Paper to be presented at

DRUID15, Rome, June 15-17, 2015

(Coorganized with LUISS)

How does external technology search become balanced? A three-dimensional approach

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Abstract

Firms need to search for external knowledge in a balanced way as over-search entails too much risks and uncertainty and local-search does not promise novel opportunities, as the literature has suggested. We conceptually position firms? search behavior within a three-dimensional knowledge search space, including cognitive, temporal, and geographic dimensions. We suggest that the balance is no longer a matter of finding optimal search distance along a single dimension. Instead, it becomes an art to maintain balance in a dynamic manner across three dimensions. Using empirical evidence from Chinese licensee firms, we show that such a three-dimension balance does exist among firms? practice. The findings in this respect provide promising opportunities for future research, which will significantly contribute to our understanding of how firms search for external knowledge and the implications thereof.

Jelcodes:M10,L

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Abstract:
Firms need to search for external knowledge in a balanced way as over-search entails too much risks and uncertainty and local-search does not promise novel opportunities, as the literature has suggested. We conceptually position firms' search behavior within a three-dimensional knowledge search space, including cognitive, temporal, and geographic dimensions. We suggest that the balance is no longer a matter of finding optimal search distance along a single dimension. Instead, it becomes an art to maintain balance in a dynamic manner *across* three dimensions. Using empirical evidence from Chinese licensee firms, we show that such a three-dimension balance does exist among firms' practice. The findings in this respect provide promising opportunities for future research, which will significantly contribute to our understanding of how firms search for external knowledge and the implications thereof.

Keywords: external knowledge search; balanced strategy; patent licensing; innovation

Introduction

The open process of innovation requires many firms to actively search for external technology to be recombined with their existing knowledge base in hope for further innovation (Henderson and Clark, 1990; Chesbrough, 2003), which in turn might lead to enhanced innovative performance and competitiveness (Ahuja and Katila, 2001; Vanhaverbeke et al., 2002; Johnson, 2002).

The literature on firms' external knowledge search is rich, suggesting that external knowledge search is beneficial for the focal firm with respect to innovation because it brings about novelty value for recombination (Schumpeter, 1934; Nelson and Winter, 1982; Nooteboom, 2000), while overly distant search may put future innovation at risk as the coordination challenges associated with remote knowledge elements will become evident (Katila and Ahuja, 2002; Laursen and Salter, 2006; Leiponen and Helfat, 2010). Researchers suggest that external knowledge search needs to be balanced and over-search needs to be avoided (Nooteboom et al., 2007; Li and Vanhaverbeke, 2009; Laursen and Salter, 2006). The underlying logic behind a balanced search strategy stems from the theory of organization with respect to exploration (distance search) and exploitation (local search), which need to be balanced by a firm (March, 1991), given its level of absorptive capacity (Cohen and Levinthal, 1990).

Nevertheless, most prior studies in the literature conceptualize the balance of external knowledge search as a matter of cognitive or technological distance (e.g., Wuyts et al., 2005; Nooteboom et al., 2007; Li and Vanhaverbeke, 2009; Laursen and Salter, 2006, Grimpe and Wolfgang 2009), referring to the fundamental difference of knowledge basis between organizations. Interestingly, other dimensions of knowledge search have been relatively overlooked in the streamline literature on balanced search strategy, even though they do not lack sound theoretical foundations. Besides the cognitive dimension, the recent development in the literature has suggested that a firm's search for external technology can be conceptualized with at least two more unique dimensions, i.e., the spatial and temporal dimensions (Nerkar, 2003; Hoekman et al., 2009; Criscuolo and Verspagen, 2008; Jautala and Jauhiainen, 2014). However, these prior studies are limited to addressing the role of external knowledge searching along one particular dimension so that the balanced search strategy is only discussed as one dimensional issue. Even though in some exceptional work, such as Ahuja and Katila (2004) and Criscuolo and Verspagen (2008), more than one dimension of external knowledge search is discussed, the idea of *balancing* is not addressed. Some scholars suggest that given the recognition of multiple dimensions of external knowledge search of firms, future research needs to be developed to a new stage of understanding how firms make a balance across multiple dimensions (Li et al., 2008; Li-Ying et al., 2014). However, to our knowledge, research in this respect to date has been limited in both theory and empirical evidence. Therefore, our motivation in this study is to fill in this research gap, making a number of contributions in theory and practice.

This study makes theoretical contributions by extending the theories concerning firms' external search of technology to a framework of multidimensional balance. It builds a solid foundation for future research in this respect to probe more detailed patterns of relationships among these dimensions and between the search behavior and firm performance. Second, it also provides specific measurements for the three dimensions of search and a clear visualization method to illustrate the search patterns. This article also makes practical contribution for managers and policy makers, as the results shown in this study provides them with useful insights on how to strategically monitor technology search at a firm-level for multiple projects and/or at a regional- or national-level for a large number of firms.

To make these contributions, in this article we suggest that firms' external knowledge search takes place along cognitive, temporal and spatial dimensions in a fashion that search distance needs to be balanced, where over-search or under-search on all three dimensions simultaneously is not only undesirable but also impossible. There must be somehow a balance. The balanced search strategy entails that distant search along one dimension usually compromise the search distance allowed along the other two dimensions.

The empirical base of this study is the population of licensed patents in China and their corresponding Chinese licensee firms. Information on patent licensing is used in this article because it is a unique means which represents the knowledge search strategy and technology positioning of a firm (Kollmer and Dowling, 2004). Also, compared to most of the earlier studies using patent citation data, patent licensing is more reliable to infer an actual knowledge flow from a technology owner to a technology seeker (Criscuolo and Verspagen, 2008). We trace the data obtained from the State Intellectual Property Office of China (SIPO) during the period 2000-2013 for all the Chinese firms that licensed patents from other parties.

This paper is organized as follows: First, we briefly review the literature on firms' external technology search in relation with firm-level technological innovations. The theoretical background of balanced search strategy and the three distinctive dimensions for firms' external knowledge search, i.e., technical, geographic, and temporal dimensions is explained in detail. Second, three main propositions based on these theoretical argumentations are built. Next, we briefly describe the recent trends in China towards an innovation-oriented economy and how technology licensing has been actively used by Chinese firms for innovation. After that, we present the data, measures and methods, based which we address the propositions. Finally, after the results are presented, this paper concludes with an in-depth discussion of the findings. Suggestions for future research are also proposed.

Theoretical background and propositions

The theoretical foundations of external knowledge search

The theoretical basis for firms' external knowledge search and innovation can be found in the resource-based view (RBV) and organizational ambidexterity (exploration and exploitation). From a RBV, firms differ in their resource positions, which form an important source of performance differences across firms (Penrose, 1959; Barney, 1991). Thus, for a focal firm, it is crucial to access a wide variety of knowledge sources that are not available in-house. Technology search by a firm can be defined as "the problem-solving activities that involve the creation and recombination of technological ideas" (Katila and Ahuja, 2002: 1184). Search processes can be seen as a dynamic capability that allows firms to sustain their competitive advantage over time (Eisenhardt and Martin, 2000).

The extant literature distinguishes *path creating search* (which entails the exploration of new knowledge) from *path deepening search* (which existing knowledge is reused or exploited). Both types of search can play important roles in shaping success in product innovation and eventually create resource heterogeneity among industrial firms (Katila and Ahuja, 2002; Ahuja and Katila, 2004; Laursen and Salter, 2006). The focus of this paper is on the former, i.e., the breadth of new knowledge search.

As far as search breadth is concerned, the literature has suggested a commonly accepted understanding as following: firms usually tend to search for solutions to their problems in a small range of knowledge areas that are close to their existing knowledge base, which eventually yields 'local search' myopia (Rosenkopf and Nerkar, 2001). Since novelty resides in the differences among various knowledge elements, firms that search external knowledge within a wide scope are more likely to obtain access to complementary resources, which, in turn, will lead to more creative opportunities. This is the value of search breadth for creativity and novelty. However, over scanning in too wide contexts can be dysfunctional. First, over-search challenges a firm's existing absorptive capacity and makes it hard to absorb new knowledge (Nooteboom, 2000); second, high uncertainty created by over-searching makes it difficult for managers to decide ex ante which technical and market directions deserve future investment (Koput, 1997). This is the downside of search breadth, creating higher levels of uncertainty. Thus, search breadth needs to be balanced with constant pressures from various constraints in order to sustain the creativity and novelty value (Sætre and Brun, 2012). Such a balance sometimes is interpreted as there is an optimal range of external knowledge search distance and an inverted U-shaped relationship is found between the breadth of technical search and firms' subsequent innovations (Wuyts et al., 2005; Nooteboom et al., 2007; Li and Vanhaverbeke, 2009; Laursen and Salter, 2006).

The idea that external knowledge search needs to be balanced can also find its roots in theories of organizational ambidexterity, which posits that a firm's short-term and long-term survival is determined by the balance of exploitation and exploration (March, 1991; Gupta et al., 2006). A number of studies have accepted that exploitation and exploration denote local and distant knowledge search, respectively: exploitation represents searching for familiar, mature, current or proximate knowledge and exploration represents searching for unfamiliar, distant and remote knowledge (Ahuja and Lampert, 2001; Rosenkopf and Nerkar, 2001; Benner and Tushman, 2002; Katila and Ahuja, 2002; Nerkar, 2003). While local search provides a firm with advantages in making incremental knowledge accumulation, distant search is by nature more variation-seeking and risk-taking so that it might bring path-creating opportunities for a firm to achieve radical innovations (Nerkar and Roberts, 2004). A balance search strategy in this sense suggests that a firm's external knowledge search activities should neither be skewed to distance search nor to local search. In other words, a balance of exploration and exploitation needs to be achieved at a portfolio level, even though a single search activity can be either distance or local (Li et al., 2008; Gupta et al., 2006).

Dimensions of external knowledge search and cross-dimensional balance

Although the extant literature has provided us with great insights on the relationship between firms' external knowledge search and innovation performance, most of the previous studies focus on the cognitive dimension of search, which is a matter of the degree of familiarity between the external knowledge holders' knowledge base and a focal firm's existing knowledge base. Cognitive distance between organizations exists because organizations with time being develop mental models, where networks of concepts and ideas affect its unique way of thinking and acting (Weick, 2001; Huff, 1990). It is usually a measure that denotes the technological distance (e.g., in terms of patent classes) between firms (Jaffe, 1986; Nooteboom, *et al*., 2007; van der Vrande, *et al*., 2011). The cognitive dimension of search can also be understood by measuring the type of knowledge sources or innovation objectives (Laursen and Salter, 2006; Leiponen and Helfat, 2010; Sofka and Grimpe, 2010).

Besides cognitive innovation, several scholars have suggested that distant or local knowledge search may take place along the geographic and temporal dimensions (Nerkar, 2003; Hoekman et al., 2009; Criscuolo and Verspagen, 2008; Jautala and Jauhiainen, 2014; Wang et al., 2014). The *spatial (geographic)* dimension refers to the knowledge search within physical space. Geographic dimension denotes the object space (Jautala and Jauhiainen, 2014), in which distance matters because common resources (Saxenian, 1994) and sticky knowledge (von Hippel, 1994; Szulanski, 1996) that resides within a geographical area are often only available to the locals where organizations have sufficient interactions and joint practices (Asheim and Isaksen, 2002), given the local institutions and culture (Knoben and Oerlemans, 2006). Another dimension is the *temporal* dimension, which examines the role of linear time[1] and its implication on organizational learning (Katila, 2002; Nerkar, 2003). Often there is a time lag between the availability of emerging technological opportunities and complementary technologies. This requires a firm's to explore technologies over time (Garud and Nayyar, 1994). These three different dimensions construct the knowledge search space (Li et al., 2008; see Figure 1). A recent study finds preliminary results, suggesting the balance of a firm's external knowledge search is a matter concerning all three dimensions (Li-Ying et al., 2014).

Insert Figure 1 here

We recognize that prior studies have verified the distinctiveness of three dimensions of knowledge search space (Criscuolo and Verspagen, 2008; Li et al., 2008; Wang et al., 2014) and some preliminary understanding how firms balance can be achieved across multiple dimensions has been established (Li-Ying et al., 2014). However, while most of the previous studies focus on the cognitive dimension of firms' external technology search (Wuyts et al., 2005; Nooteboom et al., 2007; Li and Vanhaverbeke, 2009), few have investigated how firms search along the geographic and temporal dimensions (e.g., Li and Vanhaverbeke, 2009; Nerkar, 2003). Moreover, knowledge on how the disadvantage of over-search along one dimension can possibly be moderated by balancing search distance along the other two search dimensions is almost completely underdeveloped in the literature. Therefore, it is our intention in this paper to advance the theories on the balanced strategy of external knowledge search by addressing a number of key questions. In particular, in this paper we reveal (1) whether search activities of firms over a relatively long period are balanced across three dimensions, using a longitudinal database on a unique external knowledge searching activity: technology licensing and (2) how cross-dimensional balance is achieved, probing the impact of search distance along one dimension on the other two dimensions. The empirical findings with respect to these questions are used for further theory building, which will be discussed later in this paper.

[1] In this paper, we limit our focus only on linear time. We do not address relational time, which is the subjective feeling of how fast time passes (Jautala and Jauhiainen, 2014).

We posit that though the extant literature may provide theoretical insights, they are not sufficient to account for the cross-dimensional balance of search as we observe in this study. Therefore, it is not our intention to test well-argued hypotheses. Rather, we are going to develop two propositions, based on the research questions. These propositions are reasoned, using knowledge in the extant literature and an abductive logic, the process of forming an explanatory hypothesis, to introduce a new idea (Hoffman, 1995). We use abduction to generate an idea, deduction to follow the ideas to their logical consequences and predict the outcomes, and testing of the idea by empirical evidence (Dunne and Martin, 2006). First, as the extant literature suggests that balanced external knowledge search is to find the 'optimal distance' by avoiding local search and over search along the cognitive dimension (Wuyts et al., 2005; Nooteboom et al., 2007; Laursen and Salter, 2006), it is reasonable to expect that it is neither desirable nor possible for a firm to search external knowledge with a very large or a very short distance simultaneously along all three dimensions in the three-dimensional knowledge search space. In other words, we expect that the cases where a firm searches external technology from a very far distance simultaneously along cognitive, geographic and temporal dimensions do not exist. Neither do the cases where a firm searches external technology from a very short distance simultaneously along cognitive, geographic and temporal dimensions. Therefore, we suggest the following:

Proposition 1: External knowledge search of firm takes place along three distinctive dimensions - cognitive, temporal and spatial- in a fashion that search distance needs to be balanced, where over-search with a very large distance or under-search with a very small distance along all three dimensions simultaneously is not possible.

Second, as a firm develops it unique mental model, in which ideas, thoughts, concepts and logics are connected through interactions of people and formulate a wide knowledge base (Weick, 2001; Huff, 1990). The knowledge base of a firm becomes the foundation of its absorptive capacity with which a firm is able to evaluate, learn, and assimilate external technology (Cohen and Levinthal, 1990; Tsai, 2009). Although the mental model and absorptive capacity of a firm evolves and can be developed over time as a firm learns and corrects false actions through both internal and external interactions (Jautala and Jauhiainen, 2014), learning associated with searching external knowledge inevitably imposes challenges on the firm. For instance, when external technology is from an unfamiliar technological field, a firm needs to invest heavily in internal R&D (Nooteboom et al., 2007; Wang and Li-Ying, 2014); when a firm searches external knowledge from a foreign partner, it faces communication challenges associated with different culture, language and institution (Li and Vanhaverbeke, 2009); when a firm searches for old knowledge, additional effort is needed to identify its compatibility with state-of-the-art technologies (Nerkar, 2003). Therefore, we expect that it is too demanding for a firm to handle the challenges associated with external knowledge search when search distance along all three dimensions is large. More specifically, search stretched along one dimension may create high value of novelty, but it also yields high a high level of constraint on the freedom of search on the other two dimensions. As a consequence, search distance on the other dimensions has to be relaxed, meaning shortened. In this way, external knowledge search is balanced within the entire search space, rather than along a single dimension. Therefore, we suggest the following:

Proposition 2: The balanced search strategy entails that distant search along one dimension usually constrains the search distance allowed along the other two dimensions.

These propositions will be put into test against data on the licensing of Chinese firms during the period 2000-2013. We introduce the empirical data and methods in a great detail in the next section.

Methods

Data overview: patent licensing in China

Patent data are commonly used in the literature to measure firms' external technology search activities. Often, patent citation is used to infer the owner of the new patent, which cites a prior art, manage to learn from the knowledge owner of the cited patents (Katila and Ahuja, 2002; Nerkar, 2003; Ahuja and Katila, 2004). However, one of the greatest disadvantage of using patent citation information to infer external knowledge search is that it is hard to know whether a citation to a prior art is added by the inventor or by the examiners. If a citation is added by the examiner, it does not necessarily indicate that the inventor has knowledge of the cited prior art (Criscuolo and Verspagen, 2008). Thus, other patent statistics is needed to better represent the knowledge flow between knowledge owners and knowledge seekers. In this respect, we prefer technology licensing data.

Technology licensing refers to a license agreement under which a licensee is granted to have access to a licensor's technologies. A technology license agreement involves the licensor, exploiting the economic value of its knowledge externally, and the licensee, learning the in-licensed technologies to create future opportunities (Cummings and Teng, 2003). From a licensee's perspective, in-licensing technology can provide firms with strategic assets that are unavailable internally but crucial for building competencies needed to sustain competitive advantages (Li-Ying and Wang, 2014).

The dataset used for this study was obtained from the State Intellectual Property Office of China (SIPO). According to Chinese legislation ('Regulations on Administration of Record Filing of Technology Licensing'), since 2001 the SIPO has been authorized to register patent-licensing contracts within three months after a contract is signed between the licensor and licensee. Each technology transfer record registered at the SIPO contains the following information: licensor's name, licensee's name, licensing patent number, patent title, contracting number and date, and license type (exclusive or non-exclusive). License agreements can be signed between individuals and firms in various forms. While licensors of a licensing agreement can be either Chinese or foreign individuals or firms, all licensees are Chinese individuals or firms. So far, this dataset only includes licensing agreements that involved patented technologies. The complete records from 2000 to 2013 are available to the public on the SIPO website (http://www.sipo.gov.cn/). The data has been used by some prior studies, extracting a small sample to address various research questions (e.g., Li-Ying et al., 2014; Li-Ying and Wang, 2014; Li-Ying et al., 2013; Wang and Li-Ying, 2014), but it has never been used as extensively as we do in this paper.

During these 14 years there were a total of 103,119 patents licensed to Chinese licensees. Since we are interested in firms' behavior, we remove individual as licensees in the dataset. We also excluded the cases where Chinese subsidiaries of foreign parent company licensed technology from their parent company. Finally, we also excluded the 232 cases where the licensee is located in Taiwan and Hong Kong. These approaches result in 46,871 licensed patents are the empirical base of this study. Figure 2 presents the yearly distribution of the patents licensed by Chinese firms. It is clear that the number of patents licensed by Chinese firms has consistently increased during the last 14 years. In 2000, while very few patents were licensed by Chinese firms, more than 13,000 patents were licensed in 2012. The dramatic decrease in this number in 2013 should not be misinterpreted as it is mainly due to the fact that the data is only available till June 30th, 2013. Figure 3 shows the distribution of technological fields among the licensed patents during the observed period[2]. The technological field that relied heavily on licensed technologies is the "electronic device and engineering" category, followed by "control and instrumentation technology" and others. With regard to the geographic origin of the licensed patents, Figure 4 shows that the top three regions of technology sources are Guangdong province, Jiangsu province and Beijing. Many technologies are licensed from Taiwan as well. Not surprisingly, Chinese firms licensed a great deal of foreign technologies during the last 14 years. Next, among all the licensed technologies, some are relative new, others are rather old. Technology age refers here to the number of year's difference between the time when a patent is licensed to a Chinese firm and when the licensed patent was granted. Figure 5 shows that the majority of licensed technologies were patented during the period 2004-2011. Old technologies that were patented before 1994 were licensed in a very small scale.

Insert Figure 2 here

Insert Figure 3 here

Insert Figure 4 here

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[2] The technology fields and relevant IPC classification are presented in detail in the Appendix.

Insert Figure 5 here

Measurements

Geographic distance is measured using the Great Circle Method, which measures the shortest distance between two locations (cities) on a sphere (see e.g., Brian and Francisco, 2010; Li-Ying et al., 2014). The formula to calculate the distance between point A and point B on the Earth is provided,

$$d_{AB} = R \times \arccos\left[\sin\left(lat_A\right)\sin\left(lat_B\right) + \cos\left(lat_A\right)\cos\left(lat_B\right)\cos\left(\left|long_A - long_B\right|\right)\right],$$

where R is the average radius of the Earth, usually taken as 6,371 km; lat_A and lat_B refer to the latitude of point A and point B, respectively. $long_A$ and $long_B$ refer to the longitude of point A and point B, respectively. All latitudes and longitudes are in degrees. This way to measure geographic distance has been widely used in innovation literature (e.g., Brian *et al.*, 2010). To test the accuracy of using this formula, we use the latitude and longitude of Beijing and Shanghai and calculate the geographic distance. The result is 1,067.08 km, which is very close to the straight line distance indicated on Google Earth (1,066.55km). Therefore, we are confident that this measure is reliable.

Temporal distance is measured by the number of years between the year when a patent was first filed in China and the year when this particular patent was licensed by a Chinese firm (Li-Ying et al., 2014).

Cognitive distance between organizations is well established in the literature (Nooteboom, 1992, 2000; Nooteboom et al., 2007; Wuyts et al., 2005). People in different organizations share base perceptions and values to sufficiently align their competencies and motives. Differences in their mental models and aligned competencies and the perceptions, interpretation and evaluation towards the external world determine what they learn and what to become (Weick, 1979; Nooteboom, 2000). Difference as such yields cognitive distance between organizations. In the literature on external knowledge search of firms, the concept of cognitive distance is often implicitly deployed by viewing competitors, suppliers, customers, collaborating universities, and research institutes as different knowledge providers (Laursen and Salter,2006; Grimpe and Sofka, 2009; Leiponen and Helfat, 2010) or explicitly measured by calculating the difference between firms' technological knowledge base using patent class information (Nooteboom et al., 2007; Wuyts et al., 2005; Li-Ying et al., 2014). In this paper, as we are not able to obtain comprehensive information on the patent bases of all licensees and licensors, we rely on the first approach to measure the distance between organizations on the cognitive dimension.

As all licensees in the SIPO licensing data are Chinese firms, we seek a systematic measure of cognitive distance, recognizing the substantial difference in the collective way of perception and behavior among organizations. In the context of licensing, the literature has already suggested that firms, universities (including higher-education institutes), and other (private or public) research institutes are the three major types of knowledge generating organizations (Belderbos et al., 2004). Thus, we measure the cognitive distance between a Chinese licensee firm and a licensor organization in the following way: first, we assign '1' as the value of distance when the licensor is also a firm; next, we assign '5' as the value of distance when the licensor is a university[3]; then we assign '3' as the value of distance when the licensor is a research institute other than university. This approach, assigning progressive value to the distance to other firms, research institutes, and university is based on the observation that between firms they have similar values and ways of conducting research and development. Compared to universities and research institutes, industrial firms prioritize R&D projects differently: (1) they tend to spend more on applied R&D projects, which have more predictable value for further product development and manufacturing; and (2) they are more likely to be constrained by current financial performance. Due to the for-profit nature of industrial firms, their R&D activities are mostly applied and focus on finding solutions to specific technical problems. The distance between a licensee firm and university licensor is assigned with the largest distance value because since the economic reform in China, universities have become mostly oriented towards basic research. Though universities in China also have the majority of research resources and the top research personnel (Chang and

[3] In this paper, university also includes other higher-education institutes, such as colleges in China. This approach is in line with the extant literature (see Laursen and Salter, 2006).

Shih, 2004) and universities generally possess a relatively higher level of scientific knowledge, technology, and technical services (Zhou, 2012), universities usually generate knowledge that is relatively far from being directly utilized by the industry due to their different goal orientation. Nevertheless, research institutes are mostly not qualified as universities but receive public and/or private funding for research into relatively specific technological areas applied to industries (Gill and Mulvenon, 2002). They include, for instance, all national- or provincial-level research institutes and laboratories in the fields of aerospace, agriculture, aquaculture, military, petroleum, etc. These research institutes are as important as universities in generating new knowledge. According to the *China Science and Technology Statistics Data Book 2007*, the shares of R&D expenditure for universities and research institutes respectively are sustaining and decreasing (Guan et al., 2005), but Chinese research institutes are becoming increasingly industrialized and commercialized so that their ways of generating knowledge and the knowledge outputs are more close to the industry, compared to universities. Therefore, we assign a medium value of cognitive distance for research institutes in China.

Furthermore, sometimes a patent is licensed to a licensee by more than one licensor if a patent was co-patented. In these cases, we have more than one type of licensor. We assign the average value for the cognitive distance in these cases. For instance, when a patent is licensed by two types of licensors, one is a firm and the other is a research institute, we calculate the distance value as (1+3)/2 = ‘2’; when a patent is licensed by a university and a research institute, we calculate the distance value as (5+3)/2 = ‘4’. Table 1 illustrates the licensor type and the cognitive distance value assigned to each possible licensor combination. There is no case where a patented had three types of organizations as licensors in the data. The total number of different combinations of licensor(s) is also provided. Most cases in our dataset are those Chinese firms licensed technology from other industrial firms (with 37,723 cases out of the total 46,871 cases). The distribution of cases with respect to cognitive distance is illustrated in Figure 6.

Insert Table 1 here

Insert Figure 6 here

The raw measures for search distance on the geographic, temporal and cognitive dimensions are not on the same scale. Thus, for the ease of numerical computation, visualization, and programming using Matlab®, we adopted the method of subclassification to transform continuous variables, the geographic and temporal dimensions, to ordinal variables. Following Cochran (1968), the frequency distribution of the original value of the continuous variables are used to form (at least) five subclasses for the value of each dimension of knlwedge search. The cut-off value of frequency distribution is set as 0%, 11%, 35%, 65%, 89% and 100%. Although this data transforming method to some extent simplifies the raw measures, it has reached a 92.0% of maximum reduction, a reliable level of data transformation.

As far as geographic distance is concerned, we assign the cases that have a distance to the licensor within the range of 0%-11% with a value of ‘1’, indicating the closest distance; and the cases that have a distance to the licensor within the range of 89% - 100% with a value of ‘5’, indicating the largest distance. The cases falling in the ranges of 11%-35%, 35%-65%, 65%-89% are assigned with values of ‘2’, ‘3’, and ‘4’, respectively. However, as in many cases the geographic distance between a Chinese licensee and a foreign licensor is extremely large, if we simply assign these cases with a value of ‘5’, the consequence will be that the majority of cases in our data will be classified as either ‘1’ or ‘2’, without having many cases having a value of ‘3’ or ‘4’. This will severely distort the accuracy of the raw measure. To avoid this, we use six subclasses and we assign the cases having a large distance to foreign licensor(s) with a value of ‘6’. The distribution of cases with respect to geographic distance is illustrated in Figure 7.

As far as temporal dimension is concerned, as the challenges associated to learning from the latest technologies are supposed to be higher than learning from well-established mature technologies (Wang et al., 2013), we define the largest value on the temporal dimension is associated with licensing the *newest* technologies ant the smallest value is associated with licensing the *oldest* technologies. Thus, we assign the cases that have a distance value to the licensor within the range of 89%-100% with a value of ‘1’, indicating the largest year difference (i.e., oldest technologies) between the time when a patent was granted and then licensed to a Chinese firm; and the cases that have a distance value to the licensor within the range of 0%-11% with a value of ‘5’, indicating the shortest year difference (i.e., newest technologies) between the time when a patent was granted and then licensed to a Chinese firm. The cases falling in the ranges of 65%-89%, 35%-65%, 11%-35% are assigned with values of ‘2’, ‘3’, and ‘4’, respectively. The distribution of cases with respect to geographic distance is illustrated in Figure 8.

Insert Figure 7 here

Insert Figure 8 here

Results

The data analysis includes two parts: first, using the Matlab® software, we generate 3D visualizations of firms’ external knowledge search pattern based on the licensing data from SIPO; second, we use regression analysis to investigate the relationships among the three search distance along three dimensions. For both analyses, we show the patterns of the entire sample and the possible difference between larges firms and SMEs.

First, using the Matlab® software, we present a 3D visualization for the three-dimensional external knowledge search space. Figure 9 shows the overall distribution of licensed patents during 2000-2013, plotted in the space that is composed of geographic, temporal and cognitive dimensions. We find that there was no case with large distances along all three dimensions simultaneously and there were very few cases with small distances along all three dimensions simultaneously. This suggests somehow a balance have been maintained in the external knowledge search space: search distantly along all three dimensions is too risky and search locally along all three dimensions is not worthwhile.

Insert Figure 9 here

As the number of licensed patents before 2007 was relatively small and licensing has been widely used during 2011-2013, we separate three historical time periods, i.e., 2000-2007, 2008-2010, and 2011-2013, to make sure the balanced search pattern was not predominated by a particular time period. The search patterns of these three periods are compared to each other to reveal any time-related change. Figures 10, 11 and 12 present the search patterns of Chinese licensee firms during the periods 2000-2007, 2008-2010, and 2011-2013, respectively. We find that besides a small number of cases during the period 2000-2007 where some technologies are licensed from small distances along all three dimensions, a balanced pattern holds throughout the last 14 years. Particularly, it has become more obvious in the more recent periods that (1) there was no case with large distances along all three dimensions simultaneously, and (2) when search distance along one dimension is high, the search distance along the other one or two dimensions will be reduced. Thus proposition 1 receives supporting evidence.

Insert Figure 10 here

Insert Figure 11 here

Insert Figure 12 here

To further probe the balancing relationships among the three dimensions of external knowledge search, OLS regression models are used by making one dimension as the dependent variable and the other two dimensions as the independent variable. Table 2 presents the descriptive statistics of the variables.

Table 3 shows the OLS regression analyses, where temporal dimension, geographic dimension, and cognitive dimensions are the dependent variables in models 1, 2, and 3, respectively. It is interesting to find that when distance in one dimension is used as the dependent variable, the distances along the other two dimensions always present significant and negative effects on the dependent variable. In model 1, when temporal dimension is the dependent variable, we find that the coefficients for the distance along both geographic and cognitive dimensions are significant and negative (β= -0.219, p<0.01; β= -0.0538, p<0.01, respectively). In model 2, when geographic dimension is the dependent variable, the coefficients for the distance along both temporal and cognitive dimensions are significant and negative (β= -1.319, p<0.01; β= -0.248, p<0.01, respectively). In model 3, when cognitive dimension is the dependent variable, the coefficients for the distance along both temporal and geographic dimensions are significant and negative (β= -0.267, p<0.01; β= -0.204, p<0.01, respectively). These findings suggest that the increase of distance along one of the three dimensions in the external knowledge search space constrains the search distance along the other two dimensions. This rends supporting evidence to proposition 2.

For the different time periods, we run the OLS regress analysis as well. Tables 4, 5 and 6 present the results of the analysis in the same manner as in table 3. It is interesting to see that the effects of two dimensions as independent variables on the other dimension as dependent variable are all negative and significant, except for the one between cognitive dimension and temporal dimension during the period of 2000-2007 (in Table 4, model 1 and model 3). It is likely that during the period, the cases in the sample are rather homogenous with regard to the cognitive dimension, as among the 4049 licensors there were 4003 firms, 39 research institutes and only 7 universities (higher-education institutes).

Discussion

General issues and limitations

The literature on firms' external knowledge search has a long tradition in suggesting a balanced search strategy and this research field is by no means foreign to a multi-dimensional approach to understand firms' external knowledge search patterns. Based on these sound common grounds in the literature, this study push forward the theory of external knowledge search by proposing that a balance is (and ought to be) maintained when a firm searches for external knowledge to innovate. Such a balance is no longer a matter of defining the optimal distance along a single dimension, e.g., the technological/cognitive dimension. Instead, the balance is about manipulate and control the novelty value, management challenges and uncertainties associated with search distance along three dimensions of the knowledge search space. Based on a large longitudinal sample of Chinese licensee firms, we found that (1) no firm has simultaneously searched with a large (or small) distance along all three dimensions; (2) when the search distance along one dimension is large, it always constrains the search distance along one or two other dimensions. Many possible situations exist: for instance, when firms search for new technologies, they usually tend to look for knowledge owners located in nearby geographic areas because it is convenient for frequent interactive learning from the licensors; when firms search for technologies from knowledge owners located from afar, they might find those mature technologies are the easiest for knowledge transfer and learning; and when firms search for technologies from organizations have different objectives and research priorities, e.g., universities, they also tend to look for local ones to ensure the technologies invented by the universities are fully understood and transformed to marketable products/services. All in all, a balance has been maintained along the three dimensions of knowledge search space.

It is also important to note that the exact pattern of the three-dimensional balance is perhaps contingent on many other factors, such as firm size and industrial sectors (Grimpe and Wolfgang, 2009). Another important contingency is absorptive capacity (Cohen and Levinthal, 1990). We have little knowledge on how different the search patterns would become when firms have different levels of absorptive capacity. In this respect, an earlier work by Laursen, Leone and Torrisi (2010) was a good example, from which researchers may dig deeper. Therefore, future research is encouraged to further explore the impact of other contingencies on the balanced patterns of external knowledge search. Other limitation to this study is that the empirical base is a large number of the Chinese licensee firms. Future research testing the three-dimensional balanced search patterns should be applied to other countries. Finally, Due to the fact that we used licensing data, for each dimension we only used one single measurement. Future research may well explore other alternative measurements for each dimension. For instance, to measure geographic distance, one may instead measure the number of borders lines across there are between a knowledge seeker and a knowledge owner; similarly, research using patent citation data or alliances data may consider other measurements for cognitive distance. The validity of our study will be tested by trying these alternative empirical contexts and measurements.

Furthermore, a number of issues need to be further investigated to enrich our understanding. For instance: when one dimension is stretched, do other two dimensions respond in the same way and to a similar extent? Here it is interesting to research the impact of an over-searched dimension on the other two dimensions. Also, as the over-stretched dimension will create a rebounding force onto itself and make room for the other two dimensions to enlarge, how much time does it take to rebound? Here a dynamic perspective and a longitudinal research design are needed. Next, since the over-stretched dimension is the one that creates energy for rebounding, is it possible to manipulate this dimension so that the rebounding effect will be created later? If it works, which dimension needs to be prioritized to over-stretch? Isn't the capability of manipulating search distance a dynamic capability? The answers to these questions may provide very interesting managerial insights for managers. Last but not least, our findings only suggest balance and rebound. It does not imply that a balanced search necessarily lead to better innovation performance. It will be interesting to have nuanced findings with regard to the relationship between three-dimensional balance and firms' innovation performance.

Conclusion

Firms need to search for external knowledge in a balanced way as over-search entails too much risks and uncertainty and local-search does not promise novel opportunities, as the literature has suggested. When firms' search behavior is conceptually positioned within a three-dimensional knowledge search space, including cognitive, temporal, and geographic dimensions, the balance is no longer a matter of finding optimal search distance along a single dimension. Instead, it becomes an art to maintain balance in a dynamic manner across three dimensions. Using empirical evidence from Chinese licensee firms, this paper shows that such a three-dimension balance does exist among firms' practice. The findings in the study provide promising opportunities for future research, which will significantly contribute to our understanding of how firms search for external knowledge and the implications thereof.

Appendix: Technological categorization and relevant patent classifications

Technological Field	Patent Classification
Electrical Devices and Engineering	F21,G05F,H01B,H01C,H01F,H01G,H01H,H01J,H01K,H01M,H01R,H01T, H02,H05B,H05C,H05F,H05K
Audio-visual Technology	G09F,G09G,G11B,H03F,H03G,H03J,H04N,H04R,H04S
Communication	G08C,H01P,H01Q,H03B,H03C,H03D,H03H,H03K,H03L,H03M,H04B, H04H,H04J,H04K,H04L,H04M,H04Q
Information Technology	G06,G10L,G11C
Semiconductor	B81,H01L
Optics	G02,G03,H01S
Control and Instrumentation Technology	G01B,G01C,G01D,G01F,G01G,G01H,G01J,G01K,G01L,G01M,G01N, G01P,G01R,G01S,G01V,G01W,G04,G05B,G05D,G07,G08B,G08G,G09B, G09C,G09D,G12
Medical Technology	A61B,A61C,A61D,A61F,A61G,A61H,A61J,A61L,A61M,A61N
Nuclear Engineering	G01T,G21,H05G,H05H
Fine Organic Chemistry	C07C,C07D,C07F,C07G,C07H,C07J
Polymer Chemistry	C08B, C08F,C08G,C08H,C08K,C08L,C09D,C09J
Chemical Engineering	B01,B02C,B03,B04,B05B,B06,B07,B08,F25J,F26B
Surface Processing, Coating	B05C,B05D,B32,C23,C25,C30
Material, Metallurgy	B22,B82,C01,C03C,C04,C21,C22
Biotechnology	C07K,C12M,C12N,C12P,C12Q,C12S
Pharmaceuticals, Cosmetics	A61K,A61P
Agriculture, Food	A01H,A21D,A23B,A23C,A23D,A23F,A23G,A23J,A23K,A23L,C12C,C12F,C12G, C12H,C12J,C13D,C13F,C13J,C13K
Petroleum Industry & Material Chemistry	A01N,C05,C07B,C08C,C09B,C09C,C09F,C09G,C09H,C09K,C10,C11

Hauling & Printing	B25J,B41,B65,B66,B67B,B67C,B67D
Food Processing, Machinery and Equipment	A01B,A01C,A01D,A01F,A01G,A01J,A01K,A01L,A01M,A21B,A21C,A22, A23N,A23P,B02B,C12L,C13C,C13G,C13H
Material Processing, Textile, Papermaking	A41H,A43D,A46D,B28,B29,B31,C03B,C08J,C14,D01,D02,D03,D04B, D04C,D04G,D04H,D05,D06(except F、N),D21
Environmental Technology	A62D,B09,C02,F01N,F23G,F23J
Machine Tool	B21,B23,B24,B26D,B26F,B27,B30
Engine, Pump, Turbine	F01B,F01C,F01D,F01K,F01L,F01M,F01P,F02,F03,F04,F23R
Heat Treatment and Equipment	F22,F23B,F23C,F23D,F23H,F23K,F23L,F23M,F23N,F23Q,F24,F25B, F25C,F27,F28
Mechanical Components	F15,F16,F17,G05G
Transportation	B60,B61,B62,B63B,B63C,B63H,B63J,B64B,B64C,B64D,B64F
Space Technology and Weapon	B63G,B64G,C06,F41,F42
Consumer Goods and Equipment	A24,A41B,A41C,A41D,A41F,A41G,A42,A43B,A43C,A44,A45,A46B, A47,A62,A63,B25B,B25C,B25D,B25F,B25G,B25H,B26B,B42,B43, B44,B68,D04D,D06F,D06N,D07,F25D,G10B,G10C,G10D,G10F,G10G, G10H,G10K
Civil Engineering, Mining, Architecture	E01,E02,E03,E04,E05,E06,E21

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Figure 1: Three-dimensional space for external technology search (sources: Li, Vanhaverbeke and Schoemakers, 2008)

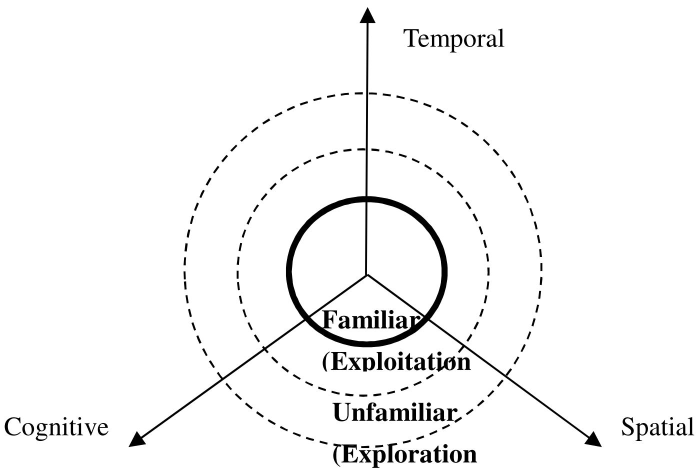

Figure 2: Yearly distribution of licensed patents

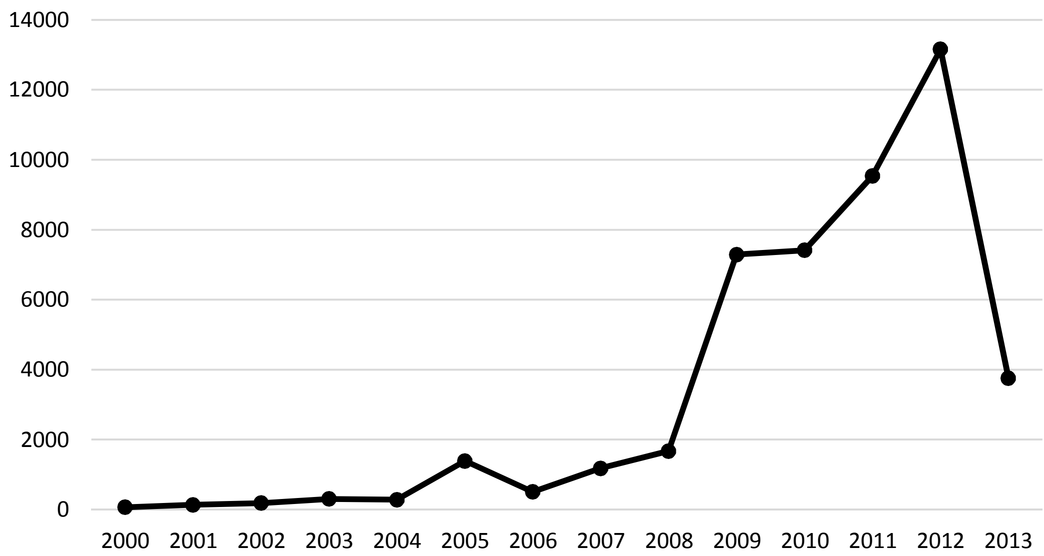

Figure 3: Distribution of technological fields among licensed technologies

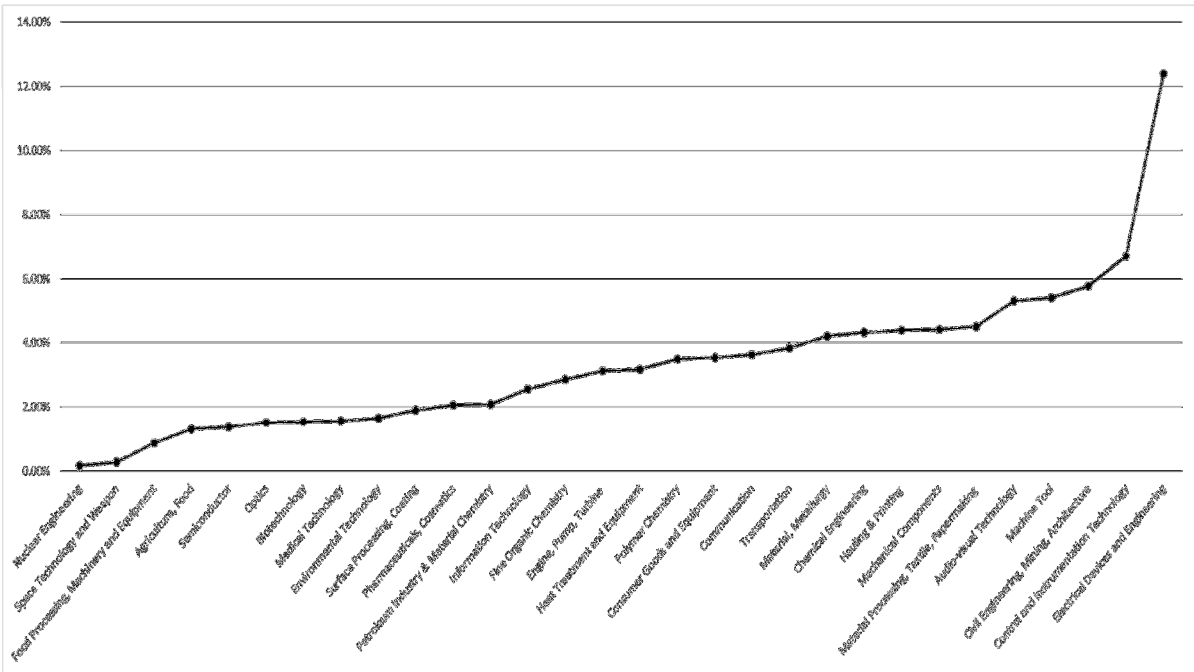

Figure 4: Geographic distribution of sources of licensed patents

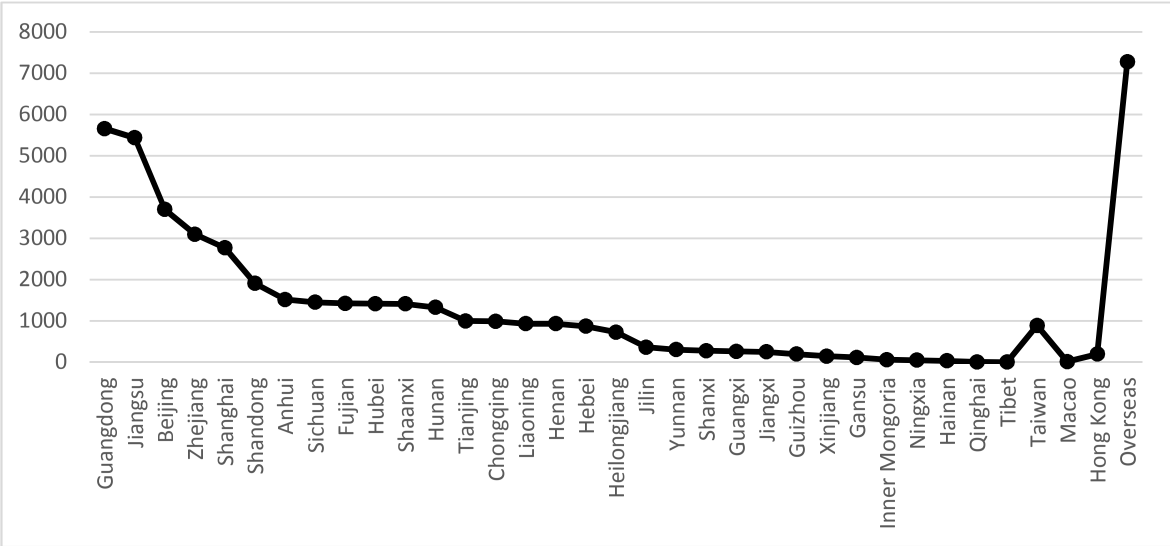

Figure 5: Distribution regarding the year when a licensed patent was granted (only including patents granted by SIPO)

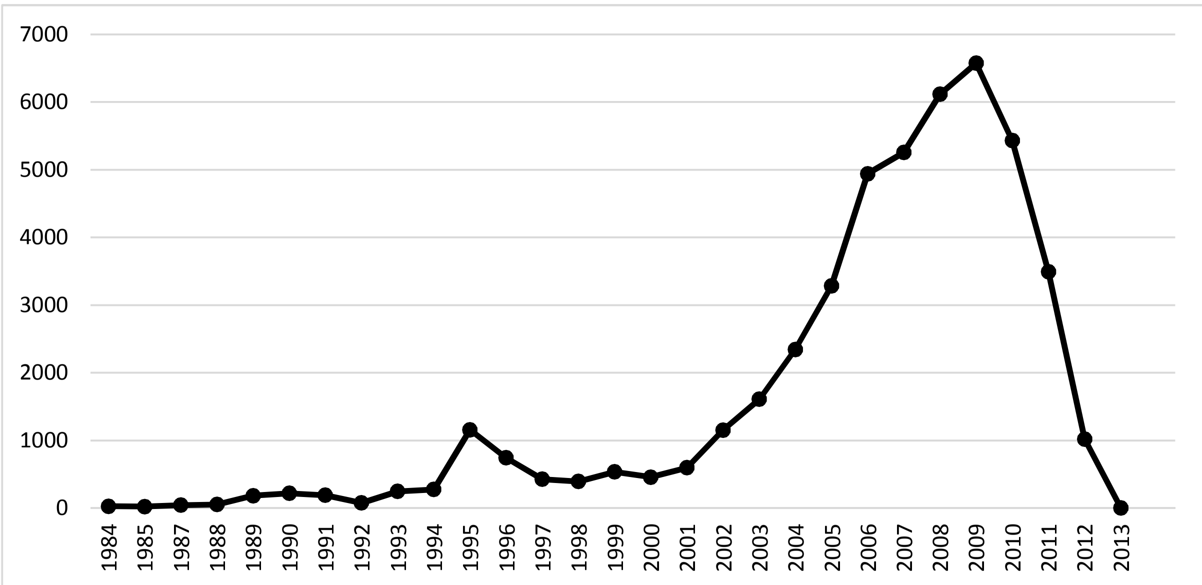

Figure 6: Distribution of cases regarding cognitive distance

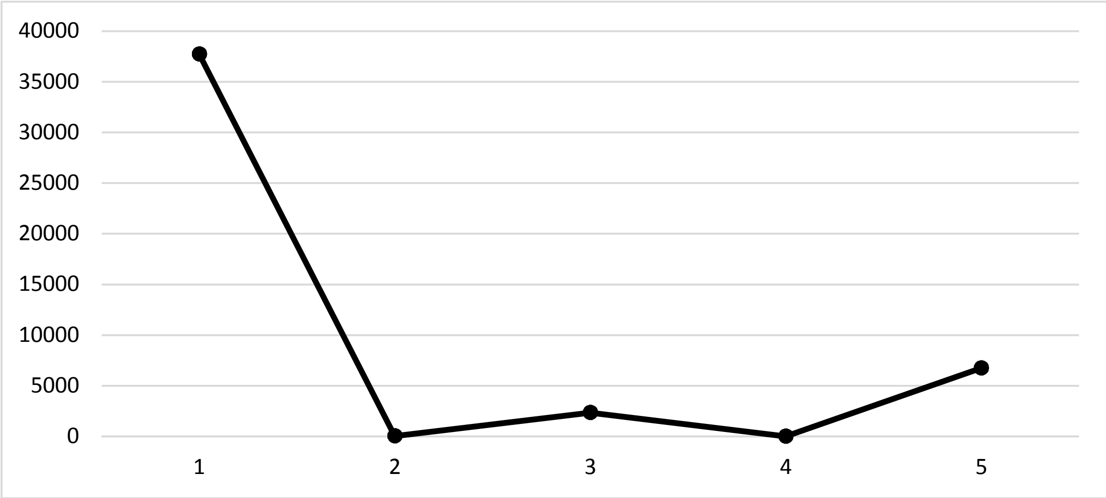

Figure 7: Distribution of cases regarding geographic distance

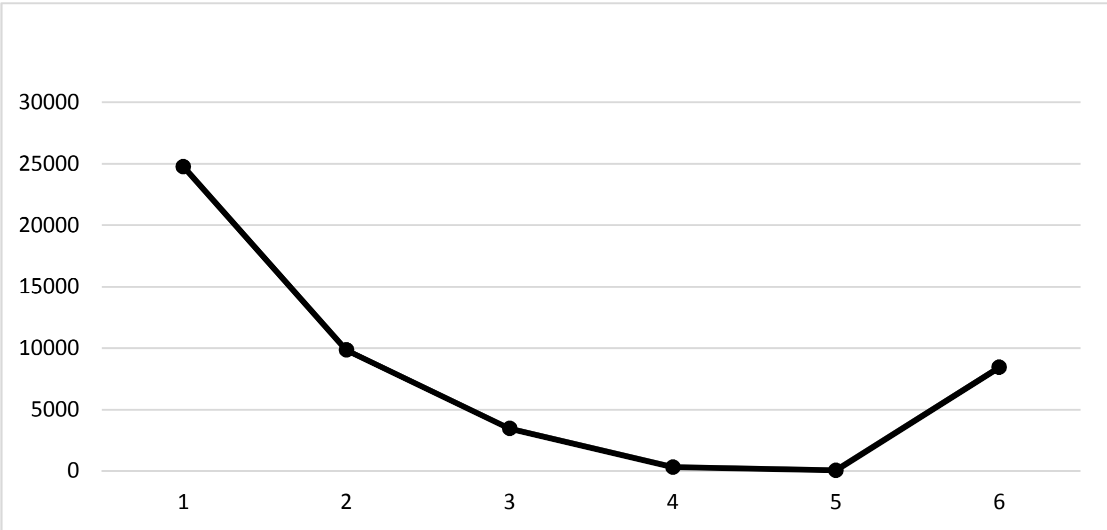

Figure 8: Distribution of cases regarding temporal distance (a larger value indicates newer technology)

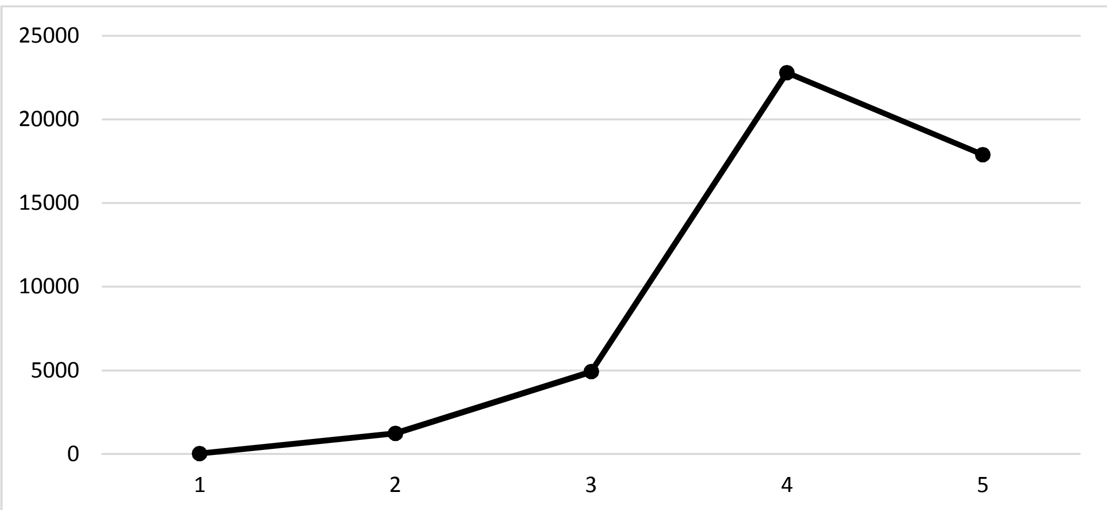

Figure 9: Three-dimensional external knowledge search space (Chinese licensee firms 2000-2013)

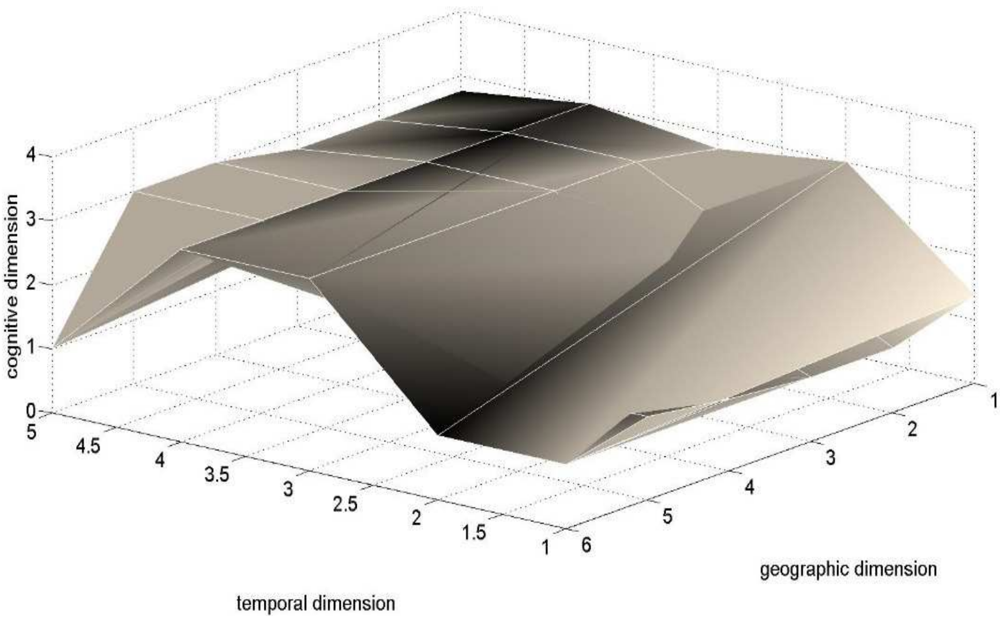

Figure 10: Three-dimensional external knowledge search space (Chinese licensee firms 2000-2007)

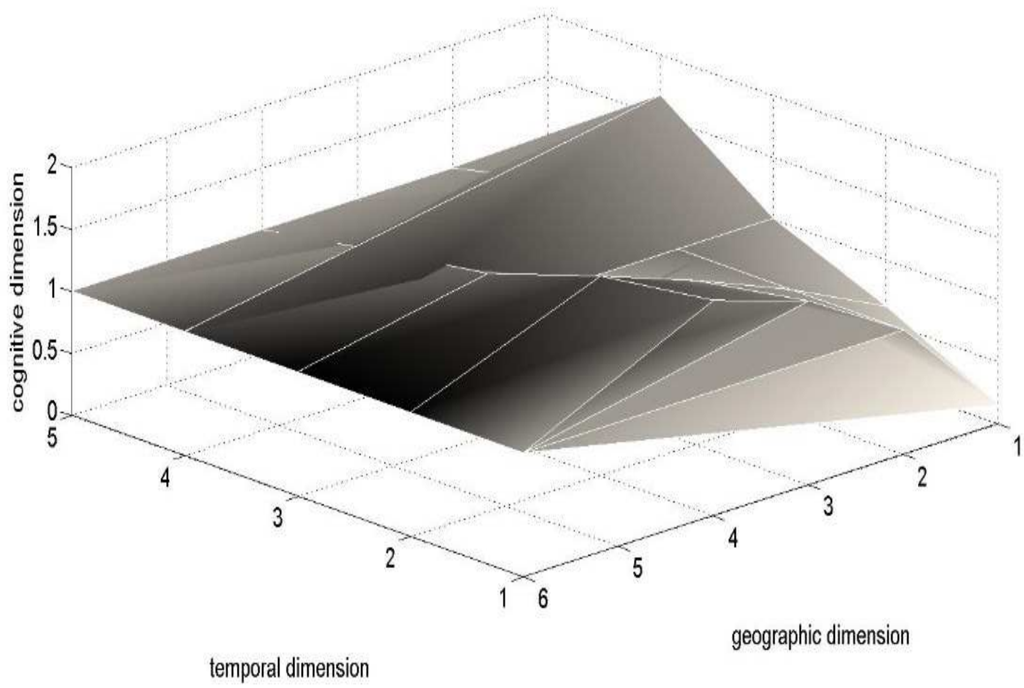

Figure 11: Three-dimensional external knowledge search space (Chinese licensee firms 2008-2010)

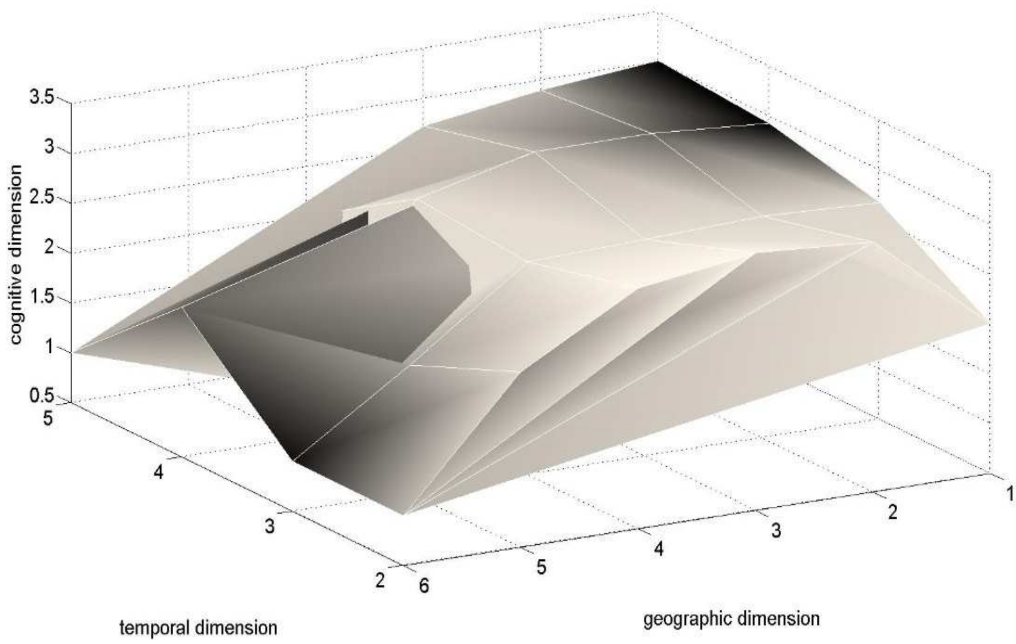

Figure 12: Three-dimensional external knowledge search space (Chinese licensee firms 2011-2013)

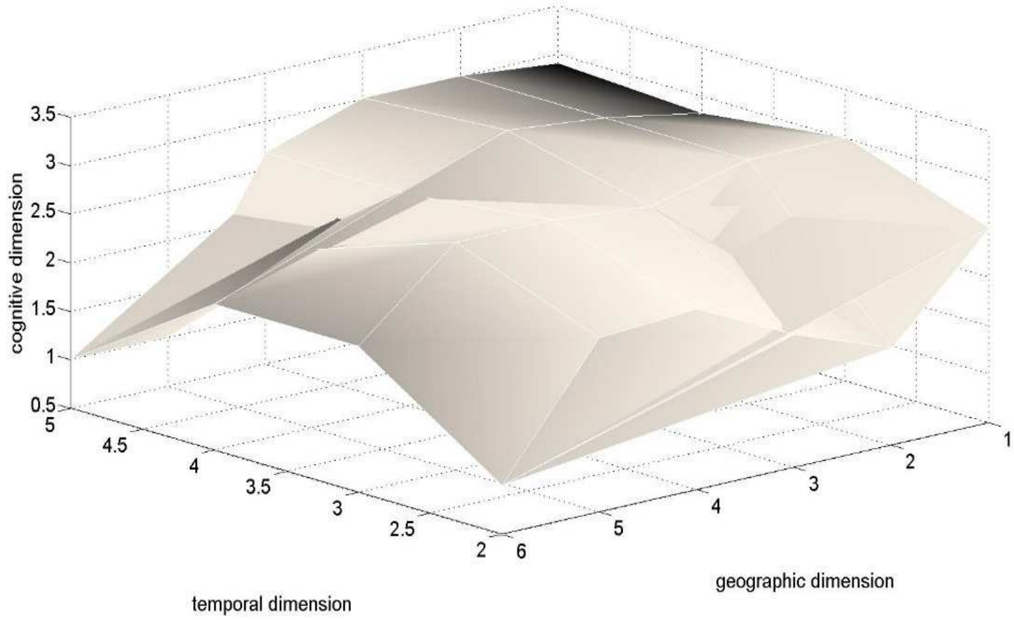

Table 1: Measurements of Cognitive distance

Licensor type	**Nr. of cases**	**Cognitive distance to licensee**
Firms	37723	1
Universities (higher-education institutes)	6744	5
Research institutes	2213	3
Firms **and** Universities (higher-education institutes)	144	3
Firms **and** Research institutes	39	2
Universities (higher-education institutes) **and** Research institutes	8	4
Total	46871	

Table 2: Descriptive statistics and correlations

Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Temporal distance	46871	4.221587	0.741535	1	5
Geographic distance	46871	2.282221	1.854275	1	6
Cognitive distance	46871	1.677455	1.430651	1	5

Table 3: OLS regression analysis (all Chinese licensee firms, 2000-2013)

Models	(1)	(2)	(3)
VARIABLES	Temporal dimension	Geographic dimension	Cognitive dimension
Temporal dimension		-1.319***	-0.267***
		(0.00956)	(0.0102)
Geographic dimension	-0.219***		-0.204***
	(0.00159)		(0.00409)
Cognitive dimension	-0.0538***	-0.248***	
	(0.00206)	(0.00496)	
Constant	4.812***	8.264***	3.273***
	(0.00618)	(0.0418)	(0.0491)
Observations	46,871	46,871	46,871
R-squared	0.289	0.315	0.051

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4: OLS regression analysis (all Chinese licensee firms, 2000-2007)

Models	(1)	(2)	(3)
VARIABLES	Temporal dimension	Geographic dimension	Cognitive dimension
Temporal dimension		-0.664***	0.00520
		(0.0318)	(0.00510)
Geographic dimension	-0.146***		-0.0256***
	(0.00702)		(0.00236)
Cognitive dimension	0.0494	-1.102***	
	(0.0484)	(0.102)	
Constant	4.024***	8.359***	1.137***
	(0.0670)	(0.146)	(0.0240)
Observations	4,049	4,049	4,049
R-squared	0.102	0.127	0.033

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5: OLS regression analysis (all Chinese licensee firms, 2008-2010)

Models	(1)	(2)	(3)
VARIABLES	Temporal dimension	Geographic dimension	Cognitive dimension
Temporal dimension		-1.278***	-0.386***
		(0.0179)	(0.0194)
Geographic dimension	-0.186***		-0.241***
	(0.00260)		(0.00727)
Cognitive dimension	-0.0609***	-0.261***	
	(0.00307)	(0.00787)	
Constant	4.724***	8.050***	3.975***
	(0.00992)	(0.0779)	(0.0911)
Observations	16,375	16,375	16,375
R-squared	0.239	0.270	0.064

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6: OLS regression analysis (all Chinese licensee firms, 2011-2013)

Models	(1)	(2)	(3)
VARIABLES	Temporal dimension	Geographic dimension	Cognitive dimension
Temporal dimension		-0.999***	-0.309***
		(0.0125)	(0.0144)
Geographic dimension	-0.196***		-0.169***
	(0.00244)		(0.00637)
Cognitive dimension	-0.0550***	-0.153***	
	(0.00257)	(0.00579)	
Constant	4.835***	6.537***	3.359***
	(0.00768)	(0.0565)	(0.0698)
Observations	26,447	26,447	26,447
R-squared	0.199	0.206	0.030

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1