Gaining from Your Losses: The Backward Transfer of Knowledge through Mobility Ties

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ABSTRACT

A host of studies have demonstrated that the mobility of technical employees among firms is associated with some transfer of knowledge from their previous firms to their new employers. This effect is typically attributed to a mechanism rooted in human capital, where the employee carries the knowledge with him/her to the new firm. However, this effect may also be attributable to a mechanism rooted in social capital, where the mobility of the employee to the new firm creates interfirm communication channels derived from the social relationships between the employee at his/her new job and his/her social contacts at the previous employer.

To distinguish the human and social capital mechanisms in this process, we separate "inbound mobility" from "outbound mobility". When an employee moves from firm i to firm j, we say that firm i experiences inbound mobility, while firm j experiences outbound mobility. Most studies of mobility's effect on knowledge transfer have focused on inbound mobility, which does not allow one to distinguish between human and social capital mechanisms on the transfer of knowledge from firm i to firm j. In contrast, we focus on outbound mobility from firm i and whether it is associated with knowledge transfer from firm j to firm i. In this situation, only the social capital approach would predict that firm j's knowledge would be accessible to firm i.

We examine these phenomena in the semiconductor industry between 1980 and 1995. Our results are based on a sample of 161 firms with at least one patent in the US. Using zero-inflated negative binomial regressions, we demonstrate that a firm experiencing outbound mobility (losing an employee) is more likely to cite the firm receiving the mobile employee even after controlling for alternative mechanisms (alliances, hiring, geographic and technological distances, and knowledge stock). This effect is stronger for firms that are geographically distant than firms that are geographically proximate, suggesting that the communication channels formed are more valuable when they provide access to distant, presumably non-redundant, knowledge. These results demonstrate the validity of a social capital approach to knowledge transfer and call into question the conventional wisdom that losing employees means losing knowledge.

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, 2004).

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. Pennings et al. (2005) 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 not only carrying resources attributable not only to human capital but also to their accumulated social capital in the form of client and within-firm relationships.

In this paper, we utilize a stronger variant of a social capital approach: An employee moving from firm i to firm j does not just remove something from firm i and transfer it to firm j, but also generates a communication channel between the new employee of firm j and his/her social contacts at firm i. In this case, the channel can transmit information from firm i to firm j, as the mobile employee can access information from his/her contacts. Of course, in a study of gains for firm j, it is challenging to discern whether the underlying resources transferred relate more directly to human capital or social capital mechanisms.

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 firms i and j as a result of employee mobility are assumed to be bidirectional, while the transfer of human capital is assumed to be unidirectional. Thus, Agrawal et al. (2003) 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.

The purpose of this paper is extend the idea of enduring social relationships 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 aim to answer the following questions: does a firm losing an employee receive knowledge from the firm hiring the employee? Also, under what conditions is this effect significant?

Our empirical setting, semiconductor industry research and development, is particularly suited to explore these questions for three 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 effect on actors' decisions under conditions of uncertainty (cf. Coleman et al., 1966; Rogers, 2003), communication channels forged through enduring social relationships should influence knowledge development. Third, firms in this industry are locally clustered across diverse geographic regions, enabling us to contrast the effects of mobility within and across regions.

The rest of the paper is organized as follows: the next section discusses knowledge transfer between semiconductor firms and develops propositions about the effects of outbound mobility and geographic proximity on technological knowledge transfer. It is followed by a section describing the methodology, sample and variables. A section presenting and elaborating on the results precedes the concluding section where contributions and implications are discussed.

THEORY

In this paper, we focus on knowledge transfer across firm boundaries in the semiconductor industry. We conceptualize knowledge transfer as the process by which an organization is affected by the experience of other organizations (Argote, Ingram, Levine,

& Moreland, 2000). This process may result in changes in 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 & Allen, 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-tech 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 & 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 strategies and tactics 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 is the establishment of communication channels between the mobile employee at his/her new firm with his/her colleagues at 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 tie between people endures. 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, p. 82-3) 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 et al. (2004) note:

> "He [research engineer] usually maintained links to these individuals [earlier research collaborators] by passing back old information relating to his prior work, rather than by applying that same information to his new work going forward."

And

> "…[Firm] XYZ did not, "give you time for any outside life [that would enable knowledge transfer]." Yet, before starting a project, he reported that XYZ 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, 1986) among technical employees working at different firms. Preexisting social connections such as those created by mobility events are likely to facilitate these sorts of knowledge flows.

In addition to the establishment of interfirm communication channels, another mechanism by which outbound mobility may generate knowledge flows is by increasing the salience of the receiving firm as a producer of useful knowledge. 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 the solutions. The patterns of information search become routinized (Nelson & 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 proved themselves as sources of information leading to innovations.

In our case, when an employee leaves one firm for another, his/her 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 was 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: *Outbound Mobility increases the likelihood of the firm losing the employee (focal firm) drawing on the knowledge of the firm hiring the employee (alter firm).*

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 to the focal firm from the alter is found associated with the event, absent an employee hired by the focal firm from the alter, 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*.**

While our interest will be in how geographic proximity or distance affects the relationship between outbound mobility and knowledge transfer, we begin by reviewing the baseline effect of geographic proximity on knowledge transfer. The notion that knowledge spillovers are localized is well-established in the literature (cf. Hagerstrand, 1967; Jaffe et al., 1993; Almeida and Kogut, 1997; DeCarolis and Deeds, 1999; Agarwal et al., 2001). While mobility is acknowledged as one of the key mechanisms by which knowledge spillovers occur within regions (Almieda and Kogut, 1999), a host of informal contacts arise through the multitude of professional associations, casual gathering places, and other social contacts that arise between geographically proximate people (Saxenian, 1990). Inkpen and Tsang (2005) claim that the social networks of industrial districts are one of the mechanisms supporting the transfer of knowledge. These social networks are based on personal ties, nonhierarchical and dense in a geographic region, and are intrinsically dynamic because of the mobility of their members. Industrial district networks are sustained by a shared culture and high levels of trust developed at the interpersonal level.

Hypothesis 2: *Geographic proximity between two firms (focal and alter) increases the likelihood of the focal firm drawing on the knowledge of the alter.*

While mobility is more common within geographic regions than across them, recent work has argued that the knowledge transfer effects of mobility across geographic regions is more pronounced (Rosenkopf and Almeida, 2003; Agrawal et al., 2003). These arguments are premised on traditional sociological arguments that bridges to new contexts provide the most valuable knowledge (cf. Granovetter, 1973; Burt, 1992). In our context, this means that a 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, a mobility event to a distant regions is more likely to create a unique channel by which useful (i.e., non-redundant) knowledge can flow.

A network based on ties created by inventors who left the focal firms in the semiconductor industry is likely to share the same characteristics of the industrial district network, except for the fact that the network is not geographically constrained. The shared culture and trust is originated in the shared socialization process scientists are exposed to during their training years in universities and technological centers (DiMaggio & Powell, 1983).

For these reasons, we expect that the access to information obtained by means of a tie generated by outbound mobility is more likely to be available through other ties. As a result of this redundancy, we propose:

Hypothesis 3: *Geographic Proximity decreases the effect of Outbound Mobility on the likelihood of the focal firm drawing on the knowledge of the firm hiring the employee (alter firm).*

METHODOLOGY

Data and Variables

Data was collected in the context of the semiconductor industry. In order to collect the different variables, the information on the front page of the patents granted by the USPTO 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 U.S. 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 location, 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 et al., 1999; Jaffe, Trajtenberg, & Henderson, 1993). As discussed by Jaffe *et al* (1993) this is not to say that the 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 US (Cohen, Nelson, & Walsh, 2000; Cohen, Goto, Nagata, Nelson, & Walsh, 2002) and, as per our definition, parent citations are records that allow us tracking 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 of the inventor and the firm (which allows tracking of mobility and geographic location) and citation of previous patents from where the innovation draws (a process refereed by patent examiners that control the adequacy and completeness of the citations) (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) 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 with at least one US semiconductor patent, as per NBER classification, between 1980 and 1995 are included in the sample. This results in a total of 161 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 being cited (*alter* firm). All the independent variables preceded in time the dependent variable (count of citations). The dependent variable was measured for each dyad-year for the period 1985-1995. In other words, our dataset contains one observation for each dyad in the sample for each year of observation.

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 (Jaffe et al., 1993) reported that patent citations reach a peak between 3 to 5 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 80s has an effect on citation patterns for the period 1990-1995 (Almeida et al., 2003; Rosenkopf et al., 2003). For these reasons, we selected the 5-year window to measure the different types of mobility and alliances. In a similar manner, we utilized 5-

year windows to count the number of patents as a proxy for firms' knowledge stock and measure technological distance. Since citations tend to decrease after 5 years of granting, we consider that a patent's value has depreciated after that period of time, as well as the stock of knowledge. In the case of the number of patents at risk of being cited, we utilized a 10-year window, which, according to Jaffe and colleagues' finding, is the time it takes a patent to start receiving a negligible number of citations per year.

Citation Count (cites). For each dyad (focal and alter firms), this variable is a count of the number of times the focal firm cited the *alter* for each year of observation. Each citation is treated as one instance of the focal firm's drawing upon the knowledge of the cited firm. This variable is compiled from the NBER dataset.

Outbound Mobility (OutMob). This variable identifies the instances when an inventor moved from a focal firm to a alter firm in our sample, thus creating the possibility of interfirm transmission of knowledge from their receiving firm to the focal firms. To track mobility, we examined the set of semiconductor patents for each firm in our sample between the years 1980 and 1995. Each inventor listed on the semiconductor patents through the 1980–1995 period was then tracked, looking for instances where an inventor was employed by more than one firm over his/her patent trajectory. A case of mobility was identified when a researcher is listed as inventor in patents granted to two different firms.[2] Since it is impossible to pinpoint the exact date of mobility, we use the following approach: the time of the mobility event is the application year of the first

[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. 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 the high human capital of the researcher). As described above, we would expect a negative impact on the firm losing this kind of employee.

alter's patent where the mobile employee appears as inventor. Therefore, we coded Outbound Mobility as 1 if at least one case of outbound mobility has occurred in the 5-year window preceding the year of observation, otherwise it is coded as 0.[3]

Geographic proximity (GeoProx). When two firms are located in the same Metropolitan Statistical Area (MSA) or same country (in the cases of foreign firms) *geographic proximity* is coded as 1, otherwise it is coded as 0. This variable is a proxy for proximate two firms are and as such for how easy it is to transfer information. We utilized the MSA for 1993 as defined by the US Office of Management and Budget (6/30/1993) (See Table 1 for MSA codes and names). The location of the firm was obtained from the first page of the USTPO patents granted to the firm during the year of the observation.

Controlling for Alternative Mechanisms of Knowledge Transfer

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

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 access each other knowledge or to develop common knowledge (Inkpen et al., 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, & Grant, 2002; Rosenkopf et al., 2003; Song et al., 2003; Stuart, 2000). Therefore, we use *Alliances* (a dichotomous

3 This procedure ensures that the employee was in the alter firm by the year the mobility event was recorded, and in any event, it only introduces a lag to the actual time of the mobility event, which would only move the window of observation further in time from the one we report.

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 1 when at least one alliance (either technological or marketing) is found in the 5-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 signing confidentiality contracts, 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 et al., 2003; Song et al., 2003). For this reason, we included a control variable showing hiring of employees, which we expect to have a positive effect on knowledge transfer across firms' boundaries.[4]

To control for this mechanism, we utilize *Hiring* (a dichotomous variable) that captures the existence of the move of at least one inventor from the alter firm to the focal firm during the 5-year window before the year of observation. A hiring event is recorded in a similar manner to the recording of outbound mobility events; the time of the hiring

[4] 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 a outbound mobility tie for ABC (focal) to XYZ (alter) and a hiring tie for XYZ(focal) from ABC(alter). Absent an employee moving from XYZ to ABC, we do not have a hiring tie for ABC (focal) from (XYZ).

event is the year of the application of the first patent of the focal firm on which the employee appears as inventor.

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 & Levinthal, 1990) Two variables are used to control for both dyad-specific and firm-specific characteristics of this type. Following Stuart and Podolny (1996), *Technological Distance (TechDist)* reflects the dyad's common citation patterns. It is measured as the Euclidean distance between the vectors representing the niche overlap of each firm with all the other firms in the industry. We measure the niche overlap for the 5-year window previous to the year of observation. Smaller values indicate technologically proximate firms, and *TechDist* is expected to be negatively associated with our dependent variable.

Focal firm's number of patents (FocPat) represents the firm's stock of knowledge. It is the count of patents granted to the firm that have application dates in the 5-year window previous to the year of observation. Larger values of this variable are expected to be associated to a larger stock of knowledge for the focal firm. We utilized the natural log of this variable because it is heavily skewed.

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

Alter firm's number of patents (AltPat). This variable measures the number of patents granted to the *alter* of the dyad during the 10-year window previous to the year of observation. In this way we control for the increase in the probability of citing another firms resulting just from the sheer number of patents. We utilized the natural log of this variable because it is heavily skewed.

Year86-Year95. These are 10 dummy variables that capture all the unobserved effects associated for each year of observation.

Model and Results

Our dataset includes firms in 23 MSAs in the US (see table 1) and 11 foreign countries. 12 MSAs and 5 foreign countries contain only one of the firms in the sample. Another aspect to consider in our data is the number of firms in each region, as defined by MSA or country. The MSA where Silicon Valley is located (MSA code = 7362) concentrates 56 of the 161 firms in the sample with the second largest region being Japan with 23 firms and the third largest is the MSA where Los Angeles, CA is located (MSA code = 4472) with 9 firms. The rest of the MSA's have 6 or less firms. In table 2, we present the number of events of outbound mobility, hiring and alliances found for the period 1980 to 1995. These events generated the observations for OutMob, Hiring and Alliances reported below.

Tables 3 and 4 present the distribution for the *OutMob*, *Hiring* and *Alliances* in our sample. Regarding to *OutMob*, 229 of the 943 observations involved a focal firm in Silicon Valley's MSA, and, of those, 155 involved movements between two firms in Silicon Valley's MSA. The total number of *OutMob* observations involving firms in the same region is 401. Japan ranks second, with same-region *OutMob* accounting for 195 observations of mobility. The next MSA with more cases of same-region outbound mobility is the one where New York City is located (MSA code = 5602), with only 14 observations.

Similar patterns are found in the dataset for hiring and alliances. First, Silicon Valley's MSA accounts for 293 out of the 943 observations of hiring, from which 138 are cases of hiring from other regions. On the other hand, Japan only accounts for 252 observations of hiring (57 from other regions) and New York City's MSA ranks third with a total of 71 observations (57 from other regions). The rest of the regions account for 398 observations (347 from other regions). Second, Silicon Valley's MSA accounts for 869 observations for alliance (630 to other regions), Japan for 742 observations (608 to other regions), New York City's MSA for 207 observations (all of them to other regions, and the rest of the regions account for 1118 observations (1072 of them to other regions). Descriptive statistics for the variables are presented in Table 5.

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. We hypothesized that this variable is a function of a set of independent variables with the following functional form:

$$\mathrm{Log}(Cites_{ijt}) = b_0 + \beta\, X_{ijt} + \gamma\, Y_{ijt} + \delta\, PatAlt_{jt} + \varphi_t + \varepsilon_{ijt}$$

where X is a vector that includes *OutMob*, *GeoProx* and *OutMob*GeoProx*,

Y is a vector that includes *TechDist, PatEgo, Alli*, and *Hiring*;

φ is a vector capturing year effects;

ε is the error term with a log-gamma distribution; and

i, j, and *t* indicates the observation correspond to the focal firm (*i*), the alter firm (*j*) on year (*t*).

Since our dataset includes repeated observations for each focal firm (for different alters and years), it violates the assumption of independence across observations. In addition, an estimation of a Poisson model indicates that the dataset suffers of overdispersion and it also has the problem of excess zeros (the number of non zeros for the dependent variable is less than 12% of the total number of observations, see table 6). For these reasons, we estimate a fixed effect zero inflated negative binomial regression (which corrects for overdispersion and excess zeros) with fixed effect on the focal firm (which corrects for the interdepencence between observations of the same focal firm) with SAS v. 9.1. Therefore, our model has the following form:

$$\text{Log}(\textit{Cites}_{ijt}) = b_0 + \beta\, X_{ijt} + \gamma\, Y_{ijt} + \delta\, \textit{PatAlt}_{jt} + \varphi_t + \alpha_i + \varepsilon_{ijt;}$$

Where α_i is the term that captures the fixed effect of focal firm i.

The fixed effect estimation controls unobserved heterogeneity, corrects spuriousness, and reduces endogeneity concerns. We model the inflation equation as a function of *TechDist*, log(*PatEgo*) and log(*PatAlt*). The correlations between the independent variables are low and VIF and tolerance tests (SAS v.9.1) show that the data do not have multicollinearity problems.

We ran a series of nested models in which we added variables consecutively. The base model (Model A) included the year's dummies (to capture unobserved differences across the period 1986 to 1995), log(*PatAlt*), *TechDist,* log(*PatEgo*), *Alliance* , and

Hiring. Then, five other models were estimated by consecutively adding *GeoProx* (Model B), and *OutMob* (Model C) and *OutMob***GeoProx* (Model D). (See Table 7)

Results. Log Likelihood Ratio tests[5], calculated from the log Likelihood of the models, show that each addition of variables to a model resulted in a significant improvement with respect to the base model, with *p-values* smaller than 0.05. The same test shows that model C is not significantly better than model B (*p-value* = 0.31); however, model D is significantly better than models B and C (*p-value* < 0.001).

Examining the full model (D), the coefficient for *OutMob* is positive and significant at the 0.05 level in the presence of all the control variables, supporting Hypothesis 1. Hypothesis 2 is also supported in models B, C and D, where the coefficients for *GeoProx* are positive and significant at the 0.01 level. Hypothesis 3 finds support in model D, where the coefficient for the interaction *OutMob* and *GeoProx* is negative and significant at the 0.1 level (*p-value* = 0.064).

A look at the control variables shows that in general the effects associated with each year are not significantly different (when compared with the omitted year – 1985). The only year that is consistently different from 1985 across models is 1995, while 1988 is significantly different at the 0.1 level in models B to F. Most other variables behave as expected in all the models. As predicted by the absorptive capacity perspective, log(*PatEgo*) and *TechDist* are significant (at 0.01 level) and associated with citations (positively and negatively, respectively). The effect of alliances is positive and significant at 0.01 level. An unexpected result is found for *Hiring*. When *GeoProx* is added to the

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[5] The Likelihood Ratio test statistic -- ABS($2\log L_{modelA}$-$2\log L_{modelB}$) -- has approximately a χ^2 distribution with d.f. equal to the difference in the number of parameters between Model A and Model B. This tests Ho that the reduce model is equivalent to the full model.

model, *Hiring* goes from being significant at the 0.01 level to not significant in models B, C and D.

DISCUSSION

In this study, we claim that the tie between firms created by an employee moving from one firm to another is not unidirectional, as research has typically operationalized it, but bidirectional in its capability of transferring knowledge and study how geographic proximity affects the transfer of knowledge from the firm receiving the employee. By doing this, the paper advances our understanding of knowledge flows, and gives a more complete picture of the processes involved in knowledge transfer while providing empirical evidence that suggests an important role for social capital in this process. Our results simultaneously show that organizations receive knowledge by mechanisms that operate at organizational, individual and regional levels. Mechanisms based on organizational structures (alliances), acquisition of human capital (hiring) and acquisition of social capital (outbound mobility), social networks contained in a geographic region (proxied by *GeoProx*), and observing others (Nonaka, Takeuchi, & Umemoto, 1996) which is proportional to the absorptive capacity of the firm (stock of knowledge and the technical distance to the firm under scrutiny) facilitate the transfer of technological knowledge across firms in the semiconductor industry.

Overall, the results support our hypothesis, even after other mechanisms of knowledge transfer are controlled for. When outbound mobility involves the moving of employees between regions, the overall effect is positive. However, the similar size of the coefficients for *OutMob* and the interaction *OutMob*GeoProx* suggests that the effect disappears when the mobility event occurs inside a MSA or in a foreign country. This would indicate that outbound mobility is a redundant mechanism in a contained region or, as per Inkpen and Tsang's description (2005), industrial districts involve 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 to 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. Nevertheless, outbound mobility or hiring could play another role that is not captured in our measurement. A network of mobility of non-inventor employees is also more likely to be located inside an industrial district, and the personal ties of those employees might be the mechanism utilized to reach inventors in other firms. This can also explain why *Hiring* lost significance when *GeoProx* is included in the models. Since mobility of employees tends to involve geographically proximate firms, in model A, *Hiring* may be summazing the effect of all the mechanisms of knowledge transfer associated to geographic proximity. When *GeoProx* is included in models B to D, *Hiring* only captures the effect of hiring of inventors while the rest of the mechanisms are captured by *GeoProx*.

A look at the structure of our data illuminates limitations and opens new questions. 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 et al., 1984; Saxenian, 1994). Our results regarding the interaction between geographic proximity and outbound mobility may have been driven by these facts, since, as described above, Silicon Valley accounts for almost 40% of the observations of outbound mobility and 35% of the firms. In addition, Japan accounts also for almost 50% of the total number of the cases of outbound mobility in the same region. For this reason, the effect of outbound mobility when contained in a geographic region has to be taken with caution because it may just reflect idiosyncrasies of these 2 regions. On the other hand, Silicon Valley and Japan together account only for 20% of the cases of outbound mobility across a region, which provides some reassurance about the generalizability of the results over distance. Another interesting fact is that Silicon Valley is the MSA accounting for the largest number of hiring from different regions (138 observations out of 542) and the single largest number of employees leaving one region (74 out of 401). This provides some evidence that Silicon Valley is acting as a hub of technological knowledge.

That technological knowledge transfer is mainly contained inside the region may have found support in the previous literature by only looking at firms located in one region, or by ignoring the interaction between outbound mobility and geographic proximity. When this interaction is taken into account, our model shows that the transfer of technological knowledge follows a mechanism similar to scientific knowledge. At the end of the day, whether technological knowledge is able to flow across organizational boundaries or firms are able to contain it is a matter of empirical verification. Our results support the position that despite organizations' efforts to contain this flow (Rogers et al., 1984), knowledge appears to flow across organizational boundaries in ways that involve strategic moves (alliances and hiring) or non strategic ones (losing employees). It appears that even technological knowledge spreads in a manner that is similar to 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 particularly important when this access is not available.

This study opens a series of questions that future research should address. First, what other knowledge transfer mechanisms are involved in industrial districts, their level of redundancy with each other, and the level of resilience this redundancy provides. Second, whether outbound mobility has different effects in particular regions; in other words, whether firms can benefit from outbound mobility inside some regions while other regions experience enough redundancy to make outbound mobility trivial. Finally, this study isolates the acquisition of knowledge through social capital from the acquisition through human capital. 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. Future research should examine these effects to further isolate them from alternative explanations by eliminating the possibility of confounding variables, such as the convergence of technological trajectories that facilitate the mobility of employees between firms.

CONCLUSION

This paper advances our understanding of the effect of mobility in the transfer of technological knowledge by conceptualizing the mobility of 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 members of both firms. In addition, we were able to empirically isolate the mechanism of social tie creation by means and found a positive effect of the mobility of an employee on the knowledge transferred backward to the firm losing her; 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.[6] 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 *et al. (2003)* 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 associates the loss of and employee with a firm-level gain of skills or knowledge of any sort. Work in this area has typically found firm-level losses, 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 replaces and ongoing conferral of status (Dokko and Rosenkopf, 2004). Our paper clearly highlights the importance of the mobility ties in the organizational learning process, even when employees leave the firm.

[6] In this particular context, we are studying the mobility of researchers that have been productive at their former job and are still productive in their new job (at least to the point of being recognized as inventors in a patent), which limits the number of cases where the firm was trying to fire the employee. If that is the case, this should reflect in a loss at least at the aggregate level. Otherwise, we would be assuming that firms pay for employees that subtract rather than add value to the firm.

Finally, this work corroborates the importance of networks based on individual's 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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Table 1. Metropolitan Areas and Components Where Semiconductor Firms Are Located

(Metropolitan areas defined by Office of Management and Budget, 6/30/93)

Source:	U.S. Census Bureau
Internet Release Date:	September 1996
Revised date:	April, 1999

The file layout is located at the end of the data file.

ABBREVIATIONS:
MSA = Metropolitan Statistical Area

MSA CODE	Metropolitan Area Names
1080	Boise City, ID
1122	Boston-Worcester-Lawrence, MA-NH-ME-CT
1602	Chicago-Gary-Kenosha, IL-IN-WI
1692	Cleveland-Akron, OH
1720	Colorado Springs, CO
1922	Dallas-Fort Worth, TX
2162	Detroit-Ann Arbor-Flint, MI
3280	Hartford, CT
3362	Houston-Galveston-Brazoria, TX
4472	Los Angeles-Riverside-Orange County, CA
4992	Miami-Fort Lauderdale, FL
5120	Minneapolis-St. Paul, MN-WI
5602	New York-Northern New Jersey-Long Island, NY-NJ-CT-PA
6162	Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD
6200	Phoenix-Mesa, AZ
6280	Pittsburgh, PA
6442	Portland-Salem, OR-WA
6480	Providence-Fall River-Warwick, RI-MA
6640	Raleigh-Durham-Chapel Hill, NC
7320	San Diego, CA
7362	San Francisco-Oakland-San Jose, CA
8520	Tucson, AZ

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

Table 2. Number of Oubound Mobility, Hiring and Alliance Events per Year between 1980 and 1995.

Year	Outbound Mobility Events Freq	Outbound Mobility Events Percent	Hiring Events Freq.	Hiring Events Percent	Alliance Events Freq.	Alliance Events Percent
1980	3	0.55	3	0.55	3	0.46
1981	11	2.02	11	2.02	8	1.23
1982	6	1.10	6	1.10	19	2.92
1983	6	1.10	6	1.10	17	2.61
1984	9	1.65	9	1.65	24	3.69
1985	10	1.83	10	1.83	38	5.84
1986	15	2.75	15	2.75	43	6.61
1987	17	3.12	17	3.12	49	7.53
1988	32	5.87	32	5.87	58	8.91
1989	41	7.52	41	7.52	50	7.68
1990	37	6.79	37	6.79	46	7.07
1991	57	10.46	57	10.46	74	11.37
1992	56	10.28	56	10.28	61	9.37
1993	70	12.84	70	12.84	55	8.45
1994	80	14.68	80	14.68	65	9.98
1995	95	17.43	95	17.43	41	6.30
Total	545		545		651	

Table 3. Observations for Outbound Mobility (*OutMob*), *Hiring* and *Alliances* per focal firm location and Geographic Proximity (same region) between firms.

Focal Firm's Location	Geog. Proximity	*OutMob* Sum	*Hiring* Sum	*Alliances* Sum
Silicon Valley	0	74.00	138.00	630.00
	1	155.00	155.00	239.00
Japan	0	54.00	57.00	608.00
	1	195.00	195.00	134.00
NY City	0	59.00	57.00	207.00
	1	14.00	14.00	0.00
Other	0	355.00	290.00	1072.00
	1	37.00	37.00	46.00
Total		943.00	943.00	2936.00

Table 4. Observations for Outbound Mobility (*OutMob*), Hiring and Alliances per focal firm location and Geographic Proximity between firms

Focal Firm's Location	Geo Dist	OutMob Sum	Hiring Sum	Alliances Sum
	0	3.00	2.00	1.00
	1	.	.	.
1080	0	0.00	19.00	24.00
	1	.	.	.
1122	0	20.00	21.00	38.00
	1	4.00	4.00	0.00
1602	0	51.00	41.00	73.00
	1	.	.	.
1692	0	20.00	7.00	42.00
	1	0.00	0.00	10.00
1720	0	1.00	9.00	18.00
	1	.	.	.
1922	0	35.00	20.00	171.00
	1	0.00	0.00	6.00
2162	0	9.00	5.00	3.00
	1	0.00	0.00	0.00
3280	0	3.00	7.00	1.00
	1	.	.	.
3362	0	2.00	10.00	20.00
	1	.	.	.
4472	0	59.00	12.00	144.00
	1	14.00	14.00	8.00
4992	0	40.00	21.00	24.00
	1	.	.	.
5120	0	15.00	28.00	23.00
	1	5.00	5.00	0.00
5602	0	59.00	57.00	207.00
	1	14.00	14.00	0.00
6162	0	24.00	11.00	12.00
	1	0.00	0.00	0.00
6200	0	0.00	0.00	1.00
	1	.	.	.
6280	0	16.00	0.00	16.00
	1	.	.	.
6340	0	10.00	0.00	4.00
	1	.	.	.

Focal Firm's Location	Geo Dist.	OutMob Sum	Hiring Sum	Alliances Sum
6442	0	10.00	9.00	67.00
	1	3.00	3.00	10.00
6480	0	0.00	0.00	0.00
	1	.	.	.
6640	0	0.00	0.00	0.00
	1	.	.	.
7320	0	0.00	2.00	27.00
	1	0.00	0.00	0.00
7362	0	74.00	138.00	630.00
	1	155.00	155.00	239.00
8520	0	0.00	5.00	0.00
	1	.	.	.
CA	0	6.00	12.00	10.00
	1	0.00	0.00	0.00
DE	0	1.00	9.00	75.00
	1	0.00	0.00	2.00
FR	0	0.00	3.00	5.00
	1	0.00	0.00	0.00
GB	0	15.00	8.00	33.00
	1	0.00	0.00	0.00
IN	0	0.00	5.00	10.00
	1	.	.	.
IT	0	14.00	5.00	88.00
	1	.	.	.
JP	0	54.00	57.00	608.00
	1	195.00	195.00	134.00
KR	0	1.00	7.00	123.00
	1	10.00	10.00	10.00
SE	0	0.00	0.00	3.00
	1	.	.	.
SG	0	0.00	7.00	9.00
	1	.	.	.
TW	0	0.00	5.00	7.00
	1	1.00	1.00	0.00

Table 5. Correlation Matrix and Descriptive Statistics.

	cites	OutMob	Hiring	Alliance	TechDist	GeoProx	Log (PatEgo)	Log (PatAlt)	OutMob* GeoProx
cites	1.000	0.082	0.091	0.139	-0.215	0.001	0.234	0.231	0.056
OutMob	0.082	1.000	0.103	0.053	-0.064	0.063	0.083	0.054	0.651
Hiring	0.091	0.103	1.000	0.052	-0.065	0.064	0.056	0.085	0.092
Alliance	0.139	0.053	0.052	1.000	-0.082	-0.003	0.103	0.101	0.032
TechDist	-0.215	-0.064	-0.065	-0.082	1.000	0.105	-0.347	-0.353	-0.037
GeoProx	0.001	0.063	0.064	-0.003	0.105	1.000	-0.074	-0.080	0.127
Log(PatEgo)	0.234	0.083	0.056	0.103	-0.347	-0.074	1.000	0.016	0.051
Log(PatAlt)	0.231	0.054	0.085	0.101	-0.353	-0.080	0.016	1.000	0.031
Outmob*GeoProx	0.056	0.651	0.092	0.032	-0.037	0.127	0.051	0.031	1.000
MEAN	0.232	0.0067	0.0067	0.021	0.588	0.151	1.764	2.034	0.003
STD	0.909	0.0816	0.0818	0.143	0.350	0.358	2.456	2.568	0.053
N	140614	140614	140614	140614	140614	140614	140614	140614	140614

Note: all the correlations are significant at *p-value*<0.001

Table 6. Frequency counts for Cites for the period 1985-1990.

cites	Frequency	Percent	Cumulative Frequency	Cumulative Percent
0	126098	89.68	126098	89.68
1	7558	5.37	133656	95.05
2	2838	2.02	136494	97.07
3	1429	1.02	137923	98.09
4	885	0.63	138808	98.72
5	598	0.43	139406	99.14
6	452	0.32	139858	99.46
7	322	0.23	140180	99.69
8	254	0.18	140434	99.87
9	180	0.13	140614	100.00

Table 7. Zero-Inflated Negative Binomial Regression Models with Fixed Effects on Focal Firm.

Number of obs	= 140614	Nonzero obs	= 14516
		Zero obs	= 126098
Inflation model	= logit		

Model	A	B	C	D
cites	Coef.	Coef.	Coef.	Coef
Constant	-3.139	-3.432 **	-3.423 **	-3.618 ***
	(2.968)	(1.492)	(1.565)	(1.042)
Log(PatEgo)	0.092 ***	0.102 ***	0.101 ***	0.101 ***
	(0.015)	(0.015)	(0.015)	(0.015)
Log(PatAlt)	0.223 ***	0.230 ***	0.229 ***	0.229 ***
	(0.008)	(0.008)	(0.008)	(0.008)
TechDist	-0.414 ***	-0.424 ***	-0.421 ***	-0.424 ***
	(0.060)	(0.060)	(0.060)	(0.060)
Alliance	0.131 ***	0.140 ***	0.139 ***	0.141 ***
	(0.032)	(0.032)	(0.032)	(0.032)
Hiring	0.133 ***	0.051	0.037	0.040
	(0.050)	(0.404)	(0.464)	(0.436)
GeoProx		0.314 ***	0.310 ***	0.320 ***
		(0.027)	(0.027)	(0.028)
OutMob			0.061	0.145 **
			(0.054)	(0.071)
OutMob*GeoProx				-0.200 *
				(0.108)
-2 Log Likelihood	100750	100603	100602	100595
p-value LR test†		<0.001	>0.3	<0.010

Standard Errors in parentheses

†Tests for Ho that full model and reduced models are equivalent

* *p-value* <0.1 ** *p-value* <0.05 *** *p-value* <0.01