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SHOULD AULD ACQUAINTANCE BE FORGOT? THE REVERSE TRANSFER OF KNOWLEDGE THROUGH MOBILITY TIES†

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While mobility's effect on knowledge transfer to firms that hire mobile employees is well demonstrated, we choose to explore mobility's effect on knowledge transfer to firms that lose these employees. Focusing on this 'outbound mobility' allows us to isolate effects of social mechanisms associated with mobility. We find that semiconductor firms losing employees are more likely to subsequently cite patents of firms hiring these employees, suggesting that mobility-driven knowledge flows are bidirectional. In addition, the outbound mobility effect is pronounced when mobility occurs between geographically distant firms, but attenuates for geographically proximate firms since other redundant knowledge channels exist within regions.

INTRODUCTION

Research on the effects of interfirm mobility focuses on how the gain or loss of employees shapes various organizational outcomes, including survival rates, access to knowledge, and influence. A well-established perspective in this research holds that mobile employees are repositories of skills, routines, and knowledge that they carry with them from their prior employer to their new employer. Such a perspective, rooted in notions of portable human capital, tends to find that hiring firms gain from importing these employees. Thus, hiring firms have been found to import product line strategies (Boeker, 1997) and technical knowledge (Rosenkopf and Almeida, 2003) in the semiconductor industry; to increase product innovation in the mutual fund industry (Rao and Drazin, 2002); and to increase their influence in technical committee activity (Dokko and Rosenkopf, 2006).

A straightforward corollary of this notion is that the loss of employees to other firms can have negative consequences for the firms losing these employees. For example, Phillips (2002) demonstrates that the movement of partners between Silicon Valley law firms leads not only to an increase of the likelihood of survival for the hiring firms, but also a corresponding decrease in the likelihood of survival for the firms that lost partners. Wezel and colleagues (2006) note similar hazards for Dutch accounting firms that lose employees, particularly when the employees move in groups to nearby firms. In these cases, it is clear that mobile employees are carrying resources attributable not only to human capital but also to their accumulated

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social capital in the form of client and within-firm relationships.

This paper departs from most previous studies by exploiting a unique characteristic of social capital: the bidirectionality of social ties in the context of information transfer. Employees moving from one firm to another remove and transfer something from the firms they leave to the firms they join—as we know from previous research—but also generate a communication channel between both firms (i.e., their social contacts at the firm they left). We consider that these channels become part of the social capital of both firms involved in the mobility event. Of course, in a study of gains for the firm hiring the employee, it is challenging to discern whether the underlying knowledge transferred relates to human capital, social capital, or a combination of both mechanisms. For this reason, we theorize about the impact that losing an employee has on interfirm transfer of knowledge, which is our approach for isolating social capital mechanisms.

Thus, while both human capital and social capital arguments predict gains for firms receiving mobile employees, they generate opposing predictions when we consider firms losing mobile employees. Specifically, while the human capital argument predicts losses for the prior employer, the social capital mechanism predicts gains for the prior employer. This is because the communication channels established between the two firms as a result of employee mobility are assumed to be bidirectional, while the transfer of human capital is assumed to be unidirectional. In this spirit, Agrawal, Cockburn, and McHale (2006) suggest that 'enduring social relationships' between inventors who have moved to new regions and their prior colleagues increase the likelihood of knowledge spillovers to the original locations of the inventors, while Somaya, Williamson, and Lorinkova (2008) suggest that the effects of both losing and gaining patent attorneys vary with whether the other firm is a client or a competitor.

The purpose of this paper is to test whether the loss of an employee to another firm, which we term 'outbound mobility,' is associated with a subsequent transfer of information from the firm that hired the employee to the firm that lost the employee. Such a transfer is in the reverse direction from the transfer of knowledge to the hiring firm that has been well demonstrated. We examine this relationship by systematically exploring linkages between firms while controlling for a host of alternative mechanisms that might also affect knowledge flows to firms experiencing outbound mobility of inventors. In other words, we explore the questions of how and when a firm losing an employee may subsequently draw upon the knowledge of the firm hiring the employee.

Our empirical setting, semiconductor industry research and development (R&D), is particularly suited to explore these questions for four reasons. First, patent activity in the industry is pervasive, providing a thick trail of documentation of knowledge development. Second, the industry is well recognized as a context where innovation rests on the R&D capabilities of individuals and firms operating under uncertainty. Since a long tradition of research on the diffusion of innovations suggests social interactions and ties have strong effects on actors' decisions under conditions of uncertainty (Rogers, 2003), mobility is likely to influence communication channels and monitoring behaviors, which influence knowledge flows. Third, firms in this industry are locally clustered across diverse geographic regions, enabling us to contrast the effects of mobility within and across regions. And finally, inventor mobility may be inferred from patent records, which facilitates the study of the impact of interfirm mobility among crucial employees with a proven record in the development of patentable inventions.

THEORY

In this paper, we focus on knowledge transfer across firm boundaries in the semiconductor industry. Knowledge transfer occurs when an organization is affected by the experience of other organizations (Argote *et al*., 2000). This effect can change the knowledge stock or performance of the organization receiving the transfer of knowledge. Among the mechanisms accounting for knowledge transfer across organizations identified in the literature are strategic alliances, employee mobility, informal communications, patents, and scientific publications.

Previous research on knowledge transfer has distinguished between the transfers of technological or scientific knowledge (Allen, 1977). Regarding the transfer of technological knowledge, Allen and colleagues (Allen, 1970, 1977; Marquis and Allen,

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1966) have advanced the thesis that it is contained inside organizations and does not transfer across research centers in different firms, and that this manner differs from the transfers of scientific knowledge, which diffuses across organizations freely. Their argument is based on the fact that organizations face a competitive environment and are profit seekers. This constrains and prohibits the emergence of social networks of the type of invisible colleges among researchers. On the other hand, Levin (1988) has found that in the case of high-technology industries (which according to his definition included the semiconductor industry), firms report conversations with employees of innovating firms as a relevant mechanism for learning from other firms. This is consistent with accounts of the importance of informal communications in Silicon Valley as a mechanism of knowledge transfer across organizations (Rogers and Larsen, 1984; Saxenian, 1994).

Outbound mobility and knowledge transfer

In developing innovations, firms learn from others, and this transfer of knowledge across firms' boundaries is a crucial part of the development process. While studies have demonstrated the effects of activities like alliances and inbound mobility on knowledge access and transfer, the effects of outbound mobility for firms losing employees have not been explored systematically. There are two distinct mechanisms by which firms losing employees may obtain increased access to the knowledge of the new employer.

The first mechanism by which outbound mobility may generate knowledge flow is the establishment of interpersonal communication channels between the firm hiring the employee and the old firm. In some sense, the term 'establishment' is misleading here, as the interpersonal relationship between the employees already existed when they worked together at the prior employer; the ties between people endure. However, when firm-level networks are considered rather than individual-level networks, the mobile employee's arrival at the new firm establishes a link between the old employer and the new one. Despite the proprietary concerns that would theoretically arise with knowledge transmission after such a move, substantial anecdotal evidence supports that it does occur. Rogers and Larsen (1984: 82–83) note:

> *'In Silicon Valley an engineer may disclose technical information to a former colleague who now works for a competing firm... Information-exchange due to friendship was described... [by an executive at National Semiconductor in this way]...: "We all know each other. It's an industry where everybody knows everybody because at one time or another everyone worked together."'*

Likewise, Fleming and colleagues (2004: 16) note that the research engineer:

> *'usually maintained links to these individuals [earlier research collaborators now working in another firm] by passing back old information relating to his prior work, rather than by applying that same information to his new work going forward.'*

And that the firm

> *'did not, "give you time for any outside life [that would enable knowledge transfer]." Yet, before starting a project, he reported that [the firm's] engineers call their friends (who include colleagues at other firms), contact professors at universities, and read the patent and scientific literature.'*

Thus, professional allegiance and its norm of generalized reciprocity (Merton, 1973; Price, 1986) facilitate know-how trading (von Hippel, 1987) among technical employees working at different firms. The social connections across firms' boundaries created by a mobility event (i.e., social ties that were developed between the mobile employee and fellow workers who worked together in the old firm) are likely to facilitate these sorts of knowledge flows.

The second mechanism by which outbound mobility may generate knowledge flows does not rely on interpersonal communication channels; rather, the movement of an employee to another firm may lead former colleagues to devote more attention to monitoring knowledge output at the new employer. Indeed, Ocasio's (1997) attention-based view of the firm suggests that firm-level cognition is bounded and influenced by particular events. Ocasio identifies the patterns of interactions between members of the firm—interactions that are forged by formal and informal structures over time—as playing a crucial role in the process of finding solutions. The patterns of information search become routinized (Nelson and Winter, 1982) and over time individuals are recognized as the source for particular types of information; which, in the case of research centers, means that inventors have proven themselves to be sources of information leading to innovations.

In our study, we posit that when employees leave one firm for another, their colleagues remaining at the prior employer can become more aware of the new employer as a site where knowledge worth knowing is being produced. Such effects would be more pronounced when the new employer is a startup that has not yet become fully legitimized in the industry. By having one of their own going to that firm, work in the receiving firm gains credibility and saliency. The firm receiving the employee thus becomes more highly monitored for innovation opportunities. Through this monitoring process, the firm that has lost the employee may gain knowledge (which may have even been in the public domain, but not incorporated to its own knowledge reservoir).

Whether the underlying mechanism is posited to be the establishment of a communication channel or increased salience and monitoring of the activities of the receiving firm, both mechanisms lead us to predict:

Hypothesis 1: When an inventor leaves one focal firm and joins another, the likelihood increases that the focal firm subsequently draws upon the new employer's knowledge.

It is important to note that the mechanisms described above are not limited to the case of outbound mobility but can also work in parallel with the transfer of skills and knowledge embedded in the employee for the hiring firm. What is unique about outbound mobility is that if an instance of transfer of knowledge from the hiring firm to the focal firm is found associated with the event, absent another employee hired by the focal firm from the hiring firm, the transfer of knowledge cannot be explained by the inflow of skills and knowledge embedded in any employee.

Outbound mobility, geographic proximity, and knowledge transfer

It is well established in the literature that knowledge spillovers are localized (e.g., Hagerstrand 1967; Jaffe, Trajtenberg, and Henderson 1993). It is also well established that social networks within industrial districts or regions generate these localized knowledge spillovers (e.g., Saxenian 1994; Inkpen and Tsang 2005). Such spillovers are rooted in a shared culture and trust that develops by numerous mechanisms, including mobility (Almeida and Kogut, 1999), shared socialization during training (DiMaggio and Powell, 1983), and the host of informal contacts that arise through the multitude of professional associations, casual gathering places, and other social contacts that take place between geographically proximate people (Saxenian, 1994).

Thus, geographic proximity is likely to proxy for a host of mechanisms that may facilitate knowledge spillovers, of which mobility is one. Yet mobility, while perhaps more prevalent within regions, certainly occurs across regions as well, and should confer similar spillovers. Indeed, while access to information obtained through an outbound mobility tie is likely to be available through other mechanisms when the tie is contained inside a region, it may not be readily available through other mechanisms when mobility occurs across regions. Rosenkopf and Almeida (2003) suggest a similar argument—that the knowledge transfer effects of hiring within geographic regions may be less pronounced than those of hiring across geographic regions—based on traditional sociological arguments that bridges to new contexts provide the most valuable knowledge (Burt, 1992; Granovetter, 1985).

Therefore, an outbound mobility event within a geographic region is more likely to create a duplicative channel for the transfer of knowledge due to the multiplicity of channels already available within a region. In contrast, an outbound mobility event to a distant region is more likely to create a unique channel by which useful (i.e., nonredundant) knowledge can flow. As a result, we propose that proximity moderates the relationship between outbound mobility and knowledge flow:

Hypothesis 2: When an inventor leaves one focal firm and joins another, the likelihood is greater that the focal firm subsequently draws upon the new employer's knowledge when this outbound mobility occurs between geographically distant firms than proximate ones.

METHODOLOGY

Data were gathered from the semiconductor industry. In order to collect the different variables, the information on the front page of the patents granted by the United States Patent and Trademark Office (USPTO,) obtained from the National Bureau of Economic Research (NBER) U.S Patents Citation Data file (Hall, Jaffe, and Tratjenberg, 2001) and the National University of Singapore Patent databases, was utilized together with data from ICE, Dataquest, and SDC Platinum databases.

Among all the types of knowledge transferred, scientific and technological knowledge leaves a trace on paper when that knowledge is granted a patent. Patent legislation in the United States requires the inclusion of the following elements in the patent: the knowledge patented (which has to be original and innovative), the owner of the patent, the inventors and their geographic locations, and citations to all the relevant patents that this new invention has built on. Therefore, and because an officer of the patent office controls the appropriateness and comprehensiveness of the citations, a patent becomes a physical record of the transfer of knowledge to the firm (represented by each instance of a citation of another patent) (Almeida and Kogut, 1999; Jaffe *et al*., 1993). As discussed by Jaffe *et al*. (1993) as well as Alcacer and Gittelman (2006), this is not to say that patents are able to capture all instances of knowledge transfer between firms (knowledge transferred may result in no patent granted) or that every citation is an instance of knowledge transfer (the citation could have been included by the patent officer).[1] Despite these limitations, patents are generally acknowledged as sources of information transfer in the United States (Cohen, Nelson, and Walsh, 2000; Cohen *et al*., 2002), and patent citations are records that allow us to track when a firm draws on another firm's knowledge stock—as per our definition, a case of knowledge transfer. In addition, the concern about a firm acting on knowledge transferred without resulting in a patent is partially lessened by the fact that the semiconductor industry relies on patenting as a mechanism to protect firms' ability to profit from their intellectual capital. Thus, the patent process is standardized and requires the inclusion of information about location(s) of the inventor(s) and the firm(s) (which allows tracking of mobility and geographic location), and citation of previous patents from which the innovation draws (Jaffe *et al*., 1993).

[1] Nevertheless, a citation, despite being included by the patent officer, can still be an actual record of knowledge transfer of which the grantee is unaware (a case of cryptomnesia [Jung and Franz, 1968; Merton, 1973]) or unwilling to disclose. Even in the case that the inclusion does not represent an actual record of knowledge transfer, we cannot see a reason why this mandatory addition by the officer is correlated in any form to the mobility event. Thus, this may introduce noise to our measure but does not bias the results in the direction predicted in this paper.

Sample

All the firms that design or manufacture semiconductor devices and have at least one U.S. semiconductor patent between 1980 and 1994, as per NBER classification (main classes 257, 326, 438, and 505), are included in the sample. This results in a total of 154 firms. All the patents granted to those firms that have application dates between 1975 and 1995 were gathered from the NBER database. This results in a dataset of around 42,000 patents. Information for all firms that designed or manufactured semiconductor devices was obtained from databases compiled by ICE and Dataquest, two private research firms specializing in semiconductor industry analysis, for the period 1980–1989, and from SDC Platinum for the period 1990–1995.

Variables

The unit of analysis for these variables is the dyad—the firm citing (*focal* firm) and the one at risk of being cited (*alter* firm). Our measurement includes: unidirectional dyadic variables (e.g., for citations, hiring, outbound mobility); bidirectional dyadic variables (e.g., for alliances, geographic proximity, technological distance); focal firm variables (e.g., number of patents granted to the focal firm); and alter firm variables (e.g., number of patents granted to the alter firm). The dependent variable was measured for each dyad year for the period 1985–1995. In other words, our dataset contains one observation per year for each dyad in the sample. All the independent variables preceded the dependent variable in time. Due to the time lags introduced in the patenting process, several of our independent variables are measured over multiyear windows as we describe below.

Citation count (cites). For each focal-alter dyad, this variable is a count of the number of times the focal firm cited the alter firm on patents granted with application dates on the year of observation.

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Each citation is treated as one instance of the focal firm's drawing on the knowledge of the cited firm. *Cites* is compiled from the NBER dataset.

Outbound mobility (OutMobility). This variable identifies the instances when an inventor moved from a focal firm to an alter firm in our sample. According to our previous discussion, mobility provides a channel for new information to reach the firm. The firm has to act on this new information and create an innovation to be patented. Jaffe and colleagues (1993) reported that patent citations reach a peak between three to five years after the patent was granted. However, the pattern of citations clearly indicates that there is not an exact lag between access to information and the generation of a patent drawing on that information. In addition, studies on the effect of mobility and alliances have found that mobility of inventors during the 1980s has an effect on citation patterns for the period 1990–1995 (Almeida, Dokko, and Rosenkopf, 2003; Rosenkopf and Almeida, 2003). For these reasons, we analyzed the effects of mobility and alliances on citations across a five-year window following each event.

We examined the set of semiconductor patents for each firm in our sample between the years 1980 and 1995 in order to find mobility events. All inventors listed on the semiconductor patents through the 1980–1995 period were then tracked to identify instances where inventors were employed by more than one firm over their patent trajectory. The Appendix details the procedure we used for this purpose. A case of mobility was identified when a researcher was listed as inventor in patents granted to two different firms.[2] Since with this procedure it is impossible to pinpoint the exact date of mobility, we use the following approach: the time of the mobility event is estimated as the year *before* the application year of the first alter firm's patent where the mobile employee appears as inventor. This assumes that inventors are able to apply for a patent fairly quickly once in the new firm; therefore, on average they moved into the new firm one year before being able to produce a patent.[3] This mobility event leaves open the possibility for employees in the old firm to incorporate in their new patents information that may be available immediately after the employee's arrival at the new firm. We coded *outbound mobility* as one if at least one case of outbound mobility has occurred in the five-year window preceding the year of observation; otherwise it was coded as zero. Ninety-nine of the 154 firms in the sample experienced an outbound mobility event.

Geographic proximity (GeoProximity). When two firms are located in the same metropolitan statistical area (MSA) or same country (in the case of foreign firms), *GeoProximity* is coded as one, otherwise it is coded as zero. We utilized the MSAs for 1993 as defined by the U.S. Office of Management and Budget (30 June 1993) (See Table 1 for MSA codes and names). The location of the firm was obtained from the first page of the USPTO patents granted to the firm during the year of the observation. For firms reporting more than one location across their patent portfolios, we assumed the primary location to be the site with the majority of the patents.[4]

Controlling for alternative mechanisms of knowledge transfer

In order to increase the confidence in the results for outbound mobility of this study, we also considered the following alternative mechanisms of knowledge transfer.

[2] By this procedure we are able to identify only those mobility cases of researchers that appeared as inventors in patents granted to both firms. A mobility event is not detected when a researcher moves from one firm to another without being listed as an inventor in any patent of any of the firms, which leads to underestimation of mobility. Despite only tracking researchers listed as inventors, the results of this study are relevant because we are capturing the mobility of researchers with higher human capital (being acknowledged as an inventor is a clear indicator of high human capital). As described above, purely human capital explanations would expect a negative impact on the firm losing this kind of employee.

[3] For mobility events identified between 1975 and 1994, the average period of time between application years of the last patent in the old firm and the first patent in the new firm is 4.43 years. While 73 percent of the lags were more than one year, 89 percent were at least one year, suggesting that our estimation is reasonably conservative, certainly more so than estimating the timing of mobility via interpolation. As another check, we also ran models defining the mobility event the year after the application year of the first patent granted to the hiring firm where the employee appears as an inventor. This more conservative test yielded results similar in sign, but outbound mobility and hiring effects are smaller and achieve lower significance levels.

[4] Of the 154 firms, 76 have presence in multiple regions. The average number of patents accounted for in the primary location, based on the first inventor's address, is 89 percent with a median of 99.9 percent. For firms with presence in multiple regions, the average number of patents accounted for in the primary location is 80 percent with a median of 83 percent. A model with a dummy variable capturing whether the firm has multiple locations (see Table 8) yields robust results.

Table 1. Metropolitan statistical areas (MSA) where semiconductor firms are located (metropolitan areas defined by Office of Management and Budget, 30 June 1993)

MSA CODE or COUNTRY	Metropolitan area or country names	Number of firms
7362	San Francisco-Oakland-San Jose, CA	56
4472	Los Angeles-Riverside-Orange County, CA	9
5602	New York-Northern New Jersey-Long Island, NY-NJ-CT-PA	7
1122	Boston-Worcester-Lawrence, MA-NH-ME-CT	4
1922	Dallas-Fort Worth, TX	4
6442	Portland-Salem, OR-WA	4
1692	Cleveland-Akron, OH	2
2162	Detroit-Ann Arbor-Flint, MI	2
5120	Minneapolis-St. Paul, MN-WI	2
6162	Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD	2
7320	San Diego, CA	2
1080	Boise City, ID	1
1602	Chicago-Gary-Kenosha, IL-IN-WI	1
1720	Colorado Springs, CO	1
3280	Hartford, CT	1
3362	Houston-Galveston-Brazoria, TX	1
4992	Miami-Fort Lauderdale, FL	1
6200	Phoenix-Mesa, AZ	1
6280	Pittsburgh, PA	1
6340	Pocatello, ID	1
6480	Providence-Fall River-Warwick, RI-MA	1
6640	Raleigh-Durham-Chapel Hill, NC	1
8520	Tucson, AZ	1
US	Not in a MSA	3
JP	Japan	23
TW	Taiwan	6
CA	Canada	3
KR	Korea	3
DE	Denmark	2
FR	France	2
GB	Great Britain	2
IN	India	1
IT	Italy	1
SE	Sweden	1
SG	Singapore	1

NOTE: MSA names reflect the major cities in the area. As an example, Silicon Valley is located in MSA 7362 (San Francisco-Oakland-San Jose, CA). Components for each area (counties and towns) can be found at: http://www.census.gov/population/estimates/metro-city/93mfips.txt

Localization of knowledge. As we have acknowledged, the notion that knowledge spillovers are localized is well established in the literature (cf. Agrawal, 2001; Almeida and Kogut, 1997; DeCarolis and Deeds, 1999; Hagerstrand, 1967; Jaffe *et al*., 1993; Singh, 2003). Although mobility is acknowledged as one of the key mechanisms by which knowledge spillovers occur within regions (Almeida and Kogut, 1999), a host of informal contacts and knowledge flows arise through the multitude of professional associations, casual gathering places, and other social contacts that arise between geographically proximate people (Saxenian, 1994). While our interest is in how geographic proximity or distance affects the relationship between outbound mobility and knowledge transfer, we include a *GeoProximity* main effect in the models to control for the localization of knowledge.

Strategic alliances. Organizations reach knowledge across firm boundaries by means of strategic alliances. In this mode, organizations create a structure that allows the participating firms to

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access each other's knowledge or to develop common knowledge (Inkpen and Tsang, 2005). Extant research has shown that firms that engage in strategic alliances (technically or marketing motivated) experience a transfer of knowledge across their boundaries (Almeida *et al.*, 2003; Almeida, Song, and Grant, 2002; Rosenkopf and Almeida, 2003; Song, Almeida, and Wu, 2003; Stuart, 2000). Therefore, we use *alliances* (a dichotomous variable) to control for this expected positive effect. We obtained the alliances between each dyad of firms from databases compiled by ICE and Dataquest for the period 1980–1989, and from SDC Platinum for the period 1990–1995. We coded this variable one when at least one alliance (either technological or marketing) was found in the five-year window previous to the year of observation.

Hiring of employees. Organizations also access other firms' knowledge by hiring away each other's employees. Although it is common practice to have employees sign confidentiality agreements, what is learned in one place travels with the employee over time. And without necessarily infringing the confidentiality agreement, employees are able to build around the knowledge they gained in their previous jobs, which is even easier when that knowledge is publicly available in the form of a patent. Empirical studies have shown that firms, when hiring away employees from other firms, access the knowledge of those firms that lost the employee (Bui-Eve, 1997; Dokko and Rosenkopf, 2006; Song *et al.*, 2003). For this reason, we included a control variable showing the hiring of employees, which we expect to have a positive effect on knowledge transfer across firms' boundaries.[5]

To control for this mechanism, we utilize *hiring* (a dichotomous variable), which captures the existence of the move of at least one inventor from the alter firm to the focal firm during the five-year window before the year of observation. We recorded hiring events in a similar manner to the recording of outbound mobility events; the time of the hiring event is the year before the application of the first patent of the focal firm on which the employee appears as an inventor.[6]

Outbound mobility productivity (OutMobilityProductivity). As an additional control for the human capital carried by star inventors to hiring firms, we calculated inventor productivity as the cumulative number of patents generated by each mobile inventor prior to a move. For the set of outbound mobility events included in the *OutMobility* variable, we then took the maximum inventor productivity of this set as the value of this control variable. We also ran models not reported here with the count of citations received by the author over 1963–2004 as a measure of inventor quality (impact). The productivity and impact measures are correlated at 0.44 and results remain unchanged.

Absorptive capacity. According to the absorptive capacity view, firms are more likely to learn from others the more knowledge they have and the closer this knowledge is to the source of information (Cohen and Levinthal, 1990). Two variables are used to control for both dyad-specific and firm-specific characteristics of this type. Following Rosenkopf and Almeida (2003), *technological distance (TechDist)* reflects the dyad's common patenting patterns. For each patent with an application date on the 10-year window previous to the year of observation, we tabulated to which technological class and subclass it was assigned,[7] and created a vector with the percentage of patents assigned to each class/subclass for each firm. Then, we calculated the technological distance between two firms as the Euclidean distance between the vectors just described.[8] Smaller values indicate technologically proximate firms and *TechDist* is

[5] By including this variable, we have effectively decomposed employee mobility into two types of ties: hiring and outbound mobility. Although each mobility event generates one tie in each network, the networks are not identical because the ties have directionality. This means that, by definition, a focal firm's outbound mobility ties can be uncorrelated with its hiring ties. For example, if John left firm ABC to go to firm XYZ, we record an outbound mobility tie for ABC (focal) to XYZ (alter) and a hiring tie for XYZ (focal) from ABC (alter). Absent another employee moving from XYZ to ABC, we do not have a hiring tie for ABC (focal) from XYZ (alter).

[6] As in the case of outbound mobility, this leaves open the possibility of the new employee sharing his or her knowledge with members of the hiring firm and influencing the output of their research efforts even before the mobile employee is able to apply for a patent in the new firm.

[7] Data on patent's class/subclass was obtained from the National University of Singapore Patent dataset.

[8] Other researchers have utilized measures of technological distance based on citation patterns (Mowery, Oxley, and Silverman, 1998; Stuart and Podolny, 1996); however, using this patent class derived measure of technological similarity follows in a long tradition of studies initiated by Jaffe (Jaffe, 1986; 1989) and pursued by several scholars in economics and strategy since. It also allows us to keep the technological similarity and knowledge flow variables conceptually and empirically separate.

expected to be negatively associated with our dependent variable. We also included the squared term in order to capture a possible U-shaped relationship.

Focal firm's number of patents (FocPat5) represents the firm's stock of knowledge. It is the count of patents granted to the firm that have application dates in the five-year window previous to the year of observation. We utilized five-year windows to count the number of patents as a proxy for firms' knowledge stock to account for knowledge depreciation. Larger values of this variable are expected to be associated with a larger stock of knowledge for the focal firm. We utilized the natural log of this count because it is heavily skewed.

In addition to these variables we also included the following controls:

Alter firm's number of patents (AltPat10). This variable represents the number of patents granted to the alter firm of the dyad during the 10-year window previous to the year of observation. In the case of the number of patents at risk of being cited, we utilized the 10-year window, which is the time it takes a patent to start receiving a negligible number of citations per year (Jaffe *et al*., 1993). In this way we control for the increase in the probability of citing another firm as a result of the sheer number of patents owned by that firm. We utilize the natural log of this variable because it is heavily skewed.

Focal firm's number of patents during year of observation (FocPat) is the count of patents granted to the firm that have application dates during the year of observation. In this way we control for the increase in the probability of citing existing patents as a result of the sheer number of patents generated by a firm in that year. We utilize the natural log of this variable because it is heavily skewed.

Cites(t-1). We include the one-year lagged value of the dependent variable. This controls for the focal firm's past propensity to cite the patents of the hiring firm.

Year86–Year95. We include 10 dummy variables to control for unobserved effects associated with each year of observation.

Data description

In total, the dataset contains 140,614 observations, one per each combination focal firm-alter firm-year for which all the variables can be measured. Table 1 displays the geographic distribution of our firms across 23 MSAs in the United States and 11 foreign countries. Several regions appear to be well populated with firms in our sample. Indeed, the four regions with seven or more firms (Silicon Valley, Japan, New York, and Los Angeles) contain approximately two-thirds of the firm population, which suggests geographic clustering. At the same time, 16 regions (four countries and 12 MSAs) contain only one firm, which cannot, by our construction, experience intra-regional mobility. Furthermore, three firms in the United States are in three locations that do not belong to any MSA and, for this reason, they are not assigned to any region.

During the period of 1980 to 1994, 450 cases of mobility and 610 alliances between firms in our sample were identified. Figure 1 displays the yearly number of events of each type. Clearly the levels of both mobility and alliances trend upward; however, alliances appear to have peaked while mobility appears to be still growing. As described above, these events were used to generate the observations for *OutMobility, hiring*, and *alliances*; given our five-year windows, the number of observations exceeds the number of actual events.

Table 2 presents the number of observations of *OutMobility, hiring*, and *alliances* by geographic proximity and key regions in our sample. Clearly, mobility within regions occurs more frequently than would be expected given the distribution of

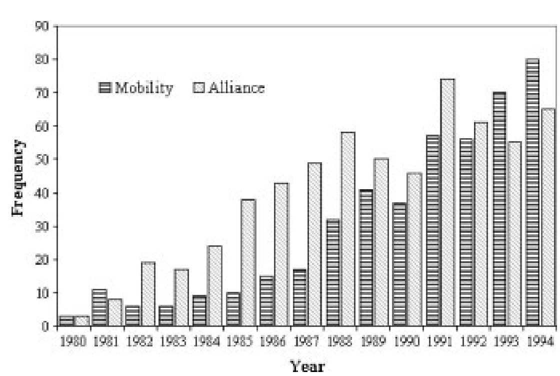

Figure 1. Distribution of mobility and alliance events (1980–1994)

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Table 2. Observations for outbound mobility (*OutMobility), hiring*, and *alliance* per focal firm's region and geographic proximity between firms
Table 2a

Geographic proximity	Outmobility	Hiring	Alliance	Obs
1	549	549	419	21266
0	683	683	2517	119348
χ2-tests†	<0.00001	<0.00002	0.19	

† Test for interdependence with geographic proximity.

Table 2b.

Region	Geographic proximity	Outbound mobility	Hiring	Alliance	Obs
Silicon Valley	1	186	186	239	15753
	0	81	175	630	31400
Japan	1	299	299	134	4294
	0	71	72	608	21756
Los Angeles	1	25	25	8	464
	0	64	12	144	8179
New York	1	14	14	0	240
	0	92	58	207	6089
Other Regions	1	25	25	38	515
	0	375	366	928	51924
Total		1232	1232	2936	140614

firms across regions (Table 2a, significant χ 2-tests).[9] In contrast, alliances actually occur within and across regions proportionally to the distribution of alliance opportunities within and across regions. Table 2b examines how the distribution of cases of *OutMobility* within and across regions varies by the region of the focal firm. Two regions in our sample, Silicon Valley and Japan, lose more employees to other firms in the same region than firms outside their regions. Furthermore, these regions account for most of the mobility within, but not across, regions. Focal firms located in Silicon Valley (MSA code = 7362) are responsible for 33 percent of the same-region and 12 percent of the across-region *OutMobility* cases, while Japan is responsible for 54 percent and 10 percent, respectively. Similar patterns are found in the dataset for hiring and alliances. Another interesting fact is that Silicon Valley is the MSA that accounts for the largest number of hires from different regions (175 observations out of 683) and the second largest number of employees who leave one region (81 observations out of 683). This provides some evidence that Silicon Valley is acting as a hub of technological knowledge. Full descriptive statistics are presented in Table 3.

Model

Our dependent variable is a count of the number of citations the alter firm receives from the focal firm over the year of observation. Since our dataset includes repeated observations for each focal firm (for different alter firms and years), it violates the assumption of independence across observations. In addition, the dataset suffers from overdispersion and excess zeros (the standard deviation is larger than the mean and the number of nonzeros for the dependent variable is less than 15% of the total number of observations, see Figure 2) and Vuong tests confirm that zero-inflated negative binomial regression (ZINB) provides a better fit than Poisson or zero-inflated Poisson regressions. For these reasons, we estimate a ZINB (which corrects for overdispersion and excess zeros) with

[9] Results from Mantel-Haenzel tests (Mantel and Haenszel, 1959) show a significant, positive association between geographic proximity and OutMobility and hiring even after controlling for the region where the focal firm is located (results available from the authors).

Table 3. Correlation matrix and descriptive statistics

		Obs	Mean	Std.dev.	v1	v2	v3	v4	v5	v6
v1	*Cites*	140614	0.592	3.458	1.00					
v2	*Cites(t-1)*	140614	0.485	2.944	0.85	1.00				
v3	*TechDist*	140614	0.621	0.322	−0.24	−0.23	1.00			
v4	*TechDist*Sq	140614	0.490	0.451	−0.17	−0.16	0.97	1.00		
v5	*LogFocPat*	140614	0.727	2.195	0.22	0.22	−0.49	−0.45	1.00	
v6	*LogFocPat5*	140614	1.866	2.278	0.20	0.20	−0.58	−0.54	0.73	1.00
v7	*LogAltPat10*	140614	2.131	2.397	0.23	0.23	−0.59	−0.55	0.00†	0.01
v8	*TechConvergence*	60662	0.172	0.265	−0.07	−0.07	0.06	0.01	0.06	−0.09
v9	*GeoProximity*	140614	0.151	0.358	0.02	0.01	0.10	0.10	−0.08	−0.08
v10	*Alliance*	140614	0.021	0.143	0.22	0.22	−0.12	−0.10	0.11	0.11
v11	*Hiring*	140614	0.011	0.102	0.27	0.28	−0.12	−0.08	0.09	0.08
v12	*OutMobilityProductivity*	140614	0.033	0.536	0.19	0.19	−0.08	−0.05	0.08	0.08
v13	*OutMobility*	140614	0.011	0.102	0.24	0.25	−0.12	−0.08	0.11	0.12
v14	*OutMobility(Instrument)*	140614	0.010	0.040	0.59	0.64	−0.29	−0.22	0.28	0.29
v15	*OutMobility_GeoProximity*	140614	0.005	0.070	0.16	0.16	−0.07	−0.05	0.07	0.07

		v7	v8	v9	v10	v11	v12	v13	v14	v15
v7	*LogAltPat10*	1.00								
v8	*TechConvergence*	−0.17	1.00							
V9	*GeoProximity*	−0.08	0.06	1.00						
V10	*Alliance*	0.10	−0.01	0.00†	1.00					
V11	*Hiring*	0.12	−0.03	0.09	0.10	1.00				
V12	*OutMobilityProductivity*	0.06	−0.02	0.06	0.07	0.16	1.00			
V13	*OutMobility*	0.08	−0.03	0.09	0.10	0.21	0.6	1.00		
V14	*OutMobility(Instrument)*	0.20	−0.07	0.23	0.26	0.55	0.27	0.38	1.00	
V15	*OutMobility_GeoProximity*	0.05	−0.01†	0.17	0.06	0.20	0.42	0.68	0.40	1.00

All correlations are significant at p-value <0.01 except for those marked with †.

fixed effects on the focal firm (which corrects for the interdependence between observations of the same focal firm) utilizing SAS v. 9.1.

We utilize a mixed model where the count of citations is predicted by a negative binomial model, which is simultaneously estimated with the inflation model utilizing maximum likelihood (Cameron and Trivedi, 1998). We model two mechanisms acting simultaneously and independently. We model zeros based on the probability of the alter firm having patents that are useful for the focal firm. Firms that do not have patents or are technologically distant from the focal firm are more likely not to receive citations. In addition, focal firms with no patents do not cite other firms. This process, which does not involve any transfer of private information, explains why a focal firm does not cite an alter firm even when information is public, as in the case of a patent. Therefore, the inflation model predicts zeros by the number of patents of the alter firm during the previous 10 years, the number of patents of the focal firm with an application date during the year of observation, and the technological distance between the firms. We also include *GeoProximity* in the inflation model to account for a firm's higher probability of being aware of neighboring firms' work. To summarize, this logistic model predicts no citation

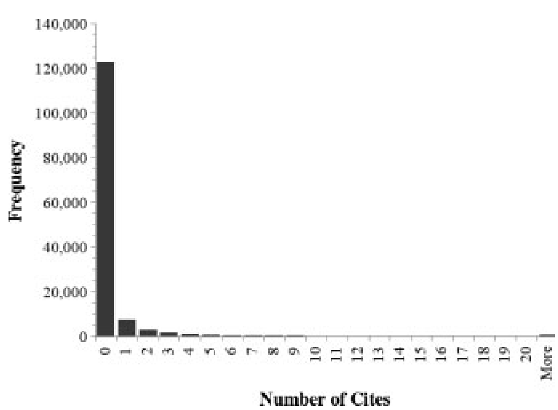

Figure 2. Distribution of citations (1980–1994)

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based on how many patents are available to be cited, how many patents have a chance to cite those available for citation, and the firms' technological and geographic proximity.

Therefore, the inflation model has the form:

$$\text{Log } (1/1 - \pi_{\text{ijt}}) = \text{b}_{0pr} + \beta_{pr}\ \text{X}_{pr} + \varphi_{\text{t}} + \alpha_{pr\_\text{i}}$$

where π_{ijt} is the probability of $cites_{\text{ijt}} > 0$, X_{pr} is a vector of the variables predicting the occurrence of no citation, β_{pr} is a vector of coefficients to be estimated, φ_t is a vector capturing year (t) effects, α_{pr_i} is the term that captures the fixed effect of focal firm (i), and i, j, and t indicate the observation corresponds to the focal firm (i), the alter firm (j) on year (t).

Consistent with the position advanced regarding knowledge transfer in our theory section, we model the count of citations based on mechanisms (such as alliances, hiring, and outbound mobility) that involve the existence of private information transfer or attention focusing to overcome constraints from limited information processing capabilities. In addition, we introduce controls for geographic proximity, absorptive capacity, year effects, alter firm's number of patents, and technological distance. Therefore, the negative binomial model has the form:

$$\text{Log}(cites_{\text{ijt}}) = \text{b}_0 + \beta\ \text{X}_{\text{ijt}} + \gamma\ \text{Y}_{\text{ijt}} + \delta\ Z_{\text{t}} + \varphi_{\text{t}} + \alpha_{\text{i}} + \varepsilon_{\text{ijt}}$$

where X is a vector of dyadic variables that test our hypotheses; Y is a vector of dyadic control variables; Z is a vector of firm control variables associated with the focal (i) and alter (j) firms; β, γ, and δ are vectors of coefficients to be estimated; φ_{t} is a vector capturing year (t) effects; α_{i} is the term that captures the fixed effect of focal firm (i); ε is the error term with a log-gamma distribution; and i, j, and t indicate the observation corresponding to the focal firm (i), the alter firm (j) on year (t).

The fixed-effect estimation controls unobserved heterogeneity, corrects spuriousness, and reduces endogeneity concerns (Allison, 1999). The correlations between the independent variables are low (see Table 3), and VIF and tolerance tests (SAS v.9.1) reveal no multicolinearity problems.

We ran a series of nested models in which we added variables consecutively. The baseline model (Model 4.A) included the year effects (to capture unobserved differences across the period 1986 to 1995), log(*AltPat10*), *TechDist,* log(*FocPat5*), *alliance, hiring,* and *GeoProximity*. Due to its close relationship with *OutMobility, OutMobilityProductivity* was added separately as an additional control (Model 4.B). Two other models were estimated by consecutively adding *OutMobility* (Model 4.C), and *OutMobility* × *GeoProximity* (Model 4.D).

RESULTS AND ROBUSTNESS CHECKS

Table 4 presents the estimation of the models described above. In order to confirm that our mixed model conforms to our expectations about the impact of the control variables on citation patterns, we first examine the coefficients of those variables. First, in the inflation models, all variables obtain the expected effects. The significant coefficients for *TechDist* and its squared term (positive and negative, respectively) indicate that the probability of no citation increases when firms are more distant (with a slight decrease at the extreme of technological distance range), while the negative coefficients for the number of patents owned by the focal firm and the alter firm indicate that the probability of zero citation decreases the more patents were granted to the alter firm in the last 10 years, and the larger the number of patents applied by the focal firm in the year of observation. The negative sign of *GeoProximity* supports the geographic localization of knowledge due to limited search capabilities.

Second, the coefficients for the control variables in the count models generally obtain as expected. As predicted by the absorptive capacity perspective, the focal firm's number of patents (*FocPat5*) is positive and significant in all models. The significant coefficients for *TechDist* and its squared term (negative and positive, respectively) demonstrate that, within the range of observation, the farther apart the firms' technology, the less likely they are to cite each other. Across all models, the positive, significant coefficient of *GeoProximity* demonstrates geographic localization of citations. Congruent with our expectations, the effects of alliances and hiring are also positive and significant. Note also that the inclusion

Table 4. ZINB regression models with fixed effects on focal firm

Parameter	Model 4.A	Model 4.B	Model 4.C	Model 4.D
β0_prob	−28.757***	−28.713***	−29.899***	−28.806***
	(1.667)	(1.628)	(3.322)	(1.674)
βTechDist_prob	4.707***	4.658***	4.727***	4.711***
	(0.833)	(0.831)	(0.836)	(0.831)
βTechDistSq_prob	−4.292***	−4.253***	−4.324***	−4.305***
	(0.66)	(0.658)	(0.663)	(0.659)
βLogFocPat_prob	−0.305***	−0.304***	−0.305***	−0.304***
	(0.031)	(0.031)	(0.031)	(0.031)
βLogAltPat10_prob	−0.522***	−0.523***	−0.524***	−0.522***
	(0.026)	(0.026)	(0.026)	(0.026)
βGeoProx_prob	−1.041***	−1.040***	−1.058***	−1.018***
	(0.108)	(0.108)	(0.109)	(0.108)
β0_nb	−0.79***	−0.789***	−0.794***	−0.820***
	(0.104)	(0.104)	(0.104)	(0.104)
βCites(t-1)	0.039***	0.039***	0.039***	0.039***
	(0.001)	(0.001)	(0.001)	(0.001)
βTechDist	−4.414***	−4.418***	−4.398***	−4.383***
	(0.209)	(0.209)	(0.210)	(0.210)
βTechDistSq	2.251***	2.256***	2.237***	2.226***
	(0.182)	(0.182)	(0.183)	(0.183)
βLogFocPat5	0.044***	0.044***	0.045***	0.046***
	(0.011)	(0.011)	(0.011)	(0.011)
βLogAltPat10	0.537***	0.537***	0.537***	0.538***
	(0.008)	(0.008)	(0.008)	(0.008)
βAlliance	0.135***	0.135***	0.132***	0.130***
	(0.027)	(0.027)	(0.027)	(0.027)
βHiring	0.083*	0.083*	0.078*	0.084**
	(0.032)	(0.032)	(0.033)	(0.033)
βGeoProx	0.430***	0.430***	0.418***	0.447***
	(0.023)	(0.023)	(0.024)	(0.025)
βOutMobilityProductivity		0.001	−0.008	−0.010
		(0.005)	(0.006)	(0.006)
βOutMobility			0.111**	0.230***
			(0.040)	(0.050)
βOutMobility_GeoProx				−0.271***
				(0.066)
k	0.658***	0.658***	0.657***	0.655***
	(0.014)	(0.014)	(0.014)	(0.014)
-2 Log likelihood	118446	118446	118438	118422
LR test		0.9468	0.0018	0.0003
Observations	140614	140614	140614	140614

Inflation and count models include fixed effects on focal firm and year dummies (not reported in the table, available from authors). Standard errors in parentheses.
*** *p-value* < 0.001; ** *p-value* < 0.01; * *p-value* < 0.05.
Vuong tests results prefer ZINB over ZIP (vuong = 18.05), Poisson (vuong = 19.06), and negative binomial (vuong= 24.4).

of the productivity-weighted mobility count (*OutMobProductivity*) in Model 4.B is not significant.

In order to support our hypotheses about the impact of outbound mobility and its interaction with geographic proximity on citation patterns, we turn our attention to the coefficients of those variables in our count models. Hypothesis 1 is supported by Models 4.C and 4.D, which demonstrate that the effect of outbound mobility on citation is positive (with coefficients equal to 0.111 and 0.230, and *p-values less than* 0.01 and 0.001, respectively). In support of Hypothesis 2, in model 4.D we found a negative and significant coefficient for the interaction term ($\beta_{OutMob\times GeoProx} = -0.271$, *p-value* < 0.001). Due to the nonlinearity of the count model, the marginal effect of outbound mobility on citations is given by the partial derivative of citations with respect to outbound mobility (Cameron and Trivedi, 1998):

$$\frac{\partial[E(cites \mid X]}{\partial(OutMobility)} = (\beta_{OutMob} + GeoProximity \times \beta_{OutMob \times GeoProx}) \times \exp(E(X'\mathrm{B})) \quad (1)$$

Therefore, for distant firms, outbound mobility increases the expected citation rate by 25 percent ($\beta_{OutMob} = 0.230$, $p\text{-}value < 0.001$). In contrast, when outbound mobility occurs between proximate firms, the increase is not significant ($\beta_{OutMob} + \beta_{OutMob} \times \beta_{GeoProx} = -\mathbf{0}.041$, $p\text{-}value = 0.62$), suggesting that outbound mobility does not boost citations in this case.

Examining outbound mobility's impact on the conditional mean clarifies its effect on citations when outbound mobility occurs between or within regions. To do so, we calculate the ratio of these effects (Cameron and Trivedi, 1998). From Equation (1) it then follows:

$$\frac{\partial[E(cites \mid GeoProximity = 0, X_2)]/\partial OutMobility}{\partial[E(cites \mid GeoProximity = 1, X_2)]/\partial OutMobility} = \frac{\beta_{OutMob}}{\beta_{OutMob} + \beta_{OutMob \times GeoProx}} \times \exp(-\beta_{GeoProx}) \quad (2)$$

where X_2 is the vector of values taken by the rest of the variables in the model for the focal firm. The lower bound of the ratio of marginal effects in Equation (2) is significantly greater than one (based on a 95% confidence interval for the estimated coefficients), which supports Hypothesis 2. This ratio estimates that citations increase by at least 22 percent when mobility occurs across geographic regions instead of within them. In summary, these results clarify that the smaller estimate for outbound mobility obtained without an interaction term (Model 4.C) is driven by mobility between distant firms.

To increase confidence in our results, we examine four different types of issues. First, to insure that our results are robust to alternative specifications of the inflation model, we run the ZINB model over three additional inflation specifications (see Table 5). Model 5.A repeats our prior findings for ease of comparison. Should one believe that *outbound mobility* and its interaction with *geographic proximity* (the two variables for which we create hypotheses) are also relevant in the processing of public information, we include them in Models 5.B and 5.C. In each case, negative binomial estimates for all these models are similar in magnitude, sign and significance level. *GeoProximity* is significant in all the inflation models, while *OutMobility* and the interaction terms are not, increasing confidence in our specification.

Second, endogeneity is another potential concern. In order to address it, we introduced several dyadic characteristics suspected of driving focal firm citations. We ran models including technological convergence between firms, which could increase both mobility and citations among the firms (beyond the effect already controlled by technological distance). We developed a measure of technological convergence over a five-year period (where *TechConvergence* is measured as $TechDist_{t-5} - TechDist_t$). Since *TechConvergence* can only be calculated for 60,662 observations for 112 firms in the sample, results here are suggestive of firms that have longer panels in our dataset. When we include *TechConvergence* (See Table 6), we find that it is positive and significant, while the negative binomial estimates for our hypothesized variables remain similar to our reported results in magnitude, sign and significance level, increasing our confidence that our findings are not driven by this issue.

In addition, computational and statistical limitations made it impossible to estimate our zero-inflated models with fixed effects on the dyads, which would provide a more robust specification for endogeneity. In order to explore the robustness of our results, we also estimated three types of models with fixed effects on dyads:

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Table 5. ZINB regression models robustness to inflation specification

Parameter	Model 5.A	Model 5.B	Model 5.C
β0_prob	−28.806***	−28.357***	−28.354***
	(1.674)	(1.387)	(28.354)
βTechDist_prob	4.711***	4.690***	4.692***
	(0.831)	(0.827)	(0.825)
βTechDistSq_prob	−4.305***	−4.301***	−4.31***
	(0.659)	(0.655)	(0.654)
βLogFocPat_prob	−0.304***	−0.305***	−0.305***
	(0.031)	(0.031)	(0.031)
βLogAltPat10_prob	−0.522***	−0.519***	−0.519***
	(0.026)	(0.026)	(0.026)
βGeoProx_prob	−1.018***	−0.969***	−0.951***
	(0.108)	(0.109)	(0.11)
βOutMobility_prob		−0.978**	−0.621
		(0.362)	(0.412)
βOutMob_GeoProx_prob			−1.253
			(1.051)
β0_nb	−0.820***	−0.814***	−0.814***
	(0.104)	(0.104)	(0.104)
βCites(t-1)	0.039***	0.537***	0.537***
	(0.001)	(0.008)	(0.008)
βTechDist	−4.383***	0.039***	0.039***
	(0.21)	(0.001)	(0.001)
βTechDistSq	2.226***	−4.382***	−4.387***
	(0.183)	(0.21)	(0.21)
βLogFocPat5	0.046***	2.227***	2.231***
	(0.011)	(0.183)	(0.183)
βLogAltPat10	0.538***	0.046***	0.046***
	(0.008)	(0.011)	(0.011)
βAlliance	0.13***	0.131***	0.131***
	(0.027)	(0.027)	(0.027)
βGeoProx	0.084**	0.084*	0.084**
	(0.033)	(0.033)	(0.033)
βHiring	0.447***	0.451***	0.452***
	(0.025)	(0.025)	(0.025)
βOutMobProductivity	−0.01	−0.01	−0.01**
	(0.006)	(0.006)	(0.006)
βOutMobility	0.23***	0.211***	0.218***
	(0.05)	(0.05)	(0.05)
βOutMob_GeoProx	−0.271***	−0.269***	−0.285***
	(0.066)	(0.066)	(0.066)
k	0.655***	0.654***	0.654***
	(0.014)	(0.014)	(0.014)
-2 Log likelihood	118422	118413	118411
LR test		0.0023	0.36
Observations	140614	140614	140614

Inflation and count models include fixed effects on focal firm and year dummies (not reported in the table).
Standard errors in parentheses.
*** *p-value* < 0.001; ** *p-value* < 0.01; * *p-value* < 0.05.

logistic, conditional Poisson, and QML Poisson. The limitations of these models and their attendant results are summarized in Table 7.

The dependent variable for the logistic model takes the value of one when the focal firm cites the alter firm. These models fail to capture the impact of outbound mobility on the increase of citations for focal firms that cited the alter firm before the mobility event (which is captured by the count model in the ZINB estimation). Poisson

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Table 6. ZINB regression models with technological convergence

Parameter	Model 6.A	Model 6.B	Model 6.C	Model 6.D
β0_prob	−26.452***	−26.434***	−26.446***	−26.445***
	(0.808)	(0.802)	(0.805)	(0.8)
βTechDist_prob	5.46**	5.455**	5.456**	5.479**
	(1.787)	(1.789)	(1.79)	(1.786)
βTechDistSq_prob	−5.184*	−5.204*	−5.195*	−5.231*
	(2.051)	(2.052)	(2.057)	(2.05)
βLogFocPat_prob	−0.37***	−0.368***	−0.369***	−0.367***
	(0.048)	(0.048)	(0.048)	(0.048)
βLogAltPat10_prob	−0.582***	−0.585***	−0.583***	−0.584***
	(0.042)	(0.042)	(0.042)	(0.042)
βGeoProx_prob	−1.341***	−1.342***	−1.369***	−1.337***
	(0.167)	(0.167)	(0.168)	(0.167)
β0_nb	−0.596***	−0.574***	−0.593***	−0.607***
	(0.153)	(0.154)	(0.154)	(0.154)
βCites(t-1)	0.03***	0.03***	0.029***	0.029***
	(0.001)	(0.001)	(0.001)	(0.001)
βTechDist	−6.778***	−6.791***	−6.743***	−6.723***
	(0.376)	(0.377)	(0.377)	(0.377)
βTechDistSq	6.453***	6.469***	6.411***	6.399***
	(0.492)	(0.493)	(0.493)	(0.493)
βTechConvergence	0.383***	0.381***	0.38***	0.38***
	(0.051)	(0.051)	(0.051)	(0.051)
βLogFocPat5	0.034^	0.031	0.033^	0.033^
	(0.019)	(0.019)	(0.019)	(0.019)
βLogAltPat10	0.594***	0.594***	0.594***	0.595***
	(0.011)	(0.011)	(0.011)	(0.011)
βAlliance	0.108***	0.107***	0.104***	0.102***
	(0.026)	(0.026)	(0.026)	(0.026)
βHiring	0.087**	0.087**	0.08*	0.084**
	(0.031)	(0.031)	(0.032)	(0.032)
βGeoProx	0.356***	0.355***	0.34***	0.362***
	(0.024)	(0.024)	(0.024)	(0.025)
βOutMobProductivity		0.001	−0.009^	−0.01**
		(0.005)	(0.005)	(0.006)
βOutMobility			0.132***	0.209***
			(0.038)	(0.047)
βOutMobility_GeoProx				−0.178**
				(0.063)
k	0.534***	0.534***	0.533***	0.532***
	(0.013)	(0.013)	(0.013)	(0.013)
-2 Log likelihood	89123	89123	89111	89103
LR test		0.9808	0.0021	0.0203
Observations	60662	60662	60662	60662

Inflation and count models include fixed effects on focal firm and year dummies (not reported in the table).
Standard errors in parentheses.
*** *p-value* < 0.001; ** *p-value* < 0.01; * *p-value* < 0.05; ^ *p-value* < 0.10.

regression with dyadic fixed effects is estimated by Poisson regressions conditional on having at least one citation from the focal firm, which obtains equivalent results (Allison, 2005). Although this procedure eliminates observations for dyads without citations over the observation period, the models are still estimated over data that suffers from overdispersion and zero-inflation, which may result in biased estimations.

Finally, because it could also be an endogenous variable, we sought an instrument for outbound mobility. This is a challenging endeavor because the prediction of whether a particular alter firm will be the hiring firm involves a much larger

Table 7. Summary of results for endogeneity robustness checks

	Zinb	Logistic[1]	Conditional Poisson[2]	QML Poisson[3]
Year effects	yes	yes	yes	yes
Fixed effects on focal firm	yes	no	no	no
Fixed effects on dyads	no	yes	equivalent	yes
Dependent variable	Count of citations	Citations (yes/no)	Count of citations	Count of citations
Instrumental variable	no	no	no	yes
Robust to zero-inflation	yes	yes	no	no
Effect of OutMobility	(+) $p < 0.01$	(+) $p < 0.05$	n.s.	(+) $p < 0.01$
Effect of OutMobility × GeoProximity	(−) $p < 0.0001$	n.s.	(−) $p < 0.10$	n.s.
Observations	140614	140614	2268	45219

[1] Logistic with fixed-effects model fails to capture the increase in citation rates for mobility events that occur between firms when the focal firm cited the alter firm prior to the event.
[2] Conditional Poisson is run on a subset of dyads. Only those with is at least one citation from focal to alter firm over the period of observation are included.
[3] Due to the nonlinearity of the second stage, QML is the only method allowing for two-stage model estimations.

margin of error than the prediction of whether the focal firm will lose an inventor. We generated a moderately plausible instrument for outbound mobility based on citations on the prior year as well as the difference in patent impact between the focal and alter firm, and utilized this instrument in a QML Poisson estimation with fixed effects on the dyad (Wooldridge, 2002). Although QML Poisson is fairly robust to model misspecification and overdispersion, when data is zero-inflated the risk of biased results is still present.

Overall, results from these three alternative specifications are in reasonable agreement with those of our ZINB models, and, given their limitations, are consistent with our expectations. When parameter estimations were significant, results agreed with our hypotheses. We favor and report the results of ZINB models since, as discussed before, they include a variety of controls to minimize the endogeneity risk. They allow us to capture the impact of outbound mobility even when the focal firm already cited the alter firm, and to handle the overdispersion of the data and possible selection bias.

We also summarize the results of two additional robustness checks where tables are not reported due to space limitations. First, while the firm fixed-effect specification represents a strict test, it precludes the inclusion of time-invariant variables that may be of interest. Specifically, one could question whether our reported results may be driven by several characteristics, including regional effects,[10] foreign firms, and firms with multiple inventive locations. To assess the impact of these variables we ran ZINB models (STATA, version 9.2) with White-Huber correction of the standard errors clustered on the focal firm (Froot, 1989; Williams, 2000). Results (available from the authors) were consistent for the variables shared with the ZINB models. As expected, we found significant differences between Silicon Valley and other regions. We also found differences for firms with foreign headquarters and for firms with substantial presence in multiple regions; however, those results are influenced by the sample composition. Nevertheless, our key results remained robust.

In addition, since the challenge of identifying mobility precisely through patent data is substantial, we ran a Monte Carlo analysis with simulated data to test the robustness of our results to errors in capturing mobility. Our simulated datasets were similar to our empirical dataset in number of observations and variable distribution. We estimated our

[10] The particular characteristics of Silicon Valley are well documented, with one of the highest rates of mobility and abundance of social interaction between employees of different firms (Rogers and Larsen, 1984; Saxenian, 1994). In our data, Silicon Valley accounts for almost 40 percent of the observations of outbound mobility and 35 percent of the firms. In addition, Japan accounts also for almost 50 percent of the total number of the cases of outbound mobility in the same region. Interestingly, Silicon Valley and Japan together account only for 20 percent of the cases of outbound mobility across a region.

models for data that both underestimated and overestimated the actual mobility. Results (available from the authors) were robust when mobility is underestimated. In contrast, the greater the overestimation of mobility, the more the coefficient estimates for *hiring, outbound mobility*, and its interaction with *geographic proximity* attenuated toward zero. As a result of this attenuation, the significance levels for these variables decreased as mobility overestimation increased. As our method can be expected to underestimate rather than overestimate mobility, these results increase the confidence in our tests because parameter or standard error estimations were not substantially affected by undercounting of mobility events.

DISCUSSION

In this study, we have challenged the prevailing conception of mobility as an event that creates a unidirectional flow of information from the previous employer to the new employer. Focusing on sociological explanations in a network of firms tied by mobile inventors, we suggest that mobility creates a bidirectional flow of information between the firms. With this distinction in mind, the results advance our understanding of knowledge flows, providing a more complete picture of the processes involved in knowledge transfer while offering empirical evidence that suggests an important role for social capital in facilitating interorganizational flows. Our results show that despite organizations' efforts to contain these flows (Rogers and Larsen, 1984), organizations access knowledge by mechanisms that operate at organizational, individual, and regional levels. Mechanisms based on organizational structures (alliances), acquisition of human capital (hiring), acquisition of social capital (outbound mobility), social networks contained in a geographic region (geographic proximity), and absorptive capacity (stock of knowledge, technological distance) all appear to affect the transfer of technological knowledge across firms in the semiconductor industry. While several of these mechanisms, such as alliances and hiring, may be considered strategic, our focus in this paper on the loss of inventors has important implications despite the fact that it is unlikely to represent a strategic decision by a firm.

Our results replicate some well-accepted findings on geographic localization of knowledge, but we diverge from this line of research by demonstrating that while outbound mobility has a positive impact on citation, this effect is primarily driven by mobility occurring across regions. Such an approach—recognizing the value of connections to distant, nonredundant sources of information—is consonant with the general view espoused by Rosenkopf and Almeida (2003) of the effects of both hiring and alliances over both geographic and technological landscapes, as well as the specific view of Agrawal and colleagues (2006) on how knowledge spillovers across regions are promoted by enduring social relationships between individuals. To reiterate, mobility across regions creates nonredundant network connections that seem to facilitate the flow of knowledge across firm boundaries.

Overall, the results support our hypotheses, even after controlling for other mechanisms of knowledge transfer. When outbound mobility involves the moving of employees between regions, the overall effect is positive. However, the magnitude of the coefficients for *OutMobility* and the interaction *OutMobility* $\times$ *GeoProximity* suggests that the effect is essentially zero when the mobility event occurs inside an MSA or in a foreign country. This would indicate that outbound mobility is a redundant mechanism in a contained region or industrial district, which, as per Inkpen and Tsang's description (2005), encompasses many mechanisms of knowledge transfer that would provide similar access to knowledge. One would expect geographic proximity to be enough to facilitate the access to inventors in other firms. Attendance at meetings and common places, shared customers or suppliers, or shared acquaintances would provide these channels without the need of a personal tie created by working together previously. Future research must continue to address other knowledge transfer mechanisms involved in industrial districts, their level of redundancy with each other, and the level of resilience this redundancy provides.

Of course, Silicon Valley's prominence in the semiconductor industry could yield questions about the generalizability of our results in other contexts. While our analysis suggested that our overall results endure even when controlling regional propensity to cite, regional effects analyses confirmed those differences across several regions (e.g., firms in Silicon Valley and Taiwan). Future research should examine in more detail whether

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our findings are robust across industry contexts, as well as whether outbound mobility has different effects in regions of particular interest within those industries.

An interesting puzzle in our main results is that the effect of outbound mobility is not significantly different from that of hiring (inbound mobility). At one level, this is surprising, as outbound mobility can only rely on the social tie as a mechanism for knowledge transfer, while hiring implies the transfer of knowledge with the employee in addition to the social tie. We believe that this is a fruitful area for future research to understand how human capital and social ties mechanisms combine to facilitate knowledge transfer. In an attempt to reconcile this empirical finding with our theory and results, two possibilities come to mind: this empirical detail may result from 1) the influence of non-compete and nondisclosure arrangements that are so common in high-tech industries, and 2) the hiring firm being more likely to be aware about the knowledge of the firm losing the employee before the mobility event.

Our results regarding the impact of outbound employee mobility contradict recent findings by Phillips (2002) and Wezel and colleagues (2006), who suggest that losing employees means a loss for the firm. We believe that this conflict is generated because the studies address different phenomena. While these studies focus on the transfer of capabilities and may rely heavily on the transfer of clients and its implications for economic performance, our study focuses on the transfer of knowledge as measured via patents. Client relationships, repeated economic transactions by their very nature, are likely to move to the new employer and be severed at the previous employer, generating significant economic penalties for firms that lose employees and their clients. In contrast, knowledge generation relies on a more unique combination of inputs that may be utilized at both employers. As our interest is in knowledge flows among firms, we find that access to, and assimilation of knowledge is enhanced when employees move to new firms. In this context, Somaya *et al.* (2008) suggest that losing employees to clients is more beneficial than losing them to competitors. While we show that the firm losing the employee increases the utilization of the body of knowledge of the firm receiving the employee, our study is not designed to address the economic implications of this activity.

Traditional research has suggested that technological knowledge transfer is mainly contained inside the firm or region; however, our findings demonstrate that the flow of technological knowledge may not be all that different from that of scientific knowledge, at least when this knowledge is made public in patents. This is consonant with Levin's (1988) findings, in particular in the setting of the semiconductor industry, where informal conversations with employees of other firms rank high in the mechanisms of learning. Outbound mobility facilitates access to those employees, and becomes more important when this access is not available.

Future research must also continue to discern between the social and human capital mechanisms inherent in these mobility ties. If these mechanisms are truly separable, the human capital mechanism would limit the transfer of knowledge to that which is developed before the employee moves, while the social capital mechanism implies that newer knowledge may still be transferred. More extensive longitudinal studies may allow future research to specify the locus of knowledge generation and its spread via mobility events attributable to the movement of prior knowledge and newly developed knowledge. Another opportunity for future research is to distinguish between the communication and attention mechanisms by contrasting citation patterns between firms and regions.

Of course, our findings are derived via analysis of patent citations, which are used as indicators of knowledge being drawn upon. Some might argue that patents are only indicators of codified knowledge, yet, as Almeida and colleagues (2002) suggest, patents can only be well understood and built upon when an organization has a fair amount of tacit knowledge in the domain as well. This is supported by Agrawal's (2006) finding of firms benefiting from engaging inventors in the development stage when licensing. Nonetheless, the question of whether tacit knowledge is transferred in our context is still an open one, one of interest, and with important implications to both technology management and legal scholars as well.

CONCLUSION

This paper advances our understanding of the effect of mobility in the transfer of technological knowledge by conceptualizing the mobility of

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employees as an event that involves two different mechanisms: a) the transfer of knowledge and skills embedded in the individual moving between firms, and b) the development of new social ties between the firms. In so doing, we were able to empirically isolate the mechanism of social tie creation from the one of human capital transfer by means of studying outbound mobility and found a positive effect of the mobility of employees on the knowledge transferred to the firms losing them, an effect that diminishes when both firms are geographically proximate.

This study contributes to the literature on knowledge transfer by conceptualizing the effect of employee mobility as bidirectional, and recognizing and measuring the possible reverse transfer of knowledge. The migration of an employee has usually been associated with a negative effect on the firm: even laypersons' vocabulary referred to this migration as the loss of an employee. This outbound mobility has been seen as a loss of human capital, skills, and organizational knowledge. In the best case scenario, this migration would not translate into a loss if the knowledge embedded in the employee was truly organizational or redundant. The work of Agrawal and colleagues (2006) shows that, at the regional level, there is a spillover from the region that receives the employee to the region that lost the employee. But it is a more precise step forward to associate the loss of an employee with a firm-level gain of skills or knowledge of any sort. Work in this area has typically found firm-level losses (Phillips, 2002; Wezel *et al*., 2006), or, in one case, that firms were able to avert the negative consequences attributable to losing technical committee representatives to firm-level routines for personnel replacements and ongoing conferral of status (Dokko and Rosenkokopf, 2006). Our paper is part of a burgeoning stream of research (Agrawal *et al*., 2006; Somaya *et al*., 2008) that clearly highlights the importance of the mobility ties in the organizational learning process, even when employees leave the firm.

Finally, this work corroborates the importance of networks based on individuals' ties on organizational level outcomes, and helps to better understand the mechanisms behind information transfer at the frontier of knowledge. This claim should not be construed as promoting outbound mobility but as pointing to the fact that, at least at low levels, mobility facilitates the transfer of knowledge between firms at the frontier of innovation in both directions, and that there are ways for the firm experiencing outbound mobility to obtain benefits from these events.

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REFERENCES

Agrawal A. 2001. University-to-industry knowledge transfer: literature review and unanswered questions, *International Journal of Management Reviews* **3**(4): 285–302.

Agrawal A. 2006. Engaging the inventor: exploring licensing strategies for university inventions and the role of latent knowledge. *Strategic Management Journal* **27**(1): 63–79.

Agrawal A, Cockburn L, McHale J. 2006. Gone but not forgotten: knowledge flows, labor mobility, and enduring social relationships. *Journal of Economic Geography* **6**(5): 571–591.

Alcacer J, Gittelman M. 2006. Patent citations as a measure of knowledge flows: the influence of examiner citations. *Review of Economics and Statistics* **88**(4): 774–779.

Allen TJ. 1970. Communication networks in R&D laboratories. *R&D Management* **1**(1): 14–21.

Allen TJ. 1977. *Managing the Flow of Technology: Technology Transfer and The Dissemination of Technological Information within the R&D Organization*. MIT Press: Cambridge, MA.

Allison PD. 1999. *Logistic Regression Using the SAS System: Theory and Application*. SAS Institute: Cary, NC.

Allison PD. 2005. *Fixed Effects Regression Methods for Longitudinal Data Using SAS*. SAS Institute: Cary, NC.

Almeida P, Dokko G, Rosenkopf L. 2003. Startup size and the mechanisms of external learning: increasing opportunity and decreasing ability? *Research Policy* **32**(2): 301–315.
Almeida P, Kogut B. 1997. The exploration of technological diversity and the geographic localization of innovation. *Small Business Economics* **9**(1): 21–31.
Almeida P, Kogut B. 1999. Localization of knowledge and the mobility of engineers in regional networks. *Management Science* **45**(7): 905–917.
Almeida P, Song J, Grant RM. 2002. Are firms superior to alliances and markets? An empirical test of cross-border knowledge building. *Organization Science* **13**(2): 147–161.
Argote L, Ingram P, Levine JM, Moreland RL. 2000. Knowledge transfer in organizations: learning from the experience of others. *Organizational Behavior and Human Decision Processes* **82**(1): 1–8.
Boeker W. 1997. Executive migration and strategic change: the effect of top manager movement on product-market entry. *Administrative Science Quarterly* **42**(2): 213–236.
Bui-Eve H. 1997. To hire or not to hire: what Silicon Valley companies should know about hiring competitors' employees. *Hastings Law Journal* **48**(5): 981–1016.
Burt RS. 1992. *Structural Holes: The Social Structure of Competition*. Harvard University Press: Cambridge, MA.
Cameron AC, Trivedi PK. 1998. *Regression Analysis of Count Data*. Cambridge University Press: Cambridge, UK.
Cohen MD, Nelson RR, Walsh JP. 2000. Protecting their intellectual assets: appropriability conditions and why U.S. manufacturing firms patent (or not). NBER working paper 7552, National Bureau of Economic Research, Cambridge, MA. Available at: http://www.nber.org/papers/w7552.
Cohen WM, Goto A, Nagata A, Nelson RR, Walsh JP. 2002. R&D spillovers, patents and the incentives to innovate in Japan and the United States. *Research Policy* **31**(8–9): 1349–1367.
Cohen WM, Levinthal DA. 1990. Absorptive capacity: a new perspective on learning and innovation. *Administrative Science Quarterly* **35**(1): 128–152.
DeCarolis DM, Deeds DL. 1999. The impact of stocks and flows of organizational knowledge on firm performance: an empirical investigation of the biotechnology industry. *Strategic Management Journal* **20**(10): 953–968.
DiMaggio PJ, Powell WW. 1983. The iron cage revisited: institutional isomorphism and collective rationality in organizational fields. *American Sociological Review* **48**(2): 147–160.
Dokko G, Rosenkopf L. 2006. Social capital for hire? Mobility of technical professionals and firm influence in wireless standards committees. Working paper TheWharton School of Business, University of Pennsylvania, Philadelphia, PA.
Fleming L, Colfer L, Marin A, McPhie J. 2004. Why the valley went first: agglomeration and emergence in regional inventor networks. Paper presented at the 2004 Academy of Management Conference, New Orleans, LA.
Froot KA. 1989. Consistent covariance matrix estimation with cross-sectional dependence and heteroskedasticity in financial data. *Journal of Financial & Quantitative Analysis* **24**(3): 333–355.
Granovetter M. 1985. Economic action and social structure: the problem of embeddedness. *American Journal of Sociology* **91**(3): 481–510.
Hagerstrand T. 1967. *Innovation Diffusion as a Spatial Process*. University of Chicago Press: Chicago, IL.
Hall BH, Jaffe AB, Tratjenberg M. 2001. The NBER patent citation data file: lessons, insights and methodological tools. NBER Working paper 8498, National Bureau of Economic Research, Cambridge, MA.
Inkpen AC, Tsang EWK. 2005. Social capital, networks, and knowledge transfer. *Academy of Management Review* **30**(1): 146–165.
Jaffe AB. 1986. Technological opportunity and spillovers of R & D: evidence from firms' patents, profits, and market value. *American Economic Review* **76**(5): 984–1001.
Jaffe AB. 1989. Characterizing the "technological position" of firms, with application to quantifying technological opportunity and research spillovers. *Research Policy* **18**(2): 87–97.
Jaffe AB, Trajtenberg M, Henderson R. 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics* **108**(3): 577–598.
Jung CG, Franz M-Lv (eds.). 1968. *Man and His Symbols*. Dell: New York.
Levin RC. 1988. Appropriability, R&D spending, and technological performance. *American Economic Review* **78**(2): 424–428.
Mantel N, Haenszel W. 1959. Statistical aspects of the analysis of data from retrospective studies of disease. *Journal of the National Cancer Institute* **22**: 719–748.
Marquis DG, Allen TJ. 1966. Communication patterns in applied technology. *American Psychologist* **21**: 1052–1060.
Merton RK. 1973. *The Sociology of Science: Theoretical and Empirical Investigations*. University of Chicago Press: Chicago, IL.
Mowery DC, Oxley JE, Silverman BS. 1998. Technological overlap and interfirm cooperation: implications for the resource-based view of the firm. *Research Policy* **27**(5): 507–523.
Nelson RR, Winter SG. 1982. *An Evolutionary Theory of Economic Change*. Belknap Press: Cambridge, MA.
Ocasio W. 1997. Towards an attention-based view of the firm. *Strategic Management Journal*, Summer Special Issue **18**: 187–206.
Phillips DJ. 2002. A genealogical approach to organizational life chances: the parent-progeny transfer among Silicon Valley law firms, 1946–1996. *Administrative Science Quarterly* **47**(3): 474–506.
Price DJdS. 1986. *Little Science, Big Science and Beyond*. Columbia University Press: New York.
Rao H, Drazin R. 2002. Overcoming resource constraints on product innovation by recruiting talent from rivals:

a study of the mutual fund industry, 1986–94. *Academy of Management Journal* **45**(3): 491–507.

Rogers EM. 2003. *Diffusion of Innovations* (5th edn). Free Press: New York.

Rogers EM, Larsen JK. 1984. *Silicon Valley Fever: Growth of High-Technology Culture*. Basic Books: New York.

Rosenkopf L, Almeida P. 2003. Overcoming local search through alliances and mobility. *Management Science* **49**(6): 751–766.

Saxenian A. 1994. *Regional Advantage: Culture and Competition in Silicon Valley and Route 128*. Harvard University Press: Cambridge, MA.

Singh J. 2003. *Inventor networks and inter-firm knowledge diffusion*. Harvard Business School, mimeo: Boston, MA.

Somaya D, Williamson IO, Lorinkova N. 2008. Gone but not lost: the different performance impacts of employee mobility between cooperators versus competitors. *Academy of Management Journal* **51**(5): 936–953.

Song J, Almeida P, Wu G. 2003. Learning-by-hiring: when is mobility more likely to facilitate interfirm knowledge transfer? *Management Science* **49**(4): 351–365.

Stuart TE. 2000. Interorganizational alliances and the performance of firms: a study of growth and innovation rates in a high-technology industry. *Strategic Management Journal* **21**(8): 791–811.

Stuart TE, Podolny JM. 1996. Local search and the evolution of technological capabilities. *Strategic Management Journal*, Summer Special Issue **17**: 21–38.

von Hippel E. 1987. Cooperation between rivals: informal know-how trading. *Research Policy* **16**(6): 291–302.

Wezel FC, Cattani G, Pennings JM. 2006. Competitive implications of inter-firm mobility. *Organization Science* **17**(6): 691–709.

Williams RL. 2000. A note on robust variance estimation for cluster-correlated data. *Biometrics* **56**(2): 645–646.

Wooldridge JM. 2002. *Econometric Analysis of Cross Section and Panel Data*. MIT Press: Cambridge, MA.

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APPENDIX: PROCEDURE TO IDENTIFY INVENTOR MOBILITY

In order to identify inventors moving across firms, we collected the set of inventors in all the patents granted to the firms in the sample from the NBER database. That includes all the inventors of the patents classified in one of the four primary classes (257, 326, 438, and 505) assigned to the semiconductor category in the NBER patent dataset. We then utilized a two-step procedure described below. The first step insures that the portfolio of patents amassed by an individual is not compromised by any misspellings in the name. The second step insures that the mobility events suggested by this portfolio are not overestimated due to idiosyncrasies of the patent granting process.

Step 1.

1. Check for spelling errors in last names (particularly important for foreign language names), group all the inventors with last names that may have been misspelled and assigned a pseudo-last name. (i.e., Smiht for Smith, Mendeleiev for Mendeleev, Nicholaj for Nicholai or Nicholav, Masaaki for Masaki, Donwon for Dongwon, and so on).
2. Repeat Step 1 for first name and create a pseudo-first name.
3. Match inventors by pseudo-last name and pseudo-first name.
4. Discard matches where middle name or middle initial do not match. (i.e., John A. Simon and John Albert Simon is a match, John Simon is a match with the two previous names only if we do not have at least one other inventor with same first and last names but different middle initial or name).
5. Create a pseudo-last name-first name-middle name code for each inventor.
6. Track the assignees for each inventor's patent record. When inventor's patents were granted to different assignees move into Step 2 to minimize timing and identification errors:

Step 2.

1. Make sure that patents that suggest potential mobility (i.e., same inventor and different assignees) are not granted to more than one assignee. If one of the additional assignees appears in all the inventor's patents, no mobility is recorded. This step is necessary because the NBER database only records the first assignee.
2. Check the timeline of patents for sequence:

a. When inventor appears to move back and forth between firms:

i. Check that later patents are not continuations from patents originated in the old firm. If this is true, then no mobility is recorded.
ii. Check that later patents are not the result of funding granted in the old firm. If this is true, then no mobility is recorded.
iii. Check that the sequence corresponds to the same inventor. It is possible that two distinct inventors could have the same name. If patents are generated by multiple assignees for more than two years, we assume that distinct inventors generated these patents for the distinct assignees and therefore no mobility event is recorded.

b. Check that patents can be ordered in sequence. If all patent applications occurred in the same year, the direction of the event is not defined; therefore, no mobility is recorded.

This procedure minimizes the false positives resulting from NBER database's assignee reporting for each patent while maximizing the identification of mobility events, where mobility directionality can be assessed.

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