When Do Firms Trade Patents?

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Abstract

Drawing on Coase theorem, we consider firms' decisions to transfer patent ownership to another firm in the markets for innovation. We deem that the proximity of a patent's technology structure to that of a firm's patent portfolio will generally result in greater marginal productivity of the patent, leading to enhanced prospects for the firm's economic return. We thus predict that firms are more likely to trade patents when the technology structure of a patent is closer to the technology stock of a potential buyer relative to that of the original assignee. However, such a relationship will be weaker when a potential buyer and the assignee have greater product-market overlap or when the assignee has greater technological capability compared with the potential buyer. We test these predictions by employing a dyad-level analysis of transactional decisions during the 1987−2016 period on 40,110 U.S. patents assigned to 57 major biopharmaceutical firms. Our study provides novel insights on factors that facilitate and inhibit patent trade in the markets for innovation.

Keywords: patent trade, markets for innovation, technological distance, IP management strategy, Coase theorem

Introduction

In recent decades, a growing number of firms have traded their technologies with external parties in the markets for innovation (Teece 1986, Gans and Stern 2000, Shapiro 2001, Arora and Ceccagnoli 2006, Galasso 2012). An important segment of these markets involves buying and selling of intellectual property rights (IPR) such as patents. Indeed, the highly publicized sale of patent portfolios owned by Motorola, Nortel, and Novell in 2011 triggered growing interests in patent trade. Whereas some studies have focused on the patent sale as an exit strategy by high-tech startups (e.g., Hochberg Serrano and Ziedonis 2018, Serrano and Ziedonis 2018), others have considered the supply side and the efficiency of the patent-trade market (e.g., Serrano 2010, Akcigit Celik and Greenwood 2016, Kuhn 2016).

Despite important insights that these studies have provided, a few aspects require further attention. Studies have mostly considered the patent-trade market at an aggregate level and have paid limited attention to firm-level motives for buying and selling patents. Moreover, studies have provided limited insights on the bilateral nature of patent trade and what causes friction in the market for patents (Kuhn 2016). Indeed, the literature on the markets for innovation could benefit from a deeper understanding of factors conducive to patent trade and how they vary across technologies and sectors (Arora and Gambardella 2010). Examining these aspects will not only provide insights on how firms make decisions with respect to internal and external factors to enhance their performance but also inform policy makers of how to design market mechanisms to spur innovation and improve social welfare.

This study examines firm-level factors to explain when firms buy and sell patents. Drawing on a Coasian approach (1960), we deem that, because firms may gravitate toward reallocating patents among them in a mutually beneficial manner, they are likely to allocate patent ownership to a party that can better utilize a particular patent with respect to its technology stock. Specifically, we consider the relative difference between the technological distance from a patent to the technology stock of the original assignee and that from the patent to the technology stock of potential buyers. We posit that technological proximity of a patent to the patent portfolio of a firm can generally result in a better return on the patent and thus patent trade is more likely to occur when a patent is more proximate to a potential buyer's technology stock compared with that of the original assignee.

Our theory unfolds bilateral mechanisms of patent trade based on the relative technological distance differential between a patent and respective firms' technology stocks. On the one hand, although a patent has independent value on its own, its relative value to a particular owner relies on its technological interdependence with the patent portfolio of the owner. When a patent is situated in a relatively remote area from its owner's core technology stock, the owner has an incentive to sell the patent to another firm. This is because the owner is less likely to take full advantage of the patent to generate economic rent. On the other hand, patent trade also depends on the technological proximity of a patent to other patents owned by a potential buyer. Amassing unrelated patents will not strengthen a firm's technology stock to introduce new products or defend against potential infringers. As such, the potential buyer whose technology stock is more proximate to a patent will generally find the patent more valuable. Using the sample of all patents assigned to 57 major global biopharmaceutical firms, we perform a dyad-level analysis encompassing all possible seller-buyer relationships. The biopharmaceutical sector is an ideal context to conduct our research because patents in this sector are an effective value appropriation mechanism (Cohen Nelson and Walsh 2000), change hands frequently after an initial grant (Serrano 2010), and a small number of patents constitute a product in an observable and traceable manner (Ouellette 2010). Our results from a dyadic analysis of transactional decisions during the 1987−2016 period on 40,110 patents assigned to the 57 firms are consistent with our prediction.

Focusing on the bidirectional nature of patent trade, we further suggest two contingencies for patent trades. An assignee considers not only its patent's technological fit into its technology stock, but also a potential buyer who might be better suited for capitalizing on the patent as a way to leverage the external technology. Once both conditions are considered, the market for patents possibly transpires. Although potential buyers might understand an external patent better than the original assignee (Arora and Gambardella 2010) and have other ideas for potential applications of the patent, the assignee's perception of product-market rivalry with the potential buyers and assessment of its own capability play important roles. First, assignees are less likely to negotiate with a buyer with whom they directly compete because gains from the patent trade by the competing firm can lead to losses for the assignees, creating friction in the market for patents. Second, assignees are less likely to place their patents on the market when they are more capable of using proprietary technologies even if their relative technological relevance is low. Given the firm-specific nature of inventing activities, a technologically capable assignee is more likely to generate a higher economic return from its own patent. Conversely, potential buyers understand that there could be partial loss of tacit knowledge through the patent ownership transfer and may not be able to fully utilize the patent. Such a loss decreases the value of a patent in generating economic return. This would be particularly salient when the original assignee has superior technological capability and a patent transaction is less likely to proceed even if the relative technological distance of a patent from respective firms' technology stocks favors the emergence of patent trade. Our empirical results are also consistent with these conjectures.

By examining firm-level decisions on patent transactions as an IPR management strategy, this study contributes to the literature on innovation and technology management. First, it contributes to the literature examining strategic management of patent portfolio. Although a growing body of literature has considered patent trade (e.g., Serrano 2010, Galasso et al. 2013, Serrano 2018), most are descriptive in nature and consider the phenomenon at an aggregate level. Only recently, studies have begun considering patent-level decisions on ownership transfer. For instance, a patent is more likely to be sold when the scope of the patent's legal right to exclude others is broader (Kuhn 2016). Our study extends this line of inquiry by considering firm-level strategic decisions on potential dyadic relationships between an original assignee and potential buyers. This dyadic approach goes beyond the limitations of prior studies by casting light on both the supply and demand sides of the markets for innovation. Second, this study provides insights on ex post innovation management strategy employed by firms. Although the literature on the markets for innovation has mostly considered the efficiency of patent-trade market or the economic gains from vertical specialization (Teece 1986, Arora Fosfuri and Gambardella 2001, Arora and Gambardella 2010) and comparative advantages in commercialization (Arora and Ceccagnoli 2006), most have paid scant attention to a technological precursor to the market reallocation of patents. Our study complements these studies by providing insights on how firms make ongoing decisions about their intellectual property (IP) transactions following an initial legal delimitation of patent rights. Our results demonstrate not only how a well-functioning market allocates patents efficiently ex post that may increase firms' ex ante incentives to innovate (i.e., R&D) but also a specific ex post IPR management strategy to achieve that. Third, this study contributes to the application of Coase theorem to the IP market, which is characterized by imperfect information and frequent disputes in property rights (Ziedonis 2004). We find that patent trade arises by parties that can mutually benefit from trading in such a market, confirming the conjecture proposed by Coase (1960). This implies that patent trade is not limited to value exploitation, but value creation. Patent trade not only generates tangible gains by liquidating an unused or less efficiently used intangible economic assets, but also increases access to high-quality, low-priced technical solutions. At the same time, we highlight the importance of factors that condition the extent of markets of innovation (Arora and Gambardella 2010) by creating market frictions. Firms face a tradeoff between efficiency enhancement and competitive threats. By selling a patent to another firm that can utilize the patent more effectively, firms may achieve greater efficiency by appropriating greater return compared to what they could have extracted by using the technology on their own. However, such efficiency gains must be viewed in comparison to potential competitive threats that could erode prospective revenue streams and product-market competitiveness. Indeed, we find that firms are less likely to transact patents with other firms with greater product-market overlap or with superior technological capability, even if such trade could potentially lead to greater social welfare.

Theory and Hypotheses

Markets for Innovation and Patent Trade

Markets for innovation denote a technological marketplace where technology vendors convene to conduct transactions related to licensing and trading patents with potential technology buyers (Arora et al. 2001a). The locus of trade can serve as a critical incentive to engage in R&D for both interacting individual inventors and firms for whom patents are usually their strategic resource (Galasso et al. 2013). That is, patent trade can render market structures of technology-intensive sectors more efficient by reshaping the trajectories of resource allocation and the nature of competition amongst parties that have different types and degrees of specialization in innovation (Gans and Stern 2000, Gans Hsu and Stern 2002). Although the markets for innovation have emerged as an important focus for scholars in organization science and strategic management, they have paid disproportional attention to one side of the puzzle. A number of studies on patent licensing as a medium for profiting from innovation are pervasive (e.g., Degnan 1998, Anand and Khanna 2000). Given the intrinsic benefits of specialization, the motive for modern trade, and economic interdependence, societal gains could be realized through a vigorous patent-trade market.

However, there has been a growing concern about the potentially pernicious effects of the IP transfers. Given the overlapping and fragmented landscape of patent ownership (Bessen and Meurer 2008), patent trade can also backfire under conditions that the transactions transpire to appropriate gains through patent litigation, thus constituting potential ex post holdup problems, especially for firms with comparative advantage in commercialization (Lemley and Shapiro 2007). A recent empirical finding suggests a positive relationship between the patent transfers and patent litigation (Galasso et al. 2013). Further, buying IP assets and profiting from the ownership of those assets parallel acquiring intangible properties and appropriating value from the ownership of those properties. This study thus responds to a call for shedding new light on factors determining firms' transfer decisions on patent ownership that remains underexplored thus far.

Patent Trade and Relative Technological Distance

Patents possess a set of rights in common with property. These rights grant a property owner monopolistic power that excludes others from using, exploiting, selling, and enforcing. Unlike tangible assets, patents are not constituted by physical objects and are legally valid for a limited period in exchange for the public disclosure of the invention. The initial legal delimitation of patent rights plays a pivotal role in the market for patents. First, firms can generally reallocate their own initially endowed rights among them only with non-trivial transaction costs. As compared with tangible assets, patent transactions take place less frequently because the transaction costs are often sufficiently high to prevent numerous transactions. As such, initial allocations of a set of rights do matter (Kennedy 1981) in the market for patents and tend to shape far-reaching imbalance in negotiation power among parties for potential ownership transfers. Thus, although either a buyer or a seller can initiate a deal for patent trade, assignees' perception of product-market rivalry with potential buyers and their assessment of own capability play important roles.

Coase (1960) proposes that existing resources inefficiently used by initial owners in a market will be reallocated to another potential user in a mutually beneficial manner when property rights are well-defined and there are trivial or no transaction costs for buyers and sellers to reach transaction agreements. We share a consonant view with the Coasian approach in that market rearrangement of the initial legal delimitation of patent rights would lead to a reciprocally favorable outcome for both a seller and a buyer, thereby ultimately contributing to an increase in the total gains of the markets for innovation. Considering that patents are a product of statutory enactments, boundaries related to the patent rights of numerous parties are clearly demarcated. This possible articulation of delimited rights satisfies a prerequisite of transferring patent ownership for its best use through market transactions. However, to reshuffle such initial legal delimitation through a market, the second Coasian assumption about the sufficiently low transaction costs needs to be realistically adjusted. In the market for patents, no firm can foretell the most beneficial use of a patent ex ante. Coase (1960, p. 15) himself admits that transactions are "often extremely costly, sufficiently costly at any rate to prevent many transactions that would be carried out in a world in which the pricing system worked without cost." Namely, the most notable problem in the market for patents is that nobody, including the inventors themselves, knows the most valued use of a patent ex ante, and that there exists considerable costs associated with the reallocation of the patent ownership. Thus, to tease out a precursor of market transactions in patents among firms, we make a sensible adjustment to the second Coasian assumption: as in the actual market for patents, the existence of transaction costs does not necessarily prevent interfirm patent transactions. Hence, observations on real-life patent transactions would be a more conservative test of Coase theorem in that, despite the existence of non-trivial transaction costs, patent trade occurs in a relatively frequent basis.

We suggest that technological distance between a patent and the technology stock of an assignee relative to that between the focal patent and the technology stock of a potential buyer is a key determinant for patent trade. We define *technological relativity* as the relative technological distance difference between a patent and the technology stocks of two potential parties that could be involved in a patent transaction. Namely, the relative propinquity connotes the difference between the technological distance from the focal patent to the technology stock of the original assignee (d(A)) and the technological distance from the focal patent to the technology stock of the potential buyer (d(B)). We expect that relative technological proximity between a patent and the technology stock of a potential buying firm (i.e., d(A) > d(B)) increases the emergence of patent trade, as reallocating the patent between the two firms will result in a more optimal and reciprocally beneficial use of the patent. This is because a buying firm that has greater marginal productivity of using the focal patent is likely to acquire the patent from the assignee that can extract relatively low marginal productivity from that patent. In contrast, when an original assignee's technology stock is more proximate to the focal patent compared with that of a potential buyer, a patent transaction is not likely to arise because the assignee is more likely to enjoy a better return on the patent relative to others in the market. However, the difference in technological distance should be sufficient to offset the transaction costs that may arise, such as the costs related to searching, transferring, and internalizing a patent along with the knowledge embedded in the patent. When the transaction costs are low enough, a set of IPR in a patent are likely to be traded between two parties, as both a selling firm (i.e., an assignee as an initial patent owner) and a buying firm (i.e., the second owner of that patent) will benefit from such a deal. This is because the buyer can pay less than what the buyer could internally develop and extract better return from the use of the patent, whereas the seller can be compensated more through the trade than what the seller could currently produce and extract from that patent (Klein Crawford and Alchian 1978).

Such a mechanism can be exemplified by Uber's purchase of patents that were originally assigned to the Bell Laboratories of AT&T. Uber bought the patents to develop technologies used for its ridesharing service in January of 2017. These patents (e.g., US7941267B2) include technologies to automatically identify an optimal candidate driver for a trip based on selection criteria received from a passenger. These technologies not only gave Uber a competitive advantage in a location-based ride matching of passengers with drivers but also provided IPR protection against potential infringement claims from competitors. Kurt Brasch, Uber's head of patent transactions, claims that Uber did not have enough time to build up its own patent portfolio for securing fundamental technologies, considering that patents generally take four years to be granted, and protected its business from patent litigation or infringement risks by buying patents developed elsewhere. At the same time, AT&T also benefited from the trade because those patents did not generate any economic return. According to Scott Frank, the President and CEO of AT&T intellectual property, the transaction was mutually beneficial: "Not all of these (AT&T's) inventions end up being deployed in our core business. So if we can help other innovative companies put them to use and at the same time get a return on our investment, then we think we're doing right not only by our shareholders but for consumers as well (Phelps 2018)." Thus, both firms reached an agreement on trading patents.

We maintain that technological relativity between a seller and a buyer is a valid proxy for the relative marginal productivity. On the one hand, offensive value arises from technological synergies between a traded proximate patent and other patented inventions within a firm's patent portfolio that enable commercializing those inventions into new products. Such commercialization can also transpire through single-handed use of the traded patent. Royalty avoidance can be an important mechanism for firms to realize offensive value in patent trade because firms often enter into a licensing agreement when they need single use of another firm's patented invention. Further, the benefits of transferring patent ownership outstrip those of obtaining a license due to reduction in potential holdup problems of patented inventions because patent ownership grants a higher degree of residual control rights than those of a license (Grossman and Hart 1986). This offensive value is particularly high for firms with complementary manufacturing, distribution, and marketing assets (Teece 1986, Arora and Ceccagnoli 2006).

On the other hand, defensive value emerges through effort into developing patent fences (Ziedonis 2004). Complementing a technologically proximate patent to a firm's patent portfolio enables accumulating an overlapping set of patents in a concentrated technological area where the firm has cumulative knowledge. Considering that claims in a patent determine the scope of its legal rights, defensive value emanates from the conditions under which a traded proximate patent and a firm's patent portfolio at least partially share patent claims. Such a commonality will facilitate the protection of a firm's IP assets against potential infringers or litigators and enable the firm to safeguard its investments in new technologies. Due to transaction costs and uncertainties surrounding litigation outcomes, firms possessing multiple patents in the concentrated technological area could more easily defend their IPR against infringers (Hall and Ziedonis 2001), or even deter competition from entering into that area (Arora 1997).

In sum, a patent does not only have technical value on its own but also value in relation to the assignee's overall IP portfolio. When the patent is positioned at the core domain of its assignee's technology stock, the assignee does not have an incentive to sell the patent to another firm, because the assignee could take advantage of the patent to generate economic rent. In contrast, when the assignee has little use of the patent that lies far from its core technology stock, it might be better off selling the patent to another firm that could make better use of the patent. Therefore, the likelihood of a patent transaction increases when technology embedded in a patent is relatively more proximate to a buying firm's technology stock as compared with that of a selling firm.

> Hypothesis 1 (H1). *The likelihood of patent trade is higher when a potential buyer's technology stock (d(B)) is more proximate to the patent as compared with that of the original assignee (d(A)). That is, d(A) – d(B) is positively related to the likelihood of patent trade.*

Although either party can initiate a bilateral negotiation for patent trade based on the fit between a particular patent and its technology stock, it is typically the assignee who assents to the deal by taking two factors into consideration. First, assignees perceive that there are no foreseeable conflicting interests with potential buyers. They have disincentives to make a patent-trade deal with a direct product-market competitor. Second, assignees assess that they could not fully leverage a patent based on its technological distance from the rest of their technology stock but deem that there might be a market demand for the patent. Superior technological capability would allow an assignee a more effective use of the patent for its business. Thus, although the decision to trade a patent is made bilaterally, it is the assignee who ultimately determines which patents to sell and with whom to deal.

Product-Market Overlap

The effect of technological relativity may vary with competitive dynamics between traders. We suggest that product-market overlap moderates the relationship by making the positive effect of technological relativity on the emergence of patent trade less pronounced. Firms generally grapple with competitive interaction with other firms for market share (Rumelt Schendel and Teece 1991), in which their growth and survival are shaped based on obtaining a share of limited environmental resources. In technology-intensive sectors, firms engage in head-to-head rivalry for patents because the gains tend to be a function of patented inventions. A set of conferred legal rights allows a proprietary firm to effectively appropriate return in the forms of licensing and commercialization. This is more pronounced in the patent-dependent sectors where products are made from few constituent patents. For instance, unlike a smartphone composed of more than 250,000 active patents, most pharmaceutical products, generally considered as a sector that is highly contingent on patents, have the observable and tractable number of constituent patents. Specifically, the average number was approximately 3.5 patents per drug and 5 patents per best-selling drug in 2005 (Ouellette 2010). This is why an upsurge in patenting has rarely sparked any patent arms war between some of the world’s leading biopharmaceutical firms. In sum, product-market overlap implies that the similarity of the markets in which firms compete begets the rivalry between the firms (Baum and Korn 1996, Chen 1996).

We expect that the positive relationship between technological relativity and the likelihood of patent trade will be negatively affected by the level of competition between a seller and a potential buyer. Such competition can profoundly differ based on the level of product-market overlap between a seller-buyer pair. If a potential buyer competes in the same product-market with the seller, the buyer’s activity can affect market share and profitability of the seller, thereby posing threat to the seller. Even if a potential buyer has greater marginal productivity of using a patent and the assignee can be compensated through a patent transfer, the product-market overlap can act as a friction in the market for patents. This is because the buyer's use of that patent can potentially threaten the assignee's subsequent technology development effort and revenue streams. For instance, the potential buyer's acquisition of the seller's patent could lead to introducing a substitute stemming from the patent for the product of the seller, if the buyer's product directly competes with the seller's product.

Moreover, the defensive value of patents can intensify if a buyer and a seller have a high level of product-market overlap. There are two reasons for a tradeoff between efficiency enhancement and competitive forces. First, rivalry requires competing firms to strengthen the scope of the protection conferred by their patents in similar technological domains. Firms in direct competition tend to require analogous technologies, processes, resource demands, and skills (Chen 1996, Teece Pisano and Shuen 1997). A patent of an original assignee on the market in which a potential buyer operates is often located in the assignee's core business, and likely draws on technological knowledge to which the assignee places a high priority. As such, an original assignee prefers maintaining possession of its patent to monetizing by selling this patent to a rival firm because several patents in the concentrated technological area help warding off competition from the rival firm's entry into that area. Second, the original assignee may use the patent as a bargaining chip in the negotiation with the rival firm for licensing or patent litigation. In contrast, when there is low product-market overlap, the revenue streams and interests of an original assignee may not be menaced by a potential buyer's undertaking. Because their products and technologies are likely to be complements or simply unrelated, and the potential buyer's acquisition of the seller's patent is less likely to affect the seller's business. These mechanisms are particularly strong when the relative technological distance of a patent to a buyer's technology stock is more proximate compared with that of the seller. When product-market overlap is high, the loss of a patent could be particularly damaging to the seller even if the patent is remotely situated from the seller's technology stock and the buyer could better utilize the patent, suggesting a negative moderating effect of product-market overlap on the relationship between technological relativity and the likelihood of a patent transaction.

> Hypothesis 2 (H2). *Product-market overlap between the original assignee and the potential buyer weakens the positive effects of technological relativity on the likelihood of patent trade.*

Technological Capability of the Assignee

Firms in technology-intensive sectors constantly assess their patent portfolio and redefine their strategic position in the technological landscape. The valuation of their own patent assets can be carried out based on both offensive and defensive pursuits. Firms pursue offensive value to generate return through commercialization and the current and potential technological synergies with other patents in their portfolio without infringing the IPR of others. At the same time, firms seek to manage the risk of patent litigation or infringement by possessing enough number of patents mostly under conditions where their products may necessarily infringe the IPR of others (e.g., the smartphone sector). We suggest that a firm's technological capability can affect both the offensive and defensive values of a particular patent in a patent transaction and render the positive effect of technological relativity on the emergence of patent trade less salient. We conceptualize technological capability in the markets for innovation as a firm's potential to generate economic return from its patents. The value of a particular patent is determined by the marginal productivity that the patent contributes to generating economic return for the firm through technology commercialization or risk mitigation.

Although precisely estimating the marginal productivity would be beyond all reason, we suggest that technologically capable firms are likely to enjoy greater offensive value and marginal productivity from a patent compared to their counterparts with lower technological capability for three reasons. First, technologically capable firms are more likely to possess other interdependent and complementary technical expertise that could be combined with the patent for technology commercialization. That is, they can create greater complementarities with knowledge components and component combinations that they have. Second, technologically capable firms are more likely to efficiently graft the external technological knowledge onto their existing technology base (Levinthal and March 1993, Lieberman and Montgomery 1998) and employ heterogeneous technological resources (Afuah 2002). Third, even if there are no complementarities between the patent and other patents, technologically capable firms are more likely to be able to recognize, internalize, and seize technological opportunities (Cohen and Levinthal 1990) from the patent. As a result, the return that they can expect from a particular patent is higher compared with another firm that possesses lower technological capability.

At the same time, we suggest that technologically capable firms are likely to hold greater defensive value and marginal productivity from a patent compared with firms that possess lower technological capability. First, technologically capable firms are more likely to build an IP "fence" around its core technological area (Ziedonis 2004). Because technologically capable firms are likely to take a leading role in a particular technological field, they would be more likely to monopolize IPR around their core field of expertise by preemptively building a fence through consolidating patents in that field. As such, a patent becomes more defensively valuable when they can use it around the patent fence. Second, technologically capable firms are more likely to manage the risk of patent infringement or litigation by consolidating enough number of patents. A large number of patents in a core technological area allows greater ability for firms to launch another product with a lower likelihood of patent infringement risks or crippling legal issues. This is because other firms would infringe IPR in the technological area such that the risk of patent litigation subsides sufficiently by consolidating domain-specific patents, or would cross-license their IPR that lead to greater access to complementary patents. Such a need for defensive pursuits is particularly important in industries where many patents constitute a product or where a product may necessarily infringe the IPR of others as in the electronics industry (Levin 1982). Thus, the protective value that technologically capable firms can expect from a patent proximate to their core technological domain is higher, as compared with another firm that possesses lower technological capability.

Although the relativity of technological distances per se likely determines the likelihood of patent trade between an original assignee and a potential buyer, technological capability of the assignee can moderate the degree of its effect. On the one hand, high technological capability reflects that the assignee can generate greater return from its patents compared to a potential buyer. The high level of accumulated technical expertise enables the assignee to better recognize and grasp the value of patents in the existing technological trajectory, which in turn provides insights into how to leverage current patent portfolio. Such capability generally enables firms to recombine existing patents for technology commercialization. High potential return will increase the reservation price that the assignee would demand in the market for patents, lowering the likelihood of market clearing. Moreover, high technological capability helps protect the value of present IP assets in the core field of expertise. A preemptive patent fence in the focal field not only allows firms to enter new businesses while mitigating the likelihood of predatory patent litigation, but also helps access to complementary patents that can safeguard their current product lines through cross-licensing. On the other hand, patent trade may inevitably incur some transactional loss from an original assignee to another firm. This is because the value of an in-house technology is typically greater to the originator and may depend at least partially on other tacit knowledge in the assignee's technology stock. For instance, firm-specificity of a patent partly originates in other complementary technological resources, such as skilled workforce, compatible know-how, access to databases, product or engineering designs, customized production equipment, and so forth, that are heterogeneous and imperfectly mobile (Afuah 2002). In the markets for innovation, the firm-specificity of a patent creates inevitable trade friction in the form of transaction and transfer costs (Teece et al. 1997). The effect of technological relativity on the emergence of patent trade is likely to diminish when the assignee has superior technological capability that could generate greater return from its patent to a potential buyer. We thus suggest that such an effect of technological capability of the assignee will be particularly strong when the assignee's core domain of expertise is in an area proximate to that of the patent relative to that of a potential buyer.

> Hypothesis 3 (H3). *Technological capability of the original assignee weakens the positive effects of technological relativity on the likelihood of patent trade.*

Methods

Sample and Data

We consider two criteria for selecting our sample industry. First, a firm's ability to protect and appropriate gains from a patented invention varies greatly (Levin Klevorick Nelson and Winter 1987, Arora 1995, Cohen et al. 2000). Patents should be an effective isolating mechanism to protect inventions and capture economic rent in our chosen sector. Second, we should observe relatively vibrant interfirm patent trade because transaction costs are relatively low due to observability and traceability of constituent patents forming a product. For instance, patents in the electronics sector have intrinsic difficulty in enumerating circuit layout suggesting that design-around and reverse-engineering are common (Levin 1982). Patents in such a sector are typically more valuable for negotiating cross-licensing agreements (Hall et al. 2005) but not for trading agreements. In contrast, patents are efficacious in the biopharmaceutical sector because inventors can expound their ideas and any amendment to a patented invention can lead to different functionality (Arora and Gambardella 1998, Hall et al. 2005). Moreover, a limited number of inventions constituting a product preclude observing less technologically driven patent ownership transfer. Hence, the biopharmaceutical sector is an ideal context to test our theory.

We sample leading public firms in the biopharmaceutical industry that had sales revenue of over $1 billion[1] in at least one year during our 20-year observation period. Unlike other industries where a number of privately-held or small publicly-listed firms can be active buyers for patents, both potential buyers and sellers in the biopharmaceutical sector are relatively large publicly-listed firms. Given that over 2.14 million patents were issued during our sample period and 50,344 patents were granted to publicly listed assignees[2] in the biopharmaceutical sector. Without such a restriction, we would unbind the universe of potential buyers in the market for patents and the likelihood of a particular match for a patent transaction would be greatly reduced. We further limit the assignees to ones having exclusive ownership of a patent, resulting in 40,110 patents. The sample firms are technology vendors themselves and technology buyers at the same time. To employ a dyad-level analysis, we construct an array of one assignee paired with 56 potential buyers for each patent. The choice of patent-level decisions on ownership transfer and a dyad-level analysis helps account for sources of heterogeneity that an aggregate level of analysis and a focus on the supply side of the markets for innovation would not allow. Put

[1] The threshold of $1 billion sales revenue originates from an estimate of the U.S. Government Accountability Office (2017) that the aggregate sales revenue of 503 worldwide biopharmaceutical firms was $534 billion in 2006 (retrieved from https://www.gao.gov/products/GAO-18-40 on July 04, 2020).

[2] We use the Global Company Key (also known as GVKEY) in Compustat as a unique firm identifier. All subsidiaries within a parent firm share an identical GVKEY. In contrast, in the NBER database, a firm can have multiple wholly owned subsidiaries (i.e., multiple PDPASS) that do not have such an identical assignee identifier.

differently, for each patent in our dataset, its initial assignee is regarded as a potential seller and the other 56 firms are regarded as potential buyers. This gives us a dataset over 2.12 million patent-potential dyad observations, composed of 57 major biopharmaceutical firms respectively serving as an assignee or a potential buyer, owning 40,110 U.S. patents traded between 1987 and 2016.

----- Insert Table 1 here. -----

We collect patent data from seven sources: the National Bureau of Economic Research (NBER) Patent Data Project database (1976−2006), the USPTO PatentsView database (1976−2017), the Harvard Dataverse U.S. Patent Inventor database (1975−2010), the USPTO Patent Maintenance Fee Events database (1981−2018), the Derwent LitAlert database (1976−1999), the Lex Machina database (2000−2006), and the USPTO Patent Assignment database (1970−2017). The USPTO Patent Assignment database contains detailed information on eight million patent assignments and other transactions recorded by the USPTO between January 1970 and December 2017. The original dataset encompasses the names of the seller and buyer, the recorded date, the transaction execution date, the number of patents (or patent applications) included in the assignment, and the type of the assignment.

We construct our dataset by following procedures from prior studies (Serrano 2010, Akcigit et al. 2016, Figueroa and Serrano 2019). First, we focus on the technology-driven reallocation of patent ownership. Of all records on patent assignments in the USPTO Patent Assignment database, we exclude any records stemming from mergers and acquisitions, license grants, splits, mortgages, collaterals, conversions, internal transfers, assignee’s name changes, corrections, and so forth. Excluding intra-firm patent transactions is critical because it significantly curtails a potential distortion arising from seeking patent protection across countries to exploit different tax regimes for income generated by patent rights (Hines 1999, Branstetter Fisman and Foley 2006). We also exclude any records prior to the grant date of a patent. Second, we focus on the first transaction of a patent between two different firms (i.e., the first patent assignment), thus excluding 7,071 non-interfirm patent transactions such as between an individual and a firm or subsequent reassignments of the patent. For our dyad-level analysis, we uniquely configure data structure in a patent-assignee-buyer manner: an initial assignee was paired with 56 potential buyers for each patent. We manually standardize firm names[3] and paired an assignee and potential buyers together for each patent.

The seven databases are merged into one large dataset. The combined dataset contains information on patent trade records of a firm, a firm assigning a patent, a firm to which a patent is legally transferred, codes and years that the patent transactions were conducted, types of patent assignments, patent filings and grants, the U.S. patent class and subclass to which the patent is assigned, a list of citations from which the patent receives or to prior art on which the patent builds, and a patent involved in litigation. We obtain firm-level data from the Standard and Poor's Compustat North American Fundamentals Annual to control for firm characteristics that can influence interfirm patent trade.

Measures

Dependent Variable

***Patent Trade*.** We create a binary variable that equals to one if an original patent assignee sells a patent in force to another firm and zero if an original patent assignee does not transfer a patent to another firm. We call this variable patent trade.

Explanatory Variables

***Technological Relativity*.** We operationalize the technological relativity by drawing on a measure developed by Akcigit et al. (2016). Technological relativity is a relative technological distance differential

[3] Firm names of the seller and buyer in the Patent Assignment database are not standardized. The following steps are performed to construct our dataset. First, we conduct the name standardization routines of Bessen (2010) for our 1,248 sample buyer names in the biopharmaceutical industry. Then, we clean and compare the buyer names with the standardized firm names in the NBER Patent Data Project database. There are180 exact name matches between the two databases. We assign the NBER's PDPASS and GVKEY to these names and find that the 180 seemingly different buyer names are associated with only 86 GVKEY. This implies that we identify multiple affiliates that have the same parent firm and bundle them up as one firm with a unique firm identifier. Put differently, we ascribe multiple PDPASS to a GVKEY and exclude all internal patent transactions that occur from one subsidiary to another subsidiary within the same parent firm. Thus, we can investigate more accurate interfirm trade in patents and preclude observing internal patent transactions between affiliates that share a parent firm. We manually examine the rest of 1,068 unmatched buyer names between the two databases. We find that 141 manually matched names are associated with 34 different GVKEY. In total, we observe that 120 firms hold 2,589 patents up to this point. Of these, we sample largest biopharmaceutical firms that had sales revenue of $1 billion and over in at least one year during 1987−2006 period. Last, we compare GVKEY between the seller and buyer and define an observation as an interfirm patent assignment when they have different GVKEY. The procedures give a dataset over unique 812 patent trade between 57 sample firms.

between a patent and the technology stocks of an assignee-buyer dyad that could engage in patent trade. Technological distance between a patent and a firm's technology stock indicates the degree to which the firm's technology base is close to the technological knowledge nested within the patent. Here, a firm's technology stock represents all patented inventions made by the firm up to that point in time (Ozmel Reuer and Wu 2017, Figueroa and Serrano 2019). Patents that the firm acquires through merger and acquisition or other transactions during the period are excluded in its patent portfolio. The technological distance of a patent to a firm's patent portfolio is calculated by averaging the distance between the patent and every patent in the firm's patent portfolio. Then, for every patent in the sample, we compute the distance differential between each possible pair of sample firms at the assignee-buyer level as exemplified in Figure 1.

----- Insert Figure 1 about here. -----

We regard a firm's technology stock as a vector reflecting the distribution and composition of the firm's patents across patent classes. A vector representing the distribution and composition of a firm *f*'s patents across *k* patent classes is as follows: $P_f = (P_{f1}, P_{f2}, \ldots, P_{fk})$ where P_{fk} is the proportion of firm *f*'s patents that fall within patent class *k*. Technological distance between any two firms can be calculated as the difference between two corresponding vectors (Ahuja 2000, Yayavaram Manish Srivastava and Sarkar 2018). Following Akcigit et al. (2016), we consider two patent classes as distantly located if they are not frequently cited by prospective patents, suggesting that the two patent classes are rarely combined to create new knowledge or an invention. By doing so, we fully reflect information on patent citations to calculate technological distance between patent classes.

We advance the measure developed by Akcigit et al. (2016) in two ways. First, to more accurately reflect technological obsolescence and changes (Hall Jaffe and Trajtenberg 2005, Motohashi and Yuan 2010, Arora Belenzon and Rios 2014, Arora Belenzon and Patacconi 2018), we create a time-weighted measure by incorporating a 15% depreciation rate per year. We thus place greater weight on recent inventions when considering the following dyadic distance between patent classes X and Y in year t (i.e., $\mathrm{d}(\mathrm{X}, \mathrm{Y})_t$). Our patent-to-patent distance metric is as follows:

$$\mathrm{d}(\mathrm{X},\mathrm{Y})_t \equiv 1 - \frac{\#(\mathrm{X}\cap\mathrm{Y})}{\#(\mathrm{X}\cup\mathrm{Y})}, \qquad 0 \le \mathrm{d}(\mathrm{X},\mathrm{Y}) \le 1$$

where $\#(\mathrm{X}\cap\mathrm{Y}) = \sum_{i=1}^{n}(1-\delta)^{t-T}$ and $\#(\mathrm{X}\cup\mathrm{Y}) = \sum_{i=1}^{m}(1-\delta)^{t-T}$

$t > T$ and $\delta = 15\%$

#(X∩Y) denotes the number of all patents that cite patents from technology classes X and Y simultaneously by year *t* and #(X∪Y) indicates the number of all patents that cite either technology class X or Y by year *t*. For instance, when *n* patents cite technology classes X and Y simultaneously and *m* patents cite either technology class X or Y, the value of d(X,Y) is 1−*n*/*m*. Drawing on previous studies (Hall et al. 2005, Motohashi and Yuan 2010, Arora et al. 2014, Arora et al. 2018), we employ a 15% depreciation method for computing the *n* and *m* patents, considering technological obsolescence and changes. Specifically, when a patent granted in year *T* cites the X and Y classes simultaneously, we consider the 15% depreciation rate $(1-\delta)^{t-T}$, i.e., δ equals 15%, in both $\#(\mathrm{X}\cap\mathrm{Y})$ and $\#(\mathrm{X}\cup\mathrm{Y})$.

Second, we extend the observation timeframe of a firm's technology stock from five years to ten years. A firm's technology stock changes relatively slowly from one year to the next (Argote 1999),[4] particularly in sectors where a span between a patent and its use is long (e.g., biopharmaceutical industry). We measure technological distance between a patent (*p*) and a firm (*f*) by computing the average distance from *p* to each patent in *f* 's ten-year patent portfolio (P_f):

$$d_\iota(p,f) \equiv \Big[\frac{1}{\|P_f\|}\sum_{p'\in P_f} d(\mathrm{X}_p,\mathrm{Y}_{p'})^{\iota}\Big]^{1/\iota}$$

$\iota = 1$ and $-1 \le d_\iota(p, f) \le 1$[5]

[4] Our analysis indicates the correlation between patent-firm distance in the grant year and that in the following year is 0.993, and that between the grant year and the fifth year is 0.989. Moreover, the correlation between patent-firm distance in the fifth year and that in the tenth year is still 0.988.

[5] P_f indicates the set of all patents that were ever invented by firm *f* prior to patent *p*. $\|P_f\|$ denotes its cardinality and $\mathrm{d}(\mathrm{X}_p,\mathrm{Y}_{p'})$ measures the distance between the technology classes of patents *p* and *p*′. $\mathrm{d}(\mathrm{X}_p,\mathrm{Y}_{p'})=0$ means that a firm has another patent *p*′ in the same class as *p*. Different choices of the value for ι (ι=1/3, 2/3, or 1) do not result in a difference (Akcigit et al. 2016). Thus, we assign 1 to ι.

Last, we compute technological relativity by subtracting the technological distance between a given patent and a potential buyer (d(B)) from that between the patent and the original assignee (d(A)). Thus, the likelihood of patent trade will increase as the technological relativity (d(A)−d(B)) increases.

Further, we create a technological distance measure between a patent and a firm based on patent citations[6] and test it as a robustness check. We calculate the degree to which each firm cites the same prior art of a given patent. In general, the population of prior art constitutes a technological network, serving as resources for technological innovation. As such, a firm's patent citations define its position in the technological landscape. Thus, patent-citations overlap between two firms reflects the "the degree of common dependence on prior inventions as foundations for their research activity" (Podolny Stuart and Hannan 1996, p. 665) and can represent the technological distance between them. We use the following formula to calculate the ratio of citations shared between a patent and a firm.

$$Shared - citations\ based\ Technological\ Distance\ \left(Patent_p, Firm_f\right)$$
$$= \frac{Shared\ Citations\ between\ a\ Patent_p\ and\ Patents\ in\ Firm_f}{Total\ Patent\ Citations\ in\ Firm_f}$$

Product-Market Overlap. We draw a Mahalanobis distance measure from Bloom, Schankerman, and Van Reenen (2013) to operationalize product-market overlap between firms. Mahalanobis distance considers how much of sales revenue by two firms overlap based on four-digit Standard Industrial Classification (SIC) codes. First, a firm's product-market activity is characterized by a vector $S_i = (S_{i1}, S_{i2}, \ldots, S_{iK})$ where S_{iK} is the average share of the sales revenue of a firm *i* in the industry *K* over the past four-year period (Yan Dong and Faems 2020). Given that the vector S_i represents a firm's position in the product-market space, the product-market overlap between two firms *i* and *j* can be computed by using the Mahalanobis distance between two corresponding vectors S_i and S_j. When the distance between firms in the product-market space is proximate, they are in intense product-market competition. As such, the indicator adequately operationalizes competitive intensity at the firm-level dyads (Ugur et al. 2016).

[6] We are grateful for the suggestion by the Senior Editor and anonymous reviewers.

***Technological Capability*.** Adapting the construct of innovation capability (Kumar and Zaheer 2019), we measure a firm's technological capability in year t as the accumulative citation-weighted number of patents in a previous ten-year timeframe (t−1 to t−10) with a 15% depreciation rate. For a patent p granted in year T ($t-10 \leq T \leq t-1$), we compute the number of citations it receives throughout its lifespan. Then, we multiply it by $(1-\delta)^{t-T}$ where δ equals 15%. Last, we aggregate $(1-\delta)^{t-T} * \left(Citations_p + 1\right)$ for all patents in a firm's ten-year running patent portfolio to compute its technological capability in year *t:*

$$\sum_{p=1}^{n}(1-\delta)^{t-T}\,(Citations_p + 1)$$

For our regression analysis, it is scaled down to 1/10000. In general, firms seek patents as IPR protection within recent few years of R&D activities (Jaffe Trajtenberg and Henderson 1993, Arora et al. 2014). Due to the nature of moving ten-year time windows, citation-weighted patent counts have been used over simple patent counts (Sampson 2007, Vasudeva Zaheer and Hernandez 2012, Funk 2014). Citation-weighted patents tend to represent the differences in values of individual patents better in a single sector because the patenting propensity of biopharmaceuticals is fairly stable (Ahuja 2000). Considering that a firm with a more diversified technology stock could have a greater ability to exploit a patent and thus be less willing to offer the patent in the markets for innovation, we also measure the breadth of a firm's technological capability by leveraging information on unique three-digit U.S. patent classes (Miller 2004).

***Control Variables*.** We control for a number of patent- and firm-level variables that could influence decisions on patent trade. At the patent level, we create a series of binary variables for a year of patent approval decision and whether a patent is renewed in sequence. We also control for litigated patents. Patent litigation could reach an agreement on patent trade for reasons not associated with technological relevance. Galasso et al. (2013) document that 27.9 percent of patents is traded when a patents is involved in litigation, whereas merely 4.4 percent of patents is traded when they are not litigated. The Derwent LitAlert database contains information on 16,467 unique litigated patents before 2000 and the Lex

Machina database includes comprehensive information on 30,805 unique litigated patents since 2000. These databases together provide information on 47,272 patent litigation during the period 1976−2006. We create an indicator variable that equals to one if a patent enters a lawsuit and zero otherwise. Moreover, we control for backward and forward citations. Backward citations measure the number of prior art citations by a given patent. Patents that cite fewer prior art will draw on a narrower scope of knowledge, and the knowledge recombination in generating those patents may produce knowledge of lower value. We count the number of backward citations and expect that a greater number of backward citations would increase the likelihood of patent trade. Likewise, forward citations measure how many forward citations a patent receives from subsequent patents. Our truncation-adjusted forward citations measure indicates how valuable the patent is regarded by other firms in the technological community. A myriad of studies have shown that forward citations are positively associated with technological value (Trajtenberg 1990, Harhoff et al. 1999, 2003, Lanjouw and Schankerman 2004, Hall et al. 2005). Last, we control for the degree of self-citations in a patent because the share of self-citations of the assignee would reflect that a potential buyer needs to acquire greater extent of external technological knowledge and can extract lesser return by leveraging its own technological knowledge (Hall et al. 2005). Following Wang et al. (2009), we measure the share of self-citations in a patent by calculating the number of self-citations divided by the number of all citations in a patent in its grant year.

We control for environmental conditions by adjusting a measure of patent-market liquidity developed by Hochberg et al. (2018). We measure market thickness of patent trade in terms of technology classes relevant for each firm's portfolio of patents. Specifically, a firm's combined probability, averaged across patents in its portfolio as of year *t*, that patents issued in the prior years are traded in year *t*. Thicker patent markets can present greater opportunities for firms to make a deal and higher likelihood that a potential match exists (Li and Netessine 2020) because market thickness can reduce transaction costs for both sellers and buyers (Gans and Stern 2010), thus increasing the probability of patent trade.

Furthermore, we control for a number of firm-level variables. We control for R&D intensity of respective potential selling and buying firms, measuring total R&D expenditure divided by total sales in a year. Given a strong relationship between the level of technology investment and firm size (Schumpeter 1961), we control for the R&D investment by each firm. We also control for net income in million USD of respective potential selling and buying firms. Firms with greater net income tend to have greater organizational slack that typically increases their size of technology stock. Last, we control for geographical distance between an original assignee and a potential buyer, based on the postal address of a patent, to examine whether geographical distance affects the transaction costs between the two traders (Sorenson and Stuart 2001). Large geographical distance not only increases the transaction costs but also lower competitive intensity between the two firms. We create a binary variable that equals to zero if a potential buyer is geographically colocated with an assignee in the same country and one otherwise.

Analytical Approach

We employ rare events logistic regression for our analysis because our dependent variable is a dichotomous variable in rare events data (King and Zeng 2001). Rare events logistic regression better estimates the probability of a rare event than logistic regression in that it corrects a bias stemmed from the condition that one outcome is significantly rarer than the other and accordingly a sample is highly unbalanced. To control for additional sources of unobserved heterogeneity within the sample, we include robust standard errors in the analysis.

Results

We observe that 57 major biopharmaceutical firms held 40,110 U.S. patents as original assignees during the period between 1987 and 2006. Of these, 812 patents were transferred from an original assignee to another firm for the first time during their lifespan, representing about two percent of patents in our dataset. These numbers appear low as compared with prior studies. For instance, Serrano (2010) shows that approximately 16 percent of patents in the drug and medical field changed hands after an initial grant. There are four reasons why our figure is lower than prior studies. First, we restrict the patent transfers between 57 largest firms in the biopharmaceutical field. Second, many of the previously reported figures include patent transfers between two entities having the same parent firm. To examine more accurate interfirm patent trade in the markets for innovation, we apply more conservative sample selection criteria compared to those studies. That is, we identify multiple entities that have the same parent firm and consider them as one firm in this study. Third, we focus on the first interfirm transaction over a patent during its life cycle and exclude non-interfirm trade or subsequent reassignments of the patent. Last, we focus on a patent held by a single initial assignee. We find that approximately two percent of patent trade happens between 57 biopharmaceutical firms between 1987 and 2016. Approximately a half of our sample potential dyads (i.e., assignee-buyer) operates in the same sector (53.87%) or in the same country (46.77%).

----- Insert Tables 2 and 3 about here. -----

The median assignees' technological capability is 8,983, whereas the median for potential buyers is 851. The distribution of technological capability is highly right-skewed because the top 25-percentile values for assignees and potential buyers are 17,661 and 3,738 respectively during the running ten-year sample period. We observe the marked discrepancy in the number of patent ownership between the assignee and potential buyer. This is in part because a firm appears as an assignee when its patent is granted, whereas the same firm can also appear as a potential buyer whenever a patent of another sample firm is granted even when it does not have any patent in that year. The median value of the assignee's R&D intensity index is 0.128 with a range between 0.006 and 9.51, whereas that of the potential buyer is 0.131 with a range between 0.002 and 17.79. The median net income of the assignee is 1,810 million USD, whereas that of the potential buyer is 236 million USD. Overall, the assignee not only has greater size of patent portfolio as compared to the potential buyer, it also has greater financial performance in our dataset. The average value of patent-market liquidity of a firm is 0.44 with a range between 0 and 1. 546 patents are involved in patent litigation between 1987 and 2006, representing about 1.44 percent of patents in our dataset. The average value of the intensity of self-citations in a patent is 0.22 with a range between 0 and 1. The median value of the forward citations to a patent is 4.34 with a range between 0 and 622. Likewise, the median value of the backward citations from a patent is 4 with a range between 0 and 785. These findings reflect that the distributions of the total number of both backward and forward patent citations are highly right-skewed, in part due to high variance in patent quality. In less than six percent of the observations, the forward and backward citations indexes are reported as missing due to missing values in the databases. About 84.3 percent of patents is renewed for the first time and, conditional on a patent being renewed, 62.8 percent and 44.9 percent of patents are renewed for the second and third time respectively. Except for the correlations between three binary renewal variables, and those between technological capability and net income, most correlations are below 0.33. To assess the threat of multicollinearity, we calculate the variance inflation factors (VIF) for each coefficient. The maximum estimated VIF is 2.41, far below the recommended ceiling of 10 (Cohen et al. 2003).

----- Insert Table 4 about here. -----

We present the results of the rare events logistic regression models in Table 4. We first estimate a baseline model only using control variables. We add the main effect from the first hypothesis and the interaction effects from the other two hypotheses, and then include all explanatory variables in the full model. Each subsequent model shows improvement over the respective baseline models. The models estimate each limited dependent variable (LDV) that takes discrete values (i.e., a binomial decision on patent trade). For non-linear models, an explanatory variable's model coefficient cannot denote the effect of a unit change in the explanatory variable on the LDV (i.e., marginal effect) and the value of the marginal effect varies with the value of all other model variables (Wiersema and Bowen 2009). Moreover, considering the number of observations, the economic significance (i.e., effect size) is more meaningful than statistical significance. Therefore, as a supplementary analysis, we calculate the marginal effects for the change in patent trade likelihood when each explanatory variable is increased by one unit, while holding all other variables fixed at their respective medians.

In Table 4, Model 1 only comprises control variables. Most coefficients are in the directions as predicted and statistically significant. The results indicate that patents are more likely to be traded when patents are renewed, when patents are involved in litigation, or when there are more backward citations. Moreover, the results show that there is a higher likelihood of patent trade when a potential buyer is technologically capable, when the assignee has greater net income, or when firms operate in a liquid patent market. In contrast, patents held by assignees with high technological capability or potential buyers with high net income are less likely to be traded. In addition, there is a lower likelihood of patent trade when the assignee and potential patent buyer have greater product-market overlap or when patents have a high degree of self-citations.

H1 predicts the greater likelihood of patent trade under conditions that a potential buyer's technology stock is more proximate to a patent compared with that of the original assignee. In Model 2, the emergence of patent trade is greater under conditions of a high degree of technological relativity. Thus, H1 is supported. H2 and H3 examine when factors cause friction in the market for patents that moderates the effects of technological relativity on the likelihood of patent trade. H2 predicts the lower likelihood of patent trade under conditions of product-market overlap between the original assignee and a potential buyer. Our results in Model 3 support this notion by showing that firms are less likely to trade their patents when the assignee competes with a buyer for the similar product and market. Thus, H2 is supported. Finally, H3 predicts that the original assignee is less likely to sell its patent when the assignee has higher technological capability than a potential buyer. The coefficients from Model 4 and Model 6 suggest that the technologically capable assignee is less likely to sell its patent in the technological domain that is more relevant to the buyer's technology stock. Therefore, H3 is supported.

Our results in Model 7, the full model, the signs and statistical significance of coefficients for technological relativity and interaction effects remain consistent. Interestingly, as shown in Models 5 and 6, the influence of a potential buyer's technological capability on the positive relationship between technological relativity and patent trade is not statistically significant. It appears that patent trade can emerge irrespective of a potential buyer's current technological capability, because its decision on purchasing a patent is chiefly based on technological relevance and initiating a patent transaction theoretically depends on the assignee's willingness to accept.

Robustness Checks and Post Hoc Analysis

We conduct a series of additional analyses to deepen our insight into our findings. First, we use alternate measures of product-market overlap and technological capability. Specifically, we adopt the three-digit SIC codes as an alternative proxy for product-market overlap. We also consider different timeframe (e.g., three and five years) for the average share of a firm's sales revenue in each SIC, producing quantitatively similar results. We then adopt an alternate measure of technological capability by replacing the original citation-weighted patent counts with the technological diversification index that uses information on unique three-digit U.S. patent classes. We reason that highly diversified firms in terms of their technologies are more likely to exploit a patent and thus less likely to put the patent on the markets for innovation. Our results remain consistent.

Second, we conduct a survival analysis using the Cox proportional hazards model and present the results in Table 5. Along with other time-varying control variables, we consider the evolving technology stocks of both assignees and buyers over time. For the Cox proportional hazards analysis, we restructure our sample and make "patent−year" observations as our unit of analysis. For each patent−year, we select the closest sample firm among 56 potential buyers as a representative buyer. As such, each patent has a record per year. After omitting observations with missing values, our final sample contains 37,884 patents, in which 812 patents exit the risk set when they are traded and the other 37,072 patents exit at their expiration date. Subsequently, we keep the last-year observation of every patent to construct single observation-recorded data and conduct the Cox proportional hazards analysis. We also compare the single observation-recorded with the multiple observation-recorded patent data. Both yield similar results. The results of Model 2 show that technological relativity increases the hazard rate of a patent's exit, thereby indicating a greater likelihood of patent trade (i.e., H1). Model 3 suggests that the interaction between technological relativity and product-market overlap may not exist. It is possible that our strict selection criterion for one "representative" buyer out of 56 buyers might cause this result. However, we are cautious taking the result too seriously as the choice of such a representative buyer is obviously subjective but inevitable for this survival analysis. Model 4 indicates that the assignee's technological capability weakens the positive effect of technological relativity on patent trade, supporting H3.

Third, we examine several alternative formulations of technological distance measure. This includes employing our own *Shared-citations based Technological Distance* measure as the main indicator in a rare events logistic regression analysis. The results remain largely consistent with our main findings, excluding H3. That is, the interaction between our own measure and the assignee's technological capability is positive and statistically significant. Based on a measure depending only on patent citations, it is possible that a "proximate" patent tends to share the greater proportion of the same body of knowledge with that of the assignee, and the technologically capable assignee owns multiple "proximate" patents that cite the same or similar prior art. As such, the proximate patent might become more redundant to the assignee. Taken together, these analyses provide evidence of the robustness of our technological relativity measure and also offer a more nuanced understanding of the link between relative technological distance and patent trade between firms. Fourth, we examine whether firm fixed effects affect our main findings. In Appendix 1, our fixed-effects results in the logistic regression are consistent with our main findings.

Last, we conduct a split-sample post hoc analysis to examine whether the effect of product-market overlap is less salient for firms whose technological capability is high.[7] The results suggest that product-market overlap weakens the effect of technological relativity only when the assignee is less technologically capable than potential buyers. Put differently, we find that the influence of product-market overlap is less pronounced when the assignee's technological capability is superior to that of potential buyers. These results are reported in Table 6.

----- Insert Tables 5 and 6 about here. -----

Discussion

Many managerial decisions involve understanding both oneself and peers in the technological ecosystem. Understanding one's own patent assets and those of its peers is particularly important for potential sale and acquisition of patents in the markets for innovation. Managers in technology-intensive sectors tend to make decisions in a complex and dynamic environment. Decisions related to resource allocation for long-term investment such as R&D are made with a high degree of uncertainty and ambiguity (Ahuja Lampert and Tandon 2013). In such a context, we examine conditions under which firms trade patents. We find

[7] We thank the Senior Editor for suggesting this possibility.

that firms tend to reallocate patent ownership such that a firm with a presumably better use of a patent, i.e., one with shorter technological distance to its technology stock, buys the patent from the original assignee whose technology stock resides further away from the focal patent. We further show that product-market overlap between an assignee and a potential buyer weakens this relationship, because assignees are wary of competitive forces at play. Likewise, assignees with high technological capability, presumably those that can generally earn greater economic rent from a particular patent, would be less willing to sell their patents, even when technological distance of a potential buyer is more proximate compared with their own. This is because their reservation price for the patent is higher, reducing a likelihood of market clearing.

Our framework could assist managers in assessing a technological distance differential between individual patents and their overall technology stock and examining the differential in relation to other firms to assess suitability of patent trade, leading to a more productive use of such patents. Relative understanding of patent assets may facilitate effective use of patented inventions and promote social welfare through a more efficient allocation of IP rights. For instance, our findings include that Pfizer bought patents originally owned by Sanofi to effectively launch the first inhalable insulin product *Exubera* for type 1 and type 2 diabetes. Similarly, King Pharmaceuticals bought Eli Lilly's patents to circumvent the expense of R&D and lengthy clinical trials. Meanwhile, such a sale contributed to the increase in Eli Lilly's net income and possibly its stock price. This implies that marginal productivity generated by patent trade may be associated with pro-innovation and mitigation of the tragedy of the anticommons problems, which are particularly pronounced in patent-dependent industries. Moreover, firms seeking unique resources that could lead to competitive advantage are likely to deem the market for patents as an important strategic factor market. On the one hand, under conditions that firms trade a patent to generate return from it, or even implement their strategy, a patent market emerges. On the other hand, an inefficient market permits firms to acquire IP assets for competitive advantage at less than their value in use. There is a difference in gains in the strategic patent market because some firms are more accurate about their expectation of strategic value as compared to others. An interesting side note of our findings is that, although competition is generally associated with a more efficient market that would correct "misallocation" of a resource from a less-productive owner to a more productive user that can take greater advantage of the resource, competition between two parties can also trigger market friction. That is, competitive rivalry between firms in the market for patents, or factor market in general, could lead the market to be less efficient. Although such a market inefficiency partially accounts for the limited share of patents traded in the market, the paucity might stem from the large number of low quality, defensive patent applications, which are filed for reasons unrelated to the economic value of underlying technology. Future research could examine the strategic patenting considerations that remain largely beyond the scope of this study or explore the impact of acquiring a patent on the buyer's competitive advantage, thereby contributing to the strategic factor market literature. Likewise, although we do not test the overall social welfare implications as a consequence of absence for such trade in this study, it is conceivable that the market may not achieve its potential social welfare that could have been achieved through the reallocation of patent ownership between competitors.

This study contributes to the literature on innovation and technology management in three ways. First, it contributes to the literature on IPR management. Although strategic management has lent considerable insights into factors leading to the development of IP assets (Teece 1986, Gans and Stern 2003, Arora and Ceccagnoli 2006, Sternitzke 2013) as well as the effectiveness of different strategies for IPR protection (Levin et al. 1987, Cohen et al. 2000), few studies have considered how firms actively manage their IP portfolio once patents are granted. This study provides a novel theoretical framework and empirical findings on how firms actively engage in patent trade in a mutually beneficial manner. Thus, it shows how a patent market emerges by more efficiently using intangible resources. Second, this study joins the patent trade literature that has begun to come to light in recent years (e.g., Serrano 2010, Galasso et al. 2013, Serrano 2018). However, unlike prior studies that have mostly carried out an analysis of patent trade at an aggregate level, by employing a dyadic unit of analysis, this study investigates firm-level decisions encompassing a firm's overall IP portfolio as well as that of potential buyers. Our dyadic analysis overcomes the limitations of extant studies mainly focusing on the seller-driven markets for innovation. Third, this study extends our understanding of Coase theorem. Although the theorem has been the precursor to many theoretical perspectives in organization science and strategic management, its practical application has been rather limited in part because we can hardly find an actual context satisfying both of the two preconditions for the theorem, i.e., clear legal delineation of property rights and trivial transaction costs. Our context of patent trade meets these preconditions for a market to transpire and provides a meaningful setting to test Coase theorem. In addition, we extend our understanding of the theorem by presenting boundary conditions that arise in our specific context of patent-trade market, namely the product-market overlap between a buyer and a seller and technological capability of the seller.

We examine whether each traded patent can be ascribed to the core technology stock of a buyer. By the same token, we examine both offensive and defensive values of each traded patent to the technology stock of a seller. If ascribed to the core technology stock, the acquired patent augments defensive value because it will increase the technological concentration of the buyer's patent portfolio. In contrast, the acquired patent delivers offensive value when it contributes to broadening the current technological breadth of the buyer's patent portfolio. First, we do not find any significant discrepancy between single- and bundled-patent trade. Regardless of whether a deal is single or bundled, traded patents tend to be technologically broader or more novel to the buyer. Those acquired patents augment offensive value to the technology stock of a buyer by broadening the buyer's current technological breadth than defensive value stemming from strengthening technological concentration. The results may point towards a stark contrast between offensive and defensive values of the buyer and those of the seller. We suspect that such an offensive objective of patent acquisition might be more prevalent for entrepreneurial ventures. Nevertheless, future studies could examine respective offensive and defensive motives for patent trade in a more focused setting with refined measures.

Conclusion

Due to the unavailability of data and the methodological difficulty of disentangling the possible patent-market effect from the product-market value attributable to the patents, empirical evidence has largely remained qualified. Thus far, we have thought that firms have sought patents to protect their core ideas and inventions, or to manage patent risks or power of negotiation over patent infringement. However, our endeavor provides new evidence of the expanding interfirm patent trade not only underexplored in the literature but also consequential for both entrepreneurial and established firms. On the one hand, firms can buy idle patents in the markets for innovation to unlock new technological and business opportunities while reducing the need to reinvent the wheel. On the other hand, firms can satisfy not only consumers by selling their patents to another firm that can actually deploy them in its business but also shareholders by generating a greater return on investment. Indeed, a traded patent could be an essential missing puzzle for another firm in the markets for innovation, thus giving new life to the technology currently not in use. We hope that understanding interfirm patent trade can contribute to firms' value creation and appropriation.

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Table 1. Main Variables and Data Sources

	Definition	Data Source
Main Variables		
PATENT TRADE	Indicator set to 1 if a patent is involved in the first change of ownership after the patent is granted.	USPTO Assignments
TECHNOLOGICAL RELATIVITY	Relative technological distance between a patent and each firm's technology stock by calculating the average distance of the focal patent to each patent in an assignee (A)'s patent portfolio (d(A)) and to each patent in a potential buyer (B)'s patent portfolio (d(B)). Then, subtract d(B) from d(A): $-1<d(A)-d(B)<1$.	USPTO NBER
PRODUCT-MARKET OVERLAP	Using the Mahalanobis distance measure developed by Bloom et al. (2013), compute how much of sales revenue by two firms overlap based on four-digit SIC codes over the past four years.	USPTO Compustat
TECHNOLOGICAL CAPABILITY (Citation weighted)	Cumulative number of previous ten-year patents of each firm by the grant year T of a given patent, weighted by the number of citations that each patent receives during its post-grant. Subsequently, multiply by $(1-\delta)^{t-T}$ where δ equals a 15% depreciation rate. Then, scale down to 1/10000 as a firm's technological capability in year *t*.	USPTO NBER Harvard Dataverse U.S. Patent Inventor
Other Variables		
Patent Market Liquidity	Adjusting the measure in Hochberg et al. (2018), a firm's combined probability (averaged across patents in its portfolio as of year *t*) that patents issued in the prior years are traded in year *t*.	USPTO NBER
Patent Litigation	Indicator set to 1 if a patent is involved in litigation.	Derwent LitAlert Lex Machina
Self-Citation	Indicator for the degree to which the value of a patent is assignee-specific; measured as the share of patents citing an assignee's patents. The number of self-citations in a patent in a given grant year is divided by the number of all citations in the patent in the grant year.	USPTO Harvard Dataverse U.S. Patent Inventor
Patent Renewals (First, Second, and Third)	Conditional on a patent being renewed, indicator set to 1 if renewal fees are paid to maintain the patent at required intervals through the expiration of the patent.	USPTO PatentsView USPTO Patent Maintenance Fee Events
Patent Forward Citations (Truncation adjusted)	Number of citations that each patent receives during its post-grant. Subsequently, following Hall et al. (2005), address truncation bias by dividing the citation counts by the fraction of predicted lifetime citations actually observed during the lag interval.	USPTO Harvard Dataverse U.S. Patent Inventor
Patent Backward Citations	Number of citations each patent makes during its pre-grant.	USPTO Harvard Dataverse U.S. Patent Inventor
Geographical Distance	Indicator set to 1 if a potential buyer is not geographically colocated with an assignee in the identical country.	USPTO Google
R&D Intensity	Annual expenditures by each firm on R&D divided by its sales revenue (million USD).	Compustat
Net Income	A firm's annual income after subtracting expenses, depreciation, interest, and taxes (million USD). Then, scale down to 1/10000.	Compustat
Grant Year	Calendar year of a patent granted between 1987 and 2006.	USPTO NBER

Table 2. Descriptive Statistics

	Mean	Median	SD	Min	Max
Patent Trade	0.00	0.00	0.02	0.00	1.00
Tech Relativity	−0.03	−0.02	0.11	−0.86	0.82
Product-Market Overlap	0.55	0.77	0.47	0.00	1.35
Tech Capability (A)	1.21	0.90	1.00	0.00	4.25
Tech Capability (B)	0.33	0.09	0.62	0.00	4.25
Patent Market Liquidity	0.44	0.46	0.24	0.00	1.00
Patent Litigation	0.01	0.00	0.12	0.00	1.00
Self-Citation	0.22	0.00	0.32	0.00	1.00
First Renewal	0.84	1.00	0.36	0.00	1.00
Second Renewal	0.63	1.00	0.48	0.00	1.00
Third Renewal	0.45	0.00	0.50	0.00	1.00
Forward Citations	11.16	4.34	21.57	0.00	621.50
Backward Citations	8.79	4.00	17.97	0.00	785.00
Geographical Distance	0.16	0.13	0.30	0.01	9.51
R&D Intensity (A)	0.26	0.13	0.76	0.00	17.79
R&D Intensity (B)	0.23	0.18	0.24	−0.49	1.14
Net Income (A)	0.08	0.02	0.15	−0.49	1.14
Net Income (B)	0.53	1.00	0.50	0.00	1.00

Notes. N = 2,121,457; A: Assignee; B: Buyer.

Table 3. Correlations

	Variable	1	2	3	4	5	6	7	8	9
1	Patent Trade	1.00								
2	Tech Relativity	0.00	1.00							
3	Product-Market Overlap	−0.01	0.05	1.00						
4	Tech Capability (A)	−0.01	0.05	0.07	1.00					
5	Tech Capability (B)	0.01	−0.09	0.20	−0.01	1.00				
6	Patent Market Liquidity	0.00	−0.08	0.02	−0.10	0.05	1.00			
7	Patent Litigation	0.00	0.00	0.00	−0.03	0.00	0.02	1.00		
8	Self-Citation	0.00	−0.03	0.03	0.08	0.00	0.00	0.01	1.00	
9	First Renewal	0.01	−0.01	0.00	0.03	0.01	−0.01	0.05	−0.04	1.00
10	Second Renewal	0.01	−0.01	0.00	0.07	0.01	−0.07	0.07	−0.05	0.56
11	Third Renewal	0.01	0.00	−0.01	0.11	0.00	−0.13	0.09	−0.06	0.39
12	Forward Citations	0.00	0.01	0.01	0.14	−0.01	−0.15	0.07	−0.08	0.11
13	Backward Citations	0.00	−0.02	0.02	0.18	0.00	0.04	0.03	−0.06	0.07
14	Geographical Distance	0.00	−0.12	−0.02	−0.12	0.01	0.11	0.02	−0.03	0.01
15	R&D Intensity (A)	0.00	0.04	−0.07	0.00	−0.07	−0.05	0.00	0.00	0.00
16	R&D Intensity (B)	0.00	0.03	0.03	0.39	0.01	0.32	−0.01	0.05	−0.11
17	Net Income (A)	0.01	−0.03	0.06	0.00	0.54	0.10	0.00	−0.01	0.00
18	Net Income (B)	0.00	0.10	−0.08	−0.19	−0.17	0.11	0.01	−0.05	0.00

		10	11	12	13	14	15	16	17	18
10	Second Renewal	1.00								
11	Third Renewal	0.70	1.00							
12	Forward Citations	0.16	0.19	1.00						
13	Backward Citations	0.11	0.10	0.09	1.00					
14	Geographical Distance	0.01	0.02	0.01	0.00	1.00				
15	R&D Intensity (A)	0.01	0.01	0.02	−0.01	−0.01	1.00			
16	R&D Intensity (B)	−0.11	−0.10	−0.09	0.08	−0.13	−0.04	1.00		
17	Net Income (A)	0.00	−0.01	−0.04	0.03	0.02	−0.10	0.06	1.00	
18	Net Income (B)	−0.01	−0.03	−0.04	−0.04	−0.01	−0.11	−0.01	0.04	1.00

Notes. N = 2,121,457; VIF≤2.41; A: Assignee; B: Buyer; Correlations with absolute values no less than 0.0017 are significant at the 5% level.

Table 4. Patent Trade

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Estimation Method	ReLogit	ReLogit	ReLogit	ReLogit	ReLogit	ReLogit	ReLogit
Dependent Variable	Trade	Trade	Trade	Trade	Trade	Trade	Trade
Product-Market Overlap	−1.224***	−1.288***	−1.310***	−1.293***	−1.291***	−1.294***	−1.318***
	(0.088)	(0.090)	(0.092)	(0.091)	(0.090)	(0.091)	(0.092)
Tech Capability (A)	−0.563***	−0.577***	−0.579***	−0.632***	−0.578***	−0.632***	−0.632***
	(0.052)	(0.053)	(0.054)	(0.059)	(0.053)	(0.059)	(0.059)
Tech Capability (B)	0.291***	0.352***	0.348***	0.359***	0.360***	0.363***	0.368***
	(0.049)	(0.049)	(0.049)	(0.049)	(0.051)	(0.051)	(0.051)
Patent Market Liquidity	0.437**	0.720***	0.698***	0.777***	0.724***	0.779***	0.762***
	(0.212)	(0.218)	(0.219)	(0.218)	(0.220)	(0.220)	(0.220)
Patent Litigation	0.672***	0.673***	0.676***	0.670***	0.674***	0.671***	0.674***
	(0.177)	(0.176)	(0.176)	(0.176)	(0.176)	(0.176)	(0.176)
Self-Citation	−0.628***	−0.578***	−0.579***	−0.577***	−0.577***	−0.577***	−0.577***
	(0.132)	(0.132)	(0.132)	(0.132)	(0.132)	(0.132)	(0.132)
First Renewal	1.330***	1.327***	1.326***	1.334***	1.327***	1.334***	1.331***
	(0.284)	(0.284)	(0.284)	(0.284)	(0.284)	(0.284)	(0.284)
Second Renewal	0.580***	0.583***	0.585***	0.586***	0.584***	0.586***	0.587***
	(0.150)	(0.150)	(0.149)	(0.150)	(0.150)	(0.150)	(0.150)
Third Renewal	0.718***	0.710***	0.709***	0.713***	0.710***	0.713***	0.712***
	(0.102)	(0.102)	(0.102)	(0.102)	(0.102)	(0.102)	(0.102)
Forward Citations	−0.000	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Backward Citations	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Geographical Distance	−0.202	−0.124	−0.123	−0.118	−0.123	−0.118	−0.117
	(0.141)	(0.119)	(0.122)	(0.118)	(0.119)	(0.117)	(0.119)
R&D Intensity (A)	−1.050*	−1.175*	−1.188*	−1.169*	−1.175*	−1.170*	−1.177*
	(0.545)	(0.602)	(0.609)	(0.599)	(0.602)	(0.599)	(0.604)
R&D Intensity (B)	0.895***	0.707***	0.716***	0.683**	0.704**	0.682**	0.685**
	(0.270)	(0.274)	(0.274)	(0.272)	(0.275)	(0.272)	(0.272)
Net Income (A)	2.688***	2.613***	2.607***	2.611***	2.606***	2.607***	2.595***
	(0.204)	(0.201)	(0.201)	(0.201)	(0.201)	(0.201)	(0.201)
Net Income (B)	−0.700***	−0.766***	−0.767***	−0.776***	−0.765***	−0.776***	−0.775***
	(0.078)	(0.080)	(0.080)	(0.081)	(0.080)	(0.081)	(0.081)
Technological Relativity		2.763***	3.312***	4.040***	2.705***	4.011***	4.393***
		(0.220)	(0.240)	(0.301)	(0.233)	(0.327)	(0.334)
Tech Relativity *			−1.782***				−1.732***
Product-Market Overlap			(0.479)				(0.507)
Tech Relativity *				−1.845***		−1.842***	−1.752***
Tech Capability (A)				(0.398)		(0.400)	(0.404)
Tech Relativity *					0.100	0.047	0.206
Tech Capability (B)					(0.230)	(0.241)	(0.249)
Constant	−10.792***	−10.710***	−10.696***	−10.696***	−10.710***	−10.696***	−10.683***
	(0.437)	(0.440)	(0.440)	(0.439)	(0.440)	(0.439)	(0.439)
Year Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	2,121,457	2,121,457	2,121,457	2,121,457	2,121,457	2,121,457	2,121,457

Notes. ReLogit: rare events logistic regression; Robust standard errors in parentheses; *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$; A: Assignee; B: Buyer.

Table 5. Cox Proportional Hazards Regression Analysis

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Estimation Method	Cox Proportional Hazards Regression						
Dependent Variable	The Hazard Rate of a Patent being Traded in Year *t*						
Product-Market Overlap	0.098	0.093	0.101	0.095	0.092	0.094	0.106
	(0.080)	(0.080)	(0.081)	(0.080)	(0.080)	(0.080)	(0.081)
Tech Capability (A)	−0.198***	−0.210***	−0.210***	−0.213***	−0.212***	−0.216***	−0.216***
	(0.063)	(0.063)	(0.063)	(0.064)	(0.063)	(0.064)	(0.064)
Tech Capability (B)	−0.237***	−0.220***	−0.218***	−0.216***	−0.160*	−0.156*	−0.154*
	(0.084)	(0.083)	(0.083)	(0.083)	(0.087)	(0.087)	(0.087)
Patent Market Liquidity	5.280***	5.411***	5.403***	5.460***	5.445***	5.494***	5.490***
	(0.377)	(0.380)	(0.380)	(0.380)	(0.380)	(0.380)	(0.381)
Patent Litigation	1.218***	1.225***	1.234***	1.237***	1.201***	1.212***	1.225***
	(0.182)	(0.182)	(0.182)	(0.182)	(0.182)	(0.182)	(0.183)
Self-Citation	−0.898***	−0.898***	−0.898***	−0.893***	−0.901***	−0.896***	−0.894***
	(0.133)	(0.133)	(0.133)	(0.133)	(0.133)	(0.133)	(0.133)
Forward Citations	−0.002	−0.003	−0.003	−0.003	−0.003	−0.003	−0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Backward Citations	0.010***	0.010***	0.010***	0.010***	0.010***	0.010***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Geographical Distance	−0.042	−0.063	−0.060	−0.059	−0.062	−0.057	−0.054
	(0.075)	(0.075)	(0.075)	(0.076)	(0.075)	(0.076)	(0.076)
R&D Intensity (A)	0.390	0.482	0.468	0.538*	0.503	0.557*	0.543*
	(0.324)	(0.318)	(0.318)	(0.316)	(0.314)	(0.312)	(0.312)
R&D Intensity (B)	−0.136	−0.160	−0.160	−0.162	−0.160	−0.163	−0.165
	(0.105)	(0.107)	(0.108)	(0.108)	(0.108)	(0.108)	(0.109)
Net Income (A)	−0.082	−0.081	−0.082	−0.054	−0.076	−0.049	−0.046
	(0.144)	(0.144)	(0.145)	(0.145)	(0.145)	(0.145)	(0.145)
Net Income (B)	−0.247	−0.217	−0.217	−0.214	−0.162	−0.159	−0.162
	(0.199)	(0.199)	(0.199)	(0.199)	(0.199)	(0.199)	(0.200)
Tech Relativity		1.605***	1.114	2.755***	1.297***	2.462***	1.857**
		(0.412)	(0.679)	(0.586)	(0.451)	(0.618)	(0.801)
Tech Relativity *			0.809				1.103
Product-Market Overlap			(0.878)				(0.914)
Tech Relativity *				−1.532***		−1.547***	−1.620***
Tech Capability (A)				(0.572)		(0.579)	(0.580)
Tech Relativity *					2.586*	2.603*	2.577*
Tech Capability (B)					(1.340)	(1.358)	(1.361)
Year Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Log likelihood	−6994	−6987	−6987	−6984	−6985	−6982	−6981
Chi-square test	1908	1923	1923	1930	1927	1934	1935
Observations	37,884	37,884	37,884	37,884	37,884	37,884	37,884

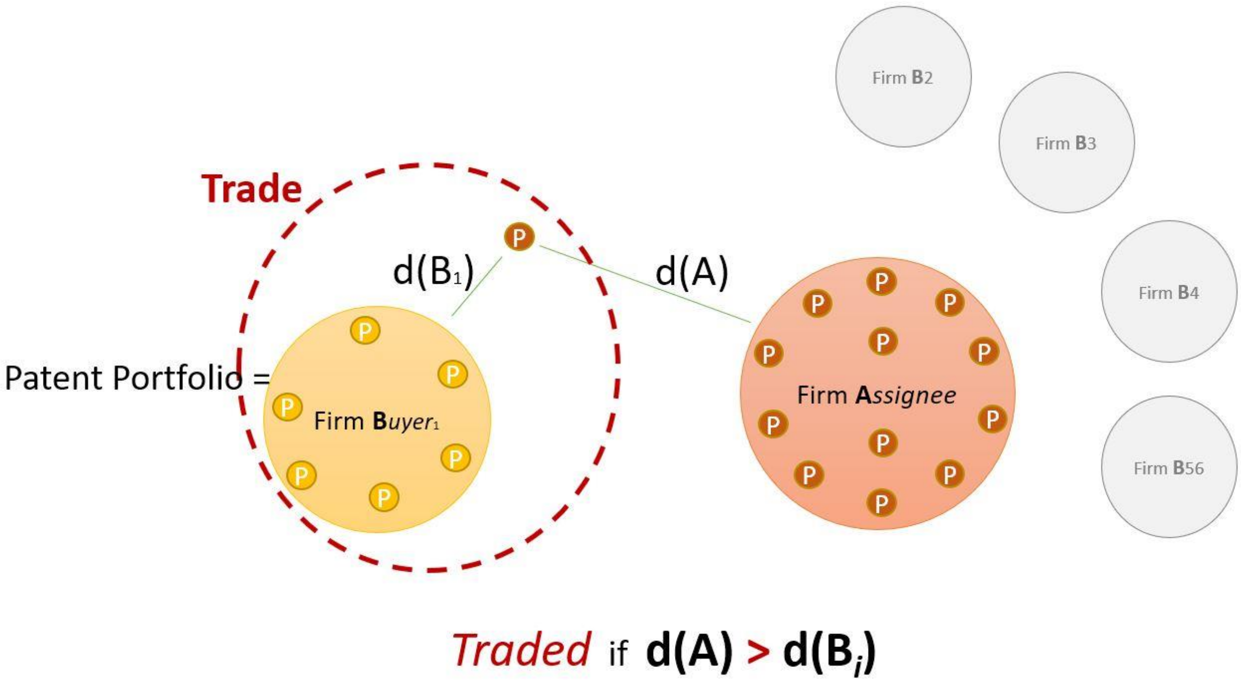
Notes. Year *t*: the last year of a patent in the survival model; Standard errors in parentheses; *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$; A: Assignee; B: Buyer.

Table 6. Subsample Analysis of the Assignee's Technological Capability

Model	(1)	(2)
Estimation Method	Rare Events Logistic Regression	Rare Events Logistic Regression
Dependent Variable	Patent Trade	Patent Trade
	Tech Capability (A) > Tech Capability (B)	Tech Capability (A) ≤ Tech Capability (B)
Product-Market Overlap	−1.409***	−0.774***
	(0.123)	(0.167)
Tech Capability (A)	−0.658***	0.690***
	(0.065)	(0.146)
Tech Capability (B)	−1.861***	0.399***
	(0.292)	(0.063)
Patent Market Liquidity	0.314	1.154***
	(0.292)	(0.403)
Patent Litigation	0.801***	0.559*
	(0.210)	(0.327)
Self-Citation	−0.889***	−0.058
	(0.180)	(0.194)
First Renewal	1.213***	1.421***
	(0.352)	(0.483)
Second Renewal	0.439**	0.817***
	(0.199)	(0.228)
Third Renewal	0.984***	0.311**
	(0.138)	(0.157)
Forward Citations	0.000	−0.005
	(0.001)	(0.003)
Backward Citations	0.004***	0.006***
	(0.001)	(0.001)
Geographical Distance	−1.460***	0.844***
	(0.100)	(0.178)
R&D Intensity (A)	−0.443	0.226***
	(0.498)	(0.088)
R&D Intensity (B)	−1.030*	−1.564***
	(0.542)	(0.456)
Net Income (A)	0.259	0.077
	(0.339)	(0.412)
Net Income (B)	5.315***	2.455***
	(0.313)	(0.273)
Tech Relativity	2.327***	4.458***
	(0.254)	(0.743)
Tech Relativity *	−0.985	−2.601***
Product-Market Overlap	(0.639)	(1.001)
Constant	−9.405***	−13.406***
	(0.512)	(0.834)
Year Fixed Effects	*Yes*	*Yes*
Observations	1,797,713	323,744

Notes. Robust standard errors in parentheses; *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$; A: Assignee; B: Buyer.

Figure 1. Technological Relativity



Appendix 1. Firm Fixed Effects

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Estimation Method	Logit	Logit	Logit	Logit	Logit	Logit	Logit
Dependent Variable	Trade	Trade	Trade	Trade	Trade	Trade	Trade
Product-Market Overlap	−1.400***	−1.418***	−1.432***	−1.418***	−1.417***	−1.417***	−1.439***
	(0.090)	(0.090)	(0.090)	(0.090)	(0.090)	(0.090)	(0.092)
Tech Capability (A)	−1.425***	−1.423***	−1.416***	−1.453***	−1.422***	−1.452***	−1.450***
	(0.182)	(0.182)	(0.182)	(0.183)	(0.182)	(0.183)	(0.183)
Tech Capability (B)	0.336***	0.365***	0.357***	0.369***	0.362***	0.367***	0.374***
	(0.045)	(0.046)	(0.046)	(0.046)	(0.051)	(0.051)	(0.051)
Patent Market Liquidity	0.945**	1.049***	1.024***	1.103***	1.048***	1.102***	1.077***
	(0.387)	(0.386)	(0.387)	(0.386)	(0.387)	(0.386)	(0.387)
Patent Litigation	0.580***	0.585***	0.588***	0.590***	0.584***	0.590***	0.594***
	(0.177)	(0.177)	(0.177)	(0.177)	(0.177)	(0.177)	(0.177)
Self-Citation	−0.491***	−0.464***	−0.460***	−0.463***	−0.465***	−0.463***	−0.458***
	(0.136)	(0.137)	(0.137)	(0.137)	(0.137)	(0.137)	(0.137)
First Renewal	1.512***	1.508***	1.503***	1.512***	1.508***	1.512***	1.506***
	(0.285)	(0.284)	(0.284)	(0.284)	(0.284)	(0.284)	(0.285)
Second Renewal	0.568***	0.565***	0.566***	0.566***	0.565***	0.566***	0.566***
	(0.150)	(0.150)	(0.150)	(0.150)	(0.150)	(0.150)	(0.150)
Third Renewal	0.766***	0.753***	0.753***	0.756***	0.754***	0.756***	0.754***
	(0.103)	(0.103)	(0.103)	(0.103)	(0.103)	(0.103)	(0.103)
Forward Citations	−0.002	−0.002	−0.002	−0.002	−0.002	−0.002	−0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Backward Citations	0.002*	0.002**	0.002**	0.002*	0.002**	0.002*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R&D Intensity (A)	0.685***	0.687***	0.693***	0.685***	0.687***	0.685***	0.691***
	(0.226)	(0.229)	(0.228)	(0.230)	(0.229)	(0.230)	(0.229)
Net Income (A)	0.878***	0.902***	0.896***	0.857***	0.901***	0.857***	0.853***
	(0.304)	(0.304)	(0.303)	(0.304)	(0.304)	(0.304)	(0.303)
Net Income (B)	2.899***	2.862***	2.863***	2.850***	2.865***	2.851***	2.841***
	(0.205)	(0.204)	(0.204)	(0.204)	(0.205)	(0.205)	(0.204)
Geographical Distance	−0.786***	−0.798***	−0.798***	−0.793***	−0.799***	−0.793***	−0.790***
	(0.094)	(0.094)	(0.094)	(0.094)	(0.094)	(0.095)	(0.095)
Tech Relativity		1.417***	1.908***	2.308***	1.443***	2.318***	2.727***
		(0.366)	(0.436)	(0.562)	(0.405)	(0.581)	(0.612)
Tech Relativity *			−1.645**				−1.800**
Product-Market Overlap			(0.839)				(0.903)
Tech Relativity *				−1.111**		−1.109**	−1.106**
Tech Capability (A)				(0.543)		(0.544)	(0.545)
Tech Relativity *					−0.047	−0.021	0.201
Tech Capability (B)					(0.313)	(0.315)	(0.339)
Constant	−23.713	−23.701	−23.756	−23.717	−23.709	−23.723	−23.770
	(413.542)	(417.486)	(455.249)	(416.506)	(418.755)	(419.834)	(452.495)
Firm Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations[8]	2,024,860	2,024,860	2,024,860	2,024,860	2,024,860	2,024,860	2,024,860

Notes. Standard errors in parentheses; *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$; A: Assignee; B: Buyer.

[8] The total number of observations becomes 2,024,860 after 96,597 observations that perfectly predict failure (i.e., no variance in the dependent variable) are excluded.

Appendix 2. Sample Selection

Selection Criteria	# of Public Firms	# of Patents
Patents issued between 1987 and 2006	6,176	2,143,267
Initial assignees in Biotechnological (SIC: 2836) Pharmaceutical (SIC: 2834) sectors	545	50,344
Sales revenue exceeds $1 billion	57	40,110
Observations	2,121,457	
Possible assignee-buyer dyads	2,246,160	
Missing values	124,703	