for each hiring firm patent was also significant and positive in the "all-patents" samples. However, both technological distance between the two firm's technological profiles and its quadratic term were not significant.[7]

Discussion and Conclusions

The results of the statistical tests generally support our hypotheses. The tests show that learning from a mobile engineer's previous firm is more likely when (1) hiring firms are less path dependent,[8] (2) hired engineers possess technological expertise distant from that of the hiring firm, and (3) hired engineers work in noncore technological areas in their new firm. In addition, our tests do not indicate any significant difference in the extent to which international mobility and domestic mobility are conducive to learning-by-hiring.

The intended contribution of the study is to examine the conditions under which mobility is most likely to facilitate interfirm knowledge transfer through learning-by-hiring. The study suggests that firms that wish to extend their knowledge bases to new distant technological areas can use mobility to good effect. Our results show that the level of interfirm knowledge transfer increases especially when firms hire engineers with skills distant from their own and use them outside their existing core technological areas. On the other hand, firms that wish to access knowledge from other firms within their established technological areas may find mobility less useful due to path dependent search behavior along their existing technological trajectories. This may be an especially serious problem because the extent to which a firm is path dependent may not be particularly obvious to managers.

Our findings suggest that there may be two different motives for hiring experienced engineers. On the one hand, firms that are still developing technological capabilities, and therefore lack well-defined technological trajectories, may be more likely to hire engineers from competing firms with the specific purpose of accessing the knowledge developed at these

[7] We also added interaction terms among selected variables, but none of the interaction terms were significant at the 0.05 level.

[8] We note that we had significant results for path dependency in the first patent samples only, not in full patent samples. We explained the possible reason for that in the results section.

firms. Therefore, mobile engineers hired by firms with weaker capabilities are more likely to build on knowledge developed at their previous firms. On the other hand, when a firm with well-established technological trajectories in its core area hires a mobile engineer, it may do so to build high-quality human capital rather than to source specific external knowledge.

Another interesting issue is the possible effect of a match between the mobile engineer's ethnicity and the hiring firm's country of origin. One may suspect that, due to cultural and linguistic factors, a mobile engineer with the same national origin as the hiring firm may be more likely and able to transfer knowledge. To check for this effect, we constructed a subsample of mobility to Taiwanese, Korean, and Japanese firms (because it was relatively easy for us to identify Chinese, Korean, and Japanese names with some precision). Of the 64 mobile engineers who moved to these firms, 52 of them had the same ethnic origin as their hiring firms. In a supplementary t-test, we failed to find any significant difference between the match and nonmatch samples. This result may suggest that, although ethnic origin may be important for determining the probability and destination of the migration of experienced engineers (52 out of 64 cases in the case of Taiwanese, Korean, and Japanese firms), ethnic origin does not seem to substantially affect the level of interfirm knowledge transfer once mobility has occurred.

The sourcing of external knowledge is especially important for emerging economies that seek to narrow the technological gap between themselves and advanced nations. Foreign technology has played an important role in the industrialization of Europe, the United States, Japan, and newly industrializing countries such as South Korea and Taiwan (Freeman and Soete 1997) through the activities of multinational firms in host countries, alliances, and licensing arrangements. New-growth theorists have argued, however, that despite the presence of these mechanisms of knowledge flow, the geographical localization of knowledge spillovers has generally made it difficult for these technological laggards to catch up (Romer 1990, Grossman and Helpman 1991). Our results indicate that the international mobility of experienced engineers could provide a mechanism to mitigate the localized nature of knowledge spillovers and perhaps reduce this technological disadvantage. This issue is especially relevant to emerging economies that have large pools of their own nationals working at leading firms and universities in the United States. The World Bank (1993, 1998) and Song et al. (2001) provided evidence of this opportunity for emerging economies like Taiwan and Korea.

In this study, we focus only on the role of mobility as a mechanism for acquiring knowledge from other firms. Of course, the hiring of experts can be useful to innovation in other ways. For instance, experienced engineers can use their skill sets to enhance the new firm's innovative abilities without building on their previous employer's knowledge. In future research, we aim to assess the innovative impact of mobility in the new firm by assessing both skill-based contributions and knowledge-sourcing contributions. We have previously pointed out that the method used to identify mobility does not permit us to observe every instance of mobility between non-U.S. and U.S. firms. In other words, our sample represents only a subset of all the relevant mobile engineers. Though we do not believe this presents any bias, we specify this as a boundary condition for our findings.[9]

[9] Regarding the possibility of bias, we acknowledge that there are mobile inventors who patent before moving, but not after moving. Because these engineers do not patent subsequently, the absence of patents (and citations) prevents us from observing the conditions under which they might cite the previous firm. Previous research suggests that a preponderance of mobile semiconductor engineers indeed patent in the hiring firm. In a study of knowledge flows to semiconductor start-ups, Almeida (1996) examined the innovative activity of engineers hired by start-ups at their founding. He found that 27 of the 33 engineers studied (82%) had patented innovations in their new firms. It is also important to note that our research question asks primarily under *what conditions* mobility is more likely to facilitate interfirm knowledge transfer through learning-by-hiring. (Using a matched pair t-test, we also showed that mobility of engineers indeed leads to substantial knowledge transfer from previous firms to hiring firms. However, this is not the main focus of our study.) Our paper looks at geographic and technological conditions pertaining to the inventor and hiring firm and relates them to the likelihood of interfirm knowledge flows. We believe the nature of our research question and design limits the possibility of bias, although the nature of our sample may limit the generalizability of our results.

This paper focuses only on external knowledge sourced, and the resultant innovation that is directly attributable to the activities of mobile engineers. However, the other important dimension of knowledge transfer from the previous firms to the hiring firms of mobile engineers is the knowledge diffusion to colleagues of these mobile engineers in the hiring firms. Through collaborative research, social interaction, and mentoring, these individuals may impact innovation more deeply than we evaluated here. Thus, another important extension would be to examine whether and under what conditions knowledge diffuses beyond the mobile engineer, and to assess the value this creates in the hiring firm.

Prior research has often emphasized the importance of external knowledge as a source of innovation. A firm's absorptive capacity, based on experiential learning and investments in R&D, has been viewed as a source of the firm's competitive advantage (Cohen and Levinthal 1990). However, although most research has focused on how a firm's existing technological capabilities help it identify, absorb, and integrate external knowledge, such work has downplayed the potential negative consequences of such capabilities (Song and Shin 2002). Given that a firm with a strong existing knowledge base is more likely to have established idiosyncratic technological trajectories, and thus to exhibit path-dependent search behavior, this knowledge may reduce the firm's receptivity to sourcing external knowledge. If so, the challenge for firms may be to balance the exploitation of current knowledge with the acquisition of new knowledge. Our study shows that hiring experienced engineers could, under certain conditions, help a firm extend the technological and geographical boundaries of its knowledge.

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Appendix. Magnitude of Estimated Effects from Negative Binomial Regressions

Variables	% change
Path dependence (H1)	54.6
Expertise fit (with hiring firm) (H2a)	18.3
Innovation area (H2b)	13.5
Domestic mobility	0.1
Technology distance (control)	9.2
# of hiring firm patents (control)	11.1
# of mobile engineer patents (control)	11.5
# of previous firm's patents (control)	24.7
# of citations by patents (control)	13.5
Expertise fit with previous firm (control)	25.5

Note. To calculate the economic significance of coefficients reported in Table 2, we computed the percentage change in the dependent variable associated with a one standard deviation change in each independent variable, evaluated at the mean of the data. Similarly for the dummy variables, we computed the percentage change in the dependent variable associated with Turning the dummy "on," evaluated at the mean of the data. We report figures for the first-patent-only model as our main model.

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