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KNOWING ME, KNOWING YOU: INVENTOR MOBILITY AND THE FORMATION OF TECHNOLOGY-ORIENTED ALLIANCES

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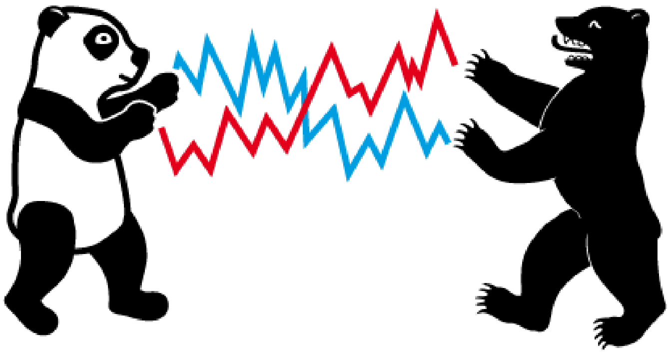

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Abstract[3]:

We link the hiring of R&D scientists from industry competitors to the subsequent formation of collaborative agreements, namely technology-oriented alliances. By transferring technological knowledge as well as cognitive elements to the hiring firm, mobile inventors foster the alignment of decision frames applied by potential alliance partners in the process of alliance formation thereby making collaboration more likely. Using data on inventor mobility and alliance formation amongst 42 global pharmaceutical firms over 16 years, we show that inventor mobility is positively associated with the likelihood of alliance formation in periods following inventor movements. This relationship becomes more pronounced if mobile employees bring additional knowledge about their prior firm's technological capabilities and for alliances aimed at technology development rather than for agreements related to technology transfer. It is weakened, however, if the focal firm is already familiar with the competitor's technological capabilities. By revealing these relationships, our study contributes to research on alliance formation, employee mobility, and organizational frames.

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INTRODUCTION

Professional mobility has drawn considerable attention from practitioners and scholars alike, as it has a profound impact on firm's innovation performance. In this context, the role of mobile inventors as carriers of valuable skills and technological knowledge is well understood. Recruiting inventors from competing firms allows the hiring firm to enjoy benefits from knowledge spillovers and to increase its innovative performance (Palomeras & Melero, 2010; Rosenkopf & Almeida, 2003; Singh & Agrawal, 2011; Song, Almeida, & Wu, 2003). Whereas existing literature provides compelling arguments on how firms acquire and internalize technological knowledge from mobile inventors into their own R&D efforts, it has not systematically taken into account how inventor mobility shapes firms' strategic actions and other innovation-related organizational outcomes (Mawdsley & Somaya, 2016). In furthering our understanding of interactions between inventor mobility and organizational outcomes, we focus on the effect of mobility on the establishment of technology-oriented alliances — a central part of most firms' broader innovation strategy (Eisenhardt & Schoonhoven, 1996; Hagedoorn, 2002). Ultimately, we argue that inventor mobility is positively associated with alliance formation.

Alliance formation is the result of a complex process whose outcome is often the result of collaborative decision-making (Doz, Olk, & Ring, 2000; Yang, Lin, & Lin, 2010). Managers and executives of one firm jointly collect and interpret available information on potential collaboration partners, as well as the benefits and risks of committing resources to an alliance (Bierly & Gallagher, 2007; Gulati, 1995b; Levitas, Hitt, & Dacin, 1997). These settings are characterized by a high degree of uncertainty and incomplete information and decisions are therefore often based on jointly held beliefs by managers and employees about their organization, its strategy and its competitive environment, i.e., by applying organizational decision frames to alliance decisions (Cornelissen & Werner, 2014; Corner, Kinicki, & Keats, 1994; Sharma, 2000). We contend that mobile inventors play an important role in this decision-making process, as they reduce information asymmetry by providing their new firm with additional insights about their prior company's technological capabilities and strategies, and also facilitate the alignment of decision frames applied by both organizations in the process leading to an alliance formation (Corner et al., 1994; Kaplan, 2008; Nadkarni & Narayanan, 2007). During their tenure at their former employer, mobile inventors have acquired technological knowledge and related cognitive elements, such as the categorization of certain technologies relative to others or the performance criteria to be used in the evaluation of different technologies (Kaplan & Tripsas, 2008). Working for a new employer, they acquire additional knowledge elements that allow them to develop a hybrid decision frame that encompasses elements of both organizations' perceptions and beliefs about aspects relevant to a potential alliance. The possession of a hybrid frame positions mobile inventors well to act as a bridge between their old and new organization thereby facilitating frame alignment (Ingerslev, 2014; Maney, Woehrle & Coy, 2005). Frame alignment renders an agreement between potential alliance partners on relevant contractual terms, and ultimately collaboration, more likely (Cornelissen & Werner, 2014; Weber & Mayer, 2014). Applying this theoretical lens, we hypothesize that recruiting R&D scientists from a competing firm is associated with higher chances of subsequent technology-oriented alliance formation.

We also present a nuanced view on how inventor mobility and alliance formation are interlinked because the effect of mobile inventors on alliance formation varies in strength depending on inventor-level characteristics and characteristics of the potential partner firms. First, the efficacy of employee mobility depends on the characteristics of mobile employees, namely the amount of firm-specific knowledge they possess (Groysberg, Lee, & Nanda, 2008). Mobile employees with a better understanding of their previous company's technological capabilities and decision frames are more likely to reduce informational uncertainty and bridge the current firm's organizational frames. Thus, firm-specific knowledge strengthens the positive link between mobility and alliance formation. Second, a firm may be familiar with the capabilities of a competitor, e.g., by working on similar core technologies or by actively monitoring its R&D activities (Ernst, 1998; Laursen & Salter, 2006). In these situations, both firms' decision frames will share common elements which reduce the need for further frame alignment in the process leading to alliance formation (Chen, 1996; Das & Teng, 2003; Kaplan & Tripsas, 2008). As a result, increased familiarity on the firm-level reduces the positive association between mobile inventors and alliance formation. Finally, we expect this association to be more pronounced in technology-development alliances, which require frequent coordination and decision-making about resource allocation, than in technology-transfer alliances, which are closer to market transactions.

We empirically test our theoretical predictions using data on inventor mobility and alliance formation amongst 42 large pharmaceutical firms between 1990 and 2005. Multivariate probit regressions provide support for our hypotheses and demonstrate that (i) inventor mobility is linked to subsequent alliance formation, and that (ii) this relationship is moderated by the mobile inventors' firm-specific knowledge and the hiring firm's familiarity with the potential alliance partner's technology. Finally, our data reveal that these clear findings hold only for collaborations which aim at the joint development of novel technology (development alliances), whereas the findings are less clear when we focus on agreements related to licensing (transfer alliances). These results remain stable after instrumenting inventor mobility to control for potential endogeneity, and are in line with qualitative insights we derived from in-depth interviews with executives and scientists from the pharmaceutical industry.[4]

Analyzing how inventor mobility enables the initiation of R&D collaborations, both theoretically and empirically, advances the existing literature in important ways. To start, we extend the literature on alliance formation (Ahuja, 2000a; Beckman, Haunschild, & Phillips, 2004; Li, Eden, Hitt, & Ireland, 2008). When focusing on the effect of individual employees on alliance formation, existing work emphasizes the importance of the upper echelons of an organization (Gulati & Westphal, 1999), while we provide theoretical arguments and empirical evidence on the pivotal role of mobile functional experts that have not been discussed to date. In particular, we develop a novel theoretical lens on alliance formation that integrates insights from work on inventor mobility and organizational frames, and highlights the importance of cognitive aspects of decision-making in this interfirm context. This line of reasoning also refines the understanding of spillovers induced by mobile inventors. We suggest that spillovers are not restricted to technical knowledge but also encompass cognitive elements that – once integrated with the hiring firm's decision frames – increases frame alignment and thus the likelihood of alliance formation between a firm and its competitor (Cornelissen & Werner, 2014; Kaplan, 2008; Weber & Mayer, 2014). On the empirical side, a novel dataset allows for testing predictions derived from this reasoning, adding to a growing body of literature interested in the effects of inventor mobility, and more generally to the effects of decision frames on organizational outcomes.

Our findings also contribute to the ongoing discussion of the effects of hiring personnel from competing firms (Mawdsley & Somaya, 2016). It has been argued that mobile inventors induce knowledge spillovers that can substitute for knowledge acquisition through M&A or

[4] To get a better understanding on the nature of R&D and the role of scientists, alliances, mobility, organizational frames and patents therein, we performed around a dozen exploratory interviews with managers and scientists in the biopharmaceutical industry. A more detailed description of this method can be found in Appendix B.

alliance activities (Palomeras & Melero, 2010; Rosenkopf & Almeida, 2003; Singh & Agrawal, 2011). Despite the implied negative relationship, our results suggest that inventor mobility and alliance formation are complements over time, rather than substitutes, since mobility is positively correlated with the chances of collaboration. Similarly, inventor mobility is described as a competitive move since proprietary knowledge developed by the former employer might be shared and used by the current firm (Png & Samila, 2013; Saxenian, 1996). Alliances, on the other hand, represent a collaborative approach to knowledge acquisition that typically is portrayed rather positively (Ahuja, 2000b; Powell, Kogut, & Smith-Doerr, 1996). This study reveals how competitive behavior and collaborative agreements co-occur and therefore informs the current discussion on whether legal institutions such as contractual non-compete clauses and other restrictions of labor mobility reduce knowledge spillovers and ultimately the speed of innovation as suggested by recent literature (Marx, Strumsky, & Fleming, 2009; Png & Samila, 2013; Prescott, Bishara, & Starr, 2016). We add to these concerns as our results imply that restricting labor mobility also reduces knowledge spillovers from inter-firm collaboration through alliances.

THEORETICAL BACKGROUND AND HYPOTHESES

Context

The formation of interorganizational partnerships, alliances and joint ventures between competitors is a frequent and increasingly important phenomenon (Hagedoorn, 2002). An oft-cited motive for collaborating is the acquisition of new competencies and skills from partner firms (Hamel, 1991; Mody, 1993; Mowery, Oxley, & Silverman, 1996). In this context, partnerships are advantageous compared to conventional contracts or market interactions. Firm-specific technological capabilities are often uncertain and tacit in nature (Grant, 1996; Polanyi, 1966) which renders contractual exchanges difficult to set up (Arora, Fosfuri, &

Gambardella, 2004; Pisano, 1990). Such contracting problems make interfirm collaboration a valuable mode of knowledge acquisition (Pisano, 1990).

From an organizational perspective, alliance formation is a process that starts with the identification of potential partners and subsequently involves bilateral negotiations on alliance purpose, structure, and the implementation of a potential collaboration (Das & Teng, 2002). An alliance can form only if potential partners agree on common objectives and reach a shared understanding of how to formulate an alliance contract considering the numerous contingencies arising from uncertain environments and the inherent risk of technology development. This process of alliance formation is best portrayed as a negotiation between the focal firm and potential alliance partners in which information is sequentially revealed to reduce information asymmetry and to develop a common understanding regarding remaining contingencies surrounding the alliance to be formed. In fact, one of the executives we interviewed, explained forming alliances with competitors as follows:

"*During the process [of negotiating a potential alliance] you gradually obtain more information on the other party which definitely affects how you think about the partner and also about the technology field in question. […] In the beginning of the process, neither party provides all relevant information but reveals it only gradually. […] This sequential revealing of information also alters your perspective as you start to realize that there are aspects of the collaboration you didn't anticipate when initiating the negotiations.*"

In this process, firms face several challenges related to uncertainty and information asymmetry. At the outset, firms have to identify suitable collaborators by evaluating the technological capabilities of and their strategic fit with competitors (Bierly & Gallagher, 2007; Shah & Swaminathan, 2008). This process is complicated by uncertainty about a competitor's technical competencies and expertise beforehand (Li et al., 2008) as well as uncertainty about a competitor's behavior regarding resource commitments during alliance execution afterward (Beckman et al., 2004; Lavie, 2006; Li et al., 2008). Moreover, firms face informational uncertainties when negotiating interfirm collaboration with potential partners. Such informational uncertainty refers to situations in which complete contracts cannot be formulated due to the impossibility of identifying possible future events affecting an exchange that could arise from environmental uncertainties (Weber & Mayer, 2014). The dynamic technological environment and unpredictable nature of R&D activities suggest that not all contingencies can be identified during the alliance formation process (Reuer & Arino, 2007). Finally, alliance formation is subject to substantive interpretive uncertainty, i.e., uncertainty stemming from alliance partners perceiving ambiguous information differently (Weber & Mayer, 2014). Different perceptions about technologies, competitors, or the industrial environment increase the chances of future disagreements when new information emerges during the alliance execution and – in anticipation – complicate alliance negotiations (Davidson, 2006; Weber & Mayer, 2014).

For these reasons, we contend that cognitive factors play a crucial role in the ambiguous alliance formation process. Firms will enter into an alliance agreement only if they foresee a successful outcome. As it is hard to measure technological competencies ex ante (Li et al., 2008) and to predict ex-post-behavior of potential alliance partners (Lavie, 2006), this is a rather ambiguous decision-problem in which decision frames are likely to be applied by organizations.[5] These organizational decision frames, defined as jointly constructed and collectively held beliefs in an organization that are used to make decisions about ill-structured problems which contain high levels of uncertainty and ambiguity (Cornelissen & Werner, 2014; Shrivastava & Schneider, 1984), are developed through a process of interactions among individuals and lead to a common interpretation of the environment

[5] A firm might track the activities of its competitors through competitive intelligence, but such information may be outdated, incomplete or unhelpful (Levitas, Hitt, & Dacin, 1997). Second, there is uncertainty about a partner's behavior once an alliance has been formed. Executives will infer such behavior from a competitor's reputation in the industry, which is also part of the organizational frame (Narayanan et al., 2011). Third, prior studies on corporate entrepreneurship have shown the importance of organizational frames for strategic decision-making. For example, Corner et al. (1994) explain how organizational frames play a critical role in the identification and evaluation of acquisition targets by executives and Kaplan (2008) uses frames to analyze decisions on a firm's R&D priorities.

within an organization. This includes points of view about industry cause-and-effect relationships, the nature of competition, and the status of competitors (Corner et al., 1994; Gilbert, 2006; Narayanan, Zane, & Kemmerer, 2011).

Organizations considering a collaboration often differ in their interpretation of the nature of a potential alliance, the associated contingencies, the resources to be committed, and the tasks involved, due to non-overlapping or misaligned decision frames. The resulting interpretive uncertainties are likely to impact and even impede 'complex, interdependent transactions (e.g., co-creation of a new technology)' (Weber & Mayer, 2014: 346). In particular, misaligned frames between two firms will amplify interpretive uncertainty and make an agreement on the relevant terms of a collaboration less likely. Instead, alignment of frames increases the likelihood that the parties agree on a mutual interpretation of uncertainties surrounding an intended alliance, and both firms are therefore more willing to enter a partnership (Zardkoohi & Bierman, 2015). Prior work implies that alliance negotiations can be portrayed as interfirm frame challenges in which participating firms try to create shared frame elements in order to increase frame alignment (Snow, Rochford Jr, Worden, & Benford, 1986; Weber & Mayer, 2014). Frame alignment occurs when one firm adopts organizational frames from its competitor (Kaplan, 2008) or through an implicit process of frame contestation where one firm gradually align its frames with a competitor's counterframes and vice versa (Entman, 1993).

Inventor mobility and alliance formation

It is important to highlight that R&D alliance formation and the associated frame alignment are complex interactive processes involving executives, managers, and firms' scientists (Doz, 1996; Oliver & Liebeskind, 1997). While the final decision on alliance formation is made by executives[6] (Eisenhardt & Schoonhoven, 1996; Gulati & Westphal, 1999), non-managerial employees, scientists in particular, are important in shaping the frames applied by their organizations. Explorative interviews confirm this view and one R&D manager linked the decision of entering an alliance to a joint decision-making process:

"*We always believe that the best way of dealing with things is actually working more in a collegial approach, because everybody has their own expertise, and everybody should be allowed to sit down at the table and have as much value given to his or her position as the others. So that we come to – as I said – democratic decision as to the pluses and the minuses of each case and the way ahead.*"

In deriving our key hypothesis, we theorize about how mobile inventors (R&D scientists that currently work for one firm but were previously employed by a competing firm) are related to the likelihood of a collaboration between a firm and its competitor.

Extant literature documents that mobile employees bring novel information and knowledge from competitors to the hiring firm, which includes information on the competitor's technologies and strategies (Palomeras & Melero, 2010; Singh & Agrawal, 2011). In a static view, inventor mobility and alliance formation can therefore been seen as substitutes for acquiring external knowledge (Song et al., 2003), implying a negative relation between inventor mobility and alliance formation. We take a dynamic perspective of the process of alliance formation, however, and highlight how mobile inventors facilitate frame alignment between potential alliance partners and therefore increase the likelihood of alliance formation. Our key argument is that mobile inventors mitigate informational uncertainty in the initial process of screening potential partners and act as bridges between the two

[6] While several studies have pointed to the role of CEOs in selecting alliance partners through their prior appointments or board interlocks (Eisenhardt & Schoonhoven, 1996; Gulati & Westphal, 1999), alternative research has emphasized that non-executive employees are similarly important. For example, Rosenkopf, Metiu and George (2001) show how interpersonal bonds between technical specialists – who communicate during meetings of standardization bodies – predict the initiation of alliances. Such studies demonstrate that alliances are not a strictly top-down process – initiated by executives and implemented by operational workforce – but can also be a bottom-up process – alliance partners are suggested by technical specialists to their superiors who then create a formal agreement.

organizations which facilitates frame alignment during the subsequent negotiations and ultimately increases the likelihood of reaching a final agreement on a collaboration.

When moving between firms, mobile inventors transfer not only technical information but also cognitive elements such as beliefs about future developments of the industry, competitors, or technologies that are part of the organizational frames held by their prior firm (Kaplan & Tripsas, 2008; Shrivastava, 1986; Shrivastava & Schneider, 1984). If these beliefs diverge from the dominant organizational frame of their new firm, mobile employees initiate a process that replaces or integrates existing organizational frames with their beliefs. In our context, the inclusion of novel elements from a mobile inventors' frame into the frame of the hiring firm is likely to shift it closer towards the frames of their former company and therefore increases alignment of frames.

In addition to the spillover effect described above, and more importantly, mobile inventors fulfill a bridging function in the frame alignment process by developing their own hybrid frames based on cognitive elements acquired from both their prior and their current employer. Hybrid frames have been described as a mixture of different perspectives which allow for a convergent approach to complex decisions (Ingerslev, 2014:134). Equipped with an understanding of the perspectives of both alliance partners, mobile inventors can act as a bridge since they typically maintain ties to their former employer (Corredoira and Rosenkopf, 2010). In this way they can help integrating different beliefs held by both companies and therefore further foster frame alignment. For example, Ingerslev (2014) notices how different partners in a healthcare innovation project reframe problems to create hybrid frames that allow for discussion and collaboration among partners with diverging beliefs. This reasoning conforms to the insights gained in one of our interviews:

"If you have such a person [mobile inventor] on the team, he can explain to his new colleagues technical and contextual facts based on the knowledge he obtained while working at his old firm. In that sense, these people can be considered mediators in the process of alliance formation. [...] This not only facilitates and speeds up the process of alliance

formation but also leads to more stable alliances as the expectations of both alliance partners are much better aligned […] and more detailed information is exchanged early on."

An additional mechanism that relates employee mobility with alliance formation can be derived from an embeddedness argument. Embeddedness explains how business actions like alliance formation are rooted in a larger set of social interactions among individuals, organizations and institutions (Dacin, Beal & Ventresca, 1999; Uzzi, 1997). For example, informal communication among scientists can result in collaborative projects formalized through an alliance agreement when scientists convince managers of the fit between the identified joint opportunities and the firm's R&D strategy (Berends, Van Burg, & Van Raaij, 2011:950). Similarly, we suggest that mobile inventors propose collaborative R&D projects with former colleagues to their managers. Earlier research has shown that mobile employees continue to communicate with their prior colleagues (Corredoira & Rosenkopf, 2010), but that organizational boundaries also limit information exchange and knowledge (Bouty, 2000; Singh, 2005). Mobile inventors may try to overcome restrictions on knowledge exchange with their personal connections by proposing cooperative R&D projects to their superiors. A firm is therefore disproportionally faced with opportunities to collaborate with competitors whose inventors it recently hired.

Taken together, we expect a higher number of employees recruited from a competitor to be positively associated with alliance formation. Different hires might transfer different elements of their former firm's organizational frames. The more those elements are integrated into the new firm's frames, the higher are the chances of frame alignment and successful alliance formation with the mobile inventors' former firm. Moreover, altering organizational beliefs through contestation and integration is a social process including discussions among employees and managers, formation of coalitions through negotiations, and defining dominant frames through interpersonal connections (Benford & Snow, 2000; Weick, Sutcliffe, & Obstfeld, 2005). A higher number of mobile inventors will have more weight in this process and a higher number of employees hired from the same competitor will also lead to stronger ties in their former organization and therefore making collaboration more likely. Based on these arguments—mobile inventors facilitate initial screening of potential alliance partners, foster frame alignment and prefer continuing to work with prior collaborators—we formulate our main hypothesis H1:

Hypothesis 1: The likelihood of alliance formation between a firm and a competitor is positively associated with the number of inventors moving from that competitor to the firm in preceding periods.

Contingency factors

Using H1 as our baseline, we further theorize about the conditions under which the relationship between mobility and alliance formation persists. We propose that individual-level, firm-level and alliance-level moderators are likely to affect the link between inventor mobility and alliance formation (Gulati & Westphal, 1999; Song et al., 2003). Differences among mobile employees, between potential alliance partners, and the alliance objectives determine the degree of informational asymmetry and interpretive uncertainty as well as mobile inventors' ability to align organizational frames (Weber & Mayer, 2014).

At the individual level, mobile inventors' assistance in screening potential partners and their impact on the hiring firm's decision frame depends on the firm-specific knowledge of their prior company that they transfer to the hiring firm (Tzabbar & Kehoe, 2014; Zucker & Darby, 1996). To start with, mobile inventors with a larger stock of firm-specific knowledge about their prior firm's R&D activities are more effective in reducing uncertainty about that competitor's technological capabilities (Singh & Agrawal, 2011; Song et al., 2003). Moreover, well-informed mobile inventors are also more familiar with the organizational beliefs held by their prior employer, which helps in understanding important points of divergence between old and new employer and the necessity of frame alignment (Kaplan, 2008). On top of this, more knowledgeable inventors enjoy higher credibility and status, which increases their potential to influence the decision frame of their new firm. For example, more knowledgeable and more connected mobile scientists are able to influence and adapt their new firm's R&D activities (Kehoe & Tzabbar, 2015). Not only do these knowledgeable employees attract more attention, but their higher status and professional reputation gives their information greater weight in decision-making (Grigoriou & Rothaermel, 2017; Paruchuri & Awate, 2017). These arguments imply that interorganizational alignment through integrating decision frames will be strengthened by the amount of firm-specific knowledge transferred by mobile inventors. This leads to our second hypothesis:

> *Hypothesis 2: The positive relationship between inventor mobility and the likelihood of subsequent alliance formation between a firm and a competitor will be more pronounced for higher amounts of firm-specific knowledge of the mobile inventors.*

At the interfirm level, the effect of inventor mobility is a function of the degree of information asymmetry and frame (mis)alignment in the process of alliance formation. Inventor mobility is less crucial for successful alliance formation, *ceteris paribus*, if a firm's frames are already aligned to (or even overlapping with) the mobile inventor's prior company's frames (Weber & Mayer, 2014). Potential alliance partners face less interpretive uncertainty since they share a similar understanding of the alliance's objectives, technologies involved and environmental uncertainties. This reduces the need for mobile inventors to act as a bridge.

For R&D alliances, the set of technological capabilities and trajectories of both firms will determine the extent to which their technological frames are aligned or overlapping, because decision frames are based on an organization's members' shared understanding of relevant core technologies (Davidson, 2006; Kaplan & Tripsas, 2008; Shrivastava & Schneider, 1984). When two firms work on technologies with which they are both familiar, there is less need to align frames to reduce interpretive uncertainty. This effect is reinforced if the firm actively tracks the R&D activities of its competitors to remain informed about new technological developments and to identify opportunities for interfirm collaboration (Laursen & Salter, 2006; Levitas et al., 1997). Consequently, alliance formation between firms sharing similar technological capabilities and active in related technology fields is less impeded by information asymmetry and interpretive uncertainty than between firms working on distant technologies. The extent to which mobile inventors bridge organizations — by sharing private information and aligning organizational frames — is therefore less pronounced if a firm is already familiar with the technological capabilities of potential alliance partners. We hypothesize:

Hypothesis 3: The positive relationship between inventor mobility and the likelihood of subsequent alliance formation between a firm and a competitor will be less pronounced for higher levels of the firm's familiarity with that competitor's technological capabilities.

Finally, the need for frame alignment and the relevance of interpretive uncertainty are also determined by the nature of the technology-oriented alliances to be formed. Companies enter different types of technology-oriented alliances for different motives (Hagedoorn, 1993). Technology-development alliances focus on the joint development of technology with shared research endeavors and are characterized by joint commitment and resource allocation. In contrast, technology-transfer alliances are a one-way transfer of a technology from one partner to another, and are akin to buyer-seller relations where the licensor typically receives compensation from the licensee in exchange for the right to use proprietary IP, training and consulting services (Hagedoorn, 1993).

As a result, transfer alliances are fundamentally different from development alliances (Mowery et al., 1996). Contrary to development alliances, licensing agreements do not require joint coordination of activities or allocation of resources. These contracts are more complete and face less potential contingencies because they require less coordination on the joint commitment of resources to the alliance. In addition, transfer alliances have clear objectives and a high probability of success, whereas development alliances have substantial risks of failure and objectives that may require adaptation over the course of the alliance's execution. For this reason, firms negotiating technology-transfer deals face less interpretive uncertainty and frame alignment is less crucial. Contrarily, given the uncertain nature of development alliances, frame alignment is essential to ease contract negotiation and reduce the risk of alliance conflicts. Therefore, the positive relationship between mobile inventors and the formation of technology-transfer agreements is expected to be limited. Hence, we postulate:

Hypothesis 4: The positive relationship between inventor mobility and the likelihood of subsequent alliance formation between the focal firm and a competitor will be more pronounced for technology-development alliances than for technology-transfer alliances.

DATA AND DESCRIPTIVE STATISTICS

Empirical context

To answer our research question, we set up our analysis in the pharmaceutical industry. This industry is an attractive testing ground for our hypotheses for several reasons. First, it is characterized by high R&D-intensity and strong technology-driven competition where technology-related interfirm collaboration is a common mean to increase R&D productivity (Bierly & Chakrabarti, 1996; Powell et al., 1996). Moreover, there is a high degree of publicly available information on pharmaceutical R&D documented in patents, which are crucial for the protection of inventions in the pharmaceutical industry (Cohen, Nelson &

Walsh, 2000). This allows us to observe inventor mobility and pharmaceutical firms' technological trajectories over time through firms' patent filings.

At the same time, it is important to highlight that firms in the pharmaceutical industry face significant informational asymmetries vis-à-vis their competitors, despite the existence of this publicly available information through patents. The information published in patents is restricted to molecular formulations of drugs, their interactions with other molecules and their synthesis under lab conditions (Magazzini, Pammolli, Riccaboni & Rossi, 2009). Important information like scalability of synthesis, exact medical indications of the planned use of the drug and information on toxic effects of the drug (either obtained from the study of related molecules or medical tests) are not revealed. Moreover, patents reflect only past and successful activities and lag the most recent strategic R&D decisions of firms as they are published usually 18 months after filing (Johnson & Popp, 2001). Hence, patents provide only an incomplete picture of the technological capabilities of firms and their most recent developments. This allows for significant informational uncertainty that can inhibit alliance formation.[7]

Second, individual scientists are core to the innovative performance of firms in the pharmaceutical industry (Hess & Rothaermel, 2011; Tzabbar, 2009), making it a suitable context to test our hypotheses. In fact, critical knowledge is often tacit and embodied in individuals through scientific education and professional experience (Kogut & Zander, 1992; Nonaka, 1994). Besides their individual knowledge, pharmaceutical scientists acquire considerable firm-specific knowledge when interacting with colleagues within joint research

[7] Unsuccessful acquisitions in the pharmaceutical industry are a telling example of the uncertainty in the interpretation of publicly available information. For instance, Merck acquired Idenix for 3.85 billion USD in 2014 to combine its own hepatitis C (HCV) drug with one of Idenix HCV drug candidates to achieve higher efficacy, and to get access to Idenix's complementary skills in developing nucleoside-based molecules in general (Rothaermel & McKay, 2015a). Merck was not able, however, to achieve satisfactory results from this acquisition (Rothaermel & McKay 2015b) – despite a large amount of publicly available information (Idenix's patents had been published, key drug candidates were already in stage II clinical trials, and due diligence had been conducted).

projects within the firm (Reagans, Argote, & Brooks, 2005). For this reason, inventors in the pharmaceutical industry have an important influence on intrafirm decision-making regarding alliance formation with potential partners. One of the interview partners highlighted that:

"It is often the R&D personnel that identifies potential partners with a good technological fit. […] For instance, R&D approached us [Business Development] indicating that they are looking for an alliance partner in a particular area within their cancer drug research stream and then we started a screening process for potential partners. After our initial screening, it really was the R&D people selecting the short list of potential partners that then are evaluated more carefully."

and

"The Business Development Unit is responsible for conducting the due diligence-like process. It is bringing in employees from the R&D, medical affairs as well as regulatory affairs units that support the due diligence but it is the R&D people who really evaluate the technological potential offered by a potential partner."

In addition to informational uncertainty, the importance of inventors in the process of alliance formation renders the pharmaceutical industry an attractive context for our study. We seek to test the extent to which mobile inventors are associated with alliance formation between their prior and current companies in this setting.

Sample construction and data sources

We test our theoretically-derived hypotheses by empirically examining which factors are associated with the formation of alliances between pairs of firms at a given point in time. Hence, the unit of analysis is a dyad between two firms, and we observe whether an alliance has been formed or not on an annual basis. The sample consists of a longitudinal sample of large global pharmaceutical firms, for which we formed all possible dyads for the 16-year period between 1990 and 2005. We restricted our sample to the largest firms in the industry (in terms of global sales in 1985) and identified these via two sources: the twenty firms of the Scripp's 1985 League Table, and all members of the Pharmaceutical Research and Manufacturing Association (PhRMA) in that year. For a few cases, we added firms that merged later with any of these firms. This results in a global sample of 42 firms active in pharmaceuticals in 1985 which are tracked until 2005.

Restricting our sample to large companies allows us to focus on the industry's most prominent players (similar to Gulati, 1995a). Hence, we capture the behavior of core rather than peripheral firms, which is important as the pharmaceutical industry is increasingly concentrated. Moreover, restricting the sample to the large players allows us to include financial information as important controls in our regression analyses. We carefully track M&A activities of all firms in our sample to avoid contamination of our empirical results.[8] Finally, we identify inventor mobility not only by examining patenting histories of individuals for employer changes, but enhance this approach by manually inspecting additional data sources to minimize measurement error in this key variable (for more details see below). For each firm in our sample, we collected balance sheet information from Mergent WebReports. Patent data were obtained from the EPO PatStat database by matching the assignee name to the names of a firm and all its subsidiaries. Details on interorganizational alliances were obtained from the SDC Platinum database that has been used for this purpose in multiple prior studies (Schilling, 2009).

Measurement

Dependent variable

Alliance formation. Our data include information on both technology-development and technology-transfer alliances between firms. Development alliances are partnerships where

[8] If firms merge, a new entity is created that combines the previous two entities (GlaxoSmithKline is the combination of Glaxo Wellcome, which is the combination of Glaxo and Wellcome, and SmithKline Beecham, which is the combination of SmithKline and Beecham). If a firm is acquired by another firm in our sample, it ceases to exist and all inventors and patents are assigned to the acquiring entity, which continues to exist. If a firm is acquired by another firm that is outside of our sample – because this is a non-pharmaceutical firm – it simply drops out of our sample (e.g. Sterling Drug acquired by Kodak). We exclude dyads for a five-year period surrounding any acquisition events as such events tend to affect our measures for inventor mobility and technological familiarity.

firms interact to share knowledge and together develop a new technology whereas transfer alliances are agreements where one firm passes its knowledge on a specific technology over to another company. Within the technology-development alliances, we can further distinguish those agreements where firms specifically agree to jointly perform R&D activities for developing a new technology, and those where firms agree to share and combine technologies.[9] Whereas some studies focus solely on technology-development alliances (e.g. Stuart, 1998), we report separate results for development alliances (joint R&D exclusively, as well as pooled with knowledge sharing) and transfer alliances in order to test H4. For our analyses, we coded the formation of different types of alliances (joint R&D only alliances, all development alliances, and all transfer alliances) in each year as dummies (being 1 if the firms in a dyad formed an alliance, 0 otherwise). This yields a dependent variable that is varying over dyads and years.

Independent variables

Inventor mobility. Inventor mobility is a dyad-year count variable capturing the number of inventors moving from competitor j to the focal firm i during the period $t-5$ to $t-1$. We identified inventor mobility by observing the inventor names on both firms' patents, combining the methodology of Hoisl (2007) and Corredoira and Rosenkopf (2010). Moreover, as Ge, Huang and Png (2016) have shown that identifying inventor mobility based only on patent records may misestimate mobility, we tried to manually verify each mobility event through externally available information like public profiles on social networking sites such as LinkedIn.com, publication records, personal webpages, etc. This revealed a significant number of 'false positives' of the same inventors appearing on patents of different

[9] SDC Platinum differentiates technology-development alliances further into those involving new joint R&D activities and those where R&D activities build upon existing technologies that are shared and recombined. Often development of technology requires the sharing of existing knowledge between the partnering firms and for this reason R&D and technology sharing alliances frequently overlap. Empirically, this is reflected by the fact that the classification of R&D and sharing alliances is not mutually exclusive, but that many alliances have been classified as both R&D and technology-sharing simultaneously.

firms without actually being mobile. For example, the German pharmaceutical firms Bayer, BASF, and Boehringer Ingelheim independently collaborated with the same German biomedical professors who are then listed on all firms' patent applications. Similarly, employees of contract research organizations (CROs) also appeared on the patents of various American firms. Such false observations of inventor mobility were excluded from our data. Finally, we use a lagged time window (*t-5* to *t-1*) to observe mobility in order to alleviate concerns of endogeneity (see discussion below) and expect a prolonged effect of mobility on alliance formation. We use the natural logarithm of the number of inventors moving from a competitor to the focal firm over a five-year window prior to the current year (*t-5* to *t-1*) in our multivariate analyses.

Firm-specific knowledge. Firm-specific knowledge held by mobile inventors is observed through their personal connections in their prior firm. Jarvenpaa and Majchrzak (2008) show that well-connected inventors have a broader understanding of what their colleagues are working on whereas Paruchuri and Awate (2017) demonstrate that better-connected inventors have access to more distant firm knowledge. Other studies proposed alternative measures like inventor tenure or number of patents (Hoisl, 2007; Kapoor & Lim, 2007). While these measures are highly correlated, we think that personal ties provide information more relevant for alliance formation and create more awareness of dominant organizational frames as connections give more and broader information. For that reason, we measure a mobile inventor's firm-specific knowledge about her prior firm as the number of unique co-inventors on the patents that she filed before the move.[10] To aggregate on the dyad level, we consider all mobile inventors moving from a specific competitor towards the focal firm in the past five years, compute their average number of co-inventors and take the natural logarithm. In order

[10] This is equivalent to the degree centrality of an inventor in an undirected network in which nodes are constituted by inventors of a firm and ties by two inventors being listed on the same patent (co-invention). If the same pair of inventors is listed on more than one patent simultaneously, we count this tie only once.

to test our second hypothesis, we form an interaction term between firm-specific knowledge and mobility.

Familiarity. Our measure of firm *i*'s familiarity with competitor *j*'s technological capabilities is based on the extent to which the two firms cite the same pool of patents in their own patent filings (Stuart & Podolny, 1996). More specifically, familiarity is computed as the number of unique citations that patents filed by *i* and *j* in the period *t-5* to *t-1* have in common, normalized by the total number of unique cites contained in *i*'s patent filings in *t-5* to *t-1*. Note that this measure of familiarity does not rely on the number of citations made by the firm to patents filed by a competitor. Rather, it captures to what extent the two firms draw upon the same knowledge resources in their own R&D activities. A high level of familiarity according to our definition implies that the firm is familiar with the technology used by a competitor, increasing frame alignment and reducing interpretive uncertainty. This indirect approach to measure familiarity is advantageous as it is less prone to underestimating familiarity in cases where the focal firm has strategically decided not to move in a particular technological field because it is aware of a competitor's patents in this area. In such a case, there would be fewer citations to a competitor's patents despite high familiarity.[11]

Control variables

We include various control variables in the multivariate regression analysis below in order to minimize the effect of potentially unobserved heterogeneity on our regression results.

Dyad characteristics. First, we measure the extent to which the two firms forming a dyad have engaged in technology-oriented alliances prior to the focal year. The *number of prior alliances* is a simple count variable that increases by one for each year in which we observe any technology-oriented alliance. It is important to control for a dyad's alliance history as

[11] We thank an anonymous referee for pointing this out to us.

firms acquire and accumulate information and trust through repeated interactions over time, facilitating and increasing the likelihood of forming new alliances in the future (Gulati, 1995b).

We also control for the relative positioning of two firms forming a dyad in the technology space by creating variables that capture various aspects of how the R&D activities of the two firms are related. First, we capture *technological distance* by calculating the cosine similarity (coefficient of uncentered correlation) based on the IPC classification (at the main group level) of two firms' patent applications in the prior five years (*t-5* to *t-1*) as proposed by Jaffe (1986, 1988). In particular, we define two distribution vectors $\boldsymbol{f}$ ($\boldsymbol{f_f}$ for the firm and $\boldsymbol{f_c}$ for the competitor), the elements of which are the shares of a firm's patent filings in different IPC classes.[12] Technological distance is then defined as $1 - \frac{\sum f_f f_c'}{\left(\sum f_f f_f'\right)^{1/2}\left(\sum f_c f_c'\right)^{1/2}}$ and ranges from zero (lowest distance) to one (maximum distance). In addition to the technological distance of two firms in a dyad in *t*, we also control for past changes in the relative position of the two firms in a dyad. For this purpose, similar to Corredoira and Rosenkopf (2010), we define the variable *technological convergence* as the difference between the two firms' technological distance computed for patent applications filed in the years *t-10* to *t-6,* and the distance based on patent applications filed in the years *t-5* to *t-1*. Finally, we control for the effect of spatial distance as colocation because distance hampers both mobility and alliance formation. *Geographical distance* is the log-transformed distance between the headquarters of firm *i* and competitor *j* as R&D activities are usually concentrated nearby the headquarters (Belderbos, Leten, & Suzuki, 2013).

Firm and competitor characteristics. We gathered important balance sheet information to better control for the effect of heterogeneity at the organizational level, for both the firm and

[12] IPC refers to International Patent Classification system. IPC codes are assigned to patent applications by the patent examiner and describe the technological domain in which the invention can be applied.

its competitor in the dyad. Most notably, we seek to capture heterogeneity in firm size, and the intensity of their R&D activities that complement our measures on the dyad level. We capture the absolute magnitude of both firms' R&D activities by their *number of patent applications* in a given year, which is usually interpreted as a measure of R&D output. Moreover, the *number of citations* each firm's patent portfolio receives in total (not only by the focal firm) controls for the quality dimension of these mere patent counts as well as a firm's technological leadership in the industry. We include *R&D intensity*, measured as R&D expenditures over sales, in our regressions to control for the strategic importance of R&D activities for a firm. Finally, we also include the *number of employees* in our regressions to control for size differences between firms in a dyad.

Descriptive statistics

We observe the 42 largest pharmaceuticals companies between 1985 and 2005. As some of our variables – such as the number of inventors moving from the alter firm to the focal firm – are measured over a time window of five years prior to the focal year (*t-5* to *t-1*), the analysis uses the period from 1990 to 2005. Since the number of firms in our sample is decreasing over time due to M&A activity, our sample includes a total of 11,502 dyad-year observations in which we observe whether an alliance has been formed or not. Full descriptive statistics and sample correlations among all variables are included in Table A3 in the Appendix. In Table 1 we report the rates of alliance formation, broken down by technology-development and technology-transfer alliances. As we created all possible dyads between all firms in our sample over a 16-year period, it is unsurprising that the occurrence of alliances is rare. Overall, we observe the formation of technology-development alliances in 2.1% of all dyad-years and technology-transfer alliances in only 1.1% of all dyad-years. Focusing on R&D alliances exclusively (by excluding sharing alliances) we find that pure R&D alliances form in 1.5% of all dyad-years. In Table 1 we also report the rate of alliance formation for observations where the number of mobility events in the five years preceding the focal dyad-year is below the median, and above the median. While mobility is significantly associated with higher rates of technology-development alliances, there is no observable difference for technology-transfer alliances, giving some descriptive support for our fourth hypothesis.

INSERT TABLE 1 ABOUT HERE

At face value, the descriptive statistics support our key hypothesis that inventor mobility is related to technology-oriented alliances. To test the proposed moderating effects of mobile inventor knowledge and firm technological familiarity we conduct multivariate tests in which we interact mobility with these. We additionally present results from instrumental variables regressions to alleviate concerns about the potential endogeneity of inventor mobility.

MULTIVARIATE ANALYSIS

Empirical approach

The unit of observation in our multivariate analyses is a dyadic pairing ij of focal firm i and competitor j in a given year t. The outcome, y_{ijt}, is an indicator variable being zero or one for a given dyad in a given year. We employ probit models that account for the discrete nature of the dependent variable.

We face two challenges in our regressions. First, the independence assumption underlying the estimation framework is potentially violated as observations are non-independent in dyadic regressions. For instance, each company in our sample appears in multiple dyads in a given year, which introduces a common company effect. Hence, the observed outcome for a given dyad may be correlated with the observed outcome of another dyad if some unobserved attributes of a given company affects both outcomes. Moreover, the likelihood that a pair of firms will form an alliance in *t* is not independent of the likelihood of alliance formation between these two firms in other periods (autocorrelation). While this problem does not affect estimates of the regression parameters, it can cause underestimated standard errors that lead to inflated significance levels of the coefficient estimates (Kenny, Kashy & Cook, 2006). We address the non-independence problem by estimating robust standard errors that are clustered on three dimensions: on the level of each dyad *i-j*, the level of firm *i*, and the level of competitor *j*. Cameron, Gelbach, and Miller (2011) develop an approach that allows for simultaneous clustering on both firms in a dyad as well as the dyad itself that has been implemented in a Stata ado-file (Kleinbaum, Stuart & Tushman, 2013).[13] We compute marginal effects at the mean (MEM) for our key independent variables based on the results obtained from the three-way clustered estimations using the delta-method (Wooldridge, 2010). The most important results from these regressions are presented in Table 2 and Figures 1 and 2; more detailed results can be found in Table A1 in the Appendix.

The second challenge that we face is that inventor mobility is potentially endogenous to alliance formation. There are several potential sources of endogeneity including reverse causality (i.e., alliance formation leading to mobility), and unobserved heterogeneity (i.e., another factor influencing both alliance formation and employee mobility rates). Exogenous variations, such as those exploited in (natural) experiments, are difficult to find in this setting, so we are unable to conclusively rule out endogeneity. Yet, we resort to second-best methods to limit the potential for reverse causality and omitted variable bias.

First, we address potential omitted variable bias by using a comprehensive set of additional control variables that influence both alliance formation and inventor mobility simultaneously. An additional reason to discount omitted variable bias is the level of

[13] We implement the three-way clustering in Stata relying on the *clus_nway.ado* routine. It serves as a wrapper around any of Stata's model estimation commands and can cluster the standard errors on the coefficient estimates around arbitrarily many variables simultaneously. It has been made available to us by A. Kleinbaum (see http://faculty.tuck.dartmouth.edu/adam-kleinbaum/software, latest visit February 12th 2017).

aggregation of our measures. Mobility is driven by the behavior of individual inventors and will mainly be affected by unobservable person-specific factors. Alliance formations, on the other hand, are firm-level decisions of significant strategic importance and are therefore unlikely to correlate with unobservable effects that are person-specific.

Second, we use several methods to address potential reverse causality. For example, mobility might be affected by an inventor's expectation of forming (or a firm's intention to form) an alliance, which would lead to reverse causality inducing endogeneity. We introduce a time-lag between the measurement of key independent variables (mobility, inventor knowledge and partner familiarity) and the measure of alliance formation to deal with such reverse causality. Most importantly, we measure inventor mobility in the five years preceding the announcement of an alliance but not in the year of the alliance formation itself.[14] For this reason, the lag structure effectively decouples inventor mobility from alliance formation. It is unlikely that remaining omitted factors might affect both inventor mobility in the past and alliance formation in the present.

Third, we also employ an instrumental variables approach where instruments are correlated with the endogenous variables but unrelated to the error term of the regression equation (Bascle, 2008; Wooldridge, 2010). Our first instrument is the total number of inventors in our sample that move from one company to another (cumulated across all dyads and years in the time window *t-5* to *t-1*) minus the number of mobile inventors of the focal dyad (*mobility, industry total*).[15] This aggregate number of mobile inventors reflects broader trends in the labor market (such as overall availability of talent) that are independent of the focal firm's behavior (including alliance formation). Following Wooldridge (2010), we construct a second instrument as the square of the potentially endogenous mobility measure.

[14] We report results in which we measure mobility in the years *t-5* to *t-1* but the results are robust towards a change in the lag structure using a three-year window *t-3* to *t-1*.
[15] We correct for the number of mobile inventors of the focal dyad to limit the influence of the focal dyad on the industry-wide measure we are constructing.

Finally, as interaction terms with the endogenous variable are endogenous themselves, we instrument them by multiplying the instruments with our measures of familiarity and inventor firm-specific knowledge.

Table 2 reports the results from the second stage of a two-stage instrumental variables (IV) regression in which we instrument the endogenous variable and its interaction terms next to the results from non-instrumented regressions. Regarding the quality of our instruments, the F-statistics of instrument strength are clearly above the critical thresholds reported in Stock and Yogo (2005). Hence, our instruments can be considered 'strong' as there is sufficient correlation between them and the endogenous variable after controlling for the remaining covariates. Second, Wald tests of exogeneity for the different specifications do not reject the null hypothesis that the error terms of the first and second stage regressions are uncorrelated. This is a good indicator that our instruments are an appropriate way to address potential endogeneity problems (Bascle, 2008; Wooldridge, 2010). Taken together, these tests suggest that our instruments are strong and exogenous. We report detailed results from the instrumented regressions in Table A2 in the Appendix.

Results

Table 2 reports coefficient estimates for key variables obtained from probit models. In these models, we account for the fact that firms are included in multiple dyad-pairs and multiple years in our dataset by clustering standard errors on the level of the dyad, as well as both focal and competitor firm. Estimates are presented for probit regressions, but also the results from our IV regressions. All models include year dummies to capture industry-wide time-trends. The coefficients of the year indicators are jointly significant but are not reported for the sake of brevity.

We report regression results for joint R&D alliances, for all technology-development agreements (with joint R&D alliances being a subset of all technology-development alliances), and for all technology-transfer alliances. Comparing these results allows us to evaluate H4. For each of these groups, we run two different specifications: the first specification includes only the main effects of inventor mobility, inventor firm-specific knowledge stock, and firm-competitor technological familiarity, each in *t-5* to *t-1*. We then add the interaction terms between mobility on the one hand, and firm-specific knowledge stock and familiarity on the other, to test our hypotheses H2 and H3. Note that the number of observations differs slightly across alliance outcomes: in years where no such type of alliance is formed, the year dummy perfectly predicts the outcome and all observations are excluded from the regression. This reduces the number of observations relative to the total number of 11,502 observed dyad-years. Finally, Table 2 does not contain marginal effects for the interaction terms because the interpretation of interaction terms in non-linear models such as the probit model is challenging (Ai & Norton, 2003; Hoetker, 2007). Instead, we present plots of the marginal effects at the mean (MEM) of mobility across the value range of the moderating variable in Figures 1 and 2.

The estimation results reported in Table 2 largely support our hypotheses for technology-development alliances, while we have (as expected) less clear findings for the formation of technology-transfer alliances. We focus on development alliances before we discuss how the results differ for transfer alliances.

INSERT TABLE 2 ABOUT HERE

First, looking at joint R&D alliances exclusively, inventor mobility has a positive and significant relationship with alliance formation (see columns 1 of Table 2). This supports our key hypothesis H1. Moreover, in the basic specification of column 1, we also observe that familiarity has a strongly significant and positive effect on the formation of R&D alliances. This is in line with the findings of existing literature (e.g. Rothaermel & Boeker, 2008). The results from the instrumental variable regressions differ only marginally.

The inclusion of the interaction terms clearly shows significant moderated relationships as hypothesized. As the interpretation of interaction effects can be difficult in non-linear models (Ai & Norton, 2003; Hoetker, 2007), we depict the MEMs of the interaction terms in Figures 1 and 2. The left panel of Figure 2 presents the MEM of inventor mobility across a range of values of firm-specific knowledge and confirms a positive interaction. The knowledge stock of mobile inventors increases the positive association between inventor mobility and alliance formation as the positive slope of the MEMs over the range of knowledge (in line with H2). The left panel of Figure 2 presents the MEM of mobility across a range of values of familiarity. It shows a clearly negative slope which is in line with H3—increasing familiarity is associated with a weaker relation between mobility and alliances.

INSERT FIGURES 1 AND 2 ABOUT HERE

Taken together, the results regarding joint R&D alliances presented in column 2 of Table 2 and Figures 1 and 2 are in line with the proposed theoretical relationships: joint R&D alliances are more likely to form between firm-pairs that are characterized by past inventor mobility (H1). Moreover, we also observe that this relationship is more pronounced if they have more firm-specific knowledge (H2), while it is less pronounced if the recruiting firm is already familiar with the potential alliance partner's technology (H3).

Extending the set of alliance formations to all technology-development agreements, we observe similar patterns when joint R&D and knowledge sharing alliances are combined (see columns 3 and 4 in Table 2). The only notable difference is a loss in precision for the effect of mobility, which is captured in a more pronounced interaction between mobility and inventor firm-specific knowledge (see Figure 2, middle panel). Apart from this difference, the results regarding all alliances again support our hypotheses. Mobility has a positive relationship with alliance formation (H1) and is positively moderated by the mobile inventors' stock of firm-specific knowledge (H2) (see also middle panel of Figure 2). Familiarity significantly increases the likelihood of alliance formation while negatively moderating the mobility-alliance relationship (H3), which is displayed in the middle panel of Figure 2. Again, instrumenting inventor mobility does not change these results.

Inventor mobility is not related to the formation of technology-transfer alliances, as seen in columns 5 to 6 of Table 2 as well as Figures 1 and 2. None of our key variables has a significant association with the likelihood of transfer agreements. This is in line with H4 in which we postulated that the relationship between mobility and alliances would be less pronounced for technology-transfer alliances compared to development alliances. We must acknowledge, however, that a statistical test conducted in a seemingly unrelated regression framework did not reject the null-hypothesis that the coefficients are significantly different when comparing technology-development and technology-transfer alliances. In this regard, we have only weak evidence in support of H4. Looking at our controls, technology-transfer alliances seem to be driven by previous alliances between two firms rather than inventor mobility. Overall, the results regarding licensing and knowledge transfer are not surprising since – as discussed above – such partnerships relate to developed technology that is passed on, rather than the joint development of novel technologies. In such a context, frame alignment can be expected to play a less crucial role.

CONCLUSION AND DISCUSSION

Effects of inventor mobility

Scholars have identified the antecedents of interorganizational collaboration and drawn upon a variety of literature, such as resource complementarities, competitive dynamics, and social ties (Ahuja, 2000a; Li et al., 2008). More recent studies have emphasized the difficult task of assessing technological capabilities of potential partners, and uncertainty about outcomes that needs to be overcome in the alliance formation process (Beckman et al., 2004; Bierly & Gallagher, 2007). Only limited research, however, has discussed the micro-level and more cognitive aspects underlying firms' decision-making processes regarding alliance formation. In this study, we address this gap by theorizing how employee mobility is related to alliance formation. Specifically, we argue that recruiting R&D scientists from a competitor provides firm-specific information that reduces information asymmetry (Palomeras & Melero, 2010). Concurrently, new information from mobile employees challenges and changes organizational decision frames. Over time, mobile scientists can help aligning firms' decision frames as they develop hybrid frames combining beliefs of both firms making them effective bridges between the two organizations. The accompanying decrease in interpretive uncertainty will be related to higher chances of collaboration (Weber & Mayer, 2014). Our empirical results are aligned with this logic and we observe that recruiting inventors from a competitor is significantly associated with higher probabilities of subsequent collaboration. Yet, this effect of mobility is only true for bilateral agreements involving technology-development activities, and is not significant for technology-transfer partnerships which focus on unidirectional knowledge transfer.

These findings speak directly to the literature on alliance formation by discussing a novel micro-level mechanism underlying interfirm collaboration. Existing studies have pointed to the role of CEOs in alliance formation through their prior appointments or board interlocks (Eisenhardt & Schoonhoven, 1996; Gulati & Westphal, 1999). On the non-executive level, Rosenkopf, Metiu and George (2001) show how interpersonal bonds between technical specialists predict the initiation of alliances. We add to this work by focusing on mobile employees as well as by applying a novel theoretical lens emphasizing a cognitive perspective. Whereas these prior studies showed how individual-level collaboration resulted in organizational-level collaboration (Berends et al., 2011), our study reveals that non-collaborative actions like mobility also assist in alliance formation. Specifically, our study provides a clear theoretical explanation for how employees' personal knowledge can influence joint decision-making by providing additional information and bridging interorganizational decision frames in the process of alliance formation. While we cannot observe frame alignment directly, our qualitative insights obtained through interviews confirms its relevance.

We also contribute to the learning-by-hiring literature. This research has related inventor mobility primarily to knowledge spillovers (Palomeras & Melero, 2010) and reverse knowledge spillovers (Corredoira & Rosenkopf, 2010). It also explains that learning-by-hiring can be a substitute to knowledge acquisition through alliance formation (Rosenkopf & Almeida, 2003), which implies that one would expect a negative relationship between inventor mobility and alliance formation (contrary to H1). Yet, our study advances this literature in two ways: First, we discuss how mobile employees not only induce knowledge spillovers but also act as bridges between firms' decision frames. Second, we reveal an additional and indirect channel of knowledge transmission—inventor mobility is positively linked to the formation of R&D collaboration between firms, which subsequently results in an additional interorganizational knowledge transfer. From this perspective, learning-by-hiring and alliance formation are complementary rather than substitutive as earlier studies proposed (Rosenkopf & Almeida, 2003; Song et al., 2003).

Finally, our study relates to the current discussion on the effects of non-compete clauses (NCC) (Marx, 2011; Marx et al., 2009; Png & Samila, 2013; Prescott et al., 2016; Starr, Prescott, & Bishara, 2016).[16] NCCs are commonly included in the labor contracts of scientific personnel (Starr et al., 2016) despite limited legal implications (Prescott et al., 2016). As we study mobile employees, it is important to highlight that though NCCs have a dampening effect on labor mobility (Marx et al., 2009; Png & Samila, 2013), they do not prevent mobility on a large scale – which would restrict the generalizability of our findings. In particular, in the pharmaceutical industry NCCs are rarely held against inventors, as their commercially most-valuable knowledge typically is protected by patents owned by their previous employer, limiting threats of imitation. A Vice President of a leading pharmaceutical company explained to us:

"We do not enforce non-competes and let employees leave us for competitors. Actually, this is not necessarily negative but can even have some advantages as mobile inventors can create new contact points at their new employers. […]

For instance, if an employee who filed twenty patents for you moves on to a competitor – he can't take those patents with him anyway. To the contrary, the protected knowledge that he transfers might even increase your chances to find a future partner for research alliances. Non-compete clauses are typically not an issue, rather the fear of losing a critical resource for future R&D success. We try to retain mobile inventors with higher salaries rather than threatening with the enforcement of non-competes."

Prior literature argued that a restriction of labor mobility negatively affects the economic development of geographic regions due to a reduction in knowledge spillovers among firms that otherwise would lead to higher innovative performance on the aggregate level (Marx, Singh, & Fleming, 2015; Saxenian, 1996). Our findings further aggravate these concerns as our results indicate that inventor mobility and alliance formation are complements. Thus, restricting labor mobility not only reduces knowledge spillovers via mobile employees, but also subsequent knowledge spillovers through alliance.

Effects of inventor firm-specific knowledge and firm technological familiarity

[16] In 2013, Gov. Patrick proposed to make noncompete agreements completely unenforceable in Massachusetts which spurred an intense debate amongst policy makers on this topic, see http://archive.boston.com/business/technology/innoeco/2013/09/big_shift_governor_patrick_now.html (latest visit October 1st, 2017).

In addition to the relation between inventor mobility and alliance formation, we also examined the conditions under which this association is stronger or weaker. We found that the relation is stronger if a firm hires employees that have more firm-specific knowledge about their prior company, and weaker if a firm is already familiar with the technological developments of that competitor. These effects, which hold only for technology development alliances, speak to the literature on inventor mobility. For example, Song et al. (2003) already noticed that mobility is less effective for interorganizational learning when mobile inventors work in technological areas that the firm is familiar with. We build and extend upon these boundary conditions by revealing a similar pattern for alliance formation: the relationship between alliance formation and inventor mobility from a competitor is much weaker for competitors whose knowledge is already known to the firm compared to unfamiliar competitors. Similarly, Tzabbar (Tzabbar, 2009; Tzabbar & Kehoe, 2014) demonstrated that highly prolific scientists have a strong influence on their organizations and that their mobility has significant consequences for both the departed and the recruiting firm. We add to this idea by demonstrating that inventors with more firm-specific knowledge are better in changing organizational frames and reducing interpretive uncertainty to assist alliance formation. Alternatively, it also reveals that interfirm learning and alliance formation occur independent of mobile employees if the frames of both organizations are already aligned.

More broadly, it has often been emphasized that competitive and collaborative forces intersect in today's R&D environment (Chesbrough, 2003; Gnyawali & Park, 2011). We uncover an unexplored intersection of collaboration and competition. Recruitment of a competitor’s inventors and monitoring of its developments are competitive learning instruments that firms can unilaterally employ to learn from an alliance partner. Firms can also employ collaborative mechanisms, such as R&D alliances and licensing agreements, to learn from competitors. Our findings show that both mobility and monitoring (competitive mechanisms) are positively related to the formation of R&D alliances (collaborative mechanisms). Collaborative and competitive methods are therefore not substitutes, but interact and complement each other. On the other hand, we find a substitution effect for our two competitive mechanisms – mobility and monitoring – in their effect on alliance formation.

Practical implications

The findings of this study have practical implications for R&D management. In many cases, R&D alliances have received a top-down approach in business development and alliance management practices (Chesbrough, 2003; Ireland, Hitt, & Vaidyanath, 2002). Conversely, our study reveals important micro-level effects, with inventors identifying opportunities for interorganizational collaboration and helping to align organizational frames in the alliance formation process. Managers should systematically include R&D scientists in the process of identifying collaboration partners instead of only involving them in the implementation stage. Moreover, employee mobility is often considered a strategic threat by managers as the company's proprietary knowledge simply walks out the door. However, this study shows that employee mobility may be an important enabler of interorganizational collaboration, which provides large opportunities for a firm to learn proprietary knowledge from, and develop new knowledge with, its competitor.

Limitations and future research

The limitations of our study provide opportunities for future research. Our study is rooted in a knowledge-intensive industry and relies significantly on patent data and our conclusions may not be applicable to industries where knowledge is explicit or embedded in organizational-level elements (routines, objects, procedures, etc.) instead of individual employees. In addition, the use of patents to identify employee mobility has its limitations

(Ge et al., 2016), though we aim to preempt this by using patent applications instead of solely granted patents and by relying on added public information to confirm these mobility events.

Moreover, we aimed to carefully examine the relationship between inventory mobility and alliance formation by addressing omitted variable concerns through an instrumental approach, and controlling for alternative explanations through a large set of control factors. Nevertheless, in the absence of a (natural) experiment, we are unable to rule out any remaining concerns stemming from unobserved heterogeneity. Future research can build upon our findings by identifying exogenous changes to mobility (alliance formation) and relate these to alliances (inventor mobility). Additionally, it could also investigate whether alliances related to prior mobility are more effective and less likely to fail as organizational frames are bridged by such employees. Other forms of research, like case studies or ethnographies, can provide in-depth knowledge of the different activities and processes employees and organizations perform to align their frames and manage alliances.

Finally, inventor mobility is a competitive and directional move whereas alliance formation is a bi-directional event requiring commitment from both firms. We are unable to observe which firm initiates alliance negotiations, yet our asymmetric and firm-specific moderating variables are aligned with the idea that mobile inventors create circumstances that enhance the probability of alliance formation. This was also confirmed by our qualitative insights about the role of mobile employees in changing organizational frames. Nonetheless, future research could also look at the role of inventor mobility on directional events like acquisitions or at the role of reverse mobility, i.e. inventors leaving the organization and joining a competitor.

Conclusion

Firms increasingly rely upon collaborative agreements with competitors to develop new products and processes. Forming alliances is the result of decision-making under uncertainty and organizational decisions are often made jointly based on a commonly shared decision frame. This study looks into how recruitment affects these decision frames and ultimately alliance formation. We find that hiring employees from a competitor is positively and significantly related to the likelihood of collaboration between the firm and this competitor. This relationship is stronger when these mobile employees bring more knowledge from their competitor, but weaker when a firm is already familiar with this knowledge. The results suggest that mobility and alliances are not separate or substitutionary instruments for acquiring external knowledge, but are interdependent and complementary.

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FIGURES AND TABLES

Table 1: Average values of the number of inventors moving from the competitor to the focal firm in the past five years and the occurrence of different types of alliances formed in the current year broken down by below and above the median value of mobility. Note: * denotes that the difference of the mean values is significantly different from zero at the 5% level.

Mobility no/yes (*t-5* to *t-1*)	**Freq.** (dyad-years)	**Number of inventors hired from alter** (mean)	**Tech-development alliances** (0/1, mean) R&D only	all	**Tech-transfer alliances** (0/1, mean) License
≤ median	8,274	0	0.012	0.018	0.011
> median	3,228	2.550	0.024*	0.028*	0.011
Total	11,502	0.716	0.015	0.021	0.011

Table 2: Probit regressions relating the occurrence of different types of alliances to inventor mobility. Robust standard errors have been clustered on the level of the dyad, the focal firm and the competitor (three-way clustering) and are reported in parentheses. Further, we also report the results from logistic regression in which we instrumented inventor mobility in italics (IV). Note that for the interaction terms we plot marginal effects at the mean in Figures 1 and 2.

	Technology-development alliances								Technology-transfer alliances			
DV: Allicance formation	R&D alliance only				Pooled				License			
	(1)		(2)		(3)		(4)		(5)		(6)	
		IV		IV		IV		IV		IV		IV
Mobility	0.1426*	0.1367*	0.2416*	0.2139**	0.0444	0.0358	0.1318	0.1052	0.0589	0.0545	0.1931	0.0510
	(0.0745)	(0.0723)	(0.1273)	(0.0993)	(0.0695)	(0.0709)	(0.1158)	(0.0950)	(0.0990)	(0.0995)	(0.1179)	(0.1355)
Familiarity	0.2021***	0.2005***	0.2996***	0.3045***	0.2081**	0.2069**	0.3016***	0.3157***	0.3873***	0.3869***	0.4074***	0.3032***
	(0.0679)	(0.0696)	(0.0790)	(0.1056)	(0.0838)	(0.0891)	(0.1029)	(0.0930)	(0.1273)	(0.0936)	(0.1331)	(0.1005)
Firm-specific knowledge	0.0095	0.0097	0.0031	0.0031	0.0081	0.0083	-0.0060	-0.0081	-0.0215	-0.0210	0.0025	0.0843*
	(0.0120)	(0.0116)	(0.0136)	(0.0118)	(0.0082)	(0.0085)	(0.0131)	(0.0149)	(0.0131)	(0.0159)	(0.0293)	(0.0478)
Mobility			-0.2653*	-0.2958**			-0.2935**	-0.3391***			-0.1342	0.2943
***Familiarity**			(0.1597)	(0.1252)			(0.1424)	(0.1199)			(0.2542)	(0.2202)
Mobility			0.0086	0.0095			0.0175	0.0203*			-0.0286	-0.1202**
*** Firm-specific knowledge**			(0.0119)	(0.0110)			(0.0141)	(0.0106)			(0.0310)	(0.0531)
Tech. convergence	-0.5206**	-0.5197**	-0.5169**	-0.5115**	-0.0672	-0.0666	-0.0630	-0.0566	0.2964	0.2964	0.3036	0.2764
	(0.2100)	(0.2093)	(0.2064)	(0.2049)	(0.1929)	(0.1932)	(0.1905)	(0.1988)	(0.2366)	(0.2364)	(0.2311)	(0.2282)
Tech. distance	-0.2281	-0.2294	-0.2176	-0.2139	-0.3926*	-0.3936*	-0.3801*	-0.3740*	0.0418	0.0412	0.0518	0.0244
	(0.2183)	(0.2199)	(0.2188)	(0.2220)	(0.2165)	(0.2179)	(0.2164)	(0.2174)	(0.2439)	(0.2444)	(0.2434)	(0.2440)
Geogr. distance	0.0121	0.0121	0.0119	0.0111	0.0034	0.0033	0.0034	0.0027	0.0027	0.0027	0.0023	0.0014
	(0.0120)	(0.0125)	(0.0126)	(0.0127)	(0.0129)	(0.0116)	(0.0128)	(0.0119)	(0.0094)	(0.0103)	(0.0106)	(0.0118)
Prior	0.0689	0.0680	0.0680	0.0729	0.0805	0.0798	0.0812	0.0848	0.2492***	0.2494***	0.2459***	0.2362***
Alliances	(0.0816)	(0.0830)	(0.0816)	(0.0862)	(0.0713)	(0.0715)	(0.0704)	(0.0733)	(0.0808)	(0.0807)	(0.0816)	(0.0853)
Firm characteristics (focal)	YES		YES		YES		YES		YES		YES	
Firm characteristics (competitor)	YES		YES		YES		YES		YES		YES	
Year dummies	YES		YES		YES		YES		YES		YES	
Obs.	11142		11142		11142		11142		10128		10128	

All development alliances

***) significantly different from zero on the 1% level, **) significantly different from zero on the 5% level, *) significantly different from zero on the 10% level.

Figure 1: Marginal effects at the mean (MEM) of mobility for different values of inventor firm-specific knowledge. The graphs correspond to columns 2, 4, and 6 of Table 2.

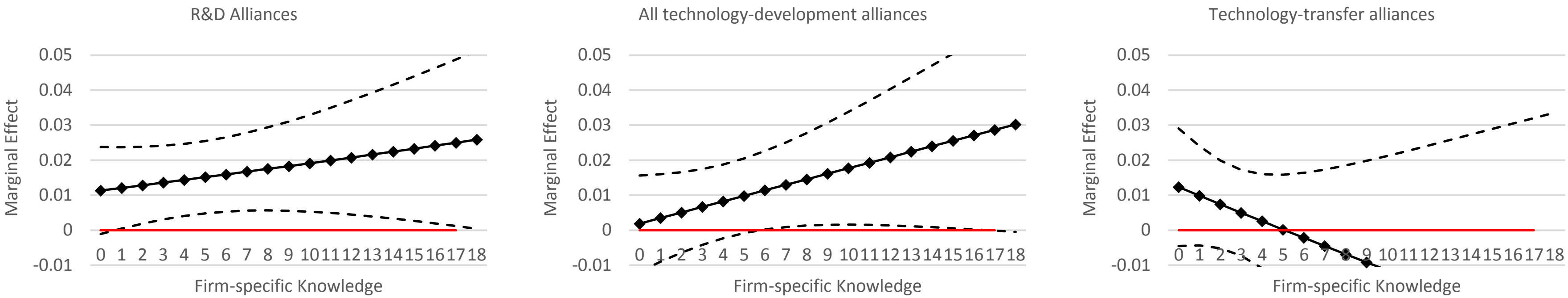
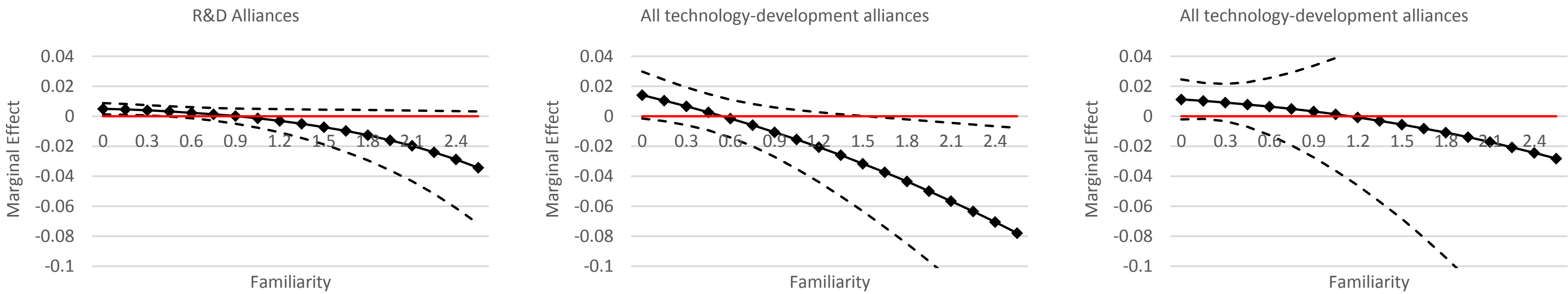


Figure 2: Marginal effects at the mean (MEM) of mobility for different values of firm-competitor technological familiarity. The graphs correspond to columns 2, 4, and 6 of Table 2.



APPENDIX A

Table A1: Logit regressions that relate the occurrence of different types of alliances to inventor mobility. Robust standard errors have been clustered on the level of the dyad, the focal firm and the competitor (three-way clustering) and are reported in parentheses. Further, we report marginal effects at the mean and their standard errors for our key variables mobility, inventor firm-specific knowledge and firm technological familiarity below the coefficient estimates in parentheses and italics. Note that for interaction terms we do not report marginal values but rather plot them (see Figures 1 and 2).

	Tech-development alliances				**Tech-transfer alliances**	
	R&D alliance only		**All development**		**License**	
	(1)	(2)	(3)	(4)	(5)	(6)
Mobility	**0.1426***	**0.2416***	**0.0444**	**0.1318**	**0.0589**	**0.1931**
	(0.0745)	**(0.1273)**	**(0.0695)**	**(0.1158)**	**(0.0990)**	**(0.1179)**
Marg. effect	*0.0117**	*0.0128***	*0.0041*	*0.0046*	*0.0048*	*0.0087*
	(0.0061)	*(0.0069)*	*(0.0025)*	*(0.0073)*	*(0.0082)*	*(0.0080)*
Familiarity	0.2021***	0.2996***	0.2081**	0.3016***	0.3873***	0.4074***
	(0.0679)	(0.0790)	(0.0838)	(0.1029)	(0.1273)	(0.1331)
Marg. effect	*0.0166****	*0.0181****	*0.0193***	*0.0200***	*0.0318***	*0.0305****
	(0.0056)	*(0.0052)*	*(0.0078)*	*(0.0080)*	*(0.0104)*	*(0.0110)*
Firm-specific knowledge	0.0095	0.0031	0.0081	-0.0060	-0.0215	0.0025
	(0.0120)	(0.0136)	(0.0082)	(0.0131)	(0.0131)	(0.0293)
Marg. effect	*0.0008*	*0.0005*	*0.0007*	*-0.0001*	*-0.0018**	*-0.0004*
	(0.0010)	*(0.0010)*	*(0.0008)*	*(0.0010)*	*(0.0011)*	*(0.0018)*
Mobility		**-0.2653***		**-0.2935****		**-0.1342**
***Familiarity**		**(0.1597)**		**(0.1424)**		**(0.2542)**
Mobility		**0.0086**		**0.0175**		**-0.0286**
*** Firm-specific knowl.**		**(0.0119)**		**(0.0141)**		**(0.0310)**
Tech. convergence	-0.5206**	-0.5169**	-0.0672	-0.0630	0.2964	0.3036
	(0.2100)	(0.2064)	(0.1929)	(0.1950)	(0.2366)	(0.2311)
Tech. distance	-0.2281	-0.2176	-0.3926*	-0.3801*	0.0418	0.0518
	(0.2183)	(0.2188)	(0.2165)	(0.2164)	(0.2439)	(0.2434)
Geogr. distance	0.0121	0.0119	0.0034	0.0034	0.0027	0.0023
	(0.0120)	(0.0126)	(0.0129)	(0.0128)	(0.0094)	(0.0106)
Prior	0.0689	0.0680	0.0805	0.0812	0.2492***	0.2459***
alliances	(0.0816)	(0.0816)	(0.0713)	(0.0704)	(0.0808)	(0.0816)
Firm characteristics (focal)	YES	YES	YES	YES	YES	YES
Firm characteristics (competitor)	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES
Obs.	11142	11142	11142	11142	10128	10128

***) significantly different from zero on the 1% level, **) significantly different from zero on the 5% level, *) significantly different from zero on the 10% level.

Table A2: Two-stage instrumental variables probit regression coefficients that relate the occurrence of different types of alliances to inventor mobility. Robust standard errors have been clustered on the dyad level and are reported in parentheses. For the second-stage regressions we report Wald-tests of the null-hypothesis of instrument exogeneity. For the first-stage regressions we report F-statistics of instrument strength.

	Tech-development alliances				**Tech-transfer alliances**	
	R&D alliance only		**All development**		**License**	
	(1)	(2)	(3)	(4)	(5)	(6)
	Second-stage estimates (Alliance formation 0/1)					
Mobility	0.1367*	0.2139**	0.0358	0.1052	0.0545	0.0510
	(0.0723)	(0.0993)	(0.0709)	(0.0950)	(0.0995)	(0.1355)
Familiarity	0.2005***	0.3045***	0.2069**	0.3157***	0.3869***	0.3032***
	(0.0696)	(0.1056)	(0.0891)	(0.0930)	(0.0936)	(0.1005)
Firm-specific knowledge	0.0097	0.0031	0.0083	-0.0081	-0.0210	0.0843*
	(0.0116)	(0.0118)	(0.0085)	(0.0119)	(0.0159)	(0.0478)
Mobility		**-0.2958****		**-0.3391*****		**0.2943**
***Familiarity**		**(0.1252)**		**(0.1199)**		**(0.2202)**
Mobility		**0.0095**		**0.0203***		**-0.1202****
*** Firm-specific knowledge**		**(0.0110)**		**(0.0106)**		**(0.0531)**
Dyad level characteristics	YES	YES	YES	YES	YES	YES
Firm characteristics (focal)	YES	YES	YES	YES	YES	YES
Firm characteristics (competitor)	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES
Wald test of exogeneity (p-value)	0.6086	0.1072	0.6070	0.0937	0.8620	0.0527
Obs.	11,142	11,142	11,142	11,142	10,128	10,128

	First-stage estimates for instrumented variables (excluded instruments only)			
	Mobility		Mobility*Familiarity	Mobility*Knowledge
First stage of columns	(1,3,5)	(2,4,6)	(2,4,6)	(2,4,6)
Mobility (total industry)	0.0013***	0.0011***	0.0006***	0.0002
	(0.0000)	(0.0000)	(0.0000)	(0.0002)
Mobility (dyad, squared)	0.3142***	0.3794***	-0.0790***	-0.1952*
	(0.0128)	(0.0172)	(0.0106)	(0.1045)
Mobility (total industry)*Famil.		-0.0068	0.5009***	0.1950
		(0.0167)	(0.0202)	(0.1432)
Mobility (total industry)*Knowl.		-0.0073***	-0.0039***	0.3043***
		(0.0012)	(0.0007)	(0.0138)
Weak identification F-statistic	11714.21	2322.24	333.71	2836.47

***) significantly different from zero on the 1% level, **) significantly different from zero on the 5% level, *) significantly different from zero on the 10% level.

Table A3: Descriptive statistics and correlation coefficients

		Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	18	19
1	R&D alliance (0/1)	0.015	0.119	1.00																	
2	Technology-development alliance (0/1)	0.021	0.143	0.83	1.00																
3	Technology-transfer alliance (0/1)	0.011	0.102	0.19	0.41	1.00															
4	Mobility (log)	0.308	0.565	0.05	0.04	0.00	1.00														
5	Firm-specific knowledge	1.781	4.225	0.03	0.02	-0.01	0.66	1.00													
6	Tech. convergence	0.037	0.143	-0.01	0.00	0.02	0.01	0.04	1.00												
7	Tech. distance	0.464	0.261	-0.01	-0.03	-0.02	-0.15	-0.15	-0.34	1.00											
8	Distance (1000km)	4.015	3.292	0.00	-0.01	0.00	-0.12	-0.09	0.04	-0.08	1.00										
9	Familiarity (log)	0.385	0.370	0.03	0.03	0.03	0.29	0.26	0.07	-0.32	-0.04	1.00									
10	Prior alliances	0.117	0.365	0.02	0.02	0.03	0.15	0.12	-0.01	-0.06	-0.03	0.14	1.00								
12	Firm patents (1000s)	0.216	0.231	0.02	0.02	-0.01	0.31	0.20	-0.12	0.25	0.00	-0.13	0.07	1.00							
13	Firm citations received (1000s)	10.140	9.680	0.02	0.01	-0.01	0.45	0.36	-0.06	0.07	0.00	0.04	0.12	0.74	1.00						
14	Firm R&D intensity	0.104	0.047	0.00	0.00	0.02	0.10	0.14	0.13	-0.41	0.00	0.26	0.05	-0.26	0.04	1.00					
15	Firm employees (1000s)	0.056	0.040	0.02	0.02	0.00	0.25	0.14	-0.14	0.22	-0.05	-0.14	0.06	0.80	0.60	-0.37	1.00				
16	Competitor patents (1000s)	0.216	0.231	0.02	0.02	-0.01	0.25	0.18	-0.12	0.25	0.00	0.44	0.07	0.05	0.15	0.07	0.02	1.00			
17	Competitor citations received (1000s)	10.140	9.680	0.02	0.01	-0.01	0.44	0.35	-0.06	0.07	0.00	0.52	0.12	0.15	0.35	0.11	0.08	0.74	1.00		
18	Competitor R&D intensity	0.104	0.047	0.00	0.00	0.02	0.11	0.10	0.13	-0.41	0.00	0.11	0.05	0.07	0.11	-0.01	0.04	-0.26	0.04	1.00	
19	Competitor employees (1000s)	0.056	0.040	0.02	0.02	0.00	0.22	0.15	-0.14	0.22	-0.05	0.38	0.06	0.02	0.08	0.04	-0.01	0.80	0.60	-0.37	1.00

APPENDIX B

Purpose

We performed explorative interviews with 15 R&D managers and scientists in the biopharmaceutical field, which covers pharmaceuticals, medical devices and biotech. This served three purposes. First, we verified the assumptions we derived from other studies about the nature of the R&D process and the role of scientists therein. Second, we explored the detailed processes related to scientific collaboration, interorganizational alliances, and employee mobility. Third, we performed two follow-up interviews to gain in-depth insights into the relationship between alliance formation and mobile scientists.

Methodology and structure

These interviews were initially exploratory in nature and have been conducted prior to and during the data collection process for this study. A few follow-up interviews were conducted during this study's review process and these were semi-structured in nature and lasted from 45 minutes to almost two hours. The topics covered during the interviews included the firm's R&D process, the origin of scientists' knowledge, functioning of alliances, mobility of employees, and the role of connections. The topics varied by respondent given their role and function. For example, the leading questions regarding alliances were:

- *What was the objective, structure and duration of the alliance?*
- *How was the alliance formed, how was the partner selected and who were involved in this?*
- *How and at which stage did individual scientists get involved in this alliance?*
- *Were the same scientists involved in the alliance continuously? How did the alliance deal with employees joining/leaving the organization?*

The answers to these questions often invoked follow-up questions going into more detail about considerations, processes and mechanisms. Interviews were transcribed though no formal analysis of these transcripts was performed as our study primarily is based on econometric analysis of dyad-level characteristics as presented in the main body of the paper.

Respondents

Table B1 below gives a short overview of the interviewees. For confidentiality reasons, we cannot disclose their names or corporation, so we provide a more generic description about their role and organization. Though a large fraction currently performs managerial tasks, nearly all had a background as research scientists and worked in such positions before moving to their current role.

Table B1: Overview of interviewees

#	Type of organization	Role of interviewee	Topics discussed
1	Mid-sized American pharmaceutical firm	Alliance manager	Alliances (partners, formation, management, dissolution, role of scientists); Scientists (HR, mobility)
2	Large American pharmaceutical firm	Principal scientist	Scientists (role within the firm, knowledge sharing mechanisms); Alliances (creation, role of scientists therein, contracts)
3	Large American CRO (contract research organization)	Manager	Partnerships (creation, contracts, management); Scientists (social networks, mobility, knowledge spillovers); Intellectual property (secrecy, patents)
4	Large American pharmaceutical firm	Director of M&A and Alliances	Alliance management (partner selection, negotiations, management, and role of scientists therein)
5	Small European medical device firm	Head of R&D	Scientists (activities, recruitment and mobility, knowledge sharing); Alliances (formation, management)
6	Large American medical device firm	Principal scientist	R&D process (activities, role of individual scientists and teams); Alliances (role of scientists in alliances)
7	Large American medical device firm	Senior principal scientist	R&D activities (management, process, role of scientists); Partnerships (role of scientists)
8	European pharmaceutical start-up	Director, founder, scientist	R&D management (role of scientists, alliances, CROs)
9	Mid-size American pharmaceutical firm	R&D scientist and manager	R&D scientists (roles, responsibilities, information sources, social networks, mobility); Alliances
10	Large American medical device firm	Lead project manager	R&D activities (process, project management); Partnerships (partner selection, process management)
11	Large American pharmaceutical firm	Associate director	Product development (R&D process, role of individuals, role of partnerships)
12	Large American pharmaceutical firm	New product development manager	Alliances (partner selection, role of scientists in alliances, managing partnerships)
13	Mid-size American pharmaceutical firm	Head of alliances	Role of scientists in partnership (creation, execution)
14	Large European pharmaceutical firm	Head of Business Unit, former VP of Business Development	Alliances (partner selection, role of scientists in alliances, managing partnerships)
15	Mid-size European biotech firm	CEO, Founder	Alliances (partner selection, role of scientists in alliances, managing partnerships)
Note: this overview is limited to the interviewees that were relevant for this study			

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