



Paper to be presented at
DRUID15, Rome, June 15-17, 2015
(Coorganized with LUISS)

Employee Mobility and Knowledge Spillovers: Integrating a Job Matching and a Social Capital Perspective

Martin C. Goossen
USI Lugano
Institute of Management
goossm@usi.ch

Gianluca Carnabuci
USI Lugano
Institute of Management
gianluca.carnabuci@usi.ch

Abstract

This study combines insights from two distinct lines of theory explaining how mobility of knowledge workers across firms relates to interfirm knowledge spillovers. On the one hand, the social capital argument posits that employee mobility generates interpersonal ties across firm boundaries, thereby increasing opportunities for interfirm knowledge spillovers. On the other hand, the job matching literature argues that mobility events tend to occur when the value of an employee's idiosyncratic knowledge is greater within the new employer than within the current one. By positing that mobility events generally improve the fit between employers and employees at the industry level, the job matching argument suggests that mobility may reduce interfirm knowledge spillovers. We integrate both mechanisms in a more general argument, proposing that although employee mobility does generally increase the likelihood of interfirm knowledge spillovers, this spillover effect is contingent on the level of fit, prior to the move, between source and target firm. Namely, we hypothesize that mobility events increase the likelihood of knowledge spillovers when firms hire from competitors distant in knowledge space but, somewhat counterintuitively, they have a weaker effect when firms hire from competitors whose knowledge they already monitor and draw from. Using a longitudinal dataset on the mobility of R&D scientists among global pharmaceutical firms between 1985 and 2010, we find broad support for this argument.

EMPLOYEE MOBILITY AND KNOWLEDGE SPILLOVERS: INTEGRATING A JOB MATCHING AND A SOCIAL CAPITAL PERSPECTIVE

Abstract

This study combines insights from two distinct lines of theory explaining how mobility of knowledge workers across firms relates to interfirm knowledge spillovers. On the one hand, the social capital argument posits that employee mobility generates interpersonal ties across firm boundaries, thereby increasing opportunities for interfirm knowledge spillovers. On the other hand, the job matching literature argues that mobility events tend to occur when the value of an employee's idiosyncratic knowledge is greater within the new employer than within the current one. By positing that mobility events generally improve the fit between employers and employees at the industry level, the job matching argument suggests that mobility may reduce interfirm knowledge spillovers. We integrate both mechanisms in a more general argument, proposing that although employee mobility does generally increase the likelihood of interfirm knowledge spillovers, this spillover effect is contingent on the level of fit, prior to the move, between source and target firm. Namely, we hypothesize that mobility events increase the likelihood of knowledge spillovers when firms hire from competitors distant in knowledge space but, somewhat counterintuitively, they have a weaker effect when firms hire from competitors whose knowledge they already monitor and draw from. Using a longitudinal dataset on the mobility of R&D scientists among global pharmaceutical firms between 1985 and 2010, we find broad support for this argument.

INTRODUCTION

There is a rich literature arguing that the mobility of knowledge workers across firms engenders interfirm knowledge spillovers (e.g. Rosenkopf & Almeida, 2003; Song, Almeida, & Wu, 2003), that is, the transfer and reuse of knowledge generated within one firm by another firm (Jaffe, Trajtenberg, & Henderson, 1993). Several recent studies suggest that when employees switch employers, they take along not only their human capital, but also part of the social capital developed within the origin firm. In line with the argument that social ties act as conduits of knowledge, for example, Singh and Agrawal (2010) and Corredoira and Rosenkopf (2010) noticed that a firm is more likely to draw upon knowledge and technologies developed by another firm after employees were recruited from, or had left for,

that firm. By focusing on the role of interfirm mobility events in generating interpersonal connections across firm boundaries, this literature emphasizes that interfirm mobility events are a key driver of knowledge spillovers within industries.

Whereas this line of research has provided useful insights, its theoretical underpinnings remain underspecified insofar as they fail to account for a second important mechanism that prior research has argued to be associated with interfirm mobility events. Specifically, parallel to the social capital perspective, a sizeable but largely separate body of literature has theorized the link between interfirm mobility and knowledge spillovers from a job matching perspective (Jovanovic, 1979; Topel & Ward, 1992). According to this latter view, firms are motivated to poach employees from competing firms insofar as they need and value those employees' idiosyncratic knowledge; similarly, employees are willing to move to a new employer when they expect the value of their own knowledge to be greater within the new employer than within their current one. Expanding consideration to this matching argument suggests that the relation between interfirm mobility and knowledge spillovers may be more articulated than previously thought. Specifically, by emphasizing how mobility events may help firms internalize valuable sources of previously external knowledge, the job matching argument suggests that mobility events may diminish a firm's motivation to monitor and draw from other firms and, as a result, they may reduce interfirm knowledge spillovers.

The goal of the present paper is to integrate both theoretical mechanisms within a unitary explanation. Towards this end, we model employee mobility as a knowledge worker (empirically, an R&D scientist) leaving one firm to join a competitor. Since mobility events may lead to distinct types of knowledge transfer between competing firms, it is important to clarify upfront that we focus here on what the extant literature has identified as the strictest definition of knowledge spillover, thereby excluding other forms of knowledge transfer that are indirectly related with knowledge spillovers (Singh & Agrawal, 2010). For example,

employee mobility implies a transfer of human capital. A mobile knowledge worker brings along the human capital s/he embodies, such as personal knowledge, skills and experiences (Møen, 2000; Ployhart & Moliterno, 2011). Additionally, a mobile employee may carry to the new employer part of the social capital s/he has built while working for the previous employer. When employees leave the firm they were embedded in, social ties with former colleagues may live on and continue to be channels of knowledge (Corredoira & Rosenkopf, 2010). Similarly, a mobile knowledge worker may integrate into a new firm and build new social capital therein by creating interpersonal ties with new colleagues, thereby facilitating the transmission of his/her knowledge within the new employer (Singh & Agrawal, 2010). Lastly, mobile knowledge workers may lead to knowledge spillovers in a strict sense: a transfer of knowledge between two firms that is caused by the move of the employee, which cannot be merely ascribed to the knowledge s/he carries to the new firm in the form of his/her human capital (Jaffe, 1986). Such knowledge spillovers may be facilitated by interfirm mobility insofar as mobile employees act as a bridge between their prior and new employer, for example by pointing out to a new colleague a technology that is being developed at the mobile employee's origin firm, which may help the new colleague with a current problem s/he is facing. Such transfers of knowledge between firms are then additional to the transfer of human capital via employee mobility, and constitute the narrow definition of knowledge spillover we focus on here.

The purpose of this study is to integrate social capital and job matching explanations for knowledge spillovers through employee mobility, particularly the joint effects of these different mechanisms. We test our predictions on a longitudinal sample of R&D divisions of global pharmaceutical firms between 1985 and 2010. Using patent inventor and citation data, we are able to observe interfirm knowledge transfer that is unrelated to the human capital of mobile inventors. Furthermore, we can observe the knowledge fit between target and source

firms, as indicated by the extent of cross-firm patent citations, allowing us to estimate when and to what extent employee mobility is driven by job matching. The theory and evidence presented here advance the extant literature by showing that both the social capital and job matching mechanisms are indeed at work and, more importantly, by demonstrating that their interaction is critical to understand knowledge spillover dynamics. Specifically, we find that interfirm knowledge spillovers increase with mobility of knowledge workers between firms. However, this positive effect reverses when there is high knowledge fit between source and target firms prior to the mobility events.

This study contributes to several areas of research, including those on job matching, social capital, and interfirm knowledge spillovers. By integrating a social capital and a job matching perspective in a unitary explanation, this study clarifies how the effect of mobility on knowledge spillovers is contingent on knowledge fit. Additionally, the present research extends our comprehension of the role of social capital in interfirm knowledge transfer processes. After carefully controlling for the impact of human capital transfer, which earlier research found to account for a significant share of knowledge transfer through mobility (Singh & Agrawal, 2010), our results still show a strong effect of mobility on knowledge spillovers. This finding provides direct support for a social capital explanation where mobile employees facilitate knowledge spillovers by leaving behind social ties that act as conduits of knowledge between the mobile employee's former and current colleagues. At the same time, our results provide a more nuanced understanding of the relationship between mobility and knowledge spillovers by showing that while this social capital mechanism affects the opportunities for knowledge spillovers, firms hiring knowledge workers from competitors through a job matching mechanism are less motivated to subsequently monitor and draw from the knowledge of those competitors. Consequently, when knowledge workers' mobility improves the employer-employee fit, it reduces subsequent interfirm knowledge spillovers.

THEORY & HYPOTHESES

Background: Employee Mobility and Knowledge Transfer

Innovation is a knowledge recombination process (Fleming, 2001; Schumpeter, 1934) whereby knowledge workers, individually or in teams, engage in targeted and purposeful search activities in order to find novel solutions for existing problems (Fleming & Sorenson, 2004). To do so, they draw upon various knowledge components, e.g., information, skills, expertise, experience and technologies, of which they either create new combinations or take existing combinations and create new configurations (Carnabuci & Operti, 2013). The set of knowledge recombination opportunities available to an individual grows with his or her human capital, such that, for example, employees mastering a broader knowledge base are more likely to envision novel knowledge combinations than their more narrowly specialized colleagues (Fleming & Sorenson, 2001). Additionally, an employee's knowledge recombination opportunities grow with his/her social capital and, specifically, the network of interpersonal contacts with whom an employee exchanges ideas, information, and opportunities.

Since recombinant opportunities deplete when using the same knowledge pool over time (Carnabuci & Bruggeman, 2009), knowledge workers are motivated to learn new practices, technologies and skills from coworkers inside and or other knowledge workers outside their firm. Since such external knowledge is often complex and tacit, it requires substantial time and efforts from knowledge workers to absorb it. They are then faced with a tradeoff between local and distant search (Fleming, 2001; March, 1991). Local search implies learning new knowledge similar or related to an employee's existing expertise and it requires relatively little effort, but often results in very similar and incremental innovations (Stuart & Podolny, 1996). Conversely, distant search implies drawing knowledge that is novel and unfamiliar to

the focal firm (Rosenkopf & Almeida, 2003). While it requires more effort and involves more risk, knowledge workers are more likely to obtain radical or breakthrough innovations when combining their current knowledge with entirely new information, skills and technologies (March, 1991). Because distant search involves more time and uncertainty, most knowledge spillovers tend to be local, i.e. among knowledge workers within the same firm (Singh, 2005). However, interfirm knowledge spillovers have a much larger potential for innovation (Rosenkopf & Nerkar, 2001). Knowledge recombination by employees is therefore strongly influenced by the degree to which a company can generate interfirm knowledge spillovers, i.e. the transfer and reuse of knowledge generated by a different firm (Jaffe et al., 1993).

Interfirm knowledge spillovers are obtained from various channels, such as alliances and joint ventures that facilitate the transfer of complex, tacit knowledge and reduces the risk and uncertainty it involves (Rosenkopf & Almeida, 2003). Additionally, knowledge tends to spill over across firms when knowledge workers leave a firm to join a competitor (Rosenkopf & Almeida, 2003; Tzabbar, Aharonson, & Amburgey, 2013). Recruiting a knowledge worker from another firm results in an influx of information, skills and experiences that have been developed by that firm (Agrawal, Cockburn, & McHale, 2006; Song et al., 2003). Such mobile knowledge workers will use their human capital and combine their knowledge with information, expertise and technologies they can access at the new firm (Agarwal, Ganco, & Ziedonis, 2009). In addition, a firm benefits from knowledge transfer through employee mobility when mobile employees integrate in their new firm and share their expertise with their new colleagues (Singh & Agrawal, 2010). Lastly, research suggests that mobile employees often carry with them ties that connect their prior coworkers with their current ones, thereby creating a bridge through which knowledge can spill over across firm boundaries (Corredoira & Rosenkopf, 2010). Extant literature pointed out that this latter type

of knowledge transfer represents a knowledge spillover in a strict sense (Singh & Agrawal, 2010). Consistent with this view, in this paper we focus on this type of knowledge spillover.

Social Capital and Knowledge Spillovers

A prevailing explanation for the relationship between employee mobility and interfirm knowledge spillovers is found in the literature on social capital. Social capital consists of the benefits individuals and firms can obtain via their personal or organizational relationships to peers (Coleman, 1988; Nahapiet & Ghoshal, 1998). For employees, social capital consists of the information, resources, and political support they can obtain via their connections to colleagues within or outside their firm (Adler & Kwon, 2002). The extent of an individual's social capital is a function of the relational and structural characteristics of his/her connections, that is, the number, structure and strength of his/her ties to others (Burt, 2000).

In settings like R&D laboratories, where knowledge is largely embodied, tacit, complex and crucial for performing one's tasks, social capital is a major determinant of employee performance (Burt, 1992; Fleming, Mingo, & Chen, 2007). First, social capital helps employees find partners for projects since collaboration is core to knowledge recombination and reconfiguration (Breschi & Lissoni, 2009). Second, social capital helps an employee in obtaining the knowledge, resources and political support to pursue innovative projects (Burt, 1992; Ibarra, 1993). Third, social ties are a major source of information exchange and knowledge transfer. In a passive manner, knowledge workers often receive novel and relevant information via informal conversations with colleagues (Brown & Duguid, 1991). In an active way, knowledge workers can approach their contacts when projects require particular skills or expertise they do not have (Borgatti & Cross, 2003; Singh, Hansen, & Podolny, 2010). For these reasons, employees' social ties are an important determinant for knowledge transfer within and between firms (Paruchuri, 2010).

Social capital does not only explain knowledge transfer within firms, but can also explain how employee mobility results in knowledge spillovers that occur in addition to the transfer of human capital. When knowledge workers change employers, they often remain in touch with their former colleagues (Agrawal et al., 2006). As long as social ties between mobile employees and former coworkers persist, they may continue to exchange knowledge despite barriers formed by organizational boundaries (Berends, Van Burg, & Van Raaij, 2011). For example, Bouty (2000: 55) describes how former colleagues now working for competing firms still continue to exchange information and resources, despite them no longer being employed by the same firm. Similarly, mobile knowledge workers will be eager to integrate in their new working environment and start building new social capital in order to access and acquire novel knowledge that they need for their R&D projects. Via this process of collaboration and communication, new colleagues may learn from mobile employees (Almeida & Kogut, 1999; Argote & Ingram, 2000), such that knowledge may flow from the mobile employee throughout the hiring firm (Tzabbar et al., 2013).

Whereas this interfirm transfer through employee mobility is still driven by human capital of mobile knowledge workers, mobility also stimulates interfirm knowledge spillovers, i.e. knowledge transfer among non-mobile employees in both firms. When mobile employees retain their social capital in their prior firm while developing social capital in their new company, they will act as a bridge spanning both firms (Dokko & Rosenkopf, 2009). Like employees participating in interfirm alliances, mobile employees allow direct or indirect communication and knowledge transfer from colleagues in their former firm to coworkers in their new company and vice versa. In other words, they act as boundary spanners between both firms (Keller & Holland, 1975; Tushman & Scanlan, 1981a). Whereas the process of interfirm spillovers through employee mobility may be influenced by characteristics of the prior firm (Agrawal et al., 2009; Wang, 2015) as well as the current company (Hussinger &

Wastyn, 2012; Wang, 2015), generally mobility results are related to interfirm spillovers. In line with this prior literature, we state the following baseline hypothesis:

Hypothesis 1: Employee mobility from firm *j* to firm *i* leads to an increase of knowledge spillovers from firm *j* to firm *i*.

Job Matching and Knowledge Spillovers

Literature explaining the relationship between employee mobility and knowledge spillovers has largely employed explanations based on employee social capital, but it overlooked an important moderating factor in the human capital of mobile knowledge workers, namely job matching. Job matching theory suggests that the mobility of employees between firms is driven by an employer-employee matching process (Jovanovic, 1979). More precisely, employees are likely to change jobs when they find a better match for their human capital, i.e. when their skills, expertise and experience are more valuable within the new employer than within the old one (Barron, Black, & Loewenstein, 1989). Since employees are heterogeneously endowed with skills and competences and have the ability to learn and develop, an initial match of human capital and job requirements may become obsolete over time (Topel & Ward, 1992). Furthermore, requirements for jobs change over time reducing the suitability of employees' human capital for their current positions (Pisano, 1990). Both employers and employees are therefore motivated to continuously improve employer-employee job matching (Jovanovic, 1979). Employees are motivated and rewarded for changing jobs and employers via intrinsic motivation, i.e. a better match allows them to better use their skills, and via extrinsic motivation, i.e. a better match normally improves their current or future wages (Topel, 1991). Mobility therefore results in an improved employer-employee job match.

For knowledge workers, the most important element of their human capital is their academic and professional training that give them unique information, skills and experiences

(Gruber, Harhoff, & Hoisl, 2013; Toole & Czarnitzki, 2009). For example, job matching for R&D divisions revolves around finding scientists with the right knowledge about new technologies and practices. Firms will therefore try to recruit employees when the unique human capital of that scientist is of interest to its research and development objectives. At the same time, employees are willing to move to firms where their rare skills and expertise are more applicable and valuable (Hoisl & De Rassenfosse, 2014; Palomeras & Melero, 2010).

Job matching is related to interfirm knowledge spillovers both before and after employee mobility. Prior to employee mobility, interfirm spillovers are largely driven by knowledge fit of two firms. Interfirm knowledge spillovers occur when knowledge workers engages in more distant search and builds upon knowledge developed by a colleague outside their own firm (Rosenkopf & Almeida, 2003). Employees are most likely to learn knowledge developed by fellow knowledge workers working on similar issues or in similar domains, i.e. colleagues with whom they have a high knowledge fit. They will then try to learn this relevant knowledge from these fellow colleagues via publicly and privately available sources, or via their social ties (Laursen & Salter, 2006). In addition, employees will continue to follow the activities of these fellow knowledge workers and their firm. For example, after an employee has obtained relevant and useful knowledge from a colleague outside his/her firm, s/he will continue to track the new projects of that colleague and probably the company that colleagues works for. Such search heuristics lead to more efficient process of locating and absorbing relevant information. Such external monitoring results in a “knowledge spillover network”, which is the set of firms that are carefully followed because they may develop more relevant knowledge (Operti & Carnabuci, 2014). In short, a better knowledge fit of a firm with employees working for competitors increases interfirm spillovers.

Job matching and the knowledge fit of new employees also influence knowledge spillovers after employee mobility. Recruiting knowledge workers with a lower knowledge fit

should result in more knowledge spillovers for two different reasons. Initially, a lower fit between the former and new employer means mobile employees can access more knowledge that has not yet been known or used by their new employer. Furthermore, coworkers are unlikely to have monitored and followed the developments of a competitor with a lower knowledge fit, i.e. a competitor that is outside a firm's spillover network. Under both conditions employee mobility provides a larger opportunity for knowledge spillovers.

Conversely, recruiting knowledge workers with a higher knowledge fit will weaken the effect of mobility on spillovers. Insofar as employee mobility is the outcome of a job matching process, the recruited employee possesses skills and develops knowledge that is relevant for the current firm. Whereas knowledge workers in this firm used to obtain this knowledge via other means before, now they can simply approach their new colleague and learn this information first hand. Hence, the source of interfirm knowledge spillovers is now internalized within the firm. In addition to that, recruiting knowledge workers from a competitor reduces the incentives of a firm to continue monitoring that company: after recruiting the employees that are relevant to the firm, the motivation to monitor further knowledge development by this competitor is reduced.

Combining this line of thought with the role of social capital points two divergent mechanisms that lie beneath the relationship between mobility and spillovers. According to social capital literature, employee mobility results in social ties that cross firm boundaries and increase a firm's opportunity to learn from its competitor. However, according to job mobility literature, a firm's motivation to learn from its competitor reduces if mobility improves employer-employee matching. Therefore we predict the following moderation effect:

Hypothesis 2: The effect of employee mobility on knowledge spillovers is weaker when there is a stronger degree of knowledge fit from firm j to firm i.

METHODOLOGY

Setting and Data Collection

We tested the above hypotheses on a longitudinal sample of R&D divisions of major global pharmaceutical firms. The pharmaceutical industry was selected for various reasons. First, R&D activities by pharmaceutical firms are largely driven by employee human and social capital. Since knowledge in the pharmaceutical industry is complex, tacit and personified (Powell, Koput, & Smith-Doerr, 1996), human capital of knowledge workers, i.e. R&D scientists, is an important determinant for success (Gruber et al., 2013). Prior research in this setting has shown how social capital among R&D scientists is a major source of information and knowledge flows, hence, interfirm knowledge spillovers (Liebeskind, Oliver, Zucker, & Brewer, 1996; Paruchuri, 2010). Second, pharmaceutical firms show sufficient variation in employee mobility. Since pharmaceutical firms operate globally but tend to specialize in certain medical areas, employee turnover is neither rare nor widespread. Third, employee mobility and knowledge spillovers are highly observable in the pharmaceutical industry because firms in this industry tend to rely intensively on patents to protect their innovations (Arundel & Kabla, 1998; Cohen, Nelson, & Walsh, 2000). This leaves us with a detailed paper trail of R&D projects, the R&D scientists it involved, and references to earlier, related work used in an invention (Jaffe et al., 1993).

The initial sample of firms consists of the twenty largest pharmaceutical firms according to Scrip's League Tables in 1985 combined with the forty-two members of the Pharmaceutical Research and Manufacturing Association (PhRMA) in 1988. This sample is supplemented by their merger partners, spin-offs and successive firms (e.g. Zeneca for ICI, Novartis for Ciba-Geigy and Sandoz) while removing subsidiaries of already included pharmaceutical firms (e.g. Knoll Pharmaceuticals which belonged to BASF). This results in a sample of 53 firms.

For each of the firms, financial and operational data are obtained from WRDS Compustat and Mergent WebReports. Details on interfirm collaboration were extracted from SDC Platinum. We also built annually-updated corporate trees of each company with its subsidiaries using Mergent WebReports and SEC Edgar 10K filings. These corporate trees are then used to collect patent data from the European Patent Office (EPO) for each firm. In our case EPO data are preferred over USPTO since they do not only include granted patents, but all patent applications made by a firm. To correct for diversified conglomerates in our sample, this study only uses pharmaceutical patent.¹

Mobility of R&D scientists among firms is observed via these patent applications. To start, we used a disambiguation algorithm to identify the unique inventors of all patents belonging to sample firms based on name similarity within the same firm or geographical region (similar to Lai et al., 2011). We assume that mobility occurs when an R&D scientist is first observed on a patent application belonging solely to one firm and subsequently on a patent application solely assigned to another firm. Each mobility event was examined manually and we excluded events driven by alternative causes, like external researchers moving between firms (academic, CROs) or scientists on a temporal assignment elsewhere (Corredoira & Rosenkopf, 2010; Hoisl, 2007).

Since our predictions are at a dyadic level, we create a panel of dyad-year relationships including all potential dyads for all possible years between 1985 and 2010. Because the pharmaceutical industry has shown a considerable number of mergers and acquisitions over the last two decades, we created each new entity as the combination of the prior two entities. For example, when AstraZeneca was established in 1999, we assume that its workforce consists of all R&D scientists previously observed at Astra and Zeneca. In addition, we exclude dyad-years were measures of spillovers and mobility could be affected by mergers

¹ All patent applications that belong to IPC sub classes A61K, A61P, C07D, C07H, C07J, C07K, C12N, C12P and C12Q (Schmoch, Laville, Patel, & Frietsch, 2003)

and acquisitions. For example, the dyad of Glaxo and Wellcome is excluded for the years prior their merger in 1995 because the re-assignment of patent applications inflates our observed mobility. Similarly, the dyad of BASF and Abbott Laboratories is excluded for the years when their mobility measures are affected by Abbott's acquisition of BASF's Knoll Pharmaceuticals division.

Measurement

Dependent Variable: Knowledge Spillovers

Knowledge spillovers from one firm to another are measured via citations made on patent applications by focal firm i to patents by alter firm j (Breschi & Lissoni, 2009; Jaffe et al., 1993; Mowery, Oxley, & Silverman, 1996). We are well aware of prior studies pointing out the limitations to use patent citations for this purpose (e.g. Alcacer & Gittelman, 2006; Criscuolo & Verspagen, 2008). Nevertheless, patent citations have shown to be a robust proxy for measuring knowledge flows and spillovers (Jaffe, Trajtenberg, & Fogarty, 2000). In addition, we rely on patent citations made on EPO patent applications, which are substantially different from USPTO patent citations. Citations made by applicants are evaluated by patent examiners reducing the impact of strategic citing (Harhoff & Wagner, 2009). Besides, EPO patents cite both successful and unsuccessful patent applications, revealing knowledge spillovers that would otherwise remain unobserved (Lampe, 2012).

Knowledge spillovers $_{s,ij}$ is measured as the number of patents cited by R&D scientists in focal firm i to patent applications made by R&D scientists working for alter firm j . We take several steps to ensure that patent citations are really related to knowledge spillovers. First, to ensure that patent citations really indicate knowledge transfer and not to knowledge that was already known within firm i , we only include citations by firm i to patents of firm j that i has not cited before. Second, we exclude citations to patents that are over ten years old. This is a

small proportion of all citations and such knowledge is probably obsolete or publicly known (Corredoira & Rosenkopf, 2010). Third, we exclude all citations made by scientists that moved from j to i in the prior five years and all citations to patents developed by mobile scientists before firm i recruited them from firm j . This eliminates knowledge transfer driven by human capital of mobile employees, like self-citations made by mobile scientists or mobile scientists citing prior colleagues.

Independent Variables: Mobility and Knowledge fit

$Mobility_{ijt}$ is a dummy variable that indicates if firm i in year t employs at least one employee that has worked for firm j in the past five years. We identify employees as those R&D scientists that had their most recent patent application assigned to firm i solely (to correct for jointly developed R&D projects). For each of these employees, we identify their prior employers by looking at their earlier patents solely assigned to other firms. Since the exact moment of job change is hard to determine and social ties and knowledge spillovers continue for a prolonged period time, a five-year time window is used (similar to Agarwal et al., 2009; Corredoira & Rosenkopf, 2010). We manually examine the career trajectory of each mobile scientist and compare it to other publicly available information to exclude false positives generated by joint projects or external researchers (Hoisl, 2007).

$Knowledge\ fit_{ijt}$ is the percentage of non-self patent citations of firm i to patents belonging to firm j during the prior five years. Job matching of R&D scientists in the pharmaceutical industry is largely related to their idiosyncratic knowledge like technological skills and experiences. The degree to which firm i could benefit from technological knowledge in firm j is reflected in the extent to which they cite firm j 's patents (Jaffe et al., 2000; Mowery et al., 1996; Operti & Carnabuci, 2014). We exclude self-citations since they do not indicate technological interdependencies and calculate citations between firms over a five-year period

because the annual number of patent citations is quite volatile. This measure of fit is preferred over technological similarity because it is asymmetric and citations are a more fine-grained measure of knowledge complementarity.

Control Variables

Several variables are added to control for alternative explanation of interfirm knowledge spillovers and patent citations. First, we add reverse mobility to control for the effects of employees leaving the focal firm and join the competitor (Corredoira & Rosenkopf, 2010). Reverse mobility_{jit} is the number of employees working for firm j in year t that have worked for firm i in the prior five years. It is the exactly the counterpart of the independent variable.

Second, knowledge spillovers may occur because employees of both firms are collaborating. Therefore we add Alliances_{ijt}, which is the number of alliances formed by firms i and j in the past three years (Schilling & Phelps, 2007). Since many interorganizational relationships are not made public, we also add another variable, Boundary spanners_{ijt}, which is the number of R&D scientists involved in boundary-spanning projects as observed by co-assigned patents of firms i and j in the preceding five years. Co-assigning patents is a more common practice for EPO granted patents since it provides better IPR protection (Belderbos, Cassiman, Faems, Leten, & Van Looy, 2014).

Third, control variables are added to correct for patent citations patterns that could bias our results. The likelihood of firms referring to each other's inventions increases with a number of factors. Technological distance_{ijt}, calculated as Jaffe's index based on patent applications in the prior five years, indicates the dissimilarity of knowledge developed by two firms. It is both negatively related to knowledge spillovers (Jaffe, 1986) and likelihood of patent citations (Mowery et al., 1996) between two firms. Technological convergence_{ijt} relates to the convergence of technological profiles between two firms and such drift may explain a change

in patent citations (Corredoira & Rosenkopf, 2010). We measure it as the difference in technological distance between firm i and firm j during time windows $[t-6;t-4]$ and $[t-3;t-1]$. Citations made $_{it}$ is the number of citations made (in 000s) by firm i on patent applications in year t . The likelihood of firm i citing patents of firm j will logically rise with the number of citations it makes. Citations received $_{jt}$ refers to the number of citations made (in 000s) in year t to patents belonging to firm j on all patents and controls for a general surge in popularity of technologies developed by that firm. Alter patents $_{jt}$ measures the number of patent applications (in 000s) filed by firm j in the prior ten years. Firm i would be more likely to cite firm j simply by chance if that firm owns more patents.

Estimation method

Since the dependent variable is a non-negative count variable, we use a negative binomial specification (Hilbe, 2011). We selected a negative binomial regression over a Poisson estimation method because our dependent variable is overdispersed. Knowledge spillovers have been measured at a one-year lead $[t_0]$ compared to independent variables $[t-5;t-1]$ to reduce concerns for reverse causality. Lastly, we control for unobserved firm and temporal heterogeneity by adding firm- and year-fixed effects.

INSERT TABLES 1 AND 2 ABOUT HERE

RESULTS

Table 1 above provides the descriptive statistics of the sample consisting of 21,650 firm-dyad-years. The statistics show that knowledge spillovers are on average around 2.5, i.e. focal firm i cites 2.5 patents belonging to competitor j that i has not cited before. Employee mobility from firm j to firm i occurs in 26.3% of all observations. Mobility and reverse

mobility have exactly the same mean and variance because each firm-dyad-year enters the sample twice (as ijt and as jit), but this causes no estimations issues since the dependent variable varies with each observation. Correlations among variables are in an acceptable range and multicollinearity statistics (mean VIF = 2.29) do not indicate serious estimation issues (Allison, 2012).

Models 1 to 4 in Table 2 presents the results of random-effects negative binomial regressions that test the hypotheses. Regarding the control variables, we observe mainly significant effects in the expected directions. Variables controlling for the effects of citations made and the number of patents to cite are positive and significant. Technological distance decreases spillovers, but this reduces when firms are technologically converging. Surprisingly, there is no effect of interfirm alliances and a negative effect of boundary spanners. This is probably because we do not include the citations of co-owned patents made by boundary spanners. Finally, there is strong evidence of reverse knowledge spillovers from employees that have left firm i and joined firm j .

Hypothesis 1 is our baseline hypothesis and predicts that employee mobility from alter firm j to focal firm i results in interfirm knowledge spillovers from j to i . All models in Table 2 provide strong significant support for this hypothesis ($p < 0.001$). Thus, R&D scientists are more likely to learn and employ the knowledge of a competitor after their firm recruited a scientist from this competitor, even when we exclude knowledge transfer related to the human capital of mobile scientists.

Hypothesis 2 predicts that knowledge fit between firms negatively moderates the effect of mobility on spillovers. We find that knowledge fit itself has a positive direct effect on spillovers: firms are more likely to learn and use new knowledge from a competitor if they have used this competitor's knowledge in the past. In support of H2, we find a negative and significant coefficient for the interaction between mobility and knowledge fit (model 4). This

indicates that knowledge spillovers reduce after firms hire employees to which they are technologically related.

To interpret the direction and magnitude of these results, regression results are plotted in Figure 1 below. Note that these are not absolute values, but multiplier rates since they are based on negative binomial regressions. As expected, stronger knowledge fit between firms i and j increases the probability of future knowledge spillovers in case there is no interfirm mobility. Similarly, employee mobility between firms i and j increases the likelihood of future knowledge spillovers in case there is low knowledge fit. However, a combination of employee mobility with high knowledge fit reduces the probability of subsequent knowledge spillovers.

INSERT FIGURES 1 AND 2 ABOUT HERE

Robustness Checks

Several robustness checks are performed to estimate the reliability of our results. To start, we retest the model using different estimation methods. Model 5 and 6 show the results of a panel Poisson specification with robust standard errors to correct for overdispersion (Hilbe, 2011). Results for random effects (model 5) are similar to earlier results, except that the direct of knowledge fit is no longer significant while results for a fixed-effects estimation show slightly less significant results for H2 ($\beta=-0.40$; $p=0.07$). Because the dependent variable has a large number of zeros (48%), we follow the approach of Corredeiro and Rosenkopf (2010) and employ a zero-inflated model negative binomial specification. The prediction of zeros in the inflated model uses two variables, namely Citations made_{it} ($\beta=-0.17$; $p=0.53$) and Alter patents_{jt} ($\beta=-8.51$; $p<0.001$) and standard errors are clustered by dyads to correct for non-independence. The results, in model 7, are similar to these obtained before.

In addition, we use an alternative measure for knowledge fit. Whereas firms may aim to hire knowledge workers from competitors with complementary knowledge, knowledge workers will probably apply to competitors whose knowledge they already use. Therefore we measure Alter knowledge fit_{it} as the citations from competitor j to focal firm i as a percentage of all non-self citations by j. This measure correlates only limitedly with our original measure of knowledge fit ($\sigma=0.35$). Results in model 8 are almost similar as these obtained before, indicating that job matching may occur on both sides.

Third, we tried to address endogeneity concerns related to employee mobility and job matching since knowledge fit may not only drive spillovers, but also mobility itself. Therefore we employed a two-stage regression. The first stage uses a panel probit estimation to predict the probability of employee mobility. Besides the control variables, it includes four instruments: scientist recruitment by firm i, scientist turnover by firm j, and recent mergers and acquisitions by firm j. Scientist recruitment indicates the number of scientists firm i hired from all other firms but j, whereas scientist turnover denotes the number of scientists that left firm j to all other firms but i. A recent merger or acquisition by a competitor may increase mobility because M&A often involves restructuring and leads to a surge in employees leaving (Younge, Tong, & Fleming, 2014). Three instruments in the first-stage model are strongly significant ($p<0.001$), so we save the predicted probability of mobility and its residual. Following Hilbe (2011: 420), we test for endogeneity by adding the residual as an endogeneity control to the initial regression (model 2). Since this variable is significant ($\beta=-11.47$; $p<0.001$), we re-estimate model 2 using the predicted probability of mobility. These coefficients are compared to the original coefficients of model 2 via a Hausman test and obtain an insignificant result, which means that our instruments are exogenous. Finally, we replicate model 4 using the predicted probability of mobility, Mobility (instrumented). The results, in model 9, are in the same direction and slightly stronger. Figure 2 above depicts

these results and shows that they are slightly more emphasized towards the lower and higher values of knowledge fit.

DISCUSSION

In knowledge intensive industries, firms rely on the human and social capital of their knowledge workers in their pursuit for innovation (Liebeskind et al., 1996). Knowledge workers create innovative solutions by recombining and reconfiguring their knowledge components. Since the value of current information, skills and experiences depletes over time, firms are continuously looking for new knowledge. Firms could either develop new knowledge internally through its own workforce or obtain new knowledge externally developed by other firms. For that reason, recruiting new knowledge workers is core to firm innovative performance: interfirm mobility of knowledge workers allows a firm to tap into the proprietary knowledge developed by their competitors (Rosenkopf & Almeida, 2003). In addition to their human capital, mobility also leads to knowledge spillovers by mobile employees acting as conduits of knowledge between their former and current colleagues (Saxenian, 1996).

Earlier empirical research focusing on employee mobility of knowledge workers like R&D scientists has demonstrated the positive impact of employee mobility. Particularly, mobile employees are a source of knowledge transfer between firms and geographical regions (Agrawal et al., 2006; Breschi & Lissoni, 2009; Casper, 2007; Saxenian, 1996). This knowledge transfer occurs both because mobile knowledge workers bring along knowledge from their original to their new employer or area (Singh & Agrawal, 2010) and because mobile employees feed new knowledge back to their connections in their prior firm or region (Agrawal et al., 2006; Corredoira & Rosenkopf, 2010). In this study, we explicitly test an even more stringent social capital mechanisms underlying interfirm knowledge transfer,

namely mobile employees acting as boundary spanners between their former and current employer. The empirical results provide robust and strong support for this mechanism, both for recruiting employees from a competitor as well as employees being hired by a competitor. Mobility of knowledge workers is thus an important mechanism for interfirm knowledge transfer and spillovers.

Whereas employee mobility provides a firm with opportunities for knowledge spillovers, it may also affect its motivation to learn from a competitor. In particular, we argued that recruiting employees from a firm with a high knowledge fit reduces its incentives for learning. By partially internalizing a competitor's relevant knowledge through employee mobility, knowledge workers within a firm have a lower motivation the activities of this competitor. Surprisingly, we find that this effect not only weakens the positive baseline hypothesis, but even reverses it: mobility augments interfirm spillovers when employees are hired from competitors with a low knowledge fit whereas spillovers reduce when employees are recruited from competitors with a higher fit.

This is an interesting finding since knowledge workers are motivated to move to firms where their human capital forms a better match with a firm's technological needs (Hoisl, 2009; Palomeras & Melero, 2010). Consequently, interfirm knowledge spillovers will reduce if employee mobility is solely driven by improving the match between employer and employee knowledge fit. However, even when controlling for the mobility driven by a job matching process, we continue to observe this negative effect. This indicates that mobility of employees from a competitor with higher knowledge fit subsequently reduces a firm's motivation to learn and acquire that competitor's knowledge.

Theoretical Contributions

The results of this study contribute to several areas of research, including social capital, job matching, and boundary spanning. First, the findings of this study speak to current research on social capital and knowledge spillovers. Prior studies have shown that social ties play an essential role in diffusing novel information among employees and social capital is an important determinant of knowledge worker productivity (Allen & Cohen, 1969; Singh & Fleming, 2010). When employees move between firms, they build new social ties in their new firm while retaining their connections in their prior company (Casper, 2007). These mobile employees are therefore in a unique position to tap into the knowledge base of two firms. However, earlier work by Singh and Agrawal (2010) argued that observed interfirm knowledge transfers are mainly driven by mobile workers continuing to build upon their work performed in their former employer. In our sample, we strictly focus on “real” interfirm knowledge spillovers, i.e. knowledge transfer that is unrelated to mobile employees’ human capital, and find strong empirical support for mobile knowledge workers acting as channels of knowledge and information between their previous and present coworkers. In addition, studies in this literature have considered factors that moderate the relationship between mobility and knowledge spillovers, like the embeddedness of mobile workers in their former and current firm (Wang, 2015), as well as firms’ strategies to enhance or limit interfirm spillovers through employee mobility (Agarwal et al., 2009; Dokko & Rosenkopf, 2009). This study demonstrates that the effect is also subject to the recruiting firm’s familiarity with a competitor’s knowledge. Particularly, knowledge spillovers are more likely when their new employer has a lower awareness of a competitor’s skills and technologies. By revealing these effects, this study identifies the extent and conditions under which social capital explains interfirm knowledge spillovers.

Second, the findings of this study have implications for current research of employer-employee job matching for knowledge workers. Job matching explains employee mobility as a continuous process of aligning employee human capital with organizational demands for such knowledge and skills (Jovanovic, 1979; Topel & Ward, 1992). For highly skilled knowledge workers like R&D scientists, their unique education, knowledge and experience are important determinants for moving between firms (Hoisl, 2007). More recently, Hoisl and De Rassenfosse (2014) revealed that voluntary employee mobility of inventors increases their productivity. Whereas this study does not explicitly test for job matching of mobile employees, we find a significant correlation between interfirm mobility and knowledge fit. The decline in interfirm spillovers after recruiting employees with better knowledge fit supports this logic: a firm tends to recruit employees whose knowledge it was already building upon before. By internalizing this human capital, interfirm spillovers will decrease. Instead, when a firm recruits employees with a lower fit, it assumes knowledge that is more novel and this results in a surge of interfirm knowledge transfer and spillovers. This counterintuitive finding that employee mobility is more likely for firms with a higher knowledge fit but subsequently reduces knowledge spillovers aids in our understanding of the relationship between job matching and knowledge spillovers.

Third, the results of this study contribute to the literature on boundary spanners. Boundary spanners are individuals who act as a bridge between firm and its external environment (Tushman, 1977). They play a pivotal role in R&D departments by learning and absorbing external information and subsequently diffusing and distributing it internally (Cohen & Levinthal, 1990; Keller & Holland, 1975). While prior studies have shown that employees may become boundary spanners simply by developing social ties beyond their firm (Tushman & Scanlan, 1981a, 1981b), this literature has remained ambiguous about how the origin of external information and the final recipient. This study reveals that the benefits of boundary

spanning expand when connections are formed with competitors whose knowledge is not currently monitored and used by a firm's knowledge workers. Moreover, these benefits are not limited to the boundary spanner, but also to his/her colleagues.

Managerial Implications

The results of this study have various managerial implications. In innovation and technology driven industries, a firm's competitive advantage and financial performance are strongly linked to its proprietary knowledge and capabilities (Grant, 1996; Kogut & Zander, 1992). In addition, these firms pursue the acquisition of external knowledge by establishing interorganizational alliances (Hamel, 1991) or monitoring technological developments by competitors (Carnabuci & Operti, 2013). Yet, most of a firm's idiosyncratic knowledge is tacit embodied in the minds of its employee. Employee turnover therefore forms both an opportunity and a threat.

First, employee mobility offers a firm the opportunity to obtain proprietary knowledge from a competing firm through hiring a competitor's employees (Almeida, Dokko, & Rosenkopf, 2003). The findings of this study have direct implications for employee recruitment. It demonstrates that firms should not only pay attention to an employee's human capital, but also to the knowledge fit of the firm this employee originates from. Specifically, the benefits of hiring a knowledge worker from a competitor are much larger when the firm is currently not using technologies developed by this competitor. However, these benefits shrink when a firm recruits knowledge workers from a competitor whose technological developments it is already closely monitoring. Whereas managers may have good reasons to internalize this external source of knowledge, they should keep in mind that it actually reduces technological exploration via interfirm spillovers. Rather, if managers aim to boost

exploration, they should recruit an employee working on a similar technological area whose work has not yet been used by their firm.

Second, employee mobility poses a threat for a firm when employees leave for competitors and cause unintended knowledge spillovers (Agarwal et al., 2009). This study shows that employee turnover has a significant impact on interfirm spillovers, but these are not all negative. To start, the results of this study demonstrate that knowledge spillovers through employee recruitment are around the same magnitude as knowledge spillovers from employees who left the firm. In line with earlier studies on reverse knowledge spillovers (Corredoira & Rosenkopf, 2010), this study implies that managers should take a more balanced view on the risks of employee turnover. Likewise, this study demonstrates that the effects of spillovers from mobile knowledge workers strongly depend on prior knowledge spillovers between these firms. In particular, firms should be less concerned when its employees join competitors who already heavily draw upon its knowledge and technology. Finally, the results of this study show that knowledge spillovers occur through employees remaining in touch with their prior colleagues. If managers aim to curb such leakage of knowledge and information, managers should develop guidelines that clearly state what information can be shared when and with whom. This would help to overcome the often ambiguous professional norms that explain interfirm knowledge sharing (Bouty, 2000).

CONCLUSIONS, LIMITATIONS AND FUTURE RESEARCH

This study investigates the role of employee mobility in interfirm knowledge spillovers. We derive hypotheses from two different theories that explain how mobility results in knowledge spillovers and find support for both mechanisms. Initially, social ties among knowledge workers result in a continued exchange of information, even after knowledge workers move between firms. Such knowledge spillovers through boundary-crossing ties

provide support for the social capital explanation. However, the effect is weaker when mobility occurs between firms with a stronger knowledge fit. In line with the job matching literature, mobility results in a better fit between a firm's needs and a knowledge worker's capabilities. Thereby it reduces the need for spillovers from that competitor and decreases the motivation to continue monitoring its new developments.

The findings of this study should be interpreted in light of its limitations. First, there may be concerns by our use of patent data for tracking employee mobility and knowledge spillovers (Alcacer & Gittelman, 2006; Lenzi, 2009). Whereas we are aware of these limitations, patent data remain the most comprehensive source of information about R&D activities in pharmaceutical firms. In addition, we try to overcome the limitations of patents by using EPO data which contain all patent applications and use a more consistent procedure for adding citations to prior art. Moreover, we compared mobility events observed in patent data to publicly available information on R&D scientists and noticed that our patent-based measure seems consistent but rather conservative.

Second, this study assumes that employee mobility and knowledge spillovers are driven by knowledge fit. Initially, a job matching process explains mobility via the knowledge fit between employers and employees. Subsequently, knowledge fit between firms explains the degree of knowledge spillovers through employee mobility. Whereas we address the potential endogeneity of employee mobility by using an instrumental variable approach, we aim to examine this job matching process between knowledge workers and firms at the micro-level to understand how knowledge fit influences employee turnover.

REFERENCES

Adler, P. S., & Kwon, S.-W. 2002. Social capital: Prospects for a new concept. **Academy of Management Review**, 27(1): 17–40.

- Agarwal, R., Ganco, M., & Ziedonis, R. H. 2009. Reputations for toughness in patent enforcement: Implications for knowledge spillovers via inventor mobility. **Strategic Management Journal**, 30(13): 1349–1374.
- Agrawal, A., Cockburn, I., & 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. **The Review of Economics and Statistics**, 88(4): 774–779.
- Allen, T. J., & Cohen, S. I. 1969. Information flow in research and development laboratories. **Administrative Science Quarterly**, 14(1): 12–19.
- Allison, P. 2012, September 12. When can you safely ignore multicollinearity? **Statistical Horizons**. <http://www.statisticalhorizons.com/multicollinearity>.
- 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. 1999. Localization of knowledge and the mobility of engineers in regional networks. **Management Science**, 45(7): 905–917.
- Argote, L., & Ingram, P. 2000. Knowledge transfer: A basis for competitive advantage in firms. **Organizational Behavior and Human Decision Processes**, 82(1): 150–169.
- Arundel, A., & Kabla, I. 1998. What percentage of innovations are patented? Empirical estimates for European firms. **Research Policy**, 27(2): 127–141.
- Barron, J. M., Black, D. A., & Loewenstein, M. A. 1989. Job matching and on-the-job training. **Journal of Labor Economics**, 7(1): 1–19.
- Belderbos, R., Cassiman, B., Faems, D., Leten, B., & Van Looy, B. 2014. Co-ownership of intellectual property: Exploring the value-appropriation and value-creation implications of co-patenting with different partners. **Research Policy**, 43(5): 841–852.
- Berends, H., Van Burg, E., & Van Raaij, E. M. 2011. Contacts and contracts: Cross-level network dynamics in the development of an aircraft material. **Organization Science**, 22(4): 940–960.
- Borgatti, S. P., & Cross, R. 2003. A relational view of information seeking and learning in social networks. **Management Science**, 49(4): 432–445.
- Bouty, I. 2000. Interpersonal and interaction influences on informal resource exchanges between R&D researchers across organizational boundaries. **Academy of Management Journal**, 43(1): 50–65.
- Breschi, S., & Lissoni, F. 2009. Mobility of skilled workers and co-invention networks: An anatomy of localized knowledge flows. **Journal of Economic Geography**, 1–30.
- Brown, J. S., & Duguid, P. 1991. Organizational learning and communities-of-practice: Toward a unified view of working, learning, and innovation. **Organization Science**, 2(1): 40–57.
- Burt, R. S. 1992. **Structural holes: The social structure of competition**. Cambridge, MA: Harvard University Press.
- Burt, R. S. 2000. The network structure of social capital. **Research in Organizational Behavior**, 22: 345–423.
- Carnabuci, G., & Bruggeman, J. 2009. Knowledge specialization, knowledge brokerage and the uneven growth of technology domains. **Social Forces**, 88(2): 607–641.

- Carnabuci, G., & Operti, E. 2013. Where do firms' recombinant capabilities come from? Intraorganizational networks, knowledge, and firms' ability to innovate through technological recombination. **Strategic Management Journal**, 34(13): 1591–1613.
- Casper, S. 2007. How do technology clusters emerge and become sustainable? Social network formation and inter-firm mobility within the San Diego biotechnology cluster. **Research Policy**, 36(4): 438–455.
- Cohen, W. M., & Levinthal, D. A. 1990. Absorptive capacity: A new perspective on learning and innovation. **Administrative Science Quarterly**, 35(1): 128–152.
- Cohen, W. M., Nelson, R. R., & Walsh, J. P. 2000. **Protecting their intellectual assets: Appropriability conditions and why U.S. manufacturing firms patent (or not)**. Working Paper, National Bureau of Economic Research.
- Coleman, J. S. 1988. Social capital in the creation of human capital. **American Journal of Sociology**, 94: S95–S120.
- Corredoira, R. A., & Rosenkopf, L. 2010. Should auld acquaintance be forgot? The reverse transfer of knowledge through mobility ties. **Strategic Management Journal**, 31(2): 159–181.
- Criscuolo, P., & Verspagen, B. 2008. Does it matter where patent citations come from? Inventor vs. examiner citations in European patents. **Research Policy**, 37(10): 1892–1908.
- Dokko, G., & Rosenkopf, L. 2009. Social capital for hire? Mobility of technical professionals and firm influence in wireless standards committees. **Organization Science**, 21(3): 677–695.
- Fleming, L. 2001. Recombinant uncertainty in technological search. **Management Science**, 47(1): 117–132.
- Fleming, L., Mingo, S., & Chen, D. 2007. Collaborative brokerage, generative creativity, and creative success. **Administrative Science Quarterly**, 52(3): 443–475.
- Fleming, L., & Sorenson, O. 2001. Technology as a complex adaptive system: evidence from patent data. **Research Policy**, 30(7): 1019–1039.
- Fleming, L., & Sorenson, O. 2004. Science as a map in technological search. **Strategic Management Journal**, 25(8-9): 909–928.
- Grant, R. M. 1996. Toward a knowledge-based theory of the firm. **Strategic Management Journal**, 17: 109–122.
- Gruber, M., Harhoff, D., & Hoisl, K. 2013. Knowledge recombination across technological boundaries: Scientists vs. engineers. **Management Science**, 59(4): 837–851.
- Hamel, G. 1991. Competition for competence and interpartner learning within international strategic alliances. **Strategic Management Journal**, 12(S1): 83–103.
- Harhoff, D., & Wagner, S. 2009. The duration of patent examination at the European Patent Office. **Management Science**, 55(12): 1969–1984.
- Hilbe, J. M. 2011. **Negative binomial regression** (2nd edition). Cambridge (UK): Cambridge University Press.
- Hoisl, K. 2007. Tracing mobile inventors—The causality between inventor mobility and inventor productivity. **Research Policy**, 36(5): 619–636.
- Hoisl, K. 2009. Does mobility increase the productivity of inventors? **The Journal of Technology Transfer**, 34(2): 212–225.

- Hoisl, K., & De Rassenfosse, G. 2014. **Knowledge fit and productivity gains from mobility**. Presented at the Druid Society Conference 2014, Copenhagen (DK).
- Hussinger, K., & Wastyn, A. 2012. Internal resistance and external knowledge (sources): A theoretical framework on the not-invented-here syndrome. **2012 IEEE International Conference on Management of Innovation and Technology (ICMIT)**, 261–265.
- Ibarra, H. 1993. Network centrality, power, and innovation involvement: Determinants of technical and administrative roles. **Academy of Management Journal**, 36(3): 471–501.
- Jaffe, A. B. 1986. Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits and market value. **The American Economic Review**, 76(5): 984–1001.
- Jaffe, A. B., Trajtenberg, M., & Fogarty, M. S. 2000. Knowledge spillovers and patent citations: Evidence from a survey of inventors. **The American Economic Review**, 90(2): 215–218.
- Jaffe, A. B., Trajtenberg, M., & Henderson, R. 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. **The Quarterly Journal of Economics**, 108(3): 577–598.
- Jovanovic, B. 1979. Job matching and the theory of turnover. **Journal of Political Economy**, 87(5): 972–990.
- Keller, R. T., & Holland, W. E. 1975. Boundary-spanning roles in a research and development organization: An empirical investigation. **Academy of Management Journal**, 18(2): 388–393.
- Kogut, B., & Zander, U. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. **Organization Science**, 3(3): 383–397.
- Lai, R., D'Amour, A., Yu, A., Sun, Y., Torvik, V., et al. 2011. Disambiguation and co-authorship networks of the US Patent Inventor Database. **Harvard Institute for Quantitative Social Science, Cambridge, MA**, 2138.
- Lampe, R. 2012. Strategic Citation. **Review of Economics and Statistics**, 94(1): 320–333.
- Laursen, K., & Salter, A. 2006. Open for innovation: The role of openness in explaining innovation performance among U.K. manufacturing firms. **Strategic Management Journal**, 27(2): 131–150.
- Lenzi, C. 2009. Patterns and determinants of skilled workers' mobility: Evidence from a survey of Italian inventors. **Economics of Innovation and New Technology**, 18(2): 161–179.
- Liebeskind, J. P., Oliver, A. L., Zucker, L., & Brewer, M. 1996. Social networks, learning, and flexibility: Sourcing scientific knowledge in new biotechnology firms. **Organization Science**, 7(4): 428–443.
- March, J. G. 1991. Exploration and exploitation in organizational learning. **Organization Science**, 2(1): 71–87.
- Møen, J. 2000. **Is mobility of technical personnel a source of R&D Spillovers?**. Working Paper no. 7834, National Bureau of Economic Research.
- Mowery, D. C., Oxley, J. E., & Silverman, B. S. 1996. Strategic alliances and interfirm knowledge transfer. **Strategic Management Journal**, 17: 77–91.
- Nahapiet, J., & Ghoshal, S. 1998. Social capital, intellectual capital, and the organizational advantage. **Academy of Management Review**, 23(2): 242–266.
- Operti, E., & Carnabuci, G. 2014. Public knowledge, private gain: The effect of spillover networks on firms' innovative performance. **Journal of Management**, 40(4): 1042–1074.

- Palomeras, N., & Melero, E. 2010. Markets for inventors: Learning-by-hiring as a driver of mobility. **Management Science**, 56(5): 881–895.
- Paruchuri, S. 2010. Intraorganizational networks, interorganizational networks, and the impact of central inventors: A longitudinal study of pharmaceutical firms. **Organization Science**, 21(1): 63–80.
- Pisano, G. P. 1990. The R&D boundaries of the firm: An empirical analysis. **Administrative Science Quarterly**, 35(1): 153–176.
- Ployhart, R. E., & Moliterno, T. P. 2011. Emergence of the human capital resource: A multilevel model. **Academy of Management Review**, 36(1): 127–150.
- Powell, W. W., Koput, K. W., & Smith-Doerr, L. 1996. Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. **Administrative Science Quarterly**, 41(1): 116–145.
- Rosenkopf, L., & Almeida, P. 2003. Overcoming local search through alliances and mobility. **Management Science**, 49(6): 751–766.
- Rosenkopf, L., & Nerkar, A. 2001. Beyond local search: Boundary-spanning, exploration, and impact in the optical disk industry. **Strategic Management Journal**, 22(4): 287–306.
- Saxenian, A. L. 1996. Beyond boundaries: Open labor markets and learning in Silicon Valley. **The boundaryless career: A new employment principle for a new organizational era**: 23–39. New York, NY: Oxford University Press.
- Schilling, M. A., & Phelps, C. C. 2007. Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. **Management Science**, 53(7): 1113–1126.
- Schmoch, U., Laville, F., Patel, P., & Frietsch, R. 2003. Linking technology areas to industrial sectors. **Final Report to the European Commission, DG Research**, 1.
- Schumpeter, J. A. 1934. **The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle**. Cambridge, MA: Harvard University Press.
- Singh, J. 2005. Collaborative networks as determinants of knowledge diffusion patterns. **Management Science**, 51(5): 756–770.
- Singh, J., & Agrawal, A. 2010. Recruiting for ideas: How firms exploit the prior inventions of new hires. **Management Science**, 57(1): 129–150.
- Singh, J., & Fleming, L. 2010. Lone inventors as sources of breakthroughs: Myth or reality? **Management Science**, 56(1): 41–56.
- Singh, J., Hansen, M. T., & Podolny, J. M. 2010. The world is not small for everyone: Inequity in searching for knowledge in organizations. **Management Science**, 56(9): 1415–1438.
- 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, T. E., & Podolny, J. M. 1996. Local search and the evolution of technological capabilities. **Strategic Management Journal**, 17(S1): 21–38.
- Toole, A. A., & Czarnitzki, D. 2009. Exploring the relationship between scientist human capital and firm performance: The case of biomedical academic entrepreneurs in the SBIR program. **Management Science**, 55(1): 101–114.

- Topel, R. 1991. Specific capital, mobility, and wages: Wages rise with job seniority. **Journal of Political Economy**, 99(1): 145–176.
- Topel, R. H., & Ward, M. P. 1992. Job mobility and the careers of young men. **The Quarterly Journal of Economics**, 107(2): 439–479.
- Tushman, M. L. 1977. Special boundary roles in the innovation process. **Administrative Science Quarterly**, 22(4): 587–605.
- Tushman, M. L., & Scanlan, T. J. 1981a. Boundary spanning individuals: Their role in information transfer and their antecedents. **Academy of Management Journal**, 24(2): 289–305.
- Tushman, M. L., & Scanlan, T. J. 1981b. Characteristics and external orientations of boundary spanning individuals. **Academy of Management Journal**, 24(1): 83–98.
- Tzabbar, D., Aharonson, B. S., & Amburgey, T. L. 2013. When does tapping external sources of knowledge result in knowledge integration? **Research Policy**, 42(2): 481–494.
- Wang, D. 2015. Activating cross-border brokerage: Interorganizational knowledge transfer through skilled return migration. **Administrative Science Quarterly**, 60(1): 133–176.
- Younge, K. A., Tong, T. W., & Fleming, L. 2014. How anticipated employee mobility affects acquisition likelihood: Evidence from a natural experiment. **Strategic Management Journal**, forthcoming.

FIGURES

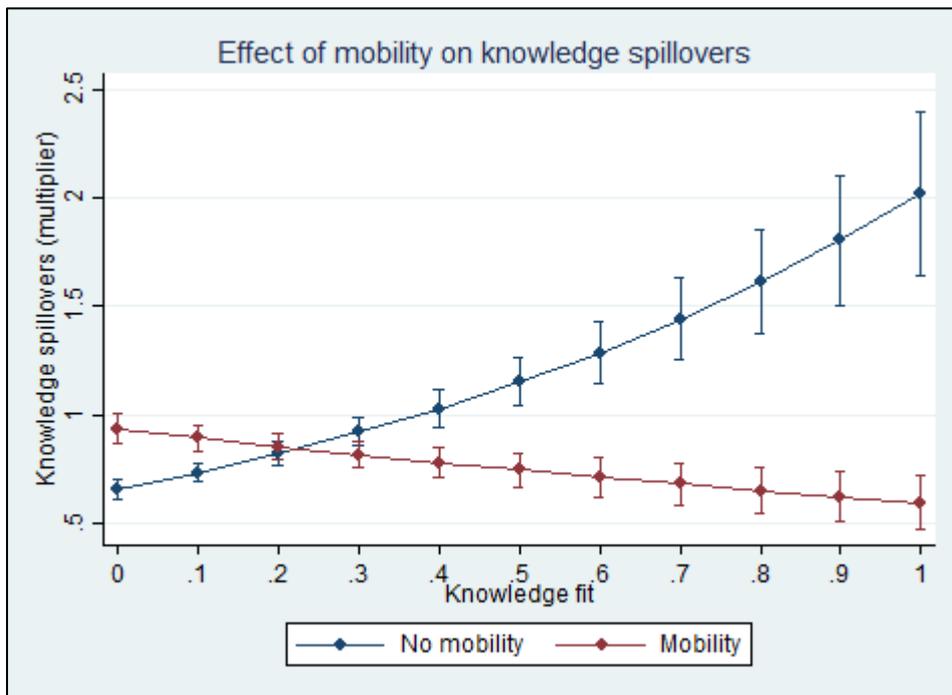


Figure 1 - Effect of mobility on spillovers

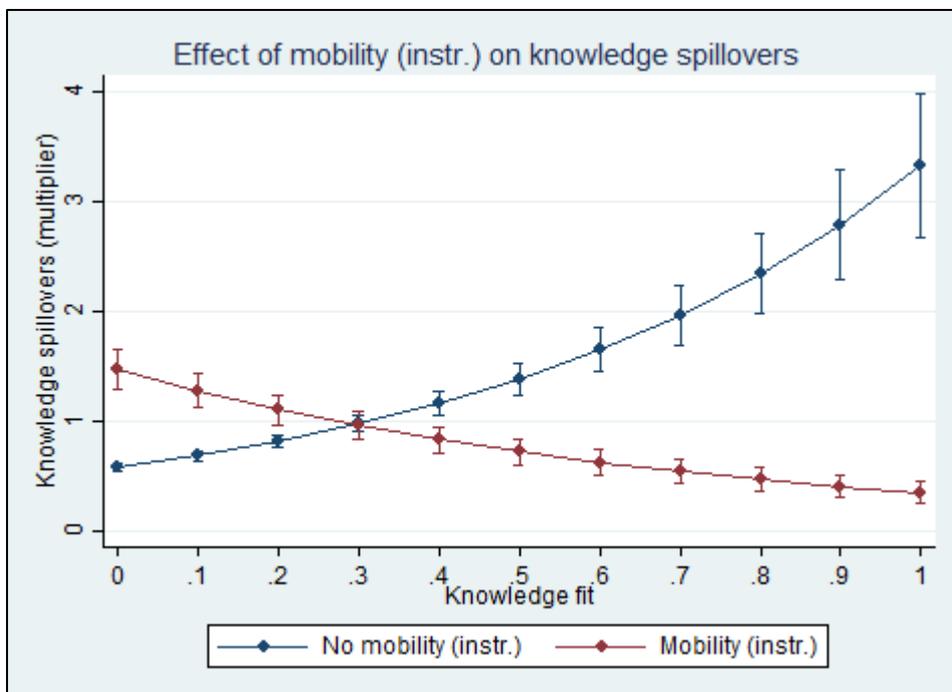


Figure 2 - Effect of mobility on spillovers (controlling for endogeneity)

TABLES

Table 1 - Sample descriptive statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Knowledge spillovers _{ijt}	1											
(2) Mobility _{ijt}	0.447	1										
(3) Knowledge fit _{ijt}	0.460	0.358	1									
(4) Citations made _{it}	0.592	0.482	0.225	1								
(5) Citations received _{jt}	0.641	0.530	0.526	0.544	1							
(6) Alter patents _{jt}	0.566	0.535	0.565	0.453	0.872	1						
(7) Tech. distance _{ijt}	-0.181	-0.141	-0.203	-0.105	-0.118	-0.065	1					
(8) Tech. convergence _{ijt}	0.054	0.067	0.070	0.060	0.070	0.085	0.042	1				
(9) Alliances _{ijt}	0.059	0.102	0.047	0.050	0.075	0.068	-0.050	0.012	1			
(10) Boundary spanners _{ijt}	0.166	0.206	0.174	0.157	0.189	0.218	-0.044	0.023	0.012	1		
(11) Reverse mobility _{ijt}	0.429	0.495	0.326	0.478	0.508	0.513	-0.141	0.067	0.102	0.206	1	
(12) Year	0.443	0.550	0.336	0.645	0.696	0.690	-0.086	0.096	0.077	0.188	0.550	1
Mean	2.516	0.263	0.078	4.557	4.711	0.82	0.141	-0.022	0.016	1.685	0.263	1993
S.D.	4.839	0.440	0.114	5.977	5.967	0.884	0.164	0.198	0.13	8.709	0.44	6.272
Min	0	0	0	0	0	0.001	0	-1	0	0	0	1985
Max	76	1	1.887	59.47	48.07	6.086	1	0.996	2	311	1	2010

N = 20,650

All correlations exceeding |.02| are significant at the 1% level.

Table 2 - Regression results for knowledge spillovers

	Main regressions				Robustness checks				
	(model 1)	(model 2)	(model 3)	(model 4)	(model 5)	(model 6)	(model 7)	(model 8)	(model 9)
Citations made _{it}	0.038*** (0.001)	0.038*** (0.001)	0.038*** (0.001)	0.038*** (0.001)	0.036*** (0.002)	0.035*** (0.002)	0.053*** (0.004)	0.037*** (0.001)	0.037*** (0.001)
Citations received _{jt}	0.017*** (0.003)	0.016*** (0.003)	0.016*** (0.003)	0.018*** (0.003)	0.032*** (0.004)	0.041*** (0.005)	0.038*** (0.006)	0.016*** (0.003)	0.023*** (0.003)
Alter patents _{jt}	0.399*** (0.024)	0.388*** (0.023)	0.366*** (0.024)	0.402*** (0.024)	0.214*** (0.047)	0.051 (0.049)	0.244*** (0.028)	0.399*** (0.023)	0.380*** (0.025)
Technological distance _{ijt}	-2.239*** (0.112)	-2.212*** (0.111)	-2.167*** (0.111)	-2.202*** (0.110)	-1.922*** (0.196)	-1.292*** (0.252)	-1.936*** (0.276)	-2.066*** (0.110)	-2.155*** (0.108)
Technological convergence _{ijt}	0.381*** (0.084)	0.367*** (0.084)	0.364*** (0.083)	0.353*** (0.083)	0.318** (0.112)	0.100 (0.145)	0.072 (0.180)	0.368*** (0.083)	0.337*** (0.083)
Alliances _{ijt}	0.005 (0.048)	-0.007 (0.048)	-0.002 (0.048)	-0.017 (0.048)	-0.002 (0.073)	0.003 (0.076)	-0.029 (0.056)	0.000 (0.048)	-0.067 (0.048)
Boundary spanners _{ijt}	-0.002* (0.001)	-0.002* (0.001)	-0.002* (0.001)	-0.002* (0.001)	-0.001 (0.002)	-0.000 (0.001)	-0.002+ (0.001)	-0.003** (0.001)	-0.002** (0.001)
Reverse mobility _{jit}	0.164*** (0.023)	0.155*** (0.023)	0.157*** (0.023)	0.148*** (0.022)	0.072* (0.030)	0.035 (0.031)	0.124*** (0.036)	0.142*** (0.023)	0.133*** (0.022)
Mobility _{ijt}		0.151*** (0.023)	0.150*** (0.023)	0.355*** (0.028)	0.240*** (0.040)	0.124** (0.043)	0.233*** (0.046)	0.208*** (0.029)	
Mobility _{ijt} (instr.)									0.928*** (0.071)
Knowledge fit _{ijt}			0.322*** (0.096)	1.125*** (0.104)	0.052 (0.179)	-0.640** (0.232)	1.869*** (0.229)		1.743*** (0.107)
Alter knowledge fit _{ijt}								1.098*** (0.108)	
Mobility _{ijt} x Knowledge fit _{ijt}				-1.579*** (0.128)	-1.040*** (0.194)	-0.404+ (0.226)	-0.784*** (0.234)		
Mobility _{ijt} x Alter knowledge fit _{ijt}								-0.412** (0.127)	
Mobility _{ijt} (instr.) x Knowledge fit _{ijt}									-3.161*** (0.177)

Constant	-0.808*** (0.090)	-0.836*** (0.090)	-0.852*** (0.089)	-0.920*** (0.087)	-0.644*** (0.119)		0.099 (0.121)	-0.862*** (0.089)	-0.969*** (0.086)
Time dummies	(included)	(included)	(included)	(included)	(included)	(included)	(included)	(included)	(included)
Firm dummies	(included)	(included)	(included)	(included)	(included)	(none)	(included)	(included)	(included)
Dyad specification	(random eff.)	(fixed eff.)	(cluster. err.)	(random eff.)	(random eff.)				
Observations	20,650	20,650	20,650	20,650	20,650	17,412	20,650	20,650	20,650
Number of dyads	2,368	2,368	2,368	2,368	2,368	1,752	2,368	2,368	2,368

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1