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Departamento de Economía de la Empresa
Universidad Carlos III de Madrid
Calle Madrid, 126
28903 Getafe (Spain)
Fax (34-91) 6249607

The Strategic Allocation of Inventors to R&D Collaborations*

Neus Palomeras[1]
David Wehrheim[2]

Abstract

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Keywords*:* R&D, collaboration, technology leakage, co-patents, inventors

JEL Classification*:* J24, L65, O31, O32, O34

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[1] Department of Business Administration, Universidad Carlos III de Madrid, Calle Madrid 126, 28903 Getafe (Madrid), Spain; E-Mail: neus.palomeras@uc3m.es.

[2] Department of Business Administration, Universidad Carlos III de Madrid, Calle Madrid 126, 28903 Getafe (Madrid), Spain; E-Mail: davidalexander.wehrheim@uc3m.es.

The Strategic Allocation of Inventors to R&D Collaborations*

Neus Palomeras[†] and David Wehrheim[‡]

Department of Business Administration, Universidad Carlos III de Madrid, Spain

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ABSTRACT

Safeguarding against unintended leakage of valuable knowledge in R&D collaboration requires careful attention to the role of inventors participating in these collaborations. In this paper, we claim that the degree of protection of the knowledge embodied by inventors affects how an opportunistic partner can use this information when technology leakage occurs. The implication is that those inventors whose set of knowledge is more protected are more likely to be assigned to joint activities than their co-workers. By relying on patent ownership and authorship data, we analyze the allocation of inventors to collaborative projects from a sample of large pharmaceutical firms. Our results confirm that inventors are strategically allocated to projects according to their degree of preemptive power.

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[†]Correspondence to: Neus Palomeras, Department of Business Administration, Universidad Carlos III de Madrid, Calle Madrid 126, 28903 Getafe (Madrid), Spain; Tel.: +34916249892; Fax: +34916249607; E-Mail: neus.palomeras@uc3m.es.

[‡]E-Mail: davidalexander.wehrheim@uc3m.es.

INTRODUCTION

Over the last few decades, inter-organizational research and development (R&D) partnerships have increased at a dramatic rate. From the early 1980s until the mid-2000s, the National Science Foundation (NSF, 2010) reports an increase of 350 percent in the number of technology alliances formed by U.S. and multinational companies, the majority being non-equity based agreements. Interestingly, the sector that represents the bulk of these alliances from the early 2000s is biotechnology. In related industries such as pharmaceuticals, big players like Merck started at the beginning of the 2000s to aggressively pursue alliance opportunities to feed its pipeline.

It is a well-established fact that a firm taking part in an alliance faces a delicate trade-off regarding the type and amount of information it shares with its partner. On the one hand, the firm has to share knowledge in order to contribute to the success of the alliance. On the other hand, it has to safeguard critical knowledge so that its partner cannot take advantage of it to compete in the future. Unintended information leakage is a very tangible risk that firms face in collaborations and, therefore, a challenge in the management of alliances. This dilemma is especially relevant in R&D collaborations, where knowledge sharing is a very central part of the alliance. Previous literature has emphasized different instruments that help to mitigate the aforementioned risk. One is partner selection, where trust is paramount (Gulati, 1995). Another is the choice of the scope of the alliance (Oxley and Sampson, 2004), by which exposure of critical knowledge can be limited. Last, but not least, is the design of alliance governance mechanisms, ranging from the choice of the organizational form (joint ventures vs. contractual arrangements) to the implementation of hierarchical controls and administrative bodies that regulate the alliance (Reuer and Devarakonda, 2012).

In this paper, we focus on one key decision concerning the protection against the consequences of unintended knowledge leakage in R&D alliances: the selection of the participating employees. We view R&D employees (i.e., inventors) working hand in hand with the R&D employees of the partner firm as the critical factor in safeguarding sensitive information in an R&D alliance. We suggest that the type of knowledge embodied by inventors affects the threat posed by unintended information leakage. Specifically, we claim that inventors who hold knowledge that is better safeguarded against potential imitation by competitors represent a lower threat in the event that technology leakage occurs. Therefore, we expect that managers will tend to allocate such inventors to collaborative projects.

Previous research acknowledges that employees are an important conduit for unintended sharing of knowledge in cooperative agreements. In a series of case studies on alliances, Hamel et al. (1989) first note that operating employees in the front line determine the information that gets traded. Oxley and Wada (2009) and Reuer and Devarakonda (2012) state that uncodified know-how may leak through informal interactions between the personnel involved in an R&D alliance. Participating firms try to control these flows of information between employees and, therefore, the associated potential unintended knowledge leakage. In particular, previous literature points to the use of different types of formal and informal practices, committees or organizational structures that aim to control the amount and type of information that is shared with the alliance partner (among other objectives). Hamel et al. (1989) underline the importance of implementing practices such as advising employees about the valuable information that should not be shared. Oxley and Wada (2009) suggest that alliances organized as joint ventures make it possible to enforce employee conduct rules and manage employee movements, thus limiting informal interactions. These types of monitoring mechanisms can also be replicated in non-equity alliances through the creation of committee structures (Reuer and Devarakonda, 2012). However, to date the literature has not addressed the strategy of directly intervening in the selection of employees in order to mitigate the risk of leakage. This is despite the fact that innovation studies have shown that inventors play a key role in inter-organizational knowledge transfer and, consequently, in firm learning and innovativeness (Agrawal et al., 2014; Almeida and Kogut, 1999; Nerkar and Paruchuri, 2005; Palomeras and Melero, 2010; Paruchuri, 2010; Rosenkopf and Almeida, 2003; Singh, 2007; Song et al., 2003). Therefore, a closer examination of the inventors that participate in R&D collaboration appears to be a promising direction to address the risk of misappropriation and knowledge leakage.

Studies on inter-organizational knowledge exchange at the individual level are rare. Existing contributions focus on self-reported individual characteristics and outcomes. In an unpublished paper on the medical devices industry, Lofstrom (2000) collects data on at least one key R&D worker from each partner involved in an alliance, and studies several factors that influence the extent to which individuals learn through alliances. His main finding suggests that learning is related to individuals' social and human capital. In a recent dissertation, Wang (2015) takes a network perspective to examine individual performance using employee survey data from an alliance between a company producing fuel cells and a research institute. Her conclusions underline the importance of job experience, centrality in the formal network and motivation as determinants of individuals' contribution to the alliance. These pieces of research, nevertheless, take teams of employees participating in alliances as given. Unlike our study, they do not address the risk of technology leakage nor the decision to allocate particular employees to alliances.

This paper contributes to the literature on R&D alliances, specifically to the stream that focuses on the mechanisms that partner firms use to minimize the risk of information leakage. We posit that firms going into collaboration select inventors who hold knowledge that is more protected because, in the event of leakage, the competitor will not be able to use this knowledge effectively. To the best of our knowledge, this is the first systematic study that analyses R&D alliances from an individual perspective, i.e., taking as the unit of observation the researchers involved in such collaborations. To this end, we rely on inventor data retrieved from patent documents in the pharmaceutical industry, where collaborations are frequent and innovative output is usually patented. Patent documents allow us to detect: (i) collaborative projects through co-assignments, i.e., patents where more than one institution share the patent holder rights, (ii) inventors participating in these co-assigned patents, and (iii) characteristics of the inventors' knowledge background, including the degree of protection afforded by the patents protecting their innovation portfolio. We examine a sample of large pharmaceutical firms and their patenting activities from 1990 to 2005. Our results suggest that inventors whose knowledge has a higher degree of preemptive power, i.e., that is more protected against potential inventing-around by competitors, are more likely to be allocated to collaborative activities. We find that this effect is more salient for central inventors in the intra-firm co-inventing network and more pronounced when the partner is less trustworthy. These findings suggest that the allocation of inventors is an important factor for reducing the information leakage risk associated with an alliance. Finally, we examine the performance implications resulting from the collaboration and find that the participation of inventors with higher preemptive power is associated with higher-quality innovation outputs. We theorize that this is because of an increased willingness to efficiently share knowledge between partners, since appropriability concerns and uncertainties involved in information sharing are mitigated.

THEORY

One of the main concerns for innovative firms is the risk of not being able to appropriate the returns of their investment in R&D. One of the determinants for this risk is the competitors' ability to replicate knowledge (Teece, 1986). Thus, when a firm engages in an alliance and exposes some of its body of information to its partner (part voluntarily and part unintendedly), it is likely that the partner learns how to replicate this knowledge, undermining the originating firm's appropriability. This is a real risk that firms face when entering into an alliance and something they have to weigh against the value of the synergistic knowledge that the alliance can yield (Arora and Merges, 2004; Katila et al., 2008). The firm's decision to enter into an alliance will largely depend on its ability to minimize this threat. This, in turn, depends on two factors: (i) preventing/reducing leakage of alliance-unrelated knowledge, and/or (ii) preventing partners from using knowledge that has been transferred voluntarily or involuntarily.

Avoiding leakage is a matter of constricting knowledge flows to those strictly related to the success of the alliance. This is achieved by organizational structures that can establish mechanisms for tightly controlling the knowledge that flows to the partner (Oxley and Wada, 2009; Reuer and Devarakonda, 2012). These mechanisms are designed to control the activity of managers and operating employees who interact with the partner and who are the actual conduits for the transfer of information (Hamel et al., 1989; Janowicz-Panjaitan and Noorderhaven, 2008). The sharing of information can be easily monitored when it is contained in (and, therefore, probably also transferred through) blueprints and other documents. If the information is non-codified, it is more difficult to establish boundaries to its transfer. This is especially the case if this knowledge involves tacit elements. The tacit dimension of a given piece of knowledge is usually transmitted inherently when working together with the individuals who embody it – these can be the creators of the underlying knowledge or other individuals who learned it through interactions with the creators or previous learners (Zucker et al., 2002). Therefore, in organizationally embedded collaborations, where individuals from both partners interact repeatedly in an organizational setting, tacit know-how is easily transmitted across firm boundaries (Kogut, 1988). This makes it difficult to limit its flow and even to realize the extent to which it is being transferred, making it especially prone to unintended leakage. Some alliance structures such as joint ventures constrain knowledge sharing to strictly formalized channels, and, consequently, limit tacit knowledge flows to the strict domain of the alliance (Oxley and Wada, 2009). Ultimately, nonetheless, the knowledge embodied by the personnel directly involved in the alliance is the key determinant of the potential risk of knowledge leakage. Their tacit knowledge, both related and unrelated to the alliance, is almost inevitably exposed to the partner (Oxley and Sampson, 2004). Consequently, the assignment of R&D personnel to alliances plays a crucial role in determining the knowledge that the firm puts at risk.

The extent to which leakage can harm the firm will depend on whether competitors end up using this knowledge. Firms involved in an alliance have a range of options to prevent partners from using the transferred knowledge to compete outside the alliance. One of these mechanisms is to select a partner the firm can trust. This would typically involve either an actor who has developed a strong reputation as a reliable collaborator (Gulati, 1995; Li et al., 2008) or some player who has less incentives to appropriate other firm's knowledge because of limited opportunities outside the focal alliance (Diestre and

Rajagopalan, 2012). Another mechanism is the use of formal intellectual property protection. Patents, in particular, make transactions in the market for technology smoother because parties are protected against appropriability hazards (Arora et al., 2001). Having the firm's technology patented also affects the likelihood of engaging in different types of cooperative agreements, as Gans et al. (2002) point out for the case of start-ups. In a more macro perspective, the effectiveness of intellectual property protection in a given sector seems not to significantly affect the likelihood of cooperating (Bönte and Keilbach, 2005), but it significantly reduces the likelihood that an alliance will fail (Lhuillery and Pfister, 2009). According to Oxley (1999), in the absence of effective protection of intellectual property rights, firms are likely to use other mechanisms, such as hierarchical governance forms, to give the partner the right incentives with respect to the use of the counterparty's technology.

The strength of an individual patent depends on its power to keep competitors at a distance in the technological space, meaning that their products will be well differentiated. This power is determined both by the intrinsic characteristics of the underlying technology (Cohen et al., 2000) and by the firm's patenting strategy. Firms, for instance, may decide to patent broad claims or to build "patent fences" by patenting close substitutes in order to deter competitors' entry into the market (Ziedonis, 2004), which is commonly referred to as "preemptive patenting". Ceccagnoli (2009) shows that both the effectiveness of protection that a patent confers against the imitation of the firm's innovations and the firm's use of preemptive patenting increase the market valuation of its R&D assets. In the same line, Czarnitzki et al. (2011) suggest that patents that effectively block competitors confer an important competitive advantage to their owner, which translates into a substantial boost of the firm's market value. Findings by Grimpe and Hussinger (2014) indicate that this competitive advantage also generates a higher valuation of the firm if it becomes a target in the market for M&As. Therefore, we expect that in the context of alliances in which firms share knowledge with potential competitors, the preemptive power associated to this knowledge is especially relevant as a protection mechanism against its appropriation by competitors.[1]

To sum up, we know that, on the one hand, the knowledge embodied by the R&D personnel assigned to alliances is what the firm puts at risk in the collaboration. This selection is, in turn, determined by the knowledge needs of the alliance but it likely includes other knowledge unrelated to it. On the other hand, we know that, if knowledge is covered by strong patents, its use by the competitor is effectively blocked. Therefore, even if leakage happens, the competitor will be unable to appropriate the returns from its partners' knowledge. Consequently, the more protected is the set of knowledge exposed to the partner, the lower is the threat posed by information sharing in general and unintended information leakage in particular. In this setting, the degree of protection of the knowledge embodied by a given R&D employee becomes a relevant factor in assessing the risk a firm incurs when allocating him to a collaborative project. Managers are thus likely to allocate those inventors to external collaborative projects whose knowledge set is strongly protected, i.e., has a high degree of preemptive power. Hence, the more protected is an inventor's set of knowledge, the more likely he is to be assigned to an external collaborative project that has to be staffed.

HYPOTHESIS 1 (H1): The greater the preemptive power of an inventor's set of knowledge, the more likely he is to be assigned to a collaborative project.

If an inventor's preemptive power acts as a mean of protection in collaboration, we should observe that its effect on the likelihood that an inventor is allocated to a collaborative project is more relevant in situations where the risk of misappropriation by the partner is larger. We next propose two characteristics that entail different levels of misappropriation risk: (i) the centrality of an inventor in the intra-firm collaboration network, and (ii) the trustworthiness of the collaboration partner.

[1] Note that we use the term "preemptive power" to define the blocking power of patents, regardless of whether the firm purposely uses patents to preempt rivals or not.

Inventor's structural centrality

Earlier research has shown that inventors who occupy a more central position the intra-firm co-inventing network have superior access to information and knowledge (Bonacich, 1987), a higher perception of their quality and a greater number of patent citations made to them (Podolny, 2001; Podolny et al., 1996); moreover, they have a significant influence on the selection of the firm's technological path (Nerkar and Paruchuri, 2005) and a greater impact on the quality of their firm's innovative outputs (Paruchuri, 2010). On the one hand, these findings highlight the potential benefits that such inventors could bring for the success of a collaboration, in terms of highly valuable contributions. On the other hand, their central position is associated with substantial challenges in terms of the risk of technology leakage. Specifically, their access to a large amount and variety of internal information increases the risk that critical information is exposed to the partner. At the same time, the amount of knowledge they put at risk reduces the decision makers' ability to identify and control unintended transfers of important knowledge to collaboration partners (Hwang and Lin, 1999; O'Reilly, 1980). In contrast, inventors occupying a less central position have (and can, therefore, potentially expose to the partner) a far smaller amount of information, which managers are also better able to assess and control. These conflicting effects related to an inventor's degree of centrality prevent us from making an unequivocal prediction regarding the impact on his likelihood of being assigned to collaboration. However, the fact that centrality is associated with a higher leakage risk suggests that the role of preemptive power in collaborations is likely to be particularly large in the case of central inventors. Hence:

> *HYPOTHESIS 2 (H2): The effect of preemptive power of an inventor's set of knowledge on his likelihood of being assigned to a collaborative project is positively moderated by his level of centrality in the intra-firm inventive network.*

Partner-specific and general collaboration experience

As previously mentioned, the selection of a trusted partner in a collaboration may help to minimize the risks of knowledge misappropriation in an alliance. Trusted partners are usually those who have developed a strong reputation in previous collaborations after multiple interactions either with the focal firm (Dyer and Singh, 1998; Gulati, 1995; Li et al., 2008) or with other firms. Specifically, Hitt et al. (2006) reveal that prior ties with the focal firm are positively related to larger contracts in dollar value terms, suggesting that interactions over time lead to greater trust between partners. The network of collaborators in which a firm is embedded also internalizes information about the reliability and trustworthiness of a potential partner that interacts in the network (Gulati and Gargiulo, 1999). Moreover, the threat of reputational damage that a potential partner embedded in the network may face in the event of misappropriation provides disincentives to act opportunistically (Gulati and Gargiulo, 1999). In the specific setting of R&D collaborations in the pharmaceutical/biotechnology industry, Robinson and Stuart (2007) find that partners with stronger reputation in the community receive larger initial payments, less supervision and less detailed contracts when they engage in alliances. These findings suggest that reputation in the network leads to relationships based on trust, which allows to reduce control on the partner. This evidence conveys the idea that trusted partners reduce the need to guard against technology misappropriation risk. That is, even when the opportunity to act opportunistically may be available, reputed partners are more likely to refrain from doing so. Consequently, we expect that trust in an R&D collaboration should offset the need to allocate inventors with strong knowledge protection. In other words, since the consequences of knowledge leakage are much less dangerous in collaborations with known partners, firms will be less concerned about the degree of protection of the knowledge embodied by the inventors allocated to the collaboration. Conversely, alliances with unfamiliar collaborators pose higher risks of misappropriation, and, therefore, we posit that partners will seek greater protection of the knowledge exposed in the collaboration. Hence:

HYPOTHESIS 3 (H3): The preemptive power of an inventor's set of knowledge has a greater impact on the probability of his being assigned to collaborate with a non-trusted partner than with a trusted partner.

METHODOLOGY

Data

We chose to conduct our research in the pharmaceutical industry for several reasons. First, R&D collaborations are a significant feature of this sector (Arora and Gambardella, 1990; NSF, 2010). Second, patents are a meaningful measure of innovation in this industry given that they assure firms fairly strong protection of their intellectual assets (Cohen et al., 2000). As prior research indicates, pharmaceutical firms tend to patent most inventions (Levin et al., 1987). Through their patenting activities, we can identify firms' R&D activities, both internal and in collaboration with others, and the inventors participating in them. Patent documents also allow us to track these inventors back in time in order to reconstruct their work history and characterize their knowledge background.

Our sample consists of the 27 largest pharmaceutical firms in terms of R&D spending. This sample was drawn from the 2006 EU industrial R&D investment scoreboard, which provides listings of the 1000 most R&D-intensive EU and non-EU firms across all manufacturing industries.[2] We use the Worldwide Patent Statistical Database (Patstat, April 2012 edition) to examine the patenting activities of these firms during the period 1990 – 2005. Given that we need to use comparable patent data across firms, regardless of their country of origin, and given that large pharmaceutical patent applicants usually seek broad international protection, we rely on the patents filed at the European Patent Office (EPO). Since we rely on information on the co-ownership of patent applications to detect collaborative innovation activities (see next section), European patent data have one specific advantage over the United States Patent and Trademark Office (USPTO)

[2] See `http://iri.jrc.ec.europa.eu/scoreboard.html`.

data. While, in both jurisdictions multiple owners have the right to exploit the patented invention for their own purposes, co-owners in most national legislations in Europe keep control over the joint property right because they need each other's permission to license the patent (this is not the case under the U.S. regime, where each owner can execute his rights without the consent of co-assignees).[3] For this reason, co-patenting is less popular in the U.S. than in Europe as Fosfuri et al. (2012) underline, showing that the co-ownership of the same innovation is observed more frequently in Europe than in the U.S.

In order to reliably identify patenting activities that correspond to our sample firms, we need to trace each firm's history to account for any name change, acquisition, foundation or dissolution of entities as well as to identify all of its divisions, subsidiaries, and joint ventures.[4,5] We do so by using ownership links provided by Bureau van Dijk's (BVD) Amadeus database, 10-K reports filed with the Securities and Exchange Commission (SEC) in the U.S., corporate annual reports, and conventional internet sources. We then retrieve all patents filed by these firms between 1985 and 2005 (we use the priority year) in the pharmaceuticals category according to the International Patent Classification system (IPC class A61K, excluding cosmetics A61K8/*). The sample of patents we analyze starts in 1990, even though we collected information from 1985 onwards because we need prior information to allocate inventors to firms (as explained below). Our initial sample compromises 27,473 patent applications by 445 patent holders (i.e., assignees) for the period between 1990 and 2005.

We are able to identify the inventors listed in our set of patents through the EP-INV dataset.[6] This dataset allows robust identification of individual inventors across EPO

[3]See 35 U.S.C. 262 Joint owners and APPI's Group Reports Q194 for European countries.

[4]For example, by reconstructing the history of Novartis, we detect it was created through the merger agreement between Ciba-Geigy AG and Sandoz AG (dated 6 March, 1996), which were dissolved.

[5]Unfortunately, we had to exclude patent applications filed by joint ventures from our sample of patents because we were unable to allocate inventors to any of the individual firms forming the venture in most of the cases. In addition, most joint-venture patents are concentrated in a relatively small number of firms. Nonetheless, we use these patents to build the history of the participating inventors. We identify 216 patent applications assigned to joint ventures. Of these, around 66 percent were assigned to MSD Sharp & Dohme through their joint ventures with DuPont (DuPont Merck Pharmaceutical Company), Sanofi-Aventis (Merial) and Johnson & Johnson (Johnson & Johnson – Merck Consumer Pharmaceuticals).

[6]The latest version is available at http://www.esf-ape-inv.eu/index.php?page=3.

patent applications and granted patents published since 1978 (the start of the Patstat database), and, therefore, accurate identification of patenting histories, thanks to specific disambiguation algorithms for inventor data (see Pezzoni et al., 2014). In order to identify a given inventor as the employee of a given focal firm at a given point in time, we require him: (i) to be listed as inventor in at least one patent application where the focal firm is the only assignee in the previous five years (i.e., from $t-5$ to $t-1$), and (ii) not to be listed over the same time period in any other single-assigned patent application with another assignee (i.e., a non-focal assignee). Using these criteria, we identify a total of 10,448 inventors as R&D workers of our sample firms (representing 78 percent of the total number of inventors listed in our original sample of patents).[7]

Dependent variables

Co-assignment

Our main dependent variable, *co-assignment*, is designed to capture collaborative research activities. Co-assignment takes the value 1 if a given patent is co-assigned between one of our sample firms and another economic institution (e.g., firm, government-affiliated body, university, hospital or research institute) that is not part of the consolidated business group; and 0 otherwise.[8]

The evidence on the use of co-patenting underlines it as a significant phenomenon behind joint technology development, especially in industries with strong intellectual property regimes, such as chemicals and pharmaceuticals (Hagedoorn, 2003; Belderbos et al., 2014; Hohberger et al., 2015). Co-patents, though, may also reflect mere IP sharing arrangements instead of actual collaboration (Belderbos et al., 2014). In order to ensure that the co-patent status in our sample entails *real* collaborative efforts between partners, we retrieve additional information on R&D agreements for each pair of co-assignees. For each co-owned patent application, we determined whether it is the result of collaborative

[7]For robustness, we also used alternate ten- and three-year cut-off points. Our findings remain unaltered using those thresholds.

[8]Note that we also excluded patent applications that are jointly assigned solely with individuals. Patent applicant names referring to individual persons are identified by the patent allocation algorithm provided in Van Looy et al. (2006).

technology development efforts in several steps. First, we checked whether the entities in question have alliances on file in the SDC Platinum database. Otherwise, we manually checked corporate websites, SEC filings, industry and trade journals, and news reports.[9] Only co-patents for which we can identify a record of R&D collaboration are included in our final sample. Our extensive data collection efforts enabled us to identify 93 percent of all co-patent applications as the results of technological partnering activities.[10]

However, co-assigned patents are limited in the extent to which they can capture firms' collaboration behavior, since not all collective innovative efforts result in a joint patent. Survey evidence across Europe shows that 15 percent of patents are generated with external co-inventors while only around 6 percent are jointly filed by independent organizations (Giuri et al., 2007). However, Azzola et al. (2010) identify, on average, 5 times more technological collaboration per region when using co-patent data than data on publicly announced R&D alliances reported in the widely used MERIT-CATI database.

Partner-specific and general collaboration experience

We follow prior literature and build two categorical variables that proxy for the partner's collaboration experience. We identify previous collaborations through past co-patenting activities, either with the focal firm or other firms. First, we compute *partner-specific experience*, as in Li et al. (2008). Specifically, we use the number of co-patents filed for by a given dyad in the past five years to categorize each partner either as a *stranger* or *friend.* The variable is set to 1 when the partner had no patent co-assigned with the focal firm in the past five years (*stranger*); 2 when they have at least one common co-patent in the past five years (*friends*); and 3 when the project is a *solitary* activity. Second, we compute the partner's *general collaboration experience*, similarly to Hoang and Rothaermel (2005). We employ the partner's number of unique collaborators (excluding the focal firm) for a

[9] For example, consider the shared ownership of patent EP1347979 with a 2000 priority date between Roche (focal firm) and Vernalis, an integrated biopharmaceutical company. Our search reveals that the two companies entered into a research collaboration in 1999 to develop novel 5-HT2C receptor agonists as potential drugs for the treatment of obesity. Similarly, Novartis (focal firm) and the University of Zurich have a history of research on nerve regeneration solutions (e.g., by blocking Nogo-A). These efforts are reflected in co-patent EP1572745 with priority date in 2002.

[10] We also repeated all our regression analyses with the less restrictive approach of including co-patents with no publicly information available. This yields similar results to those presented here.

period of five years prior to the focal observation, and then split the sample into partners with *low* (= 1) and *high* (= 2) *reputation* in the collaboration market based on the sample median (4 partners). This variable also takes a value of 3 when the project is a *solitary* activity.[11]

Independent variables

Preemptive power

To test our theory, we need a measure that allows the decision maker to assess the extent to which an individual inventor's knowledge is protected. Our identification draws on information from the patent examination process at the EPO. Specifically, we exploit the fact that the EPO patent examiner prepares a detailed search report on the "prior art" upon which an invention is built in order to evaluate whether the patent application in question meets the patentability requirements.[12] The examination guidelines require that references to prior art are categorized according to their relevance for the patent application under examination, distinguishing between: (i) conflicting prior art, and (ii) relevant but non-conflicting prior art. In particular, the patent examiner indicates the nature of each piece of prior art with respect to the patent claims by assigning specific code letters, such as A, X or Y (Harhoff et al., 2005).

In this regard, while so-called "A references" refer to the state of art that pose no threat to the novelty of claims in the application, X and Y citations are potentially harmful. "X references" indicate that the invention in question (or any of its individual claims) might not be considered to be novel if the referenced document is taken into account on its own. "Y references" are applicable if the invention (or any of its individual claims) might not be considered to involve an inventive step when the referenced document is

[11] Note that, for collaborative interactions that involve two or more partners, we are not able to compute to compute the abovementioned variables, since each partner may have a different status. This, however, affects only 4 percent of co-patents in our sample (which are dropped for this part of the analysis).

[12] Patent applicants at the EPO are not required to report relevant prior art in the application. In consequence, about 90 percent of all patent citations in EPO patents are added by the patent examiner (Criscuolo and Verspagen, 2008). The search for prior art follows the *Guidelines for Examination in the European Patent Office*. These guidelines are available at http://www.epo.org/law-practice/legal-texts/guidelines.html.

combined with one or more other documents of the same category, such combination being obvious to a person skilled in the art (Criscuolo and Verspagen, 2008; Harhoff et al., 2005). Hence, XY-type references refer to conflicting prior art and are considered as "blocking citations". The patent may still be granted in those cases because the conflict may reside in only some of its claims (this is usually the case).

Previous research has shown that patents citing prior art classified as an XY-type have a lower probability of being granted, are more often withdrawn by the applicant before the EPO has made a decision (Guellec et al., 2012), and have a higher probability of facing opposition after granting (Harhoff and Reitzig, 2004). The literature, therefore, concludes that XY-cited patents exhibit higher preemptive power than other patents. Czarnitzki et al. (2011) and Grimpe and Hussinger (2014) aggregate the share of XY-type citations received by the patents owned by a given firm in order to measure the firm's degree of preemptive power.

Similarly, in order to determine individual-level *preemptive power*, for every inventor i at every time t in our data, we take the number of XY-type citations that the individual inventor's patent portfolio receives with respect to the total number of citations received up to (but excluding) year t.[13] The variable's range is between zero and one. The larger the value of this variable, the higher is the extent to which inventors' patents blocked subsequent patent applications, invalidating the novelty of (some of) their claims.

Inventor's structural centrality

To identify the position of a given inventor in the co-inventing network, we construct an inventor-by-inventor network, which has inventors as nodes and patents among inventors working in the same firm as ties. Following standard procedures, we use a three-year running window. Using the resulting matrix of the one-mode network of inventors, we compute the structural centrality for each inventor using the Bonacich (1987) power measure with standard Matlab code. This frequently used measure has the advantage

[13] Patent equivalents filed at national patent offices are taken into account when calculating this measure. This is important because, if patent equivalents were ignored, the number of forward citations that a patent receives would be underestimated (Harhoff et al., 2005).

that, in measuring the centrality of a focal inventor, it explicitly takes account of the centrality of other inventors that co-invent with the focal inventor (Nerkar and Paruchuri, 2005; Paruchuri, 2010). Due to the right-skewed distribution of inventor centrality, we use its natural logarithm as the main measure in our analysis.

Control variables

Our analysis employs several individual-related covariates that control for inventor characteristics (observable to the econometrician) accumulated from the beginning of his patenting life up to (but excluding) year t. Specifically, we include *ln(total patents)*, measured as the natural logarithm of the inventor's accumulated number of patents filed until t, to capture his productivity. In order to control for his experience, we measure *ln(experience)* as the logarithm of the difference in years between t and his first patent priority year. We code *firm patents* as the proportion of patents applied for by inventor i with the focal firm from his first year until t. We include this measure to account for any differences that might exist between research intensities at the focal firm and previous employers. We also control for *knowledge concentration*, measured as the Herfindahl index of the concentration of the inventor's prior patenting activity across IPC four-digit classes. To account for the inventor's collaboration environment, we include the extent to which inventor i, on average, co-invented with someone with whom he had never co-invented before (*new coinventors*) and the average number of prior collaborators (*team size*).

Inventors' ability to generate high-quality output may be related with their allocation to collaboration. Because collaborative research with external partners often entails substantial transaction costs (Gulati and Singh, 1998), managers may prefer to select workers who can generate particularly high-added value in order to maximize the returns on their investment. Simultaneously, high-quality inventors may be more likely to be the authors of innovations whose patents receive more blocking citations. To account for this, we include *citations received* (a standard proxy for quality), measured as the average number of citations received by the inventor's patents filed until year t.[14]

Because allocation decisions may also depend on whether the scientist innovates in a firm's core (or peripheral) technology areas, we control for his experience in the firm's core technology areas. We consider a technology as core if the patent that covers it is classified in an IPC seven-digit class which coincides with some of the most frequent classes in the firm's patent portfolio. We adopt an approach similar to Song et al. (2003), and identify core classes as those with a frequency greater than 8 percent in a given five-year time window.[15] We code *experience in a firm's core technologies* as the proportion of the inventors' patents applied for with the focal firm that fall in its core classes.

Given that the allocation of R&D workers to collaboration may be affected by their ability to be on the technological frontier and to draw on external knowledge, we include two additional controls. First, we code *basicness* as the average number of non-patent literature (NPL) citations to total citations made by the inventor in the patents he filed up to t. NPL references have frequently been used as a proxy for the openness to new technological opportunities or for the strength of the science link (Narin et al., 1997; Von Graevenitz et al., 2013). Second, to capture the degree to which scientists innovate by using knowledge that does not reside within their existing knowledge base, we converted the scope measure of Katila and Ahuja (2002) to the inventor-level. Thus, for every inventor at every spell, we construct *search scope* as the average proportion of the citations he made up to t that were not cited by his prior work.

Because inventors who have prior experience in intra-organizational research may be more likely to be re-assigned to this type of project, we introduce a dummy variable, *prior co-assignment*, that captures whether an inventor has participated in collaborative patenting activities in the previous five years (= 1; otherwise, 0).

Finally, to control for the inventor's expertise in specific technological areas related to pharmaceutical research, we include a set of 17 dummy variables for the subclasses (IPC

[14]Since there might be concerns regarding systematic differences in citations received by patents from different years and fields, we also experimented with standardized citations (Hall et al., 2001). However, using this alternative variable delivered similar results to the unadjusted variable presented here.

[15]We also considered alternate cut-off points of 4 and 10 percent of the firm's portfolio. Our findings are robust to those thresholds.

seven-digit) nested within our main IPC four-digit class A61K. All regressions further control for a full set of firm dummies and year dummies. Year dummies refer to the priority year of the focal patent.[16] Thus, we explore how within-firm differences in inventor characteristics relate to within-firm differences in the assignment of inventors, allowing us to control for firm-level unobserved heterogeneity.

Analytical techniques

Our estimation techniques vary according to the nature of the dependent variables. First, we use probit models to examine the probability that a given inventor is assigned to a collaborative versus a stand-alone research activity (H1 and H2). The probit model is appropriate given the dichotomic nature of our main dependent variable: i.e., whether or not it is a *co-assigned* project. Second, we use multinomial logit models to analyze the likelihood of an inventor being allocated either to a stand-alone project or to a collaboration with a certain type of partner (*friend* vs. *stranger* or *high* vs. *low reputation* partner; H3). The multiple categorical (unordered) choices captured by this variable make this method necessary. In both cases, every observation corresponds to a patent-inventor pair. Because we need at least one cited patent during the inventor's prior patenting history to construct his degree of preemptive power, inventors with no citation to their previous patents are necessarily excluded from the analysis. This leaves us with a baseline sample of 26,790 inventor-patent observations on 5,297 unique inventors and 13,091 unique patents for our analysis. Standard errors are clustered by inventor to account for the non-independence of observations (Wooldridge, 2010).

[16]Alternatively, we use the (priority) year of the last patent application filed by the inventor before the focal patent in order to take into account the moment in which he finished his last project, and, therefore, became available for allocation to the focal project. This would address potential differences in the duration of collaborative versus stand-alone projects. This does not change our results. Furthermore, we get similar results if we use an exact matching procedure and consider a single-assigned inventor from the same firm to be a potential match (i.e., available for allocation) only if he applied for his last patent in the same year as the co-assigned inventors.

RESULTS

In Tables 1 and 2, we provide summary statistics and pairwise correlations, respectively. Our inventors are productive: 15.7 patent applications over a mean patenting life of 9.7 years. On average, an inventor in our sample has a 2 percent probability of being allocated to a collaborative project at a given moment in time and has a blocking citation ratio (or preemptive power) of 0.47. Table 3 presents the specifications that test for our first hypothesis. Column 1 includes inventor-related control variables along with firm dummies, time dummies and technology class dummies. Column 2 adds our main variable of interest, i.e., *preemptive power*. The likelihood ratio test shows that the inclusion of this variable has a significant effect on the model's explanatory power. More specifically, the positive and significant coefficient estimate indicates that the more blocking citations an inventor's patent portfolio has received, the more likely he is to be assigned to collaboration, in support of H1. To give an idea of the size of this effect, the next two columns display the marginal effects at the means (MEMS) and the average marginal effects (AME). According to the marginal effects results in column 3, keeping the rest of independent variables at their means, an increase in blocking citations from 0 to 100 percent increases the probability of assigning an inventor to a joint project, on average, by 0.7 percentage points. Concerning the mean of the marginal effects predicted for all the observations of the sample (column 4), a shift from 0 to 100 percent in the blocking potential of an inventor's citation stock is associated with a 1 percentage point increase in the probability of being selected for collaboration. Given that the baseline probability of being assigned to collaborations is 2 percent, this is a result of economic significance.

In column 5, we differentiate between inventors' preemptive power according to the type of blocking citations. As mentioned earlier, blocking citations can be classified as X-type references (that question the novelty of the invention under investigation *if taken alone*) or Y-type references (that question the inventive steps claimed in the invention being examined, *when combined with one or more documents*). We follow this classification and compute the preemptive power variable for each of the two groups of references. X references represent 32 percent of our sample of inventors' total number of citations received and Y references represent 15 percent. In column 5, we see that the coefficient estimates for both variants of the preemptive power variable are positive. However, the coefficient of the type-X based preemptive power variable is significantly larger than in the case of the type-Y based variable (at the 10 percent level, F-test). According to the marginal effects at the mean of the rest of variables (unreported), an increase in type-X preemptive power from zero to one increases the likelihood of being assigned to a collaboration by 1.2 percentage points while in the case of type-Y preemptive power, this implies a 0.5 percentage point increase (average marginal effects indicate magnitudes of 1.8 and 0.7 percentage points, respectively). This suggests that X references, as citations that *directly* block claims in patent applications, reflect higher levels of preemptive power than Y references, and, therefore, have a larger effect on the predicted dimension.[17]

Turning to our control variables, we obtain some interesting insights from the analysis. The inventor's experience, in terms of the quantity of patents produced, *ln(total patents)*, has a negative effect on his selection for collaboration, while in terms of quality it has no effect (*citations received*). However, the percentage of patents with the focal firm (*firm patents*) has a positive effect. We find a lower likelihood of being assigned to collaboration when the inventor has a more specialized knowledge base in a certain technology field (*knowledge concentration*), when he co-invents more frequently with new team members (*new coinventors*), when he worked in larger teams (*teamsize*) or when he has previously participated in co-assigned patents (*prior co-assignment*). This last result indicates that allocation decisions are not driven by a sequential allocation of those inventors that are experienced in inter-organizational research.

[Insert Tables 1, 2 and 3 about here]

We test our second hypothesis through the specifications presented in Table 4. Column 1 introduces the measure of inventor centrality and column 2 sequentially adds the multiplicative term with preemptive power. Including the interaction term improves the

[17] This finding is in line with Harhoff and Reitzig (2004)'s who show that it is the increase in the number of X-type references that drives the effect of an increase in the likelihood that patents are attacked in opposition proceedings.

overall fit of the model and increases its explanatory power relative to the model shown in column 1. The positive and significant estimate of the interaction term suggests that the effect of preemptive power on the likelihood of being assigned to collaboration increases when the inventor occupies a more central position, as posited in H2. Panel A of Figure 1 explores the conditional effect of preemptive power contingent on two different levels of the moderating variable (and all other variables set at their sample means): (i) high centrality (which corresponds to one standard deviation above its mean value or a value of ln(inventor centrality) of 2.01), and (ii) low centrality (which corresponds to one standard deviation below its mean value or a value of ln(inventor centrality) of -0.25). For the less central inventor, we observe that the probability of selection for collaboration increases moderately with the level of preemptive power. For the more central inventor, this increase is much steeper. While the difference between the two slopes provides indirect evidence in line with H2, it also suggests that both slopes (and the difference between them) change with the level of preemptive power. As Norton et al. (2004) and Hoetker (2007) point out, the interaction between two continuous variables in a non-linear model has different signs and magnitudes across observations. Accordingly, in Panel B of Figure 1, we display the marginal effects of the interaction term for each observation in the sample. We find that they are positive for the vast majority of the sample, though not always significant, as shown in Panel C. Therefore, we obtain partial support for H2. For the sake of completeness, we also report the marginal effects at the mean (column 3) and the average marginal effects (column 4) of preemptive power when centrality (including the interaction term) is taken into account. Not surprisingly, these results are similar to those presented in Table 3.[18]

[Insert Table 4 and Figure 1 about here]

[18]Because inventor centrality is measured in its logarithmic forms, it takes negative values for the range between zero and one. In practice, this means that, for a small set of values, the *total marginal effect* of preemptive power may not be positive and significant. Computing the total marginal effect of preemptive power with respect to centrality (holding all other variables at their means) reveals that the effect is significant for the range of values from -0.36 (the 14$^{\text{th}}$ percentile of ln(inventor centrality)) to 3.77 (the maximum of ln(inventor centrality)) and positive across almost the entire sample (for values of ln(inventor centrality) $\geqslant -1.77$, or 98 percent of observations).

Table 5 summarizes the results from the multinomial logit models that test for our third hypothesis. Panel A contains evidence related to partner-specific experience. The estimated coefficients compare the effect of being assigned to collaborative activities with either *friends* or *strangers* relative to *solitary* activities. The results show that the effect of preemptive power is to significantly increase the probability of allocating an inventor to a collaborative project with a stranger compared to the omitted solitary category. In terms of the relative risk ratio, the coefficient in column 1 implies that inventors whose blocking citation ratio increases from zero to one are more than twice as likely to be selected for collaboration with a stranger than an internal activity ($\exp(0.9) = 2.5$). The degree of knowledge protection, however, does not have a statistically significant effect on the likelihood of an inventor being allocated to a collaboration with a trusted partner (i.e., a friend). Changing the base outcome to strangers reveals that the difference between both coefficients is significant at the 10 percent level (not reported here). Panel B examines the relationship between inventor's preemptive power and the partner's reputation. The pattern of results is similar to that observed before. Specifically, the greater the preemptive power, the greater the odds of being allocated to a collaborative activity with a partner that has a lower reputation instead of an internal project, whereas the effect of preemptive power on the likelihood to collaborate is not significant in the case of partners with a stronger reputation. Again, the difference between both coefficients is significant at the 10 percent level. In sum, these findings represent strong support for H3, i.e., the degree of preemptive power of the knowledge set put at risk is more relevant in the allocation decision for collaborations with a higher perceived risk of opportunism, particularly those in which the partners are collaborators the firm does not trust.[19]

[Insert Table 5 about here]

[19]In unreported extensions, we also distinguish between collaborative activities with industry partners and universities (or research institutes). This generates very similar predictions for the pattern of inventor selection for collaboration discussed here. According to Belderbos et al. (2014), we may expect that the risk of leakage plays a more limited role in partnerships with universities since they are less likely to exploit and commercialize technologies. In line with the evidence presented above, repeating the specification of Table 5, the results show that preemptive power has a significant, positive coefficient of 0.579 (standard error of 0.304) when collaboration with firms is compared to solitary activities and a non-significant coefficient when comparing collaboration with universities to solitary activities (a coefficient of 0.010 with a standard error of 0.437).

Thus far, our results indicate that the degree to which an inventor's knowledge is protected plays an important role in inventor selection for collaborative research activities. We find evidence that is broadly consistent with the conjecture that an inventor's preemptive power is a mechanism that reduces the risk associated with information leakage in collaborations. In particular, our findings suggest that the effect of preemptive power on the likelihood of being assigned to a collaboration is greatest precisely in those cases in which the risk associated with the collaboration is greatest (i.e., more central inventors and collaborations with non-trusted partners).

Additional evidence

In this section, we provide supplementary evidence that helps to support our hypotheses. Specifically, we analyze whether the allocation of inventors with preemptive power enhances or diminishes the quality of collaborative innovation outputs. Examining the performance implications of inventor selection for collaboration strengthens our findings in two dimensions. First, it provides evidence that is consistent with the role of preemptive power as a facilitator of collaborative research. Second, it allows us to partially address a potential concern related to our concept of preemptive power, i.e., that it may capture an unobserved dimension of inventors' quality.

Related to the first point, previous work identifies the ability and willingness to transfer knowledge as the most important determinants of joint R&D performance (Sampson, 2007). Since knowledge transfer is subject to appropriation risk, firms are usually reluctant to contribute substantially to the pool of knowledge that is shared with the partner. Thus, even if the firm is able to transfer its capabilities or resources to partners, it is precisely the unwillingness to do so that may explain why inter-organizational research performance often falls short of expectations (Khanna et al., 1998; Oxley and Sampson, 2004). In this context, we argue that the selection of inventors may affect how much value can be created in the collaboration, because this selection can influence the extent to which partners are willing to transfer knowledge-based capabilities. In particular, we propose that the assignment of R&D workers with preemptive power enhances the willingness of inventors (and their managers) to efficiently share knowledge between partners, since it substantially reduces appropriability concerns and uncertainties involved in information sharing. If preemptive power is a significant factor in diminishing knowledge leakage concerns in collaboration, we should then observe that the presence of inventors with high preemptive power leads to increased innovation performance.

To probe this conjecture, we focus on the allocation of teams of inventors and regress the value of the patented innovation on the interaction between the mean preemptive power of inventors working in the team of the focal patent and a dummy variable indicating whether the patent is co-owned. To measure patent value, we follow common practice by using the number of citations a patent receives (Hall et al., 2005; Harhoff et al., 1999). We compute all citations received by a patent (and its equivalents) with a fixed five-year window (labelled *cites*). Alternatively, we use *triadic*, a dummy variable that takes the value 1 if a patent is filed at the U.S., European and Japanese patent office (otherwise, 0). While patented technologies differ in their technical and economic value, triadic patent applications are a group of especially valuable inventions whose owners expect them to generate most profits as they are willing to incur higher filing and maintenance costs (Guellec and Van Pottelsberghe de la Potterie, 2008).

The empirical specifications include the average of inventor-related control variables across team members, firm dummies, and dummies for the year of the first patent application (i.e., priority year). Following prior studies on patent citations (Belderbos et al., 2014; Fleming and Sorenson, 2004), we further control for the following patent-level characteristics: the number of *backward patent citations*, the number of *non-patent citations* (NPL references), the *number of IPC-4 classes* in which the focal patent is classified, and the *number of inventors* in the team responsible for the focal patent. The sample consists of 13,095 team-patent observations on 6,969 teams from our sample firms.[20] We apply poisson regressions to estimate the total number of forward citations and probit regressions for the probability of being a triadic patent. Standard errors are clustered at the team level.

[20]Note that the number of team-patent observations (13,095) differs from the number of unique patents (13,091) because 4 patent applications are co-assigned between two of our sample firms.

The results are reported in Table 6. In column 1, we see that the coefficient on *co-patent* is positive and significant, suggesting that the total number of citations received by a collaborative patent is substantially higher than those received by a solo-assigned patent; this result confirms the finding of Belderbos et al. (2014). In column 3, however, we find that co-patents are not significantly associated with a greater likelihood of being filed as triadic patents. However, when we introduce the interaction between members' mean preemptive power and co-patent status, we observe that co-patents receive significantly more citations than solo patents *only* when the team members have a high enough value of preemptive power (for values of this variable $\geqslant 0.51$, or 42 percent of the observed distribution). For the 11 percent of observations with lowest values of preemptive power (for values $\leqslant 0.2$), the effect of co-patents on citations is significantly negative. For triadic as the dependent variable, the coefficient estimates suggest a similar pattern. In Panel B, we then restrict our sample to only co-assigned patent applications. Consistent with the results above, we find that the level of preemptive power of the average inventor in the focal team has a significant positive effect on the value of the resulting collaborative project. Specifically, a change in the focal firm's mean preemptive power from zero to one almost doubles the number of citations received (an increase of 97 percent) and it increases the probability of being filed as a triadic patent by approximately 24 percentage points.[21] In sum, the above evidence suggests that the allocation of inventors with high preemptive power to collaboration is positively associated with the quality of the collaborative output. We interpret this as supportive of the idea that inventors' preemptive power encourages knowledge sharing by reducing knowledge leakage concerns in collaborative research, consequently leading to higher value creation.[22]

As mentioned earlier, the findings from this section also address concerns that the preemptive power measure may capture an unobserved dimension of inventors' quality (i.e., some dimension not captured by the usual proxy for quality: the citations received

[21] This latter figure corresponds to the estimated average marginal effect obtained from the specification in column 6.

[22] For robustness purposes, we also re-estimated the specifications in columns 2 and 5 with the dependent variable replaced by non-self-citations. The reasons is that self-citations may differ from other citations in various ways (Hall et al., 2005). However, doing so leads to a similar conclusion.

on previous work). If this were the case, we should observe that the degree of inventors' preemptive power is, in general, a good predictor of the quality of the outcome of the focal project. However, that interpretation is hard to reconcile with our findings: specifications 2 and 4 of Table 6 show that the effect of members' mean preemptive power on innovation quality is not significant for solo-assigned patents. The fact that preemptive power affects only the value of co-patents but not of solo-assigned patents reinforces our argument that preemptive power is relevant for collaborative activities in order to create the trust needed to promote information exchange between partners. Importantly, this holds regardless of the measure of patent quality that we use.

[Insert Table 6 about here]

DISCUSSION AND CONCLUSION

Since the seminal publication by Hamel et al. (1989), inter-organizational research efforts have increasingly emphasized the need to protect proprietary knowledge from being exposed to partners. It is somewhat surprising, therefore, that so little research has addressed the issue of how the risk of technology leakage is related to *individuals* that participate in collaborations. This is especially relevant in the context of R&D collaboration where individuals from the two partners work together to produce new knowledge, exposing valuable tacit elements to their counterparty.

In this paper, we perform the first large-scale study of the assignment of R&D employees to external collaborations. By examining the patenting activities of the largest pharmaceutical firms, we are able to detect the contribution of inventors to firms' collaborative activities as reflected in co-assigned patents (compared with their participation in internal projects, reflected in solo-assigned patents). We document patterns that support the argument that managers select specific inventors for R&D collaboration in order to minimize the consequences of information leakage. Our central finding is that the probability that an inventor is assigned to an external collaborative project is positively associated with the strength of legal protection conferred by the property rights that cover the knowledge he (co-)created. This strong legal protection prevents the partner firm from effectively using any leaked knowledge to compete with the creator of such knowledge. We provide evidence that this effect is more significant for inventors who occupy a more central position in the intra-firm inventor network, and, therefore, whose contribution in an alliance entails a higher hazard due to the quantity and quality of information they hold. Our results also show that inventor's preemptive power is more important in cases where it is difficult to assess partners' trustworthiness, i.e., when the focal firm has had no previous relationship with the partner and/or when the partner has a lower reputation in the alliance market. Finally, we observe that external collaborative projects involving inventors with more blocking power generate more significant outputs, suggesting that greater protection may result in lower concerns about sharing knowledge, and, therefore, in more successful projects. Taken together, these findings yield some important contributions.

First, our analysis contributes to the literature on the management of alliances which stresses the importance of mechanisms that minimize the leakage of information in R&D collaboration. We add to this stream of literature by suggesting a widely neglected mechanism that may minimize the *consequences* of leakage: the selection of R&D employees for collaborations. While previous work underlines the role of employees in the unintended transmission of knowledge between partners and the importance of managing them properly in order to control knowledge flows, this paper proposes a new perspective on the actions that can be taken to manage employees involved in R&D alliances. The strategic allocation of inventors is a mechanism that can either complement or replace other means of knowledge protection, such as protective governance structures, scope restrictions or the selection of trustworthy partners.

Our results also have implications for the human resource management of R&D employees, in particular for the formation of teams. Our findings suggest that managers select inventors for certain projects (in our case external vs. internal projects) according to the fit between their characteristics and the requirements of the project. Particularly in large and medium-sized firms, where different R&D projects are conducted simultaneously, the allocation of R&D personnel across projects and the resulting teams may be a significant factor behind their success. To the best of our knowledge, our paper is the first to address the question of the allocation of inventors to projects, though in a very specific context.

This paper also adds to the literature on the role of intellectual property protection in the market for technology. Our results are aligned with the idea that strong protection facilitates the transfer of information, since fewer moral hazard problems can be expected. We take a new perspective and conceptualize the strength of protection held by an individual by looking at the (patented) innovations he contributed to. We provide evidence suggesting that individual-related preemptive power is an instrument that limits the threat of knowledge leakage in alliances, and, therefore, results in more effective sharing of knowledge between partners. It is plausible that inventors' preemptive power may also be an important determinant for other knowledge "transactions" in which the scientist is involved in the market for technology, including the market for inventors. We leave this to further research.

Though this study generates new insights into the role of inventors in collaborative R&D, our empirical strategy is subject to several limitations. First, the findings of this paper arise from the study of the largest firms in the pharmaceutical sector. This poses two limitations to the generalizability of our results, i.e., regarding firm size and industry. Our argument is based on the possibility of selecting inventors among those potentially suitable (who have the necessary expertise) for an alliance. This requires a set of inventors with partially overlapping knowledge backgrounds who could be allocated, without distinction, to collaboration. We assume that this is typically possible in large, but not necessarily in small, firms. Especially in the latter, this will depend on the degree of specialization of the firm and its R&D workers. Likewise, in other sectors where different mechanisms of knowledge appropriation prevail, preemptive power at the individual level may not confer protection against appropriation. Consequently, we should be cautious about generalizing the results. The second limitation concerns the use of patent data. Although patent data allow for an inventor-level analysis at a large scale that would otherwise be difficult to conduct and, in the case of pharmaceutical firms, they are the most comprehensive data of innovation activities, they present a series of drawbacks. One common downside in studies based on patents is that they only identify successful projects (i.e., those that achieved some output that qualifies for a patent). Another disadvantage, more specific to our study, is that they do not allow us to identify those collaborations that did not result in co-patents. This means that our pool of solo-assigned patents may contain some innovations that are in fact outputs of collaborative research. If there is no particular bias in the decision to co-patent the result of a collaborative project, this potential misclassification problem may lead us to identify an effect that is actually a lower bound for the actual effect. Note that, as we detail in the paper, we avoid the opposite source of misclassification, i.e., the existence of innovations resulting from solo-projects assigned as co-patents as the result of IP sharing agreements.

Our study focuses on the decision to allocate inventors to external collaborations only from the angle of the protection of technological assets exposed in the alliance. We neglect the opposite perspective, that is, organizational learning objectives which may also be relevant for inventor selection decisions. Although we account in our empirical analysis for some dimensions that may proxy for individual-level absorptive capacity, an extension of our study could focus on the learning side of knowledge transfer in collaborative R&D. Do firms learn more from partners when specific inventors are selected? If so, does the knowledge learned from these partners deplete over time because employees involved in collaboration leave the company?

Even with these limitations, we see our study as a first step to understanding the role played by individuals participating in R&D collaborations in the trade-off that firms face when they decide to engage in alliances. As Oxley and Sampson (2004) put it, when setting up an alliance, managers have to make a number of decisions: who to collaborate with, the scope of the alliance and the governance structure to adopt. In this paper, we suggest that managers make another relevant decision when defining a collaboration strategy: which inventors to allocate to the alliance.

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FIGURES

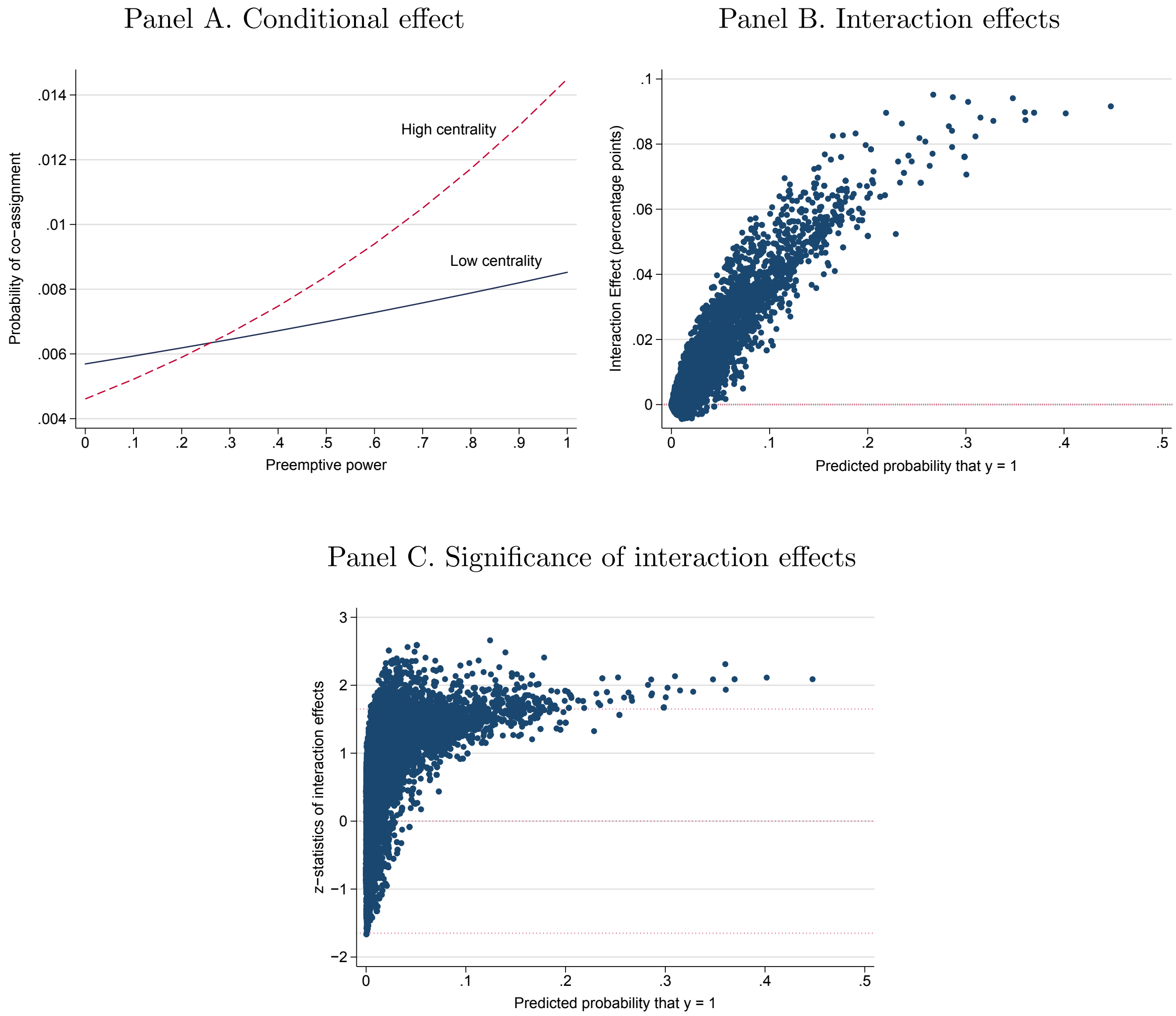

Figure 1: Preemptive power and inventor allocation: the moderating effect of inventor centrality

TABLES

Table 1: Descriptive statistics

Variable	Mean	SD	Min	Median	Max	Observations
Co-assignment	0.02	-	0	0	1	26,790
Friend	0.29	-	0	0	1	499
Partner's partner	5.24	11.40	0	4	140	499
Preemptive power	0.47	0.27	0	0.47	1	26,790
Inventor centrality	4.19	4.60	0.10	2.57	43.59	26,790
Total patents	15.69	17.16	1	10	398	26,790
Experience	9.67	5.14	1	9	28	26,790
Firm patents	0.98	0.08	0.06	1	1	26,790
New coinventors	0.67	0.19	0.14	0.66	1	26,790
Teamsize	5.56	2.60	1.05	5.09	29	26,790
Citations received	1.69	1.70	0.01	1.25	45	26,790
Experience in firm's core technologies	0.66	0.37	0	0.83	1	26,790
Knowledge concentration	0.26	0.08	0.06	0.26	1	26,790
Basicness	0.25	0.16	0	0.22	0.95	26,790
Search scope	0.84	0.14	0	0.85	1	26,790
Prior co-assignment	0.16	-	0	0	1	26,790
Patent characteristics used in the "additional evidence" section						
Citations	3.52	4.69	0	2	118	13,091
Triadic filing	0.67	-	0	1	1	13,091
Backward patent citations	4.85	7.40	0	3	142	13,091
Non-patent citations	3.19	10.48	0	1	115	13,091
Number of IPC-4 classes	3.22	1.21	1	3	10	13,091
Number of inventors	5.12	3.26	1	4	32	13,091

Table 2: Correlations

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Co-assignment																			
2. Preemptive power	0.04																		
3. Ln(Inventor centrality)	-0.06	0.00																	
4. Ln(Total patents)	-0.04	-0.05	0.48																
5. Ln(Experience)	0.00	-0.08	0.03	0.50															
6. Firm patents	0.01	0.02	0.10	0.02	-0.20														
7. New coinventors	0.02	0.07	-0.15	-0.52	-0.29	-0.04													
8. Teamsize	-0.03	0.04	0.57	-0.03	-0.18	0.07	0.05												
9. Citations received	0.02	-0.04	-0.03	0.12	0.39	-0.10	-0.15	-0.03											
10. Experience in firm's core technologies	-0.04	-0.04	0.17	0.01	-0.01	0.07	-0.11	0.06	0.05										
11. Knowledge concentration	-0.05	0.02	-0.08	-0.16	-0.16	0.08	-0.01	0.00	-0.04	0.26									
12. Basicness	0.06	0.07	-0.13	-0.12	-0.04	-0.03	0.21	-0.05	-0.06	-0.35	-0.31								
13. Search scope	0.01	0.00	-0.15	-0.41	-0.15	-0.04	0.56	0.02	-0.18	-0.11	-0.02	0.14							
14. Prior co-assignment	-0.01	0.00	0.02	0.12	0.14	-0.06	0.01	-0.05	0.06	0.06	-0.06	0.03	-0.03						
Patent characteristics used in the "additional evidence" section																			
15. Citations	0.04	0.01	0.01	-0.04	-0.01	-0.01	0.03	0.04	0.06	0.05	0.02	-0.03	-0.01	0.00					
16. Triadic filing	0.01	-0.08	0.01	-0.01	0.00	0.03	-0.05	0.01	0.00	-0.02	-0.05	-0.01	-0.05	-0.09	0.12				
17. Backward patent citations	0.00	0.06	0.04	0.03	0.00	0.00	0.01	0.03	0.00	0.01	0.04	-0.03	0.01	0.02	0.05	0.00			
18. Non-patent citations	0.11	0.03	-0.04	-0.06	-0.04	-0.01	0.10	0.02	0.00	-0.20	-0.15	0.31	0.07	0.02	-0.01	-0.01	0.24		
19. Number of IPC-4 classes	0.07	-0.07	0.05	0.03	-0.02	0.01	-0.01	0.04	-0.03	-0.12	-0.41	0.24	-0.04	-0.05	0.05	0.21	-0.06	0.14	
20. Number of inventors	0.12	0.01	0.29	0.05	0.02	0.02	0.01	0.43	0.01	-0.01	-0.07	-0.01	0.01	-0.02	0.15	0.11	0.07	0.06	0.12

Notes: $N = 26,790$. All correlations above $|0.03|$ are significant at $p < 0.01$. The correlations in the lower part of the table correspond to the variables averaged across team members of the focal firm and are based on 13,095 team-patent observations.

Table 3: Preemptive power and inventor allocation

Method Dep. var.: Co-assignment (= 1)	Probit (1)	Probit (2)	MEMS (3)	AME (4)	Probit (5)
Preemptive power	-	0.250** (0.101)	0.007** (0.003)	0.010** (0.004)	-
Preemptive power (Type X)	-	-	-	-	0.426** (0.172)
Preemptive power (Type Y)	-	-	-	-	0.175* (0.102)
Ln(Total patents)	-0.131*** (0.045)	-0.128*** (0.046)	-0.004*** (0.001)	-0.005*** (0.002)	-0.130*** (0.046)
Ln(Experience)	0.028 (0.064)	0.040 (0.064)	0.001 (0.002)	0.002 (0.003)	0.025 (0.066)
Firm patents	0.916*** (0.319)	0.871*** (0.319)	0.025*** (0.009)	0.037*** (0.014)	0.865*** (0.319)
New coinventors	-0.405** (0.178)	-0.410** (0.176)	-0.012** (0.005)	-0.017** (0.007)	-0.425** (0.176)
Teamsize	-0.027** (0.013)	-0.026** (0.013)	-0.001** (0.000)	-0.001** (0.001)	-0.025** (0.013)
Citations received	0.018 (0.012)	0.020 (0.012)	0.001 (0.000)	0.001 (0.001)	0.018 (0.012)
Experience in firm's core technologies	-0.016 (0.100)	-0.018 (0.100)	-0.001 (0.003)	-0.001 (0.004)	-0.019 (0.100)
Knowledge concentration	-1.381*** (0.489)	-1.394*** (0.488)	-0.040*** (0.014)	-0.059*** (0.021)	-1.439*** (0.491)
Basicness	0.073 (0.184)	0.060 (0.185)	0.002 (0.005)	0.003 (0.008)	0.070 (0.184)
Search scope	0.005 (0.218)	0.027 (0.221)	0.001 (0.006)	0.001 (0.009)	0.016 (0.219)
Prior co-assignment	-0.245** (0.105)	-0.247** (0.106)	-0.007** (0.003)	-0.010** (0.005)	-0.250** (0.106)
-2 Log Likelihood	4479.21	4468.07	-	-	4462.79
LR (χ^2)	-	11.14***	-	-	-

Notes: $N = 26,790$. Number of unique firms: 27. Number of unique inventors: 5,297. Robust standard errors are clustered by inventor (in parentheses). All regressions control for a full set of firm dummies, priority year dummies and technology class dummies. The time period is 1990 – 2005. The Likelihood ratio (LR) tests for the increment in the overall model fit after including the preemptive power variable. "MEMS" are the marginal effects at the means corresponding to the probit coefficient estimates in column 2; "AME" are the average marginal effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Preemptive power, inventor centrality and inventor allocation

Method Dep. var.: Co-assignment (= 1)	Probit (1)	Probit (2)	MEMS (3)	AME (4)
Preemptive power x Ln(Inventor centrality)	-	0.125* (0.074)	-	-
Preemptive power	0.251** (0.101)	0.223** (0.099)	0.008*** (0.003)	0.011** (0.004)
Ln(Inventor centrality)	-0.154*** (0.037)	-0.205*** (0.052)	-0.004*** (0.001)	-0.006*** (0.002)
Ln(Total patents)	-0.017 (0.049)	-0.020 (0.049)	-0.001 (0.001)	-0.001 (0.002)
Ln(Experience)	-0.005 (0.064)	-0.002 (0.064)	-0.000 (0.002)	-0.000 (0.003)
Firm patents	0.873*** (0.310)	0.884*** (0.310)	0.024*** (0.009)	0.037*** (0.013)
New coinventors	-0.281 (0.174)	-0.275 (0.173)	-0.008 (0.005)	-0.011 (0.007)
Teamsize	0.013 (0.014)	0.012 (0.015)	0.000 (0.000)	0.000 (0.001)
Citations received	0.017 (0.012)	0.017 (0.012)	0.000 (0.000)	0.001 (0.001)
Experience in firm's core technologies	0.050 (0.102)	0.049 (0.102)	0.001 (0.003)	0.002 (0.004)
Knowledge concentration	-1.421*** (0.484)	-1.427*** (0.484)	-0.039*** (0.013)	-0.060*** (0.020)
Basicness	-0.005 (0.184)	-0.000 (0.183)	-0.000 (0.005)	-0.000 (0.008)
Search scope	0.043 (0.220)	0.039 (0.220)	0.001 (0.006)	0.002 (0.009)
Prior co-assignment	-0.251** (0.107)	-0.254** (0.107)	-0.007** (0.003)	-0.011** (0.005)
-2 Log Likelihood	4439.51	4430.72	-	-
LR (χ^2)	28.56***	8.79**	-	-

Notes: $N = 26,790$. Number of unique firms: 27. Number of unique inventors: 5,297. Robust standard errors are clustered by inventor (in parentheses). All regressions control for a full set of firm dummies, priority year dummies and technology class dummies. The time period is 1990 – 2005. The Likelihood ratio (LR) tests for the increment in the overall model fit after including the inventor centrality variable and its interaction with preemptive power. Model 1 is compared with model 2 in Table 3, and model 2 is compared with model 1. "MEMS" are the marginal effects at the means corresponding to the probit coefficient estimates in column 2; "AME" are the average marginal effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Preemptive power, partner characteristics and inventor allocation

	Panel A: Partner-specific experience		Panel B: Partner's general collaboration experience	
Dependent variable Method: Multinomial Logit	Stranger (1)	Friend (2)	Low reput. (3)	High reput. (4)
Preemptive power	0.900**	0.328	0.793**	-0.137
	(0.455)	(0.284)	(0.325)	(0.374)
Ln(Inventor centrality)	-0.205*	-0.209	-0.281**	-0.108
	(0.111)	(0.162)	(0.121)	(0.129)
Ln(Total patents)	-0.233	-0.451*	-0.188	-0.437**
	(0.148)	(0.245)	(0.161)	(0.193)
Ln(Experience)	-0.081	0.003	0.035	-0.141
	(0.194)	(0.265)	(0.203)	(0.246)
Firm patents	1.012	1.217	0.847	1.501
	(0.883)	(1.609)	(0.998)	(1.191)
New coinventors	-0.473	-2.131***	-0.646	-1.198
	(0.534)	(0.809)	(0.563)	(0.731)
Teamsize	0.032	0.034	0.053	0.003
	(0.046)	(0.069)	(0.047)	(0.049)
Citations received	0.063**	0.076**	0.043	0.088***
	(0.025)	(0.032)	(0.031)	(0.031)
Experience in firm's core technologies	-0.536*	1.252***	-0.416	0.546
	(0.306)	(0.476)	(0.332)	(0.391)
Knowledge concentration	-2.204	-8.415***	-2.756*	-5.332***
	(1.416)	(1.996)	(1.608)	(1.578)
Basicness	1.251**	-0.263	1.042*	0.553
	(0.522)	(0.812)	(0.552)	(0.654)
Search scope	0.046	1.006	0.232	0.153
	(0.650)	(1.053)	(0.704)	(0.903)
Prior co-assignment	-0.341	0.545	-0.233	0.081
	(0.276)	(0.353)	(0.279)	(0.334)

Notes: $N = 26,768$. Number of unique firms: 27. Number of unique inventors: 5,292. Robust standard errors are clustered by inventor (in parentheses). All regressions control for a full set of firm dummies, priority year dummies and technology class dummies. The time period is 1990 – 2005. The comparison baseline in both panels is "solitary". * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Preemptive power, inventor allocation and value implications

	Panel A: Full sample				Panel B: Sub-sample of co-patents	
Method	Poisson	Poisson	Probit	Probit	Poisson	Probit
Dependent variable	Cites	Cites	Triadic	Triadic	Cites	Triadic
	(1)	(2)	(3)	(4)	(5)	(6)
Members' mean preemptive power x Co-patent	-	0.446**	-	0.810**	-	-
		(0.224)		(0.376)		
Members' mean preemptive power	0.028	0.008	-0.010	-0.036	0.978***	0.980**
	(0.052)	(0.054)	(0.067)	(0.068)	(0.197)	(0.402)
Co-patent	0.066**	-0.184***	-0.137	-0.579***	-	-
	(0.027)	(0.063)	(0.094)	(0.186)		
Members' mean ln(inventor centrality)	-0.016	-0.017	0.024	0.024	0.186**	0.155
	(0.020)	(0.020)	(0.026)	(0.026)	(0.086)	(0.130)
Members' mean ln(total patents)	-0.025	-0.025	-0.057	-0.058	-0.328**	-0.558***
	(0.030)	(0.030)	(0.040)	(0.040)	(0.139)	(0.198)
Members' mean ln(experience)	-0.041	-0.040	0.073*	0.074*	0.312*	0.592**
	(0.036)	(0.036)	(0.044)	(0.044)	(0.186)	(0.279)
Members' mean firm patents	-0.119	-0.119	0.065	0.064	0.277	-1.302
	(0.149)	(0.149)	(0.175)	(0.175)	(0.764)	(1.674)
Members' mean new coinventors	0.268**	0.267**	-0.076	-0.077	-1.162**	-0.202
	(0.107)	(0.107)	(0.126)	(0.126)	(0.465)	(0.780)
Members' mean teamsize	-0.003	-0.003	0.008	0.008	-0.006	-0.061
	(0.009)	(0.009)	(0.013)	(0.013)	(0.030)	(0.048)
Members' mean citations received	0.039***	0.039***	0.003	0.004	0.066	-0.075
	(0.008)	(0.008)	(0.012)	(0.012)	(0.043)	(0.069)
Members' mean experience in firm's core tech.	0.122**	0.124**	0.074	0.076	0.320*	0.418
	(0.049)	(0.049)	(0.059)	(0.059)	(0.185)	(0.368)
Members' mean knowledge concentration	0.325*	0.320*	0.650***	0.638***	-1.210	0.078
	(0.174)	(0.173)	(0.214)	(0.213)	(1.242)	(1.348)
Members' mean basicness	-0.122	-0.121	-0.478***	-0.476***	-0.007	0.100
	(0.095)	(0.095)	(0.116)	(0.116)	(0.356)	(0.748)
Members' mean search scope	-0.346**	-0.346***	-0.449***	-0.448***	0.606	-1.046
	(0.134)	(0.134)	(0.166)	(0.166)	(0.554)	(0.957)
Members' mean prior co-assignment	-0.076	-0.076	-0.141**	-0.141**	0.266	-0.221
	(0.051)	(0.051)	(0.056)	(0.056)	(0.171)	(0.312)
Backward patent citations $_{patent}$	0.098***	0.099***	0.058***	0.059***	0.121	-0.031
	(0.019)	(0.019)	(0.022)	(0.022)	(0.110)	(0.142)
Non-patent citations $_{patent}$	-0.057***	-0.057***	-0.030*	-0.030*	-0.209**	0.130
	(0.017)	(0.017)	(0.017)	(0.017)	(0.099)	(0.099)
Number of IPC-4 classes $_{patent}$	0.202***	0.202***	0.590***	0.589***	-0.205	0.377
	(0.042)	(0.042)	(0.047)	(0.047)	(0.159)	(0.279)
Number of inventors $_{patent}$	0.376***	0.376***	0.261***	0.261***	0.850***	0.529***
	(0.025)	(0.025)	(0.027)	(0.027)	(0.117)	(0.177)
Observations	13,095	13,095	13,095	13,095	348	348
# of unique teams	6,969	6,969	6,969	6,969	253	253

Notes: Number of unique firms: 27. Robust standard errors are clustered by teams of inventors (in parentheses). All regressions control for a full set of firm dummies and priority year dummies. The time period is 1990 – 2005. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.