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From Potential to Real Threat? The Impacts of Technology Attributes on Licensing Competition—Evidence from China during 2002–2013

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Abstract: Prior studies have extensively discussed firms' propensity of licensing under different levels of competition. This study clarifies the differences between potential technology competition (PTC) and actual licensing competition (ALC). We investigate the relationship between these two types of competition in the context of Chinese patent licensing landscape, using patent licensing data during 2002–2013. We find that the positive effect of PTC on ALC is contingent upon the nature of licensed patent, such as generality, complexity, and newness. Our findings help scholars and managers interested in licensing to understand and monitor the likelihood of licensing competition. Policy implications are presented at the end of this study.

Keywords: potential technology competition; actual licensing competition; technology attributes

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1. Introduction

Technology licensing has become a strategically important means for firms to benefit from their research and development (R&D) and a popular form of transactions on the markets for technology [1–3]. Markets for technologies have grown dramatically over recent decades, receiving increasing attention from both scholars and practitioners [4–6]. Research on technology markets has given valuable insights on issues such as the factors that drive or hinder small and large firms' participation in technology licensing [3,7,8], the way in which licensing transactions are organized [5,9], and the relevant supporting institutions [10].

However, the extant literature has left a conceptual distinction unclear regarding what makes potential technology competition (PTC) and actual licensing competition (ALC). For instance, Fosfuri [3] simply touched upon this issue in the empirical section, assuming a high correspondence between potential technology competition and actual licensing competition without addressing why and how they are related. Kani and Motohasi [10] measured the degree of technology competition by the crowdedness of a patent class to which a firm's patent belongs without distinguishing the difference between competitions on technology market and product market.

What are PTC and ALC and why is distinguishing them important? Based on the literature, we conceptually define PTC as the consideration of any alternative technologies possessed and protected by other organizations, which has a potential to compete with the focal organization on the markets for licensing and the product market, whereas ALC is defined as a matter of direct competition on the market for technology only. Figure 1 below illustrates the difference between PTC and ALC. When a firm invented a technology X in year $t-1$, technically speaking any other technology in the same technological category has a potential to be licensed out in the future, competing with technology X on the market for technology; they are PTC. However, when the firm decides to license technology X in year t, it will find out that only a small number of the PTC became the actually competing technologies on the licensing market; these are the ALC.

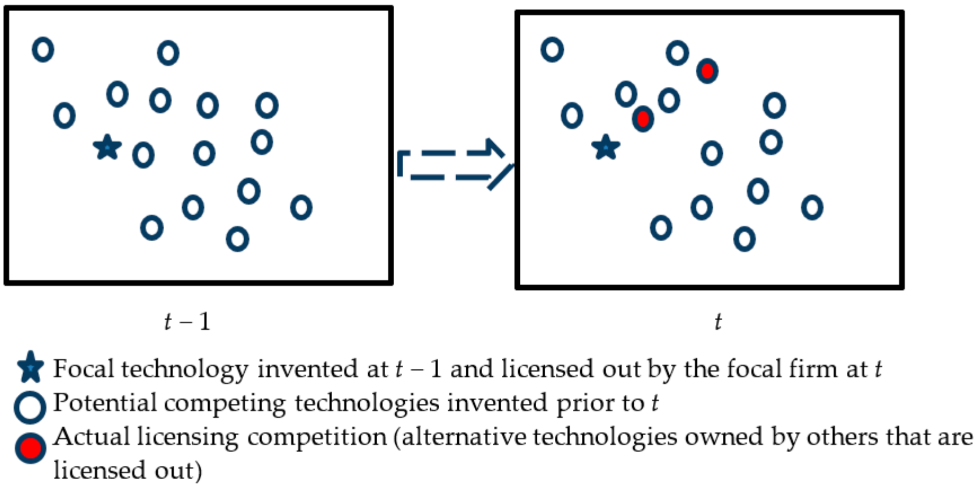

Figure 1. Illustration for the distinction between potential technology competition and actual licensing competition in a particular technology field.

We argue that it is a non-trivial issue to understand what makes potential technology competition become actual licensing competition from both managerial and theoretical perspectives. This is because, first, from a managerial perspective, as organizations invest R&D in different technological fields, managers need to understand why some technologies face ALC in the market for technology while others are licensed out without competing licensing. Second, a licensor firm must be able to posit its new technological inventions vis-a-vis other potential competing technologies to predict the likelihood of actually licensing a competitor. Third, with the knowledge on why PTC becomes ALC, the firm engaged in a technological invention may predict the level of future licensing competition for a particular invention and correspondingly develop differentiate strategies on the product market.

Second, from a theory perspective, knowing what makes PTC to be ALC has at least two obvious implications: First, such knowledge will make it possible to have a more accurate inquiry on the decrease of revenue effect of licensing, compared to the extant literature that primarily relies on estimations of PTC [10,11]. Second, as the profit dissipation effect is a result of competition on the product market, knowing the ALC will make it technically possible to specify product differentiation based on specific technologies [3]. As a result of these two implications, organizations with technological inventions will be able to have a critical overview about technology competitors, among whom some use the licensed technology to compete on the product market (licensees), some compete on the technology market by licensing out alternative technologies (other licensors), and others might apply alternative technologies licensed from other technology suppliers to a new product in different product markets (licensees that license from other licensors). Such an overview allows licensing to be strategically manageable with enhanced effectiveness.

Prior works in the literature address various internal and external conditions that influence a firm's licensing out decision [2,6,8,10,11]. However, in a case when a focal organization has a technology available to be licensed out, it needs better knowledge on how likely this particular technology will face direct licensing competition from other firms that possess alternative technologies that are offered on markets for technology through licensing. In this sense, our study complements the extant literature by asking a particular research question: How can a licensor predict the likelihood of a particular technology's PTC turning into ALC from a technology holder's perspective by considering the attributes of focal technology? Building on the literature on the market for technology, we propose that this likelihood is a function of demand (the number of potential licensees) for and supply of alternative technologies (technology crowdedness). In addition, the impact of the supply side is contingent upon the features of the focal technology itself.

This study showcases a method to identify the supply and demand of competing technologies using patent information. The factors we include in our conceptual model are feasible for R&D managers alike to monitor and strategically manage their technology-licensing portfolio. This study also offers unique data on actual licensing competition across different industries in China with a long period of real licensing recorded data, which compensates the limitations in many prior studies that were based on either cross-sectional survey data [2,6,11–13] or licensing data from a single industry [3].

The remainder of this article is organized as follows. First, we briefly review the literature on the market for technology and pinpoint the distinction between PTC and ALC. We also draw insights on the literature on the natures of technologies. Several hypotheses are developed based on these theoretical foundations. Next, the data and methods used in the empirical analysis are introduced, and then the results are presented. Finally, we discuss our findings, address some limitations, and offer a concluding remark.

2. Theories and Hypotheses

2.1. Brief Theory Review

Research on the market for technology has given valuable insights on licensing as a unique type of intellectual property transaction and technology transfer, for which the effective of patent protection, market imperfection, and transaction cost of licensing all together influence a firm's propensity to license out technologies [2,6,10,11,13]. Scholars also find that several firms' internal and relational conditions, such as complementary assets in commercialization, product differentiation, relative absorptive capacity, and centralization of decision-making, determine their licensing decisions as well [3,5,7,8].

It is important to understand how the markets for technology, especially licensing, function, because from a technology holder's (potential licensor) perspective, licensing technology may generate rent in forms of licensing payments to recoup the firm's R&D investment, thus in turn improving the firm's bottom line [3]. Surely, licensing can also be used strategically to enhance demand, block competition after a patent expires, or deter market entry [1], but the revenue effect of direct rent generation is prominent. However, licensing will also create a rent/profit dissipation effect where a licensor may experience the erosion of profit in his/her own business due to additional competitors (licensees) in the product market [1,3]. Extending the traditional transaction cost economics view [14,15], several prior studies have recognized that the interplay between the revenue effect and profit dissipation effect of licensing is subject to two levels of competition [1,3]: first, firms possessing similar technologies (or technologies with similar application possibilities) will compete in the markets for technology, a battlefield in which firms compete with each other on the chance of (and the revenue effect derived from) licensing out their technologies, and second, a licensor firm competes on the product-market with its licensees with regard to differentiated products, as licensees obtain the rights to apply the licensed technologies to new product development, creating a potential profit dissipation effect for the licensor [6,12,13]. The distinction between these two levels of competition is essential to understand firms' decision-making process for licensing or not [1].

The focus of this study is on the market for technology only. Theoretically, any technology that has not yet been licensed out by a technology holder has a future probability to be licensed out [10,12]. Therefore, from a technology holder's perspective, any technology in the same technical field with similar application possibility represents a potentially competing technology on the market for technology. However, the reality is that some of these potential competing technologies are licensed out, but many others are not. We have limited knowledge on what makes the potential to be actual competition, as the prior studies either overlooked the importance of this crucial relationship [1,3] or failed to address this distinction due to a lack of empirical data [2,6,10–13].

Similar to Kani and Motohashi [12], we define PTC as the extent to which a firm's (licensable) technology belongs in the same technology category as the others. From a technology point of view, potential technology competition reflects how crowded a particular technical field is among inventors at a given point of time. Even if inventors of these alternative technologies had no intention to license out in the technology market at the time of inventing, there is always a possibility that they are licensed out at another time that coincides with the focal organization's decision of licensing (Be aware that these potential competing technologies, even though not becoming actual competition in the licensing market, are still possible to compete with the focal organization in the product market.). In contrast, inspired by Fosfuri [3], we define ALC as the actual number of alternative technologies in the same technical field that have been licensed out by other licensors at the same time when the focal firm decides to license the technology. Note that both definitions of competition are technology-based by counting the potential and actual number of competing technologies, instead of being firm-based by counting the number of competing licensors.

The research on industry R&D's spillover effects offers an additional perspective to help understand the relevance and importance of PTC and ALC. Prior research in this topic area has found evidence that spillovers from industrial R&D are influenced by geographic and technological proximity—companies located close to each other geographically and technologically are more likely to learn from each other since knowledge spillover is prominent [16,17]. In such a context, if we do not distinguish PTC from ALC, it will be too simple to draw a common sense conclusion that firms that are proximate to each other will face stronger technology licensing competition because their technologies will be similar as the results of R&D spillover. However, we argue that it might be true to the "potential", but not necessary the case for the "actual" licensing competition, due to other factors that we are not aware of. On the other hand, only "actual" licensing competition (ALC) is likely to turn out to be the catalyst for industry R&D spillover, but not PTC. Therefore, our study, in a sense, also add more nuanced insights to the literature on industry R&D spillover.

2.2. Development of Hypotheses

The first factor that we consider is the demand of technologies in a particular technical field [1]. When an industry is developed into a stage in which certain types of technologies are highly needed, the demand for these technologies will be high. Inventors (individuals and firms) may have the incentive to invest in developing the technologies that are high in demand. Many alternative technologies in the same technology field may compete in finding its industrial applications and other means of commercialization. Thus, a great demand of a certain type of technologies encourages many technology holders to seek chances of licensing to earn economic rent from licensing payment. Moreover, licensing deals involves a great deals of transaction costs [14], including the cost of searching appropriate licensees [3,18]. When demand for licensing is high in the same technology field, there is a sufficiently large pool of technology seekers as potential licensees, making the licensors relatively easier to find licensees, compared to a situation of having low levels of demand. If the perceived searching cost is low from a technology holder's perspective, then the chance is high to invest in developing the technology, creating a crowded technology field. Based on these arguments, we hypothesize:

Hypothesis 1: *Ceteris paribus, the higher demand of licensing in a technology field, the higher level of actual licensing competition.*

Besides the impact on the demand side, competitions on the supply side of technologies have implications for an organization's licensing propensity as well. Technological inventions are made in various technology fields, some of which are very crowded, and others are not. Why are some technology fields so popular and crowded, where many relevant technologies are invented? From a technology life cycle perspective [19], at different stages of technology development in an industry, the possibility of creating completely new technology trajectories that may lead to a new technology field and the possibility of creating alternative but improved technologies within the same technology fields are different. At the early stage of industry development, all inventors are exploring different methods and technical solutions, while potential commercialization options are not totally clear to the product market. Therefore, the chance of creating new technology fields is not only possible but also making sense. This also means that it is relatively difficult to define what the "same" technology field is at the early stage. However, when an industry has developed towards a relatively mature and stable stage, the backbone technologies and complementary knowledge are widely shared within the industry [20]. Inventors are equipped to make improvement-based inventions rather than breakthrough inventions, creating many crowded technology fields where alternative technologies may deliver similar functionalities [21]. A crowded technology field puts pressure on every inventing firm in the field to consider whether to license out or not [3,12].

Kani and Motohashi [10] have shown, among others, the degree of potential technology competition has a positive effect on licensing propensity in Japan, as the competition creates increased revenue effect (motivating firms to license out), which is stronger than the profit dissipation effect (demotivating firms to license out). If this is the case in general, that means when a technology field is crowed, it is likely that more technology holders will decide to license their alternative technologies in the technology market, compared to a less crowded technology field. This argument makes sense because, all else equal, the greater the supply of different but similar technological solutions available, the more likely that we see some are licensed out on the technology market. If this prediction is true, then the licensor firm of the focal technology will be able to estimate the chance of facing ALC, as long as it has information about the technology crowdedness of the technology field to which its invention belongs. Thus, we are interested in testing the second hypothesis:

Hypothesis 2: *Ceteris paribus, the more crowded technology field to which a particular licensed technology belongs (the higher potential technology competition), the higher level of actual licensing competition.*

The crowdedness can be understood as an exogenous factor associated with a particular technology, but it is also an endogenous feature that adheres to the technology itself, because the technology is invented in a context where the popularity of such a crowd has been shaped by economic, social, and technological forces at a given time, making the creation of such an invention needed. Therefore, for a given technology that is licensed on the technology market, we argue that the concept of PTC represents on the one hand the supply side of competing technologies, and on the other hand, an adhering feature of a particular technology, which can be observed at a technology level at a given point of time and contingent upon other attributes of the focal technology.

In the literature on technology licensing, several key technical attributes, such as generality, complexity, codification, articulation, and newness, have been identified and investigated in relation to their influences on knowledge transfer [22,23]. We argue that technical attributes of the focal technology need to be considered as contingents that moderate the impact of PTC on ALC for two reasons. First, these attributes have implications on a licensors' perception of revenue effect and profit dissipation effect [3], and second, these attributes present different opportunities and resource requirements for licensees, entailing implications on licensees' perception of the value and transaction costs of the target technology [8].

Following the work by Wang et al. [24], we focus on three key attributes of the focal technology that is subject to licensing: First, generality refers to the extent to which the knowledge derived from an experiment can be applied to other distant experiments [25]. The concept of "general purpose technologies" (GPTs), which are characterized by their potential pervasive use in a broad array of industries and their technological dynamism [26,27], is the best case to illustrate the importance of considering technology generality. Most GPTs are featured as the "enabling technologies" that may open up new opportunities rather than providing complete and final solutions [28]. Second, complexity refers to a merging of several diverse disciplines or a great number of interdependencies, or a combination of both [29,30]. Third, newness refers to the age of a technology. The literature on technological innovation has a long tradition to discuss the value of technology newness for firms' innovation performance [20,31,32].

First, we argue that the level of generality of the focal technology of a licensor firm has implications for the relationship between PTC and ALC. A high level of generality implies a broad scope of application and diffusion. Thus, it can increase the chance of applying the technology to different domains of product development, potentially setting technological standard and creating technology convergence across industries [33]. Researchers have witnessed many examples, such as drug development, chemical engineering, and complex system design for general technologies [25]. As the result of holding a general technology, the inventor will perceive the lucrative revenue effect outweighing the profit dissipation effect of licensing. As general technologies are not specific to a particular technological application and relatively easy to be applied to another context, the perceived transaction cost (especially learning cost) from a licensee's perspective will be low as well. Theoretically, there is a possibility that an increasing number of alternative technologies is licensed out in the same technology field only if they are highly specific and complementary to the general technology. However, in these cases, the scope of potential licensees will be limited and high learning cost for licensees are expected, making it less interesting for these alternative technology holders to consider engaging in licensing deals. Therefore, when a general technology is licensed out, other technology holders who have alternative technologies in the same technology field will be less incentivized to compete in the technology market by licensing out, mainly due to an opposite effect on their perceived revenue effect and an estimation of high absorption cost by the potential licensees towards the alternative technologies. This results in a case where much of the potential technology competition will not be transformed into ALC, even though the technology field is crowded, leading to our next hypothesis.

Hypothesis 3: *The more general a licensed technology, the weaker the positive relationship between potential technology competition and actual licensing competition.*

Next, complex technologies involve different scientific disciplines with a high level of interdependencies. This makes it difficult for licensee firms to learn the technology and integrate into their own knowledge base [24]. Indeed, when a focal technology is highly complex, it becomes less suitable for licensing, as the learning cost on the licensee side is perceived high [8]. However, if a focal technology can be licensed out, then the implication of its complexity has a different implication for the relationship between PTC and ALC. That is, a complex technology will be licensed out, only when it has been proved to be able to create value for a licensee, who has a sufficiently high level of absorptive capacity and adaptive learning capabilities [34]. A complex technology contains a rich stream of knowledge elements that might enable firms to make recombination with their existing technologies and yield new knowledge creation [35]. The value for licensee in this case could be creating functional advantage, providing complementary assets, realizing lead time in product development, or making the end product hard to copy as well.

When a focal technology with high complexity is to be licensed out, sometimes the inventors of alternative technologies in the same technology field are aware of the focal technology is going to be licensed out; thus, they will have little incentives to license out their alternative technologies. One may in doubt about how realistic these cases will be because many technology license deals are negotiated under conditions of confidentiality, so that other alternative technology holders might not be aware that the focal technology has reached a licensing deal. This brings about the second line of argument: often before a focal technology reaches a licensing deal, the technology holder will spend time and effort in searching for potential licensees, resulting in some transaction cost of licensing [14,15]. The searching process involves explicit communication and negotiation with potential licensees who are competent to make a good use of the focal technologies. Such a business communication process results in many candidate licensees being aware of such a complex technology with high potential advantages, making other alternatives less interesting and less attractive to be licensed in. Consequently, chances that alternative technologies in the same technology field to be licensed out become thinner. Therefore, even in a highly crowded technology field, when a focal licensed technology has high complexity, alternative technology holders might be deterred to license out their competing technologies, making the level of ALC lower than normally expected. Accordingly, we offer the following hypothesis.

Hypothesis 4: *The more complex a licensed technology, the weaker the positive relationship between potential technology competition and actual licensing competition.*

Third, firms tend to temporally search in a local space for new technologies, which represents the state-of-the-art and new solutions to their technical problems [20,36]. The newest technologies make older technologies obsolete and less interesting to be licensed out for manufacturing or innovation. Therefore, new technologies have greater chance to be licensed out compared to old technologies. However, if a focal technology is managed to be licensed out, then the implication of its newness has a quite different implication for the relationship between PTC and ALC.

When a new technology is to be licensed out, other technologies in a crowded field have comparatively longer time to seek licensees, prove their value, and get complementary knowledge ready, so that the chance that some of them turn to be direct licensing competitors is higher than otherwise. In addition, when a new technology is to be licensed out, the positive revenue effect of licensing is evident, but the potential profit dissipation effect might not appear as a threat yet. Thus, the licensor of the focal technology will probably use a focused approach to secure a small number of licensees, instead of investing in a large number of resources to search for many licensees. This leaves room for other technologies in a crowded field to find licensees.

On the contrary, when a relatively old technology is managed to be licensed out, there are basically two possibilities: (1) the value and usefulness for manufacturing or innovation has been proven by the inventor firm itself before and the licensee is a slow mover, or (2) its value had not been identified before and the licensee found a very special niche to apply the technology at this time. In these cases, no matter if it is in a crowded or sparse technology field, the increasing level of technology crowdedness might not significantly increase the actual number of technologies to be licensed out at the same time when the focal technology is licensed out, because, first, if there were competing technologies suitable to be licensed out, they should have taken place and the chance that these competing technologies will appear as candidates for licensing again will be low; second, a recent niche application may be very specific, so that chances that competing alternative technologies are ready to be licensed out to the same group of potential licensees may also be low. Therefore, combining the reasoning for both new and old technologies, we expect the newness of the focal licensed technology to have a positive moderating effect on the relationship between PTC and ALC. Accordingly, we offer the following hypothesis.

Hypothesis 5: *The newer a licensed technology, the stronger the positive relationship between potential technology competition and actual licensing competition.*

3. Data and Methods

3.1. Data

In this study, we limit our attention to patent licensing for several reasons. First, patent licensing has been one of the most important ways in which firms transfer technical knowledge [34,37]. Second, patent information is consistent and reliable, making it suitable for empirical study based on quantitative methods. Last but not least, the unique database we use in this study contains the entire population of patent licensing deals in China for almost three decades, making it a perfect empirical setting to test our hypotheses.

The dataset we use in this paper was obtained from the State Intellectual Property Office of China (SIPO). The SIPO also provides the public with a patent retrieval system to search for all Chinese patent applications and granted patents since 1986 (http://search.cnipr.com/, accessed on 24 June 2021). Next to the patent application data from the SIPO, we also use the patent licensing data from the SIPO. As the result of multiple rounds of legal development, since 2002 all patent licensing contracts must be registered at the SIPO within three months after the contract is signed between licensor and licensee(s). Each technology transfer record registered at the SIPO contains the following information: licensor name, licensing patent number, patent name, licensee name, contracting number and date, and license type. License agreements can be signed between individuals and firms, where the licensors of a licensing agreement can be either Chinese or foreign individuals/firms, but all licensees are Chinese individuals/firms. The complete records of patent licensing were available to the public on the SIPO website in Chinese (http://www.sipo.gov.cn/, accessed on 24 June 2021). Several prior studies have extracted a small sample of this dataset to study issues related to technology licensing and innovation performance of Chinese firms [38,39]. Up to 2013, which is the final year when the SIPO made the patent licensing data available to the public, there were 57,867 license agreements, covering 96,906 transferred patents, among which 27,741 are invention patents, 52,848 are utility model patents, and 16,317 are design patents. To our knowledge, this study is one of the first attempts that use the entire Chinese patent licensing dataset as the sample frame.

As the term of protection for invention is the longest and their technological novelty are strictly assessed before granting, we delimit our sample to invention patents only in this study. Furthermore, as individual's invention patents are rarely licensed in the technology markets in China, we focus only on the invention patents that are granted to organizations (including firms, universities, and research institutes). This focus yields a sample of 19,346 invention patents that were subject to licensing contracts during the period of observation. The sample was further reduced to 17,879 patents because we found that there were 1467 patents with missing principal claims, making them of little use for our analysis. This final sample selection of 17,879 licensed invention patents in China involves 8100 IPC patent classes, 5022 licensors, and 10,210 licensees, covered by 24,227 unique licensing deals (There were cases where a particular patent was licensed multiple times in different years.). The unit of analysis is each patent as the subject of a unique licensing deal. As the dataset is large, C++ programing and data mining techniques based on SQLServe2008 were extensively used to formulate and calculate the value of variables.

3.2. Variables

3.2.1. Dependent Variables

Actual licensing competition (ALC): Fosfuri [3] take the number of licensed plants by firm i, in product j, and geographical area k as firm's rate of licensing, the ratio of out-licensed patents to total num of patents owned is represented as licensing propensity for studying the IP strategy by Motohashi [12]. The competitors that have already licensed out their patents are our main focus. Therefore, ALC is operationalized in the following way. First, for each patent that was licensed in a particular year, we identify its main patent class, which is interpreted as a technology field. Next, we calculate the number of other patents that were licensed out under the same main patent class within the same year when the focal patent was licensed out. The mean value of this count variable is 2.501.

3.2.2. Independent Variables

Licensing demand: Fosfuri [3] uses the number of downstream manufacturers to represent the number of potential licensees, and number of patents cited is also used as a proxy variable of licensing demand frequently [40,41]. There is no citation data in the Chinese patent database, but the number of licensees in real licensing transactions can be mined out, which is more direct and representative. Licensing demand is operationalized by first identifying the main patent class of a focal licensed patent, and then calculating a total number of unique licensees involved in any licensing deals that took place within the five years prior to the year when the focal patent was licensed out. This measure is a proxy of the market demand for technologies in a particular technology field.

Potential technology competition (PTC): Gambardella [7] use the share of the patents held by the top four applicants in each 4-digit IPC patent class as technology competition, and Fosfuri [3] use the number of firms that have licensed out their given process technology for producing the related product as potential licensors. Following them, PTC includes any patents in the same technology field of the focal patent, and they all theoretically have a possibility to be licensed out in the technology market. We measure PTC by first identifying the main patent class of a focal licensed patent, and then calculating a total number of patent applications made by other organizations within the five years prior to the year when the focal patent was licensed out. As there were in some cases many patent applications in a particular technology field (patent class) within a specific period, we take the natural logarithm for the value of this variable.

Generality of technology: It has often been measured by calculating the claims appearing in the front page of each patent [42]. The number of claims is viewed as a direct measure of generality as the claims are attributions of a potential scope of applications of the technology [24]. This approach works perfectly fine with for instance the US patent data, which contain clearly numbered claims. However, the SIPO does not require applicants to detail the claims in a clear numbering format, making the counting of the number of claims difficult. Instead, the claims of Chinse patent contain a free format of text. Therefore, an alternative approach is needed. Malackowski and Barney [43] suggested that in the case of free format text in some patenting systems, counting the number of words in the claim is an alternative proxy for measuring generality of technology. The basic argument is that the fewer words a patent's claim uses, the more general a patent with a wider spectrum of potential applications. Following this approach, scholars specialized in Chinese patent data analysis recently modified this approach by counting the number of nouns in the claim of a patent, rending a more reliable measure and sensible test results [44]. Therefore, we follow this approach by first calculating the number of nouns in the text of principal patent claim and then taking the natural logarithm of the count for each focal licensed patent. Next, we identify the maximum value of the natural logarithm (Max(ln)) in the sample and then generality is measured by taking Max(ln) minus the value of the natural logarithm of each case. This transformation ensures an intuitive interpretation of the variable value that the higher this value, the higher generality of the patented technology.

Next, following a well-adopted approach in the literature, complexity is operationalized as the number of unique technical subclasses of a focal licensed patent [45,46].

Newness: Following Almeida et al. [47] and Li-Ying [48], newness is measured by first counting the number of years between the year when a patent was licensed out and the year of patent application. A small number indicates that a relatively new patent was licensed out. As the maximum number of years for patent protection in China is 20 years, we then transform the value of this variable by using 20 minus the number of years between patent application and licensing. The higher this value, the newer the licensed patent.

3.2.3. Control Variables

Although the unit of analysis is at the patent level, we argue some organization-level variables need to be included in the analysis because the features of the focal organization that licensed out a patent provides signals to other potential technology competitors about the strength and technology strategy of the focal organization. In this way, the likelihood of potential technology competitors turning into actual licensing competitors could also be influenced by this signaling information. Note that organization-level information for all the focal licensors is not available from the SIPO, and it is hard to access organization-level information from additional data in a consistent fashion for the entire period of observation. For that, we had to make a compromise to utilize patent information to indirectly measure organization-level variables. We control for licensor type, organization age, organization's R&D capacity, and technology width.

Licensor type: It is a binary variable that indicates if the licensor is firm or not. A value of 1 indicating firms, and 0 indicating otherwise. Organizations that are not firms are typically universities and research institutions. It is important to control for this variable because firms usually have complementary assets in marketing to compete in product markets, but universities and research institutions typically do not. Therefore, other technology holders will perceive them as different types of competitors in the technology market. Organization age: Firm's age was used to study the licensing strategy by Motohashi [12]; they found that younger firms use in-house patents less and out-license a great proportion. Information on "organization age" could not be obtained from the licensing data but can be measured in a compromised way. We first find out a focal licensor's first patent application at the SIPO and identify its date of application. Then, organization age is measured by counting the year difference between the year of licensing that we observe and the year of first patent application. The disadvantage of this measure is that for some organizations the actual age could be much older if they for a long time never applied for patents.

Next, organizations with strong R&D capacity might have a dominant position in the licensing market, making other potential competitors less interested in licensing out. Therefore, we also control for the R&D capacity of the focal licensors. Aldieri, Sena, and Vinci took the percentage of citation of patents issued by the same assignee to represent the R&D capacity and found that absorptive capacity changes with the type of knowledge they may get exposed to [17]. R&D expenditures deflated with the occupational cost index for technical professionals was used as R&D capacity to measure the spillovers from industrial R&D by Orlando [16]. Instead of having a direct measure of R&D expenditure of each focal licensor, we first count the total number of its patent applications since 1985 and then count the number of unique inventors of all the patent applications for the organization. As shown in prior studies, this approach of measurement indirectly reflects the R&D strength of an organization [24]. As we do not have direct information on organizations, this measure can also be viewed as a proxy to organization size and absorptive capacity. We take natural logarithm of this count value.

A strong licensor can be actively inventing in a large scope of technology fields, signaling a strong capacity to conduct cross-disciplinary research based on sufficient resources. In contrast, when a licensor has a tradition of specializing in a specific technical field, other technology holders and potential licensees will perceive it being different from those that have a capacity to invent in many different technical fields. Therefore, we need to control for the technology width of a focal firms' patent portfolio [49,50]. We operationalize this variable by calculating the total number of main patent classes that all the patent applications of a focal organization have covered since 1985. We take natural logarithm of this count value.

The Chinese government has gradually developed Chinese IP policy, particularly related to patenting during the past 20 years. Therefore, it is necessary to control for any effects associated with time. We use dummy variables for licensing years that are added, and the year of 2002 is set as comparative reference point.

Industry is controlled because appropriability regimes are different cross-industries, which might rely on technology marketplace to different degrees [9]. Therefore, we use five dummy variables to control for six major industries of the focal licensors in our sample according to the WIPO classification [51]. These industry domains are chemistry, electrical engineering, instruments, mechanical engineering, process engineering, and consumption (with consumption used as the reference group).

3.3. Estimation Model

The foundational building block for count data is the Poisson regression model [52,53] when the dependent variable is a count variable. A restriction on the distribution of observed counts in a Poisson model is that the variance of the random variable must be equal to the mean. In studies using patent statistics, this condition is seldom met because of over-dispersion in the data, i.e., the variance largely exceeds the mean, which is the case in our data. As an alternative, negative binomial models are used for cross-sectional count data by considering repeated observations as independent observations [3,54]. Therefore, we employ a negative binomial model to test the hypotheses. As there are many zeros in the dependent variable, an alternative modeling option is the zero-inflated negative binomial model. We tested the zero-inflated negative binomial model and found that the z-score value for the Vuong test is smaller than -1.96 in all the models. This leads us to discard the zero-inflated negative binomial models. Robust Standard Error was used to shield from the heteroskedasticity problem according to the advice from the books of Introduction to Economerics, 3rd edition [55] and Advanced econometrics and Stata application, 2nd edition [56]. Specifically, the model mainly used in this study is represented as

$$
\begin{aligned}
E(Y_i) = \exp\{ & alpha + \beta_1 * R\&Dcapacity + \beta_2 * Licensortype + \beta_3 * Organizationage + \beta_4 * Techwidth \\
& + \beta_5 * Chemistry + \beta_6 * Electricalengineering + \beta_7 * Instruments + \beta_8 \\
& * Mechanicalengineering + \beta_9 * Processengineering + \beta_{10} * Licensingdemand + \beta_{11} \\
& * PTC + \beta_{12} * Generality + \beta_{13} * Complexity + \beta_{14} * Newness + \beta_{15} * PTC * \ generality \\
& + \beta_{16} * PTC * complexity + \beta_{17} * PTC * complexity + \beta_{18} * PTC * Newness + \beta_{19} \\
& * Licyear2003 + \ldots + \beta_{29} * Licyear2013 + epsilon\}
\end{aligned}
$$

where Y_i is the dependent variable and other independent variables have been defined previously, *alpha* is the constant term, epsilon is an error term and β_i are the regression coefficients to be estimated.

4. Results

Table 1 summarizes the descriptive statistics and correlations of all variables in the empirical analyses. The independent variables are neither highly correlated among themselves nor with the control variables, indicating little concern about severe multicollinearity. Table 2 presents the statistical analysis results based on negative binomial regression. All models are reported with the Wald chi-square test and loglikelihood. Model 1 is the base model, which includes only the control variables. In models 2 to 7, relevant independent variables and interaction terms are added step by step. Model 8 is the full model where all variables are included.

Table 1. Descriptive statistics and correlations.

Variables	Mean	Std. Dev.	ALC	Patenting Capacity	Firm Age	Tech Width	Licensing Demands	Licensor Type	PTC	Generality	Complexity	Newness
Actual licensing competition (ALC)	2.501	8.303	1									
R&D capacity	5.596	2.503	0.0041	1								
Organization age	7.432	7.363	0.0081	0.617	1							
Tech width	3.832	2.551	−0.0294	0.735	0.6	1						
Licensing demands	13.22	25.16	0.37	0.0965	−0.143	−0.228	1					
Licensor type	0.681	0.466	0.0515	−0.382	−0.558	−0.527	0.196	1				
Potential tech competition (PTC)	4.703	1.767	0.322	0.059	0.0238	0.044	0.277	0.0244	1			
generality	4.91	0.698	0.0398	−0.0537	−0.0533	−0.0682	−0.0044	0.104	−0.0314	1		
complexity	2.51	1.729	0.0294	−0.0212	0.022	−0.0206	0.0126	−0.0351	0.0565	0.0338	1	
newness	13.51	4.489	−0.105	−0.14	0.165	0.367	−0.55	−0.328	0.0212	−0.0065	0.0567	1

Industry dummies are included in regression models, but not shown in the descriptive statistics table. n = 24,227.

Table 2. Negative binomial regression results.

Variables	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
R&D capacity	0.157 ***	0.249 ***	0.192 ***	0.142 ***	0.192 ***	0.193 ***	0.146 ***	0.146 ***
	(4.51)	(8.94)	(8.11)	(5.80)	(8.12)	(8.22)	(5.87)	(5.93)
Licensor type	0.0432	−0.0295	0.365 ***	0.297 ***	0.360 ***	0.363 ***	0.324 ***	0.317 ***
	(0.80)	(−0.74)	(10.13)	(8.05)	(9.85)	(10.08)	(8.98)	(8.70)
Organization age	0.000171	0.0297 ***	0.0249 ***	0.0280 ***	0.0249 ***	0.0245 ***	0.0283 ***	0.0279 ***
	(0.05)	(11.40)	(11.07)	(12.36)	(11.06)	(10.88)	(12.41)	(12.26)
Tech width	−0.226 ***	−0.366 ***	−0.240 ***	−0.205 ***	−0.240 ***	−0.240 ***	−0.205 ***	−0.204 ***
	(−6.00)	(−12.29)	(−9.31)	(−7.79)	(−9.33)	(−9.37)	(−7.69)	(−7.73)
Chemistry	0.993 ***	0.690 ***	0.613 ***	0.696 ***	0.602 ***	0.593 ***	0.694 ***	0.660 ***
	(15.14)	(10.81)	(9.89)	(10.49)	(9.54)	(9.46)	(10.88)	(10.06)
Electrical engineering	0.600 ***	0.686 ***	0.0460	0.0918	0.0419	0.0321	0.0352	0.0122
	(10.49)	(10.51)	(0.71)	(1.38)	(0.65)	(0.50)	(0.54)	(0.19)
Instruments	1.038 ***	1.599 ***	1.074 ***	1.163 ***	1.070 ***	1.062 ***	1.145 ***	1.128 ***
	(14.97)	(20.46)	(14.38)	(15.27)	(14.34)	(14.26)	(15.30)	(15.10)
Mechanical engineering	−0.634 ***	−0.0644	0.182 **	0.307 ***	0.176 **	0.180 **	0.298 ***	0.294 ***
	(−9.12)	(−0.85)	(2.50)	(4.04)	(2.41)	(2.47)	(3.99)	(3.91)
Process engineering	−0.0840	0.322 ***	0.432 ***	0.533 ***	0.426 ***	0.424 ***	0.524 ***	0.510 ***
	(−1.27)	(4.60)	(6.47)	(7.62)	(6.35)	(6.32)	(7.63)	(7.38)
Licensing demand		0.0287 ***	0.0209 ***	0.0194 ***	0.0208 ***	0.0208 ***	0.0192 ***	0.0190 ***
		(51.63)	(39.39)	(30.02)	(39.21)	(39.78)	(29.43)	(29.58)
Potential tech competition (PTC)			0.558 ***	0.572 ***	0.533 ***	0.592 ***	0.398 ***	0.421 ***
			(63.00)	(60.91)	(10.09)	(42.27)	(14.77)	(6.72)
Generality				0.0160	−0.00784			0.00156
				(0.94)	(−0.12)			(0.02)
Complexity				0.0227 ***		0.0884 ***		0.118 ***
				(3.29)		(3.22)		(4.12)
Newness				−0.0340 ***			−0.105 ***	−0.109 ***
				(−9.03)			(−9.62)	(−10.01)
PTC*generality					0.00498			0.00366
					(0.47)			(0.32)
PTC*complexity						−0.0130 ***		−0.0181 ***
						(−2.90)		(−3.85)
PTC*newness							0.0135 ***	0.0141 ***
							(7.37)	(7.67)
licyear2003	0.459 ***	−0.750 ***	−0.825 ***	−0.767 ***	−0.822 ***	−0.832 ***	−0.740 ***	−0.740 ***
	(2.71)	(−3.13)	(−3.18)	(−3.04)	(−3.17)	(−3.20)	(−2.97)	(−2.96)
licyear2004	−0.389	−0.933 ***	−0.714 **	−0.744 **	−0.715 **	−0.715 **	−0.725 **	−0.727 **
	(−1.63)	(−3.36)	(−2.32)	(−2.51)	(−2.32)	(−2.31)	(−2.49)	(−2.48)
licyear2005	1.781 ***	1.196 ***	1.408 ***	1.398 ***	1.407 ***	1.407 ***	1.406 ***	1.407 ***
	(10.45)	(5.30)	(5.55)	(5.64)	(5.55)	(5.51)	(5.83)	(5.79)
licyear2006	−0.560 *	−0.584	−0.0697	−0.134	−0.0681	−0.0774	−0.152	−0.162
	(−1.67)	(−1.41)	(−0.14)	(−0.27)	(−0.14)	(−0.15)	(−0.31)	(−0.33)
licyear2007	0.750 ***	0.818 ***	1.247 ***	1.222 ***	1.251 ***	1.238 ***	1.232 ***	1.228 ***
	(3.90)	(4.10)	(5.43)	(5.45)	(5.44)	(5.36)	(5.56)	(5.49)
licyear2008	1.386 ***	1.235 ***	1.094 ***	1.058 ***	1.094 ***	1.089 ***	1.057 ***	1.052 ***
	(9.37)	(7.37)	(5.55)	(5.54)	(5.54)	(5.50)	(5.60)	(5.54)
licyear2009	2.139 ***	1.554 ***	1.405 ***	1.370 ***	1.406 ***	1.401 ***	1.375 ***	1.371 ***
	(14.35)	(9.41)	(7.18)	(7.22)	(7.17)	(7.12)	(7.35)	(7.28)
licyear2010	2.055 ***	1.243 ***	1.046 ***	1.024 ***	1.047 ***	1.039 ***	1.025 ***	1.019 ***
	(13.92)	(7.52)	(5.37)	(5.42)	(5.36)	(5.30)	(5.51)	(5.43)
licyear2011	1.820 ***	1.291 ***	1.120 ***	1.115 ***	1.122 ***	1.109 ***	1.120 ***	1.110 ***
	(12.70)	(7.88)	(5.76)	(5.93)	(5.77)	(5.67)	(6.04)	(5.94)
licyear2012	1.566 ***	1.255 ***	1.010 ***	1.005 ***	1.012 ***	1.001 ***	0.995 ***	0.988 ***
	(10.97)	(7.69)	(5.17)	(5.32)	(5.18)	(5.10)	(5.33)	(5.25)
licyear2013	2.712 ***	1.943 ***	1.802 ***	1.697 ***	1.804 ***	1.789 ***	1.697 ***	1.682 ***
	(19.22)	(11.85)	(9.32)	(9.04)	(9.32)	(9.21)	(9.16)	(9.02)
_cons	−1.643 ***	−1.860 ***	−4.938 ***	−4.579 ***	−4.890 ***	−5.150 ***	−3.546 ***	−3.779 ***
	(−10.21)	(−10.18)	(−22.17)	(−19.63)	(−12.86)	(−22.00)	(−13.11)	(−8.86)
lnalpha _cons	1.199 ***	0.834 ***	0.175 ***	0.166 ***	0.174 ***	0.174 ***	0.159 ***	0.156 ***
	(73.84)	(49.12)	(7.24)	(6.78)	(7.20)	(7.23)	(6.52)	(6.44)
Log likelihood	−41187.97	−39053.468	−35421.642	−35350.569	−35420.641	−35410.247	−35311.556	−35291.895
Wald chi square	3454.38	6725.87	13826.44	14402.36	14050.15	13947.21	14501.01	14774.85

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; all two-tailed tests. N = 24,227.

Hypotheses 1 and 2 predict that both licensing demand and potential technology competition (PTC) have a positive relationship with actual licensing competition (ALC). In Model 3, the coefficient of licensing demand and PTC are both positive and significant (β = 0.0209, $p < 0.01$; β = 0.558, $p < 0.01$, respectively). These positive relationships remain consistent across all models, even when the variables of technology features and interaction terms are added, and therefore Hypotheses 1 and 2 are supported. This means that more market demand and potential technology providers will lead to more fierce competition in actual patent licensing, which promotes the change of external competition situation. In this case, they are more inclined to obtain rental income through external technology licensing, which is faster and less risky than through product realization in the market.

In models 5–7, the interaction terms between PTC and three technology features (namely, generality, complexity, and newness) are introduced stepwise. We found that in model 5 the interaction term, PTC*generality is positive but not significant, and it shows a non-significant effect in the full model (model 8) as well. Thus, hypothesis 3, which predicts a negative moderating effect of generality, is not supported. Next, the coefficient of PTC*complexity is negative and significant (β = –0.0130, $p < 0.01$) in model 6 and remains consistent in the full model (β = –0.0181, $p < 0.01$). Therefore, we find support for hypothesis 4, which predicts a negative moderating effect of complexity. The more complex the licensed invention patent technology is, the less competition they face in the technology licensing market, when there are more potential licensed technology providers. Finally, we find that a positive moderating effect of newness (β = 0.0135 $p < 0.01$) in model 7 and it remains consistent in the full model (model 8) as well (β = 0.0141, $p < 0.01$), which supports hypothesis 5. In the case of more potential licensed technology providers, the newer the patented technology is, the more likely it is to be transformed into the actual technology licensors, because the technology competition is fierce and easily outdated. Compared with the slow and risky realization through products, obtaining the rental income of the technology is the best choice. This will worsen the external environment of foreign licensing competition.

Furthermore, we also found interesting results regarding some control variables. First, R&D capacity has a consistent positive and significant effect on the dependent variable, which suggests that licensors with strong R&D capacity have faced a relatively high level of actual licensing competition. It can be seen that the more R&D employees an organization has, the closer it is to be a pure R&D organization, which is more inclined to license out their patents. At the same time, it is also facing more fierce actual licensing competition. Second, it is not surprising that firms, comparing to other types of organizations, have faced a relatively higher level of ALC. Third, established organizations with a relatively longer history compared to new firms have faced a relatively high level of ALC. From another perspective, the longer the enterprises survive, the more mature the industry develops, and the more fierce the actual licensing competition. Next, licensors with a broad technology width have faced a relatively lower level of ALC. The R&D scope of the licensors is wide, and the customer resources are relatively broad, which is conducive to the external licensing of their technology, and the actual licensing competition will be relatively small. In addition, the coefficients of licensing years are gradually increasing, which shows that ALC environment in China's technology licensing market is constantly forming, and technology spillover is continuing Finally, among all six industry groups, electrical engineering is the only one that did not seem to experience licensing competition in the markets for technology.

5. Discussion and Conclusions

This study aims at advancing our understanding about what makes PTC in a technology field turn into ALC in the markets for technology. To our knowledge, to date this work is the first that investigated the relationship between potential technology competition and actual licensing competition. The findings of this study provide important complementary insights to the literature on the propensity of licensing, which has been found being under the influences of many external and internal conditions. We focus on particular licensed technologies per se and investigate the impact of licensing demand and the crowdedness of technology fields as the main predictors, based on the data of Chinese organizations' patent licensing.

The findings suggest that when an organization licenses out a patent, the chance that it faces actual competition on the licensing market increases with licensing demand and the crowdedness within a specific technology field. The positive impact of the crowdedness (PTC) is further contingent upon the feature of the licensed patent, e.g., generality, complexity, and newness. While generality does not show a moderating effect, we find that at high levels of complexity and high levels of newness, the increase of PTC is leads to the increase of ALC to a less degree and a greater degree, respectively.

From a theoretical perspective, the findings of this study pinpoint the importance of distinguishing PTC and ALC. With this distinction, future research on the relationship between competition and revenue effect of licensing needs to clearly identify which level of competition it observes under which conditions; future research on the profit dissipation effect of licensing should be able to specify product differentiation based on actual competing technologies, instead of potential competing technologies. From a managerial perspective, the findings of this study may provide R&D managers with a measurable framework to assess the likelihood of facing licensing competition prior to a licensing decision making (without necessarily knowing the organizational conditions of competitors) by monitoring a firm's patent portfolio with regard to the patents' prior licensing demand, the crowdedness of technology field, and a number of key features of the patents. In other words, knowledge gained from this study can be used as a tool to help firms predict the change of PTC turning into ALC. In the management strategy aspect, managers should always have insight into the transformation process from potential licensing competition to actual licensing competition and adjust their own strategies according to the situation of external technology competition. For example, in the early stage of new advanced technology, they can obtain maximum revenue through the product market first, but with the entry of other technology providers, the actual licensing competition becomes increasingly more fierce, then they can obtain revenue through licensing out their patents to get the maximum benefit from technological invention. For the patent technology with high complexity that has been licensed out, it can continue to be licensed out to obtain the revenue, because the high complexity of technology can inhibit the transformation of other potential licensing technologies into actual licensed technologies.

From a policy perspective, our findings perhaps shed light on national and regional innovation policy that is generally oriented towards making innovation clusters as a result of recognizing the positive effect of industry R&D spillover effect. We should not neglect that one of the possible scenarios of innovation clusters is that new technologies invented within a cluster will be crowded (very high PLC), a situation does not necessarily always lead to ALC, which will be crucial for further R&D spillover. Policy-makers must understand that to turn PLC into ALC, we must also pay attention to the attribute of the technologies themselves. Should it be true that complex technology is less likely to face actual licensing competition, increasing investment in deep tech makes sense. Should it be true that newer technologies are more likely to face actual licensing competition, it probably is desirable to facilitate and support the adoption and diffusion of alternative technologies on the market. Chinese government managers, enterprises, or R&D organizations should be encouraged to continuously create advanced technologies and relevant policy supporting in the process of product transformation should be carried out by the government. In addition, enterprises should be encouraged to recruit more R&D personnel to tackle key problems of complex technology and promote the continuous transformation of potential licensing competition into actual licensing competition. At present, China's technology licensing market is in a period of rapid development but far from fully competitive. Encouraging the licensing out patents of enterprises is conducive to technology spillover and industrial upgrading.

This study also has a number of limitations, which deserve the reader's attention. First, though the unit of analysis is the patent, the lack of primary data to measure firm-level variables is surely a drawback. Future studies should take a greater effort to combine firm-level data in a longitudinal fashion to replicate this study. Second, the data used in this study is only from the SIPO. It will be interesting to validate the findings in a replicated study using data from the USPTO or European patent office in Western countries. In this way, any possible difference among Chinese firms and western firms can be compared to critically reflect any institutional differences.

Inspired by the results of this study, we make some suggestions for promising future research as well. First, as this study only made a first step to distinguish PTC and ALC, there is space for a further inquiry on the determinants of the speed of licensing. That is, future research can look into how long it takes a patented technology to be licensed out, given the demand and crowdedness of a technology field and the relative position of a licensor candidate in relation to the competitors. Second, a recent study finds that online marketplaces are used to different degrees across industries [9]. It will be highly interesting to investigate to what extent the use of online market for technology influences the relationship between PTC and ALC.

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