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Nest without birds:
Inventor mobility and the left-behind patents

Abstract

The mobility of inventors leaves behind their patented inventions at sourcing firms, yet there is little scholarly insight into how firms handle those intellectual properties. We investigate this important issue by developing a framework of tacit-codified knowledge interdependence. We theorize that tacit and codified knowledge offer the intellectual and legal pillars of corporate inventions, which complement each other in value creation. Inventor mobility decouples the two pillars and reduces the maintenance likelihood of the left-behind patents. The negative impact is greater for inventions that are complex or rely less on internal prior art because the tacit knowledge loss is more destructive and unrecoverable. However, when inventors move to competing or litigious target firms, the relationship between mobility and patent maintenance becomes less negative or even turns positive because the left-behind patents can be leveraged to hedge against the risk of knowledge leakage. Applying a two-stage Coarsened Exact Matching approach to construct a sample of 36,204 U.S. patents with comparable leaving and staying inventors from public firms between 1983 and 2010, we find strong evidence supporting our framework. Our findings highlight the intricate interdependence of tacit and codified knowledge in corporate inventions and add to the literatures on inventor mobility and intellectual property management.

Keywords: inventor mobility; patent maintenance; tacit knowledge; codified knowledge; IP management.

1. Introduction

Firms turn innovation outputs of their scientists and engineers into intellectual properties to gain competitive advantages. Yet, such advantages are vulnerable to the mobility of inventors. It not only drains tacit knowledge underlying these inventions (Agrawal, 2006) but also raises the concern of knowledge spillovers (Agarwal et al., 2009). While prior work has studied the consequence of inventor mobility on sourcing firms (Corredoira and Rosenkopf, 2010; Mawdsley and Somaya, 2016; Seo and Somaya, 2021), it paid little attention to the most critical assets created by the leaving talents—corporate inventions. After inventors leave, firms face the problem of how to maintain and deploy these intellectual properties. This decision is urgent and critical because maintaining these assets without continued inventor input may waste valuable R&D resources but abandoning them risks losing competitive barriers. However, the scholarly understanding of this post-mobility decision is far from adequate.

We fill in this gap by asking: What drive firms to maintain or abandon left-behind patents after losing inventors? How do managers perceive those intellectual properties? To answer these questions, we develop a conceptual framework building on the taxonomy of tacit and codified knowledge. We theorize that corporate knowledge, differing from public knowledge, is simultaneously supported by intellectual and legal pillars. The two pillars primarily manifest in the tacit knowledge held by inventors and the codified knowledge embodied by intellectual properties. For corporate inventions, tacit and codified knowledge are interdependent in value creation (Ranft and Lord, 2002; Winter and Szulanski, 2002). Tacit knowledge augments the exploitation and modification of codified knowledge while legal protection over codified knowledge authorizes the access to specified components in innovative search. This interdependent relationship drives the maintenance decision of left-behind patents.

Specifically, inventor mobility leads to the decoupling of tacit and codified knowledge for a corporate invention. The substantial loss of the intellectual pillar undermines the commercial value of the invention. We thus conjecture a lower maintenance likelihood of the left-behind patent. The negative impact of inventor mobility is greater when the invention is technologically complex because tacit knowledge is more vital for its deployment, but it is smaller if the invention relies more on internal prior art because the lost tacit knowledge is more recoverable. Our framework also suggests that the tacit-codified knowledge interdependence can be leveraged by the sourcing firm. When the inventor moves to a competing or litigious firm and increases the threat of knowledge spillovers, the sourcing firm can exploit the legal pillar entailed by codified knowledge to lock in the inventor's tacit knowledge and reduce the spillovers. In these situations, the relationship between inventor mobility and patent maintenance becomes less negative or even turns positive. Overall, the complementarity between tacit and codified knowledge leads to subtle and contingent decisions regarding how to handle left-behind patents.

We test the hypotheses with patents granted between 1983 and 2010 and employ a two-stage matching method. We first identify comparable inventors from the same public firm with and without mobility and then use the Coarsened Exact Matching (CEM) to construct a sample of similar patents of these inventors. Analyzing a rigorously matched sample of 36,204 inventor-patent pairs, we find that when an inventor leaves, his or her patent is less likely to be maintained compared to a similar control patent with a staying inventor. This negative relationship is stronger if the invention embodies complex knowledge but weaker if it relies more on internal prior art. Moreover, the relationship becomes less negative or turns positive if the inventor joins a competing firm or a firm reputable for litigiousness. Our findings offer insights that the managerial decision regarding patent maintenance is driven by the interdependence of tacit and codified knowledge in corporate inventions.

Our study makes both theoretical contributions and practical implications. Theoretically, we add to the literature on knowledge worker mobility. Prior studies have examined mobility-driven knowledge spillovers, interfirm learning, and their competitive implications (Corredoira and Rosenkopf, 2010; Song et al., 2003). However, this literature primarily focused on interfirm dynamics induced by employee mobility, with negligence of post-mobility management issues within sourcing firms. Our paper explores this understudied field by investigating an urgent and vital managerial decision: how sourcing firms should deal with the knowledge outputs of their leaving scientists and engineers. Developing a framework of intellectual and legal pillars of corporate inventions, we not only add this important yet missing piece to this literature, but also reveal the intricate relationship of tacit and codified knowledge in corporate inventions.

Practically, our paper provides managerial implications for firms operating in R&D-intensive industries. Patents offer legal protection over technologies. Their maintenance or abandonment is a strategic decision with long-term impacts (Khanna et al., 2016). Existing research has examined patent maintenance from angles of patent value (Bessen, 2008), social pressure (Liu, 2014), and managers' cognitive limitation (Khanna et al., 2018). We expand this strand of work by incorporating inventors and their tacit knowledge into consideration. Our framework enables decision-making in a more holistic way from both the intellectual and legal perspectives, rather than only considering the competition effect of patents (Goossen and Carnabuci, 2020). Our work therefore provides valuable insights as well as empirical guidance for IP managers, especially in the turbulent period after losing key talents.

2. Theoretical framework and hypotheses

2.1. Backgrounds

In knowledge-intensive industries, knowledge workers are the basis for competitive advantages. Yet, such advantages are flimsy because employees can depart to join other firms or create entrepreneurial ventures (Campbell et al., 2012). A large literature has examined the implications of knowledge worker mobility for sourcing firms. They found that losing key employees increases knowledge spillovers (Singh and Agrawal, 2011) and leads to a loss of clients (Somaya et al., 2008). Meanwhile, some researchers argue that knowledge worker mobility can be beneficial because leaving employees build interfirm ties (Carnahan and Somaya, 2013), enhance firm reputation in the labor market (Tan and Rider, 2017), and facilitate exploration (Tzabbar and Kehoe, 2014). While this literature offered considerable insights, our understanding of how sourcing firms handle the knowledge assets created and left behind by leaving employees is still inadequate. Different from those employees in manufacturing or sales positions, the major outputs of knowledge workers are intellectual properties. Although such assets belong to the employers, their commercialization needs to engage the individuals who create these assets in the first place because they hold critical tacit knowledge (Ranft and Lord, 2002). Therefore, how to deal with the left-behind knowledge outputs after losing talents is a key managerial decision that deserves a careful investigation. This paper sheds light on this issue by studying the maintenance of corporate inventions after losing inventors.

In innovative firms, inventors create inventions to enhance firm competitiveness. To protect the inventions from imitation, firms usually obtain patents and turn the codified part into intellectual properties. In the US, patent rights are subject to periodic renewals to maintain their legal enforceability. Non-payment of renewal fees leads to patent abandonment and is thus regarded as discontinuation of value appropriation from the inventions (Khanna et al., 2016). Currently, IP managers make maintenance decisions in the 3.5th, 7.5th, and 11.5th years after patents have been granted. The maintenance of these IP assets can be expensive.[1] For example, Qualcomm paid more than $32 million in total to renew their U.S. patents in 2020 as shown by

[1] The maintenance fee for U.S. patents was $2,000 in the 3.5th year, $3,760 in the 7.5th year, and $7,700 in the 11.5th year as of January 2021. Small and micro entities identified by the USPTO enjoyed 50% and 75% fee discounts, respectively.

the USPTO record. Therefore, patent maintenance is a key decision in IP management.

In this paper, we probe the impact of inventor mobility on patent maintenance by developing a framework of tacit-codified knowledge interdependence. In the following, we introduce this framework and develop our hypotheses.

2.2. Tacit and codified knowledge

Tacit knowledge is described as "we know more than we can tell" (Teece, 1998). It includes mental models, heuristics, and know-how, which are embedded in human actions, commitments, and involvement in specific contexts (Polanyi, 1966). For corporate inventions, inventors are the major reservoir of tacit knowledge. In practice, most inventions are recombinations of previous knowledge components (Fleming, 2001). When inventors experiment with the components and try different combinations, they become familiar with the component features and gain search heuristics. They also accumulate experience of failures which is very helpful in further experiments. All these tacit understandings are difficult to be expressed in written forms and thus held by inventors themselves. Due to the nature of low transferability, tacit knowledge is hard to imitate and offers unique intellectual support to corporate inventions.

Codified knowledge is conceptualized as a recipe that specifies a "legal" sequence of procedures with technical feasibility to achieve a desirable outcome (Dosi and Nelson, 2010). Such knowledge can be explicitly expressed in forms such as scientific formulas, specific actions, and manuals. As a written recipe, codified knowledge is alienable from the creator and easily transferable (Kogut and Zander, 1992). This feature is valuable when an organization wants to replicate an activity at multiple locations (Grant, 1996). For corporate inventions, codified knowledge is especially important in the legal sense. It specifies knowledge components and working procedures that are protectable by patents and trade secrets. This feature generates the legal exclusivity and differentiates corporate innovation from public knowledge.

Although tacit and codified knowledge are valuable in isolation, we argue that they are interdependent and exhibit strong complementarity in the context of corporate inventions. The complementarity manifests in several ways. First, tacit knowledge is essential to the interpretation and execution of codified knowledge in practice. As Teece (1998) puts it, stand-alone codified knowledge, such as software codes, formulas, or blueprints, may convey little meaning. The tacit part of knowledge is usually much more than the codified part (Dosi and Nelson, 2010). To properly execute procedures specified in a codified recipe, one needs to have additional knowledge on "what was not written down." This has been proven in knowledge transfers such as replicating the best practices across operating units (Chang et al., 2012).

Second, tacit knowledge is crucial to the reconfiguration and modification of a codified knowledge for value appropriation. In practice, theory rarely predicts the performance of a technological artifact in operation with high enough certainty before sufficient testing of prototypes (Pavitt, 1987). That is, codified knowledge is usually not applicable before several rounds of iteration and modification, especially in a changing environment with emerging opportunities and the risk of obsolescence. Thus, surrounding tacit knowledge, such as search heuristics and technological know-how accumulated during the invention process, enables a firm to apply and adapt codified knowledge to real situations and generate maximum values.

Third, the exploitation of tacit knowledge also depends on the accessibility of codified knowledge components and procedures. For corporate inventions, codified knowledge expressed in written forms is legally protected by patents and trade secrets. The practicing and deployment of tacit knowledge rely heavily on the accessibility to the specified components and procedures. This is because tacit knowledge is an implicit conceptualization of these components and their interactions (Agrawal, 2006), thus local to the inventions. It generates value by facilitating the application of the same components in knowledge recombination (Arts and Fleming, 2018).

When the components and procedures represented by codified knowledge are no longer accessible due to barriers such as patents, the value of tacit knowledge will be heavily discounted.

Figure 1 outlines our conceptual representation of the above interdependent relationship. On one side, tacit knowledge augments the value of codified knowledge by enabling implementation and modification. On the other side, legal protection over codified knowledge authorizes the deployment of tacit knowledge, especially for exploitative search and knowledge reuse. They together offer intellectual and legal pillars for cultivating revenues from inventions. Given the strong complementarities between tacit and codified knowledge for corporate inventions, we expect that inventor mobility will have a profound impact on the maintenance of patents over codified knowledge. We formally hypothesize the relationship in the following section.

INSERT FIGURE 1 ABOUT HERE

2.3. Inventor mobility and patent maintenance

In the context of corporate innovation, inventors are the focal individuals who master the majority of tacit knowledge underlying their inventions while patents contain the codified part (Melero et al., 2020). Inventor mobility can thus be conceptualized as an instance in which tacit and codified knowledge are decoupled. Given the interdependence of tacit and codified knowledge, we expect that inventor mobility affects patent maintenance decisions in two major ways. First, inventors, with their technological know-how, understand the advantages and shortcomings of their inventions. Even for originating firms, most codified knowledge is not directly applicable to existing product lines. Necessary modifications are required for commercial viability (Agrawal, 2006). Tacit knowledge allows inventors to provide valuable advice on the implementation of codified knowledge, help develop prototypes, and shorten inventions' time to market (Colyvas et al., 2002). If the inventors depart during this stage, firms will face difficulties in commercializing the inventions and therefore devaluate the underlying codified knowledge.

Second, tacit knowledge embedded in inventors also improves the alterability and flexibility of codified knowledge in a dynamic environment. Knowledge explicitly codified in “hard” forms, such as documents and patents, is subject to obsolescence (Argote, 2012). In a dynamic environment, the risk of obsolescence can erode the value of inventions if they are not adapted to changes. When the environment changes, inventors and their technological know-how become critical to the adaptive development of codified knowledge. Therefore, inventor mobility and the loss of tacit knowledge reduce the adaptivity of inventions.

Due to the augmentation effect of tacit knowledge on codified knowledge, the mobility of inventors undermines the perceived value of their inventions. Given that patent maintenance decisions largely depend on whether the underlying inventions are worth protecting or not (Bessen, 2008), our framework suggests that sourcing firm managers will be less willing to maintain patents after inventors leave. Therefore, we hypothesize that:

Hypothesis (H1). *The maintenance likelihood of a patented invention is negatively associated with the mobility of its inventor.*

Our main theoretical proposition originates from the interdependence of tacit and codified knowledge and extends the arguments to knowledge decoupling after inventor mobility. Consequently, the impact of mobility as well as knowledge decoupling could be contingent on both tacit and codified parts of focal inventions. Our main arguments are built on the assumption that an inventor holds a certain amount of tacit knowledge of his or her inventions that is difficult to replace. The more important and unrecoverable the tacit knowledge, the greater the impact of inventor mobility on the left-behind codified knowledge. Moreover, since the accessibility to codified components determines how target firms can exploit inventors’ tacit knowledge, sourcing firm managers may leverage patent barriers over codified knowledge to mitigate competitive threats associated with inventor mobility. Next, we consider these contingencies and how they moderate the main relationship in H1.

2.4. Knowledge complexity and internal reliance

Building on prior research, we argue that the complexity of knowledge embedded in an invention determines the importance of tacit knowledge held by its inventor. To understand complexity, it is useful to conceptualize an invention as recombination of prior components (Fleming, 2001). These components can be interdependent with each other. Two components are interdependent if changing one affects the other's performance. When overall interdependence increases, a system becomes difficult to optimize. The optimization efforts increase exponentially with the level of interdependence, an observation termed as "complexity catastrophe" (Fleming and Sorenson, 2001). For example, optimizing an air conditioning system is much more complex than changing the design of a bicycle handle because the former requires an overall understanding of the interdependent power and circulation subsystems. Knowledge complexity is thus defined as the level of component interdependence of an invention (Ganco, 2013).

For an invention incorporating complex knowledge, the inventor's tacit know-how is more critical for the exploitation of codified knowledge. When complexity is high, a large portion of knowledge remains tacit and is carried by its inventors (Ganco, 2013), because the cost and difficulty to explicate and codify how components interact become prohibitively high for a complex system (Fleming, 2001). Testing and modifying the invention rely heavily on heuristics and tacit know-how possessed by the inventor instead of written guidance. In other words, complexity significantly increases the tacit-to-codified knowledge ratio for an invention. The loss of tacit knowledge due to inventor mobility thus causes greater disruption to the development and commercialization of a complex invention. Therefore, we hypothesize that:

Hypothesis (H2). *The relationship between inventor mobility and patent maintenance* *is more negative if the invention embodies complex knowledge.*

In addition to the importance of tacit knowledge, whether it can be recovered after inventor mobility also determines how the sourcing firm evaluates the left-behind codified knowledge. We propose that an invention's reliance on internal prior art is closely related to tacit knowledge recoverability. A technological invention is an outcome of recombinant search over internal and external prior art (Fleming, 2001). It is recognized that external search brings in new components and creates new recombinant opportunities, but internal search is usually more predictable and efficient due to tacit knowledge accumulation (Arts and Fleming, 2018). While search strategies drive the success of innovation, we conjecture that their impact extends to how managers evaluate left-behind knowledge after inventor mobility.

When an invention is generated mainly from internal search and dependent on internal prior art, we argue that inventor mobility causes less disruption because the lost tacit knowledge is more recoverable from internal knowledge paths. High reliance on internal prior art is more likely to generate an invention that is incremental to a firm's existing knowledge base (Katila and Ahuja, 2002; Laursen, 2012). Such an invention tends to be local to the firm in the sense that the tacit knowledge accumulated in prior art can be easily adapted and applied to help interpret and modify the focal invention. As a result, tacit knowledge held by its inventor is less unique and indispensable to the further development and reconfiguration of codified knowledge. Inventor mobility is thus less impactful and disruptive. The firm is still able to exploit the codified knowledge and is willing to maintain its patent protection. Therefore, we hypothesize that:

Hypothesis (H3). *The relationship between inventor mobility and patent maintenance is less negative if the invention relies more on internal prior art.*

2.5. Target firm competition and litigiousness

In addition to the exploitation of codified knowledge, we conjecture that the sourcing firm can leverage the interdependence of codified and tacit knowledge to reduce potential knowledge spillovers associated with inventor mobility. Prior research has found that patent rights effectively reduce knowledge leakages (Murray and Stern, 2007). Therefore, patent protection is considered by firms as a defensive mechanism against knowledge spillovers when inventors leave (Agarwal et al., 2009). This is because patents over codified knowledge authorize the use of specific components and have a “lock-in” effect on the tacit knowledge of leaving inventors. Patent barriers on left-behind inventions turn inventors’ tacit knowledge to be firm-specific and legally deter target firms’ exploitation of their newly recruited inventors (Agarwal et al., 2009). For example, after Microsoft’s former star scientist, Kai-Fu Lee, joined Google, Microsoft immediately initiated a legal fight with Google to control the potential loss. As a result of this legal action, Microsoft successfully restricted Kai-Fu Lee from working on projects related to Internet search and thus reduced knowledge spillovers.

We expect that a sourcing firm is more likely to use patent maintenance to lock in the tacit knowledge of a leaving inventor when the inventor joins a competing firm. If a target firm and a sourcing firm have similar or overlapping technological capabilities, the target firm’s absorptive capacity is greater and it is more able to turn the inventor’s tacit knowledge into competitive inventions (Filatotchev et al., 2011). Technological overlap also increases the anticipated hostile actions of the target firm. Due to the increased concern of knowledge spillovers, the sourcing firm manager is more likely to use legal protection to mitigate competitive threats after the inventor jumps ship. The patent over the left-behind codified knowledge as the legal pillar of the invention offers this protection. As a result, the patent is more likely to be maintained if the target firm is a competitor. Therefore, we hypothesize that:

Hypothesis (H4). *The relationship between inventor mobility and patent maintenance is less negative if the inventor moves to a target firm that competes with the sourcing* *firm in the knowledge space.*

In addition to the threat of knowledge spillovers, another concern is that the target firm may build follow-on inventions with the help of the inventor's tacit knowledge, which may limit the sourcing firm's room for technological improvement and render the left-behind codified knowledge obsolescent. This concern is best characterized by the notion of patent races along technological trajectories (Fudenberg et al., 1983). When a target firm hires away an inventor and acquires the tacit knowledge, the target firm is likely to "leapfrog" and pre-empt future development opportunities. The sourcing firm may lose the ability to sustain its competitive advantages conferred by the invention.

We argue that the above threat is greater if a target firm is more litigious and the left-behind patent can be used to reduce this threat in both offensive and defensive ways. On the one hand, the sourcing firm can proactively sue the target firm for exploiting a similar technological trajectory. If the target firm is reputable for litigation, the sourcing would anticipate a more difficult legal interaction. In this situation, holding more valid patents will confer more legal advantages. On the other hand, when the target firm indeed leapfrogs with the help of the newly hired inventor, its strong legal capacity would help the target firm turn the follow-on inventions into IP weapons against the sourcing firm. This suppresses the sourcing firm's technological development and increases the concern that the original invention is substituted. In this case, the left-behind patent rights can be used as a bargaining chip with the target firm for a defensive purpose. Therefore, we hypothesize that:

Hypothesis (H5). *The relationship between inventor mobility and patent maintenance is less negative if the inventor moves to a target firm that is reputable for litigiousness.*

3. Methods

3.1. Data and sample

To empirically investigate the relationship between inventor mobility and the maintenance of left-behind patents, we started with all patents granted by the USPTO from 1983 to 2010. To trace inventor mobility, the patent data were triangulated with the inventor disambiguation data from PatentsView. We restricted our sample to patents and inventors of U.S. public firms because of the availability of firm financial records. Patent assignee names were disambiguated and matched to U.S. public firms in the Compustat database. Firms from financial and utility sectors were excluded because these sectors are highly regulated. This procedure yielded 2,149,496 inventor-patent pairs, involving 854,868 patents.

To examine patent maintenance decisions, we retrieved the maintenance records from the USPTO database. Following existing studies (Khanna et al., 2018; Liu, 2014), we focused on the first maintenance decision (i.e., the 3.5^{th} year after the patent grant) because the value appropriation and follow-up development of an invention are still in progress. The impact of inventor mobility is therefore more relevant in this stage than that in later stages.[2] In the rest of the paper, patent maintenance will refer to the first maintenance decision unless otherwise specified. In all of the analyses, we excluded patents sold or purchased before the maintenance date to avoid mismatches between initial assignees and current patent owners.

To identify inventor mobility, we followed the literature and used patent filing information (Tzabbar, 2009). We assumed that a patent application date captures the inventor-firm relationship around that date (Corredoira and Rosenkopf, 2010; Ganco et al., 2015). We then adopted a rigorous approach to identify inventor mobility events. Specifically, we recorded inventors as “leave” or “stay” on the maintenance date only when there was solid evidence in patent application records. Figure 2 depicts our identification strategy. If a focal inventor filed another patent before the maintenance date with another firm and the original firm never

[2] In a later robustness test, we examined the second maintenance decision at the 7.5^{th} year after the patent grant.

appeared again in the inventor's subsequent patenting records, we treated the inventor as having left the original employer before the maintenance date (Case 1 in Panel A). Similarly, if the first application filed by the inventor after the maintenance date had the original assignee, we regarded the inventor as having stayed with the original employer (Case 2 in Panel A). We dropped all other cases because we were unable to determine the inventor-firm relationship around the maintenance date with certainty (Cases 3-5 in Panel B). Such an approach effectively excluded "false leaves" due to interfirm R&D collaboration and "false stays" due to inventors' retirement (Ge et al., 2016). Applying these strict identification criteria, we were able to figure out mobility status for 779,588 inventor-patent pairs involving 410,872 patents from 1,853 firms. Of these observations, 185,315 were labelled as "leaves" while 594,273 were labelled as "stays."

INSERT FIGURE 2 ABOUT HERE

Even though, Ge et al. (2016) suggested that inventor mobility identification based on patent records can introduce both "false leaves" and "false stays." To check the accuracy of our identification, we randomly chose 100 observations in both "leave" and "stay" groups and validated them via other channels such as Google search and LinkedIn to evaluate the possibility of false identification (Wagner and Goossen, 2018). Of all the 200 cases, only 4 stay cases were falsely identified as "leaves" and 5 leave cases were falsely identified as "stays," yielding false identification rates much lower than those reported by Ge et al. (2016). The validation confirmed the rigor of our categorization criteria. The low false rates allowed us to test the hypotheses with a high level of measurement precision.

A potential challenge to our empirical analysis is the endogeneity concern. Specifically, unobserved quality differences across patented inventions may simultaneously determine inventor mobility and patent maintenance, leading to spurious inferences about the impact of mobility. One way to address the concern is sample matching. The intuition is that patents that are more similar in their observed characteristics are less likely to differ in unobserved ways. Therefore, although invention quality is unobservable, matching on observed pretreatment characteristics and achieving a balanced sample helps reduce unobserved heterogeneities (Heckman and Navarro-Lozano, 2004).

To improve the balance between patents with leaving and staying inventors, we followed Azoulay et al. (2014) and adopted a two-stage matching method. We first identified groups of similar inventors with and without mobility and then matched patents of inventors within the same group. In both stages, we used the Coarsened Exact Matching (CEM) approach. The CEM is a non-parametric sample matching method that matches treated units with similar control units based on pre-defined variables to improve pre-treatment sample balance (Iacus et al., 2012). First, we grouped comparable inventors. We required that inventors in the same group belonged to the same original firm, had a similar tenure, and showed a similar level of productivity before the maintenance date.[3] Second, we matched patents within inventor groups. Specifically, we matched each patent of a leaving inventor with another patent of a staying inventor. Matched patents belonged to the same Cooperative Patent Classification (CPC) subclass[4] and the same grant year. Furthermore, we required matched patents to have a similar number of claims, co-inventors, and forward citations before the maintenance date. Another issue in our matching is that a patent with multiple inventors may be sampled more than once. This could lead to non-independence of observations as well as estimation errors. To avoid this problem, we restricted that each patent was only sampled once in the matching process, regardless of whether it was in the treatment or

[3] For the definitions and measures of inventor tenure and productivity, see the "Control variables" section.
[4] On January 1, 2013, the USPTO moved from the United States Patent Classification (USPC) system to the CPC system. Compared with the USPC, the CPC system is more granular with over 260,000 subgroups and maintained more actively on a monthly basis. The USPTO has stopped using the USPC system in June 2015.

control group. After the above stages, we successfully matched 18,102 patents produced by leaving inventors with 18,102 similar patents by comparable staying inventors, yielding a final sample of 36,204 observations.

3.2. Dependent variable

The dependent variable for this study was a binary indicator *maintenance decision*, coded as 1 if a patent was maintained by the IP manager on its first maintenance date and 0 otherwise. A maintenance decision was indicated by the payment of a renewal fee to the USPTO. Although the renewal fee is relatively small for an established firm, the maintenance decision is non-trivial given the cost of value appropriation from a patented invention. The payment of a renewal fee thus represents a mindful and deliberate managerial decision on the continuation of patent protection over the invention (Khanna et al., 2018).

3.3. Independent and moderating variables

The main independent variable was *inventor mobility*. It was an indicator equal to 1 if the focal inventor had left the sourcing firm before the maintenance date and 0 otherwise. As discussed above, our identification strategy for inventor mobility was rather rigorous. We only included the cases for which we could clearly judge the mobility status.

The first moderator was *knowledge complexity*. In line with Ganco (2013), we measured knowledge complexity as the ratio of the level of interdependence between components to the number of components in an invention. The idea behind this measurement is that when the relative level of interdependence rises, any modification to a single component will affect the performance of other interacting components, making it more complex to optimize. For example, we assume that invention A is composed of components *i* and *j* and invention B is composed of *k* and *l*. If *i* and *j* are highly interdependent (as indicated by more past combinations) while *k* and *l* are loosely coupled (as indicated by fewer past co-appearances), invention A is more difficult to optimize than B because one needs to consider i, j, and their interaction *i-j* simultaneously, yielding a higher degree of cognitive and computational complexity. We operationalized knowledge complexity in three steps. First, for a CPC subgroup i covered by a patent P, we measured its interdependence (K_i) with other subgroups in P (i.e., $j \epsilon P_{-i}$):

$$Interdependence\ K_i = \sum_{j \epsilon P_{-i}} \frac{number\ of\ patents\ in\ both\ subgroup\ i\ and\ j}{number\ of\ patents\ in\ subgroup\ i},$$

where j belonged to subgroups of P except i. Second, we computed the interdependence of patent P by averaging the interdependence of all its subgroups:

$$Interdependence\ K_p\ of\ patent\ P = \frac{\sum_{i \in P} K_i}{number\ of\ subgroups\ of\ patent\ P}.$$

Last, knowledge complexity was measured by dividing the interdependence K_P by the number of subgroups N_P: $Knowledge\ complexity\ C_P = K_P/N_P$.

The second moderator was *internal reliance*. It measured the extent to which an invention is built on internal prior art. We used patent backward citations as indicators of prior art and operationalized this variable as the ratio of self-citations to inventions originated within the firm among all backward citations. In an unreported robustness check, we extended the scope of internal prior art to all inventions that had been previously cited by patents of the firm before the focal invention. This alternative measure yielded similar results.

The third moderator was *target firm competition*. It captured the level of competition between the sourcing firm and the target firm in the knowledge space. We measured this variable as the cosine similarity between the domain expertise of the two firms and calculated it in two steps. First, for each firm, we generated a vector of domain expertise E, whose entry e_A was the natural log of 1 plus the number of patents filed by the firm in the CPC subclass A in the past five years. Second, for firms f_1 and f_2, their level of competition was calculated as:

$$Competition_{f_1,f_2} = \frac{E_{f_1} \cdot E_{f_2}}{|E_{f_1}|\,|E_{f_2}|}.$$

For example, suppose that f_1 created 4 patents in subclass *A* and 10 patents in subclass *B* while f_2 created 9 patents in subclass *A* and 5 patents in subclass *C*. The vectors of expertise for f_1 and f_2 were (1.61, 2.40, 0) and (2.30, 0, 1.79), respectively. The level of competition between the two firms was calculated as 0.44 (= $(1.61 * 2.30 + 2.40 * 0 + 0 * 1.79)/(\sqrt{1.61^2 + 2.40^2 + 0^2} * \sqrt{2.30^2 + 0^2 + 1.79^2})$). For "stay" cases, this variable was 0 because managers do not need to consider sourcing-target interfirm competition when making patent maintenance decisions.

The last moderator was *target firm litigiousness*. It captured the target firm's willingness and ability to pre-empt competitors using patent litigation. We follow Agarwal et al. (2009) to measure this variable using the target firm's past litigation records. We retrieved patent litigation records filed at U.S district courts from the Westlaw database of Thomson Reuters. Repeated lawsuits between the same parties within three years were excluded. For litigiousness, we only counted cases initiated by a target firm (i.e., the target firm as a plaintiff). We matched plaintiffs in all the cases to target firm names in our sample. Litigiousness was calculated as the natural log of 1 plus the number of patent litigation cases initiated by the target firm in the past five years. For example, if a target firm initiated 12 patent lawsuits as the plaintiff in the past five years, this variable was equal to 2.56 (=ln(1+12)). Again, for "stay" observations, this variable equaled to 0.

3.4. Control variables

Unless otherwise specified, all of the models included firm and primary CPC subclass fixed effects to control for time-invariant firm and technological domain heterogeneity. We also included the maintenance year fixed effects to account for the time trend in maintenance decisions. In addition, we added time-variant controls at the patent, inventor, and firm levels.

At the patent level, we controlled for the number of *claims*, as it may indicates the legal scope and affect managers' maintenance decisions. Prior research has also shown that sequential inventions in larger patent families are more valuable (Liu et al., 2008). The *family size* of the focal patent was thus included. The number of *backward citations* and the number of *CPC subclasses* were also added to control for the search scope and technological breadth (Arts and Fleming, 2018). Patent maintenance decisions also depend on whether an invention is in a technological domain that is central or peripheral to the firm. To control for this effect, we included *firm domain stock* as measured by the natural log of 1 plus the number of patents filed by the firm in the focal patent's primary CPC subclass in the past five years. As the number of forward citations is often used to indicate patent quality, we controlled for the number of *pre-maintenance forward citations* to further reduce the confounding effect of patent quality. We also included the number of *pre-maintenance forward self-citations* to account for the internal development of the focal invention.

At the inventor level, we controlled for several variables that may influence maintenance decisions. First, we included *inventor tenure*, as measured by the number of years from the inventor's first patent application to the focal patent, because a more experienced inventor tends to be more productive but his or her inventions are less novel (Conti et al., 2013). Second, we controlled for *inventor current productivity* measured by the natural log of 1 plus the number of patents filed by the inventor within the 5 years prior to the maintenance date. Third, we included the number of *co-inventors* for the focal patent to control for team size, which has been found to influence the maintenance decision (Liu, 2014). Fourth, anecdotal evidence suggests that lead inventors differ from other inventors in their contributions and are often listed as the first inventor in patent documents (No and Walsh, 2010). We thus included a *first inventor* indicator in all of the models.

The final set of controls captured the time-variant firm-level factors that may affect managers' maintenance decisions. We controlled for *firm size* by the natural log of total assets in the maintenance year. We also controlled for firm financial performance and R&D intensity by the return on assets (*ROA*) and R&D to assets ratio (*R&D ratio*) in the maintenance year to capture the resources available to maintain and carry on research projects (Liu, 2014). To account for the firm's overall maintenance propensity, we included *firm past maintenance rate* in the past three years. Last, the number of *patents to maintain* in the maintenance year was added to control for the workload and cognitive burden of IP managers (Khanna et al., 2018).

3.5. Estimation

As described above, we conducted a matching procedure before model estimation to improve the balance of patent samples between leaving and staying inventors. Table 1 provides t-tests of the key variables before and after matching. Panel A shows that, before matching, leaving and staying inventors exhibit significant differences across patent quality, tenure, and productivity. Such differences may confound our estimation and undermine its reliability, confirming the necessity of a pre-estimation matching. After our two-stage matching procedures, Panel B shows that treatment and control groups were relatively balanced. The groups of "stay" and "leave" observations did not exhibit significant differences across all the key observed dimensions.

INSERT TABLE 1 ABOUT HERE

The dependent variable in the study was a binary indicator of the maintenance decision. We tested the hypotheses by estimating logit models with firm, primary CPC subclass, and maintenance year fixed effects. All of the models were estimated with robust standard errors.

4. Results

4.1. Inventor mobility and patent maintenance

Table 2 reports the summary statistics and correlation coefficients for all variables included in the estimation. Table 3 shows the estimation results. Model 1 included only control variables. The results align with prior findings on patent maintenance. At the patent level, a patent is more likely to be maintained if it is more valuable as indicated by more forward citations, more claims, and larger family size (Bessen, 2008; Liu et al., 2008). At the inventor level, an inventor with higher productivity and more co-inventors is more likely to have his or her inventions maintained by IP managers (Liu, 2014). At the firm level, R&D intensity reflects innovation resources and is positively associated with the patent maintenance likelihood.

INSERT TABLES 2 AND 3 ABOUT HERE

Model 2 reports the estimate of the key independent variable, *inventor mobility*. The coefficient of *inventor mobility* shows strong support to H1 that managers are less likely to maintain patent protection over codified knowledge after losing tacit knowledge held by inventors. There is a significantly negative relationship between inventor mobility and the maintenance likelihood of a left-behind patent ($\beta = -0.115$, $p < .001$). The odds of maintaining a patent by a leaving inventor over a staying inventor is 0.891 [= exp(−0.115)], or a 10.9 percent decrease. To evaluate the economic significance of the coefficient, we held other controls at mean values and estimated the change in the maintenance likelihood when *inventor mobility* changed from 0 to 1. We found that inventor mobility causes a 1.4 percent drop in the maintenance likelihood. Given the low discontinuation rate of 13.3 percent for the patents in our sample, this effect size is considerable. The continuous engagement of original inventors is a critical determinant of patent maintenance decisions. It is also worth noting that our level of analysis is inventor-patent, which implies that the estimated effect is associated with the mobility of individual inventors on specific patents. We speculate that the mobility of an entire inventor team could be more disruptive, yet we are unable to test this conjecture due to identification problems.

Future research is encouraged to explore the effect of team mobility when such data is available.

Next, we examine whether the importance and recoverability of tacit knowledge moderate the above relationship as hypothesized in H2 and H3. We tested the moderating effects of *knowledge complexity* and *internal reliance* in Models 3 and 4. We find that the negative relationship between inventor mobility and patent maintenance becomes more negative when the patented invention embodies complex knowledge (Model 3: $\beta = -0.714$, $p < .05$) but less negative if it relies more on internal prior art (Model 4: $\beta = 0.349$, $p < .05$). As logit models are non-linear models, testing moderating effects requires additional attention to the marginal effects (Hoetker, 2007). We thus examined the moderating effects using the simulation-based method suggested by Zelner (2009). The method simulated the marginal effects and the confidence intervals of *inventor mobility* on *patent maintenance* at different values of the moderating variables (i.e., *knowledge complexity* and *internal reliance*) (for details, see Zelner, 2009). Figure 3 graphically depicts the moderating effects. It is clear that the negative effects of inventor mobility on patent maintenance decrease with *knowledge complexity* but increase with internal reliance, corroborating our findings.

INSERT FIGURE 3 ABOUT HERE

Our framework also predicts that the legal pillar provides authorization for tacit knowledge. Firms can therefore leverage this critical dependence to reduce knowledge spillovers to target firms. We argue that when the competitive threats are prominent, sourcing firms are more likely to use legal protection over codified knowledge to lock in inventors' tacit knowledge. Therefore, we tested two contingencies, *target firm competition* and *litigiousness*, in Models 5 and 6. The positive coefficients of the interaction terms *inventor mobility* × *target firm competition* (Model 5: $\beta = 0.263$, $p < .001$) and *inventor mobility* × *target firm litigiousness* (Model 6: $\beta = 0.041$, $p < .05$)

suggest that managers are more likely to maintain patent protection over the left-behind codified knowledge when inventors move to competing or litigious firms. Figure 3 presents the moderating effects graphically. At low values of *target firm competition* and *litigiousness*, interfirm competition is not a major concern and maintenance decisions are mainly driven by tacit knowledge loss. At high values of the two variables, however, managers take the competitive implications of inventor mobility seriously. The maintenance likelihood of left-behind patents rises. At high values of *target firm competition,* the relationship between inventor mobility and patent maintenance is even positive. These findings indicate that managers consider using patent protection in a more strategic way when inventors move to competitors.

4.2. Robustness tests

We performed several robustness tests to validate our findings. First, as we used strict criteria to identify "leave" and "stay" inventors, we were unable to precisely tell the mobility status for all the inventors. This limitation reduces our estimation accuracy for patents created by a team of inventors because our estimation on single inventor mobility may reveal a partial impact. To address this concern, we performed a robustness check by restricting our sample to patents generated by solo inventors. In the case of solo inventorship, our estimation can capture the full impact of inventor mobility. Models 1 and 2 in Table 4 report the results for this robustness check. Compared to the results in the main analysis, the effect size of inventor mobility is greater ($\beta = -0.314$, $p < .001$), suggesting that the main effect of inventor mobility should have been greater if we can accurately measure mobility at the team level. In other words, our results in the main analyses tend to be conservative. In an unreported analysis, we find that the effect of mobility was slightly greater if the focal inventor was the leading inventor as indicated by his or her first position in the inventor list. This provides further evidence to the tacit-codified knowledge interdependence because the leading inventor usually carries more tacit knowledge.

INSERT TABLE 4 ABOUT HERE

Second, we coded *target firm competition* and *litigiousness* as 0 for the control group in which inventors did not leave. These two variables are thus correlated with *inventor mobility*, leading to a multicollinearity concern. To address this issue, we did robustness tests on our treatment group (i.e., a subsample of patents with leaving inventors only) and examined whether the likelihood of patent maintenance increases with *target firm competition* and *litigiousness*. The results are reported in Models 3 and 4 in Table 4. The coefficients of the two variables are positive, supporting our arguments in H4 and H5. When inventors move to competing or litigious target firms, the sourcing firms are more likely to maintain patent protection over codified knowledge as a strategic response.

Third, in the main analyses, we investigate managers' maintenance decisions by examining the first maintenance event at the 3.5th year after patent issuance. In the U.S., patents are subject to maintenance three times at the 3.5th, 7.5th, and 11.5th years after grant. One may wonder whether our theoretical framework and findings apply to later maintenance decisions. To answer this question, we re-identified mobility status, built a new matched sample, and performed the tests for the second maintenance decision. Models 5 and 6 in Table 4 report the results. The overall results are qualitatively similar to our findings for the first maintenance decision.

Fourth, we check the robustness of our findings to alternative sampling methods. We reported estimation using the full sample without sample preprocessing in Models 7 and 8. The coefficients of *inventor mobility* remain significantly negative, similar to our main findings. The moderating effects of *knowledge complexity* and *target firm competition* remain qualitatively similar, but *internal reliance* and *target firm litigiousness* do not show significant moderating effects. We also report results using propensity score matching (PSM) to match treatment and control groups. In this robustness test, we first estimated the likelihood of treatment (i.e., inventor mobility) using patent, inventor, and firm characteristics. We then applied a 1-on-1 match based on the nearest propensity score and dropped those matches whose scores differed more than 10 percent. Models 5 and 6 in Table 4 show the results using the PSM. The coefficients of our interested variables remain consistent with those reported in Table 3.

Fifth, in the test of H3, we measured *internal reliance* as the ratio of self-citations to the firm's internal prior art among all the backward citations. In our sample, some prior internal patents were generated by the same focal inventors who left the sourcing firms. Such prior knowledge base was also fragile to the mobility of the focal inventors and contributed little to the recoverability of the lost tacit knowledge. Therefore, we performed a robustness test by excluding the citations to the focal inventor's own patents from the measurement of internal reliance. In an unreported table, we find that the findings in Table 3 are robust to this alternative measurement.

Last, we considered heterogeneities across industries. The literature has pointed out that industries show considerable differences in their types of innovation. Specifically, innovation is more complex and cumulative in information, computer, and telecommunication (ICT) sectors while technologies in industries such as pharmaceuticals and chemistry are more discrete (Hall and Ziedonis, 2001). In an unreported test, we find that the relationship between inventor mobility and patent maintenance is more positive in ICT sectors, possibly because patent ownership is more fragmented and firms are more litigious in these industries due to the cumulative nature of their technologies (Ziedonis, 2003). This result accommodates recent findings by Goossen and Carnabuci (2020), who studied patent maintenance using four semiconductor firms. In Models 11 and 12, we report robustness tests with industry fixed effects to control for industry heterogeneities. The results are qualitatively similar to those in Table 3.

5. Discussion

Knowledge worker mobility has become a major topic in the management literature and gained substantial attention from scholars and practitioners (Mawdsley and Somaya, 2016). One critical yet underexplored strategic issue is how to deal with the intellectual properties created and left behind by leaving employees. Our study addresses this gap by investigating the maintenance decision of left-behind patents. We theorize that corporate inventions are simultaneously supported by intellectual and legal pillars that embodied by tacit and codified knowledge underlying the inventions. The two types of knowledge are interdependent in value creation. By conceptualizing inventors as carriers of tacit knowledge, our framework generates insights into how managers perceive and assess left-behind patents. Our empirical analysis supports the framework and shows that after inventors leave, managers are less likely to maintain patent protection over the left-behind codified knowledge. This relationship is more negative for inventions embodying complex knowledge but less negative if the inventions rely more on internal prior art. We also find that managers consider competitive threats of inventor mobility and leverage legal protection over codified knowledge to lock in the tacit knowledge of leaving inventors. The relationship between inventor mobility and patent maintenance becomes less negative or even positive when inventors leave to join other firms that compete with the sourcing firms or have a reputation for patent enforcement. Overall, we proffer a nuanced understanding of corporate inventions and highlight the interdependence between tacit and codified knowledge.

Our study makes important theoretical contributions. In the literature on knowledge worker mobility, scholars have examined the strategic implications of losing key employees. Some prior studies found that the outbound mobility of knowledge workers increases knowledge spillovers (Agarwal et al., 2009), leads to a loss of clients (Raffiee, 2017; Somaya et al., 2008), and reduces competitive advantages (Aime et al., 2010), while others focused on potential benefits such as interfirm network building (Carnahan and Somaya, 2013), reverse knowledge spillovers (Yang et al., 2010), and strategic repositioning (Tzabbar and Kehoe, 2014). However, the literature provides little guidance on how to handle the knowledge outputs of leaving employees. This managerial decision is critical because these outputs are the major assets contributed by knowledge workers to their employers and subject to severe value depreciation and spillovers after the creators leave. We fill in this gap by proposing a theoretical framework based on the taxonomy of tacit and codified knowledge. We find that the complementarity between tacit and codified knowledge imposes contingent impacts on managers' perception of left-behind patents, especially when inventors move to competing firms.

Our study also adds to the understanding of patent maintenance decisions and offers implications for innovative firms. In addition to considerations such as patent quality and project interdependence (Bessen, 2008; Khanna et al., 2018), our framework and findings suggest a paradox faced by managers in the maintenance of left-behind patents. There is a tradeoff between the loss of inventors' tacit knowledge and the competitive threat of knowledge spillovers. Managers should carefully consider the internal and external conditions such as knowledge complexity and interfirm competition for better decision-making. In addition, our study also suggests that HR policies and IP management are related. Managers should consider incorporating IP-related metrics in their talent management tools to identify key employees and avoid the potential loss caused by their mobility.

Some limitations of this study are worth noting. First, although we adopted the two-stage matching with the CEM approach to alleviate endogeneity concerns, we cannot fully rule out alternative explanations due to unobserved heterogeneities such as patent quality or inventor productivity. The causal inference can be further strengthened with exogenous shocks such as inventors' sudden death. Upon the public data availability, future studies could perform this test and explore the differential impact of mobility and sudden death. Second, to accurately identify inventor mobility status, we applied very strict criteria using patenting records. This identification strategy, though accurate, may lean toward productive inventors because our identification relied on repeated patenting. If possible, researchers can consider using the census data of employment or taxpayers to trace inventor mobility. Third, our analysis is at the inventor-patent level. We did not choose the patent level because we were unable to accurately identify mobility status for every member of an inventor team. Our results should thus be interpreted as the effect of individual inventor mobility. Future studies are encouraged to explore whether there are additional effects of the mobility of a whole inventor team.

Future research could also extend our study in other fruitful directions. First, in the study, we examine the maintenance of patents after inventor mobility. However, patent maintenance is only the first post-mobility decision to make. It will be practically meaningful to investigate how these left-behind IP assets are commercialized and re-deployed by sourcing firms. In an unreported supplementary analysis, we find that after maintenance, knowledge components embodied by left-behind patents are more likely to be recombined with components in other patents. This leads to an intriguing question: will inventor mobility invoke any unintended consequences such as knowledge rejuvenation and novel recombination? In addition, research has shown that knowledge worker mobility can lead to reverse knowledge spillovers from target firms to sourcing firms (Corredoira and Rosenkopf, 2010). Will inventor mobility unintendedly benefit the internal commercialization of left-behind inventions with reverse knowledge spillovers? Or will the target firms' use of inventor knowledge provide guiding insights for sourcing firms in the future development of left-behind inventions? Second, our theory concerns interaction and interdependence between codified and tacit knowledge. We used inventor mobility for empirical analysis as tacit and codified knowledge are clearly distinguishable in this case. Nevertheless, researchers are encouraged to consider other knowledge workers such as designers, lawyers, and programmers. Capitalizing on the increasing accessibility and variety of data, future research could test the hypotheses in other interesting contexts. For example, open-source platforms allow researchers to trace the activities of programmers and identify the codified knowledge generated by these knowledge workers in open-source projects.

6. Conclusion

In an age that increasingly emphasizes collaboration and open innovation, knowledge worker mobility becomes prevalent. This poses an unprecedented challenge to managers in knowledge-intensive industries. The new trend calls for a careful re-examination of the traditional practices of knowledge and human resource management. Our study investigates how inventor mobility affects the maintenance decisions of left-behind patents. We show that managers are less willing to maintain patents after inventors leave due to the loss of tacit knowledge. However, when mobility induces greater competitive threats, the above decision may be reversed. The results reveal the duality of corporate knowledge (i.e., intellectual and legal pillars) and suggest that HR and IP management should be examined and evaluated in a holistic manner.

REFERENCES

Agarwal, R., Ganco, M., Ziedonis, R.H., 2009. Reputations for toughness in patent enforcement: Implications for knowledge spillovers via inventor mobility. Strategic Management Journal 30 (13), 1349-1374.

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

Aime, F., Johnson, S., Ridge, J.W., Hill, A.D., 2010. The routine may be stable but the advantage is not: Competitive implications of key employee mobility. Strategic Management Journal 31 (1), 75-87.

Argote, L., 2012. Organizational Learning: Creating, Retaining and Transferring Knowledge. Springer, New York.

Arts, S., Fleming, L., 2018. Paradise of novelty—or loss of human capital? Exploring new fields and inventive output. Organization Science 29 (6), 1074-1092.

Azoulay, P., Stuart, T., Wang, Y., 2014. Matthew: Effect or fable? Management Science 60 (1), 92-109.

Bessen, J.E., 2008. The value of US patents by owner and patent characteristics. Research Policy 37 (5), 932-945.

Campbell, B.A., Ganco, M., Franco, A.M., Agarwal, R., 2012. Who leaves, where to, and why worry? Employee mobility, entrepreneurship and effects on source firm performance. Strategic Management Journal 33 (1), 65-87.

Carnahan, S., Somaya, D., 2013. Alumni effects and relational advantage: The impact on outsourcing when a buyer hires employees from a supplier's competitors. Academy of Management Journal 56 (6), 1578-1600.

Chang, Y.-Y., Gong, Y., Peng, M.W., 2012. Expatriate knowledge transfer, subsidiary absorptive capacity, and subsidiary performance. Academy of Management Journal 55 (4), 927-948.

Colyvas, J., Crow, M., Gelijns, A., Mazzoleni, R., Nelson, R.R., Rosenberg, N., Sampat, B.N., 2002. How do university inventions get into practice? Management Science 48 (1), 61-72.

Conti, R., Gambardella, A., Mariani, M., 2013. Learning to be Edison: Inventors, organizations, and breakthrough inventions. Organization Science 25 (3), 833-849.

Corredoira, R.A., Rosenkopf, L., 2010. Should auld acquaintance be forgot? The reverse transfer of knowledge through mobility ties. Strategic Management Journal 31 (2), 159-181.

Dosi, G., Nelson, R.R., 2010. Technical change and industrial dynamics as evolutionary processes, in: Hall, B.H., Rosenberg, N. (Eds.), Handbook of the Economics of Innovation. Elsevier, pp. 51-127.

Filatotchev, I., Liu, X., Lu, J., Wright, M., 2011. Knowledge spillovers through human mobility across national borders: Evidence from Zhongguancun Science Park in China. Research Policy 40 (3), 453-462.

Fleming, L., 2001. Recombinant uncertainty in technological search. Management Science 47 (1), 117-132.

Fleming, L., Sorenson, O., 2001. Technology as a complex adaptive system: Evidence from patent data. Research Policy 30 (7), 1019-1039.

Fudenberg, D., Gilbert, R., Stiglitz, J., Tirole, J., 1983. Preemption, leapfrogging and competition in patent races. European Economic Review 22 (1), 3-31.

Ganco, M., 2013. Cutting the Gordian knot: The effect of knowledge complexity on employee mobility and entrepreneurship. Strategic Management Journal 34 (6), 666-686.

Ganco, M., Ziedonis, R.H., Agarwal, R., 2015. More stars stay, but the brightest ones still leave:

Job hopping in the shadow of patent enforcement. Strategic Management Journal 36 (5), 659-685.
Ge, C., Huang, K.W., Png, I.P., 2016. Engineer/scientist careers: Patents, online profiles, and misclassification bias. Strategic Management Journal 37 (1), 232-253.
Goossen, M.C., Carnabuci, G., 2020. When employees walk out the door, their memories remain: The effect of inventor mobility on patent renewal. Advances in Strategic Management 41 (1), 245-265.
Grant, R.M., 1996. Prospering in dynamically-competitive environments: Organizational capability as knowledge integration. Organization Science 7 (4), 375-387.
Hall, B.H., Ziedonis, R.H., 2001. The patent paradox revisited: An empirical study of patenting in the US semiconductor industry, 1979-1995. The RAND Journal of Economics 32 (1), 101-128.
Heckman, J., Navarro-Lozano, S., 2004. Using matching, instrumental variables, and control functions to estimate economic choice models. Review of Economics and Statistics 86 (1), 30-57.
Hoetker, G., 2007. The use of logit and probit models in strategic management research: Critical issues. Strategic Management Journal 28 (4), 331-343.
Iacus, S.M., King, G., Porro, G., 2012. Causal inference without balance checking: Coarsened exact matching. Political Analysis 20 (1), 1-24.
Katila, R., Ahuja, G., 2002. Something old, something new: A longitudinal study of search behavior and new product introduction. Academy of Management Journal 45 (6), 1183-1194.
Khanna, R., Guler, I., Nerkar, A., 2016. Fail often, fail big, and fail fast? Learning from small failures and R&D performance in the pharmaceutical industry. Academy of Management Journal 59 (2), 436-459.
Khanna, R., Guler, I., Nerkar, A., 2018. Entangled decisions: Knowledge interdependencies and terminations of patented inventions in the pharmaceutical industry. Strategic Management Journal 39 (9), 2439-2465.
Kogut, B., Zander, U., 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. Organization Science 3 (3), 383-397.
Laursen, K., 2012. Keep searching and you'll find: What do we know about variety creation through firms' search activities for innovation? Industrial and Corporate Change 21 (5), 1181-1220.
Liu, K., 2014. Human capital, social collaboration, and patent renewal within US pharmaceutical firms. Journal of Management 40 (2), 616-636.
Liu, K., Arthurs, J., Cullen, J., Alexander, R., 2008. Internal sequential innovations: How does interrelatedness affect patent renewal? Research Policy 37 (5), 946-953.
Mawdsley, J.K., Somaya, D., 2016. Employee mobility and organizational outcomes: An integrative conceptual framework and research agenda. Journal of Management 42 (1), 85-113.
Melero, E., Palomeras, N., Wehrheim, D., 2020. The effect of patent protection on inventor mobility. Management Science 66 (12), 5485-5504.
Murray, F., Stern, S., 2007. Do formal intellectual property rights hinder the free flow of scientific knowledge? An empirical test of the anti-commons hypothesis. Journal of Economic Behavior & Organization 63 (4), 648-687.
No, Y., Walsh, J.P., 2010. The importance of foreign-born talent for US innovation. Nature Biotechnology 28 (3), 289.
Pavitt, K., 1987. The objectives of technology policy. Science and Public Policy 14 (4), 182-188.
Polanyi, M., 1966. The Tacit Dimension. Routledge & Kegan Paul, London.
Raffiee, J., 2017. Employee mobility and interfirm relationship transfer: Evidence from the

mobility and client attachments of United States federal lobbyists, 1998–2014. Strategic Management Journal 38 (10), 2019-2040.

Ranft, A.L., Lord, M.D., 2002. Acquiring new technologies and capabilities: A grounded model of acquisition implementation. Organization Science 13 (4), 420-441.

Seo, E., Somaya, D., 2021. Living it up at the Hotel California: Employee mobility barriers and collaborativeness in firms' innovation. Organization Science (In print).

Singh, J., Agrawal, A., 2011. Recruiting for ideas: How firms exploit the prior inventions of new hires. Management Science 57 (1), 129-150.

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

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

Tan, D., Rider, C.I., 2017. Let them go? How losing employees to competitors can enhance firm status. Strategic Management Journal 38 (9), 1848-1874.

Teece, D.J., 1998. Capturing value from knowledge assets: The new economy, markets for know-how, and intangible assets. California Management Review 40 (3), 55-79.

Tzabbar, D., 2009. When does scientist recruitment affect technological repositioning? Academy of Management Journal 52 (5), 873-896.

Tzabbar, D., Kehoe, R.R., 2014. Can opportunity emerge from disarray? An examination of exploration and exploitation following star scientist turnover. Journal of Management 40 (2), 449-482.

Wagner, S., Goossen, M., 2018. Knowing me, knowing you: Inventor mobility and the formation of technology-oriented alliances. Academy of Management Journal 61 (6), 2026-2052.

Winter, S.G., Szulanski, G., 2002. Replication of organizational routines, in: Bontis, N., Choo, C.W. (Eds.), The Strategic Management of Intellectual Capital and Organizational Knowledge. Oxford University Press, New York, pp. 207-221.

Yang, H., Phelps, C., Steensma, H.K., 2010. Learning from what others have learned from you: The effects of knowledge spillovers on originating firms. Academy of Management Journal 53 (2), 371-389.

Zelner, B.A., 2009. Using simulation to interpret results from logit, probit, and other nonlinear models. Strategic Management Journal 30 (12), 1335-1348.

Ziedonis, R.H., 2003. Patent Litigation in the US Semiconductor Industry. Washington, DC: The National Academies Press.

Table 1
T-tests before and after the two-stage matching

Panel A: Before the two-stage matching	Mean Stay	Mean Leave	Difference	Std. Error
Claims	19.546	18.656	0.890***	0.040
Family size	1.889	1.646	0.243***	0.007
Backward citations (Ln)	2.424	2.304	0.119***	0.003
CPC subclasses	1.864	1.807	0.057***	0.003
Firm domain stock	4.968	3.971	0.997***	0.007
Pre-maintenance forward citations (Ln)	1.892	1.805	0.088***	0.003
Pre-maintenance forward self-citations (Ln)	0.915	0.512	0.403***	0.002
Inventor tenure	7.211	6.820	0.391***	0.018
Inventor current productivity	2.262	1.681	0.571***	0.003
Co-inventors	2.669	2.560	0.109***	0.007
First inventor	0.422	0.412	0.010***	0.001
Firm size	9.814	9.353	0.462***	0.005
ROA	0.151	0.115	0.036***	0.001
R&D ratio	0.068	0.086	−0.018***	0.000
Firm past maintenance rate	0.893	0.904	−0.011***	0.000
Patents to maintain (Ln)	5.709	5.353	0.356***	0.004

Panel B: After the two-stage matching	Mean Stay	Mean Leave	Difference	Std. Error
Claims	18.915	18.786	0.128	0.143
Family size	1.695	1.682	0.013	0.017
Backward citations (Ln)	2.304	2.314	−0.010	0.010
CPC subclasses	1.520	1.528	−0.008	0.009
Firm domain stock	6.960	6.960	0.000	0.018
Pre-maintenance forward citations (Ln)	1.945	1.938	0.006	0.012
Pre-maintenance forward self-citations (Ln)	0.800	0.790	0.010	0.009
Inventor tenure	6.952	7.043	−0.091†	0.068
Inventor current productivity	1.903	1.894	0.009	0.012
Co-inventors	2.249	2.254	−0.005	0.020
First inventor	0.427	0.420	0.007†	0.005
Firm size	10.577	10.577	0.000	0.013
ROA	0.172	0.172	0.000	0.001
R&D ratio	0.075	0.075	0.000	0.001
Firm past maintenance rate	0.894	0.894	0.000	0.001
Patents to maintain (Ln)	6.756	6.756	0.000	0.012

† $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$. The number of observations was 779,588 for the full sample in Panel A. The number of observations was 36,204 for the matched sample in Panel B.

Table 2
Summary statistics and correlations

Variables	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Maintenance decision	0.867	0.340												
(2) Claims	18.851	13.626	.087											
(3) Family size	1.689	1.611	.057	.017										
(4) Backward citations (Ln)	2.309	0.925	.056	.201	.196									
(5) CPC subclasses	1.524	0.826	.004	.003	.154	.047								
(6) Firm domain stock	6.960	1.751	−.047	.106	.021	.132	−.202							
(7) Pre-maintenance fwd citations (Ln)	1.941	1.155	.113	.268	−.002	.253	−.013	.311						
(8) Pre-maintenance fwd self-citations (Ln)	0.795	0.888	.081	.216	.081	.243	.005	.254	.634					
(9) Inventor tenure	6.997	6.502	−.018	−.038	.100	.065	.046	−.106	−.131	−.058				
(10) Inventor current productivity	1.898	1.127	.048	.030	.166	.045	.004	.037	.028	.108	.195			
(11) Co-inventors	2.252	1.868	−.045	.042	.078	.071	.074	.014	.067	.126	.028	−.026		
(12) First inventor	0.423	0.494	.024	−.011	−.019	−.029	−.022	−.032	−.041	−.072	.003	.045	−.348	
(13) Firm size	10.577	1.278	−.099	.026	−.091	.051	−.037	.428	.167	.109	−.012	−.167	.108	−.073
(14) ROA	0.172	0.091	.006	−.019	−.013	.021	−.061	.255	.065	.049	−.020	−.110	.018	−.016
(15) R&D ratio	0.075	0.052	.089	.008	.064	−.137	−.032	−.117	−.006	−.065	−.093	.140	−.040	.032
(16) Firm past maintenance rate	0.894	0.108	.266	.193	.106	.119	−.019	−.016	.157	.081	−.038	.069	−.131	.055
(17) Patents to maintain (Ln)	6.756	1.167	−.089	.029	−.006	.099	−.119	.668	.216	.131	−.043	.071	−.005	−.029
(18) Knowledge complexity	0.072	0.074	.024	.004	.120	.063	.068	−.038	.000	.021	.073	.128	.036	−.008
(19) Internal reliance	0.203	0.239	−.026	−.015	−.002	.005	−.003	.045	−.059	.083	.069	.033	.068	−.035
(20) Target firm competition	0.209	0.330	−.007	.015	.005	−.002	−.049	.124	.047	−.007	−.052	−.002	−.008	−.004
(21) Target firm litigiousness	0.505	1.052	−.005	.025	.010	.017	−.028	.085	.052	−.005	−.034	−.001	.002	−.015
(22) Inventor mobility	0.500	0.500	−.020	−.005	−.004	.006	.011	.000	−.003	−.066	.019	−.070	.001	−.019

Variables	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(14) ROA	.259								
(15) R&D ratio	−.510	−.176							
(16) Firm past maintenance rate	−.216	−.022	.246						
(17) Patents to maintain (Ln)	.615	.197	−.196	−.109					
(18) Knowledge complexity	−.065	−.027	.028	.040	−.010				
(19) Internal reliance	.057	−.019	−.116	−.098	.038	.012			
(20) Target firm competition	.026	.044	.035	.002	.068	.001	−.019		
(21) Target firm litigiousness	.052	.023	.034	.034	.101	−.004	−.019	.511	
(22) Inventor mobility	.000	.000	.000	.000	.000	.007	−.030	.532	.480

Note: n = 41,292.

Table 3
Results of logit regression for maintenance decisions

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Claims	0.010**	0.010**	0.010**	0.010**	0.010**	0.010**	0.010**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Family size	0.134***	0.135***	0.135***	0.134***	0.135***	0.135***	0.135***
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
Backward citations (Ln)	0.019	0.020	0.020	0.019	0.020	0.020	0.019
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.020)	(0.020)
CPC subclasses	−0.056*	−0.056*	−0.055*	−0.055*	−0.054*	−0.054*	−0.054*
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Firm domain stock	0.058	0.059	0.059	0.060	0.056	0.059	0.058
	(0.060)	(0.060)	(0.060)	(0.060)	(0.061)	(0.060)	(0.061)
Pre-maintenance forward citations (Ln)	0.215***	0.219***	0.218***	0.219***	0.219***	0.218***	0.218***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Pre-maintenance forward self-citations (Ln)	0.143*	0.136*	0.136*	0.136*	0.135*	0.136*	0.136*
	(0.067)	(0.067)	(0.066)	(0.066)	(0.067)	(0.067)	(0.067)
Inventor tenure	0.004	0.004	0.004	0.004	0.005†	0.004†	0.005†
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Inventor current productivity	0.080***	0.075***	0.075***	0.075***	0.073***	0.074***	0.073***
	(0.023)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.021)
Co-inventors	0.034***	0.034***	0.034***	0.034***	0.034***	0.034***	0.034***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
First inventor	0.002	−0.001	−0.001	−0.001	−0.001	−0.001	−0.000
	(0.045)	(0.046)	(0.045)	(0.046)	(0.046)	(0.046)	(0.046)
Firm size	0.137	0.137	0.136	0.137	0.135	0.136	0.134
	(0.211)	(0.211)	(0.211)	(0.211)	(0.212)	(0.212)	(0.213)
ROA	−0.363	−0.367	−0.362	−0.344	−0.370	−0.379	−0.352
	(1.055)	(1.056)	(1.057)	(1.061)	(1.055)	(1.055)	(1.059)
R&D ratio	9.482**	9.488**	9.486**	9.488**	9.466**	9.474**	9.458**
	(3.390)	(3.391)	(3.385)	(3.388)	(3.374)	(3.385)	(3.363)
Firm past maintenance rate	3.266***	3.270***	3.270***	3.264***	3.274***	3.280***	3.273***
	(0.779)	(0.781)	(0.779)	(0.783)	(0.774)	(0.778)	(0.774)
Patents to maintain (Ln)	−0.197	−0.195	−0.195	−0.198	−0.196	−0.199	−0.202
	(0.201)	(0.202)	(0.201)	(0.202)	(0.202)	(0.201)	(0.201)
Knowledge complexity	−0.292	−0.272	0.120	−0.275	−0.279	−0.278	0.099
	(0.278)	(0.282)	(0.375)	(0.282)	(0.283)	(0.283)	(0.379)
Internal reliance	0.115†	0.107†	0.108†	−0.066	0.107†	0.106†	−0.067
	(0.064)	(0.063)	(0.063)	(0.117)	(0.063)	(0.064)	(0.118)
Inventor mobility		−0.115***	−0.066*	−0.191***	−0.183***	−0.155***	−0.228***
		(0.026)	(0.027)	(0.044)	(0.033)	(0.035)	(0.062)
Inventor mobility × Knowledge complexity			−0.714*				−0.698*
			(0.295)				(0.296)
Inventor mobility × Internal reliance				0.349*			0.348*
				(0.157)			(0.157)
Inventor mobility × Target firm competition					0.263***		0.228***
					(0.045)		(0.047)
Inventor mobility × Target firm litigiousness						0.041*	0.031
						(0.020)	(0.021)
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maintenance year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CPC subclass fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,204	36,204	36,204	36,204	36,204	36,204	36,204
Log-likelihood	−11,168	−11,162	−11,161	−11,159	−11,159	−11,160	−11,154

† $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$. Robust standard errors were shown in parentheses.

Table 4
Robustness tests

	Solo inventors		Leaving inventors only		Second maintenance	
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Inventor mobility	−0.314***	−0.132			−0.094*	−0.123
	(0.094)	(0.208)			(0.041)	(0.088)
Inventor mobility ×		−7.010***				−0.539*
Knowledge complexity		(1.460)				(0.264)
Inventor mobility ×		0.533†				0.004
Internal reliance		(0.311)				(0.156)
Inventor mobility ×		0.237*				0.158**
Target firm competition		(0.108)				(0.063)
Inventor mobility ×		0.079				0.041*
Target firm litigiousness		(0.076)				(0.017)
Target firm competition			0.155**			
			(0.051)			
Target firm litigiousness				0.047*		
				(0.023)		
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Maintenance year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
CPC subclass fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,466	7,466	18,102	18,102	26,188	26,188
Log-likelihood	−2,233	−2,207	−5,715	−5,714	−9,869	−9,839

	Full sample		Propensity score matching		Industry fixed effects	
Variables	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Inventor mobility	−0.302***	−0.375***	−0.253***	−0.166***	−0.115***	−0.230***
	(0.035)	(0.043)	(0.028)	(0.025)	(0.026)	(0.060)
Inventor mobility ×		−0.418*		−0.530*		−0.663*
Knowledge complexity		(0.204)		(0.237)		(0.300)
Inventor mobility ×		0.081		0.219*		0.342*
Internal reliance		(0.088)		(0.094)		(0.142)
Inventor mobility ×		0.179**		0.398***		0.129**
Target firm competition		(0.065)		(0.089)		(0.050)
Inventor mobility ×		0.024		0.065†		0.036†
Target firm litigiousness		(0.019)		(0.036)		(0.020)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	
Industry fixed effect						Yes
Maintenance year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
CPC subclass fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	779,588	779,588	90,466	90,466	36,204	36,204
Log-likelihood	−195,244	−194,568	−40,756	−40,733	−11,371	−11,363

† $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$. Robust standard errors were shown in parentheses.

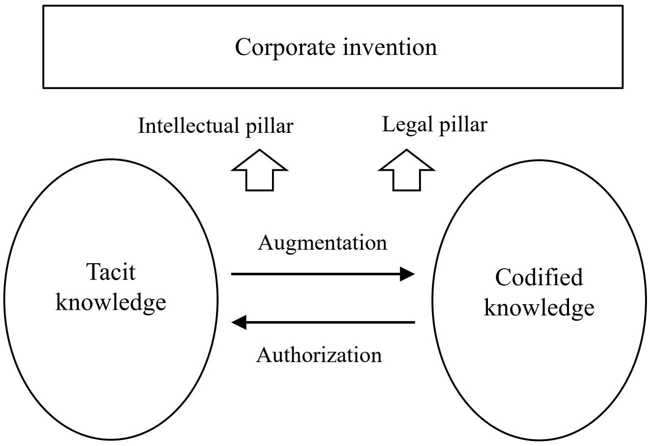
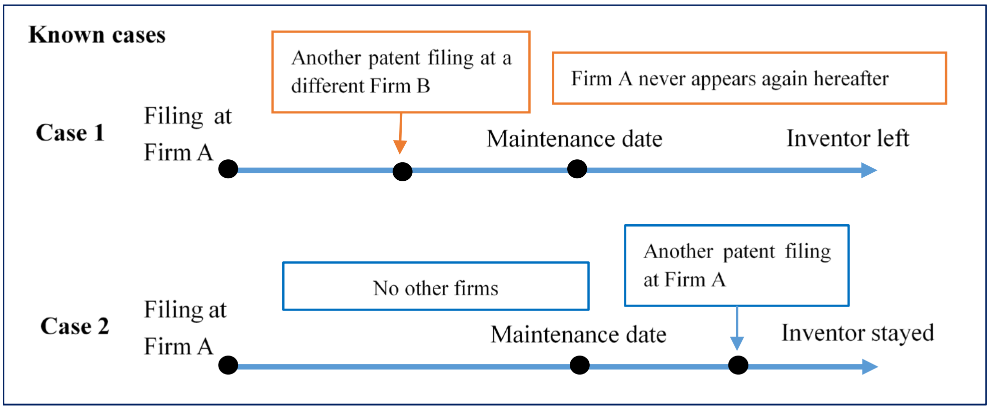
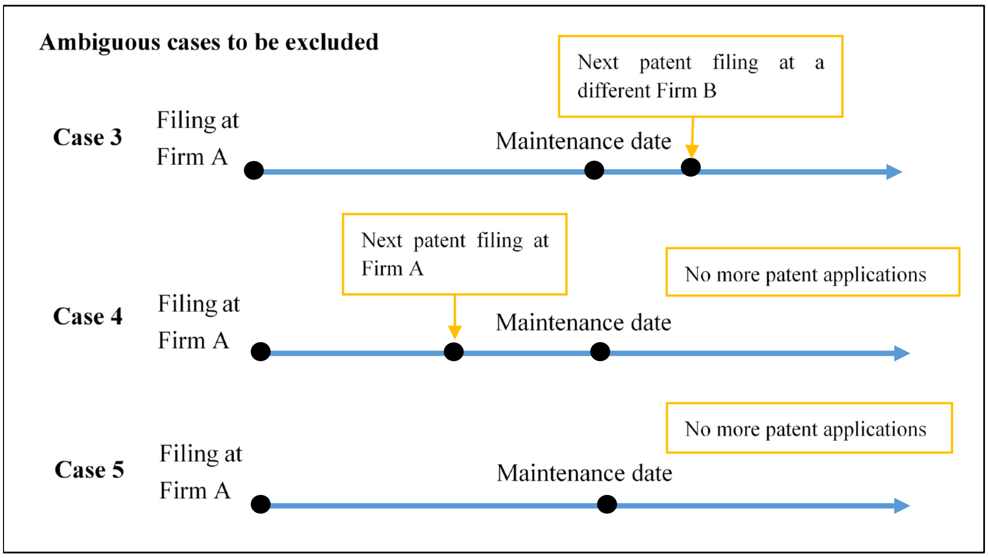


Fig 1. Interdependence of tacit and codified knowledge



Panel A: "Leave" and "stay"



Panel B: Ambiguous cases to be excluded

Fig 2. Identification strategy for inventor mobility

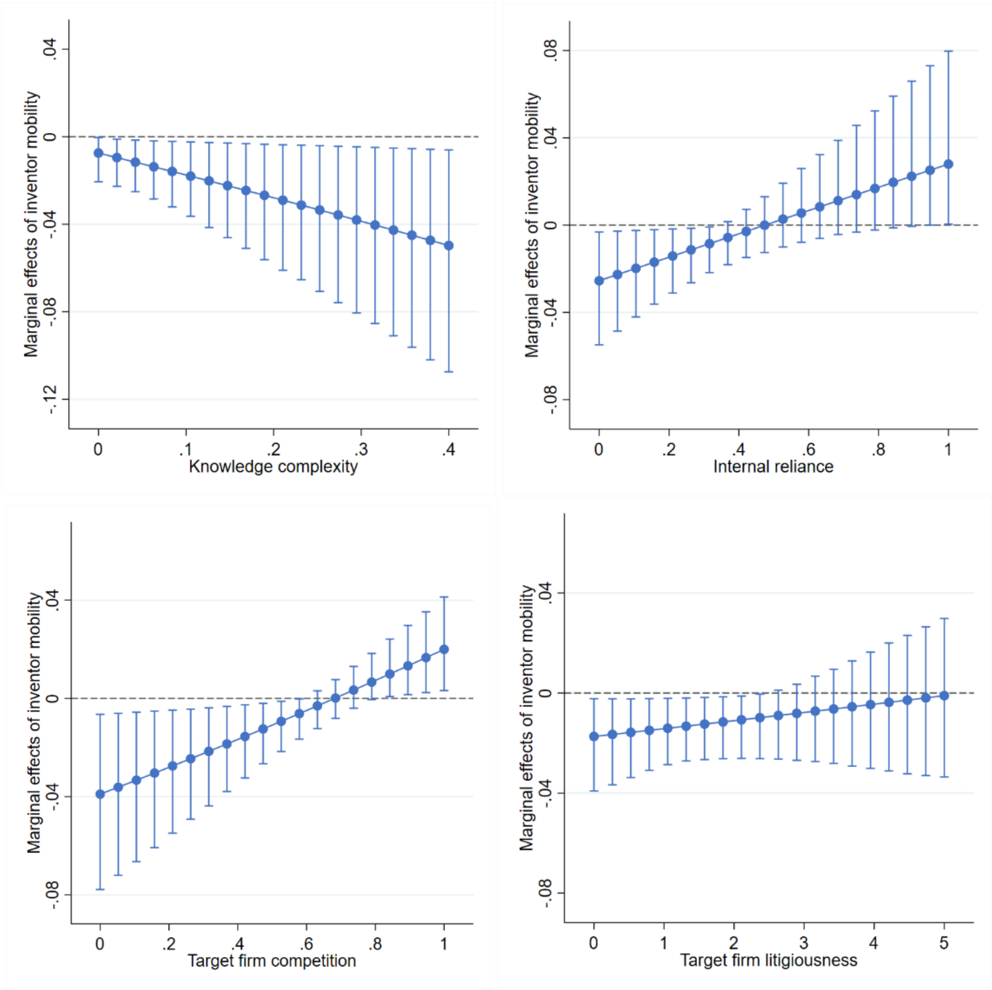


Fig 3. Illustration of moderating effects