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Technology stocks: A study on the characteristics that help transfer public research to industry

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ABSTRACT

Technology transfer from public research institutes and universities to industry is an effective way to promote social and economic development. However, although many studies have explored the various factors that affect technology transfers, few focus on the characteristics of an organization's technology stocks. In this study, we test which of technological diversity, uniqueness, combinative power, and proximity make a public research entity's knowledge stocks appealing. The study is set in the developing economy of China, using the research-subsidized Project 985 universities and the Chinese academy of sciences as the origins of public research. From an ERGM analysis, we find diversity and proximity have a significant positive effect; uniqueness has a significant negative effect; and combinative power has little to no effect at all. These insights have substantial theoretical implications for scholars in the technology transfer field and practical implications for public institutions engaged in research who are looking to improve their transfer rates.

1. Introduction

Researchers argue that technology transfers from the public sector to the private are influenced by entrepreneurship, the entity's working culture, the prevailing legal and regulatory environment, and many other organizational factors (Aldridge and Audretsch, 2011; Algieri et al., 2013; Bjerregaard, 2010; Steruska et al., 2019; Theodorakopoulos et al., 2012; Villani et al., 2017). However, in reality, technology transfer is also influenced by the characteristics of the technologies held on offer. For instance, Martin (2012) points out that technology transfer is more likely to occur between firms and research institutions with similar technologies, while Yu (2013) demonstrates that the diversity of an institution's knowledge stocks makes them a more appealing source of technology. There is debate, too, with Fisch et al. (2016) and Huang et al. (2013) contending that an over-diversified technology portfolio can be a deterrent to transfer. What is clear is that more research is needed to examine which characteristics of a technology promote transfer and which do not. To date, few studies have integrated such features into their analytical framework, let alone fully analyzed the effects of technological characteristics on technology transfer.

The properties and structure of an organization's knowledge stocks influence the usefulness of inventions and are a significant factor in an organization's ability to explore and exploit future innovation (Brennecke and Rank, 2017; Guan and Liu, 2016; Wang et al., 2019; Yayavaram and Ahuja, 2008). As more and more studies confirm that knowledge stocks play an important role in innovation outcomes, some scholars are beginning to analyze how these characteristics link with the innovation process (Brennecke and Rank, 2017). Technology is knowledge in tangible form, and technology transfer is a type of relationship related to knowledge diffusion. The relationships surrounding knowledge diffusion, such as citations, suggestions, and collaborations, are all informed by the knowledge stocks held by the parties concerned (Brennecke and Rank, 2017; Carnabuci and Operti, 2013; Guan et al., 2017). Further, the popularity of a research institution's overall knowledge stocks will likely determine its popularity as a technology transferor–that is, the extent to which firms want to buy its technologies. Therefore, to understand the technology transfer process, it is appropriate and necessary to consider the technological characteristics of an organization's knowledge stocks (Brennecke and Rank, 2017).

In addition, studies on technology transfer mainly focus on universities because of their significant contribution to technological development and innovation. However, public research institutes are another important source of research. Some strikingly self-describe their role as actors that help technologies cross the valley of death; others claim to fill

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the gap between basic research and development (Chen et al., 2017; Povoa and Rapini, 2010; Intarakumnerd and Goto, 2018). Yet, despite their importance, public research institutes have attracted less attention from scholars than universities (Zhang et al., 2016). We address this gap in the literature by including both universities and public research institutes in our sample. To avoid cumbersome language, however, we will refer to both with one all-encompassing term, public research institutions, i.e., PRIs. Our aim is to pinpoint whether technology stocks have particular characteristics that help to translate public research into private knowledge. In other words, we ask: What makes a publicly-conceived technology conducive to transfer?

The selected attributes of the organizations' technology stocks to be tested are diversity, uniqueness, combinative power, and technological proximity between the PRI and the firm. We applied an exponential random graph model (ERGM) to a two-mode network as our method of analysis (Jiao et al., 2017; Wang et al., 2009). ERGMs treat the observed network as the dependent variable and model the network structures in terms of endogenous effects (i.e., combinations of structural ties) and exogeneous effects (i.e., attributes of actors and ties) (Lusher et al., 2013).

The results show that diversity and proximity have a significant positive effect; uniqueness has a significant negative effect; and combinative power has little to no effect at all. These insights have substantial theoretical implications for scholars in the technology transfer field and practical implications for public institutions engaged in research who are looking to improve their transfer rates.

The rest of this article is organized as follows. Section 2 reviews the literature on factors influencing technology transfer and discusses the relationship between different technological characteristics and technology transfer. Section 3 introduces the data, the variables, and the estimation procedure. Section 4 presents the analytical results. In the last section, we discuss the main research findings and contributions of the study and highlight some limitations of this study.

2. Theoretical background and hypothesis development

2.1. Technological characteristics and technology transfer

Contemporary researchers tend to discuss the factors that influence technology transfer at three levels: individual, organizational, and environmental. At the individual level, scholars have mainly examined the role of scientists and investors. The two main barriers to technology transfer for scientists are their lack of entrepreneurial skills and insufficient capital. For investors, the difficulty is usually one of determining which technologies are valuable. In addition, technologies purchased from academic institutions must always be adapted to existing production lines, and this is commonly associated with high investment risk (Frank et al., 1996; Markham, 2002). At the organizational level, most studies focus on the cultural barriers between academic institutions and industry (Bjerregaard, 2010; Villani et al., 2017), the differences between various institutions (Bruneel et al., 2010), regulatory barriers (Jacobsson and Karltorp, 2013), and geographic distance (Minguillo and Thelwall, 2014). Interestingly, studies on some of the intermediary organizations, such as technology transfer offices, university incubators, science and technology (S&T) parks, and collaborative research centers, show that they have largely succeeded in bridging the cognitive and geographic distance between universities and industry (Alexander and Martin, 2013; Algieri et al., 2013; Steruska et al., 2019). At the ecosystem level, most of the literature pertains to law and policy, such as the famous Bayh–Dole Act of 1980 (Aldridge and Audretsch, 2011; Coriat and Orsi, 2002; Grimaldi et al., 2011; Kenney and Patton, 2009).

Sitting to the side of these levels is the technology itself, and, surprisingly, how the characteristics of an organization's technology stocks influence transfers has been less studied. Many articles emphasize the effect of knowledge stocks on social and relational capital (especially those on innovation systems), but few discuss the role played by the technology itself in the transfer. Yet it only makes sense that the structure and properties of an organization's knowledge stocks would play a very substantial role in its dissemination (Brennecke and Rank, 2017). In innovation management, there is a strong consensus that a single study, a single patent, one person, or one organization can have a huge influence on future opportunities and interactions, particularly in terms of knowledge sharing within and between organizations (Guan et al., 2017). Guan and colleagues demonstrated this by taking the knowledge elements of one study, represented by its keywords, and showing that the number of citations that study received was purely a function of the knowledge it contained. Similarly, Brennecke and Rank (2017) show that the knowledge stocks held by inventors can have a significant impact on the shape of a firm's advice network. Technological distance also affects the propensity for knowledge and technology transfer activities between universities and firms, as revealed in survey data and two case studies conducted by Martin (2012). However, these three studies are among the few that explore how specific characteristics of knowledge stocks influence knowledge sharing activities. More are needed.

In this study, we view technology transfer as a selection process where firms search for the technology they need. Thus, the PRI is simply a purveyor of wares, and a firm's decision on whether or not to buy is solely based on the features of the technology. Hence, that technological characteristics are a key factor in public to private technology transfers is the main assumption of this paper.

2.2. Attributes as influential factors

Many studies have examined the dimensions with which we might measure the attributes of scientific knowledge. Within these studies, there are two broad research designs: the first considers the individual elements of the knowledge stocks, while the second applies network theory.

In the first category, the measures tend to be simple macroscopic indicators of a knowledge portfolio, such as counts of knowledge elements, or the similarity in knowledge elements between two organizations (Brennecke and Rank, 2017; Fleming and Waguespack, 2007; Martin, 2012). Knowledge elements are often embodied in discrete artifacts such as patents, products, or scientific publications. In our study, the technologies indicate patents hold by organizations, and knowledge elements are represented by IPCs (International Patent Classifications). While useful for some purposes, these approaches tend to ignore the different combinative powers associated with knowledge. For example, computer knowledge is frequently combined with other knowledge, while agricultural knowledge is less integrated into other areas.

In the second category, the measures are drawn from network and social network theory, of which most pertain to the position of a knowledge element within a knowledge network. Network theory holds that position reflects function. For instance, a central element linked to many other elements usually has good combinative properties and so may be a key ingredient in future innovations (Chen et al., 2017), whereas an element with high betweenness may be an important interdisciplinary link. In a study of the scientific literature, Guan et al. (2017) find that papers with high centrality are cited more because the knowledge has combinative power and so is helpful to other researchers. Another approach taken is to trace the pathways of innovation, charting how knowledge elements rise, combine, split, and/or fade over time. Commonly, these evolutions are depicted as a series of networks, each representing a time slice of evolution (Guan and Liu, 2016; Phelps et al., 2012; Yayavaram and Ahuja, 2008).

These multi-dimensional characteristics of knowledge stocks have been identified as important factors influencing knowledge diffusion (Brennecke and Rank, 2017; Fleming and Waguespack, 2007; Guan and Liu, 2016; Guan et al., 2017; Yayavaram and Ahuja, 2008). However, to fully understand whether and how a technology's characteristics affect its transfer, we have selected four attributes that span both categories.

These are diversity, uniqueness, combinative power, and proximity (Brennecke and Rank, 2017; Chen et al., 2017; Fleming and Waguespack, 2007; Guan and Liu, 2016; Guan et al., 2017; Yayavaram and Ahuja, 2008). The first three are discrete measures, the last is comparative, and each is discussed in greater detail in the next section.

2.3. Hypothesis development

2.3.1. Diversity

Technological diversity refers to the variety of technological areas an institution has strength in Brennecke and Rank (2017) and Fleming and Waguespack (2007). More simply, it can be understood as the variety of knowledge elements an entity holds. Some organizations are highly specialized. They develop technologies within a narrow spectrum and connect them to only a small number of knowledge elements in a network. By contrast, others hold a variety of different knowledge elements in technologies that span many disciplines (Brennecke and Rank, 2017). Some scholars identify diversity as one of the most important factors affecting technology transfer. For example, Liu et al. (2015) assert that high diversity is vital in technological innovation, as recombining diverse knowledge from others is the avenue most likely to lead to innovation. According to Yu (2013), technological innovation is a process of recombining existing knowledge to solve current problems. Firms need to continuously acquire diverse and unique technologies and then combine them in different ways giving rise to something new to maintain their competitive advantage. Accordingly, PRIs with high diversity should be better situated to industry's demand for technology. Likewise, firms should be more likely to acquire technology from such PRIs. In addition, diversity can improve a firm's ability to quickly absorb external technologies, especially when acquiring unfamiliar technologies (Moreira et al., 2018). Thus, a firm with high diversity is more likely to become a technology transferee.

However, not all scholars agree that high diversity will have a positive influence on technology transfer. Sampson (2004, 2007), for instance, argues that high diversity will lead to more time and money spent negotiating and solving problems, which both parties want to avoid. He also points out that a firm's ability to absorb technology is limited and that diversity in a PRI increases the complexity of identifying and developing new technologies suitable for the firm. Therefore, the impact of diversity on a PRI's technology transfer is related to a firm's ability to bear the time and money devoted to identifying or developing suitable new technologies. In other words, if the transferee is a small firm with limited time and money to search for new technologies, high diversity may reduce the chances of PRIs becoming technology transferors. Considering these arguments, we propose Hypotheses 1 and 2:

Hypothesis 1. A PRI's technological diversity positively influences its appeal as a technology transferor.

Hypothesis 2. A firm's technological diversity positively influences its tendency to become a technology transferee.

In this study, "appeal" refers to the possibility that a PRI will be selected as a technology transferor by firms, and "tendency" refers to the possibility that a firm will decide to buy technology from a given PRI.

2.3.2. Uniqueness

Technological uniqueness refers to strengths in areas of technology that other organizations do not have (Brennecke and Rank, 2017). In network terms, organizations with unique knowledge are typically among the few or only organization connected to a knowledge element (Brennecke and Rank, 2017).

Prior studies interpret the value of uniqueness differently. Far from confusing the issue, these different perspectives help us to understand the influence of uniqueness on technology transfer from different angles. For example, studies based on social network theory show that unique resources can be some of the most valuable resources for individuals or organizations (Granovetter, 1973; Burt, 1992). An empirical study by Schulz (2001) demonstrates that the more unique the experience or knowledge of a unit compared with its peers, the stronger its outflows of knowledge. Therefore, an institution with a unique strength may attract greater attention from industry. In turn, this may translate to greater opportunities to transfer their technology (Brennecke and Rank, 2017). However, there are scholars on the opposite side of the debate who believe that uniqueness could indicate a lack of importance or value (Brennecke and Rank, 2017; Yayavaram and Ahuja, 2008; Zhang et al., 2016). If this should prove true, uniqueness would likely make a PRI's knowledge stocks less attractive to industry. Considering these arguments, we propose Hypothesis 3:

Hypothesis 3. A PRI's technological uniqueness negatively influences its appeal as a technology transferor.

2.3.3. Combinative power

While diversity and uniqueness depend on an entity's position in the knowledge network relative to other organizations, combinative power relates to the technology's position relative to other technologies (Brennecke and Rank, 2017; Carnabuci and Bruggeman, 2009). Social network theory holds that different positions of nodes within a network have different abilities to access new information and resources (Burt, 1992). For example, consider a knowledge network where the nodes denote the industry classification of a patent and the edges represent patents coded to two classifications. It is in these edges that we find combinatorial knowledge, and the more links that are or could be created, the greater the combinative power.

The combinative power of a knowledge element also varies depending on its combinatorial history, which is usually reflected by two social network analysis indicators: structural holes and degree centrality. Brennecke and Rank (2017) divide the combinative power of a knowledge element into opportunities and potential–the structural holes represent opportunities and degree centrality represents potential–-whereas Guan and Liu (2016) and Zhang and Luo (2020) only consider potential as measured by degree centrality. However, Guan et al. (2017) subsequently revise this definition to include opportunities, relying on both degree centrality and structural holes as measures. We believe that both are important considerations and that, for our purposes, the distinctions between the two are too fine to warrant splitting the category. Hence, our measure does not distinguish between current and potential opportunity.

The knowledge elements held by firms and PRIs are not usually the same. Hence, they vary in their combinative power. However, despite their different approaches, Guan and Liu (2016), Brennecke and Rank (2017) and Guan et al. (2017) all agree that inventors with low combinative power will seek external technologies from organizations or inventors with high combinative power. Hence, we propose Hypotheses 4 and 5:

Hypothesis 4. The average combinative power of a PRI's technological elements positively influences its appeal as a technology transferor.

Hypothesis 5. The average combinative power of a firm's technological elements negatively influences its tendency to become a technology transferee.

2.3.4. Proximity

Unlike the three other indicators, technological proximity is a comparative dimension. It measures the similarities between the technological backgrounds of the firm and PRI (Brennecke and Rank, 2017). Martin (2012) states that technological proximity determines whether a firm and a PRI speak the same language. If they do, the chances of a successful collaboration improve. It is thought that having a similar technological orientation to one's technology partner(*s*) enables each organization to better perceive, process, and apply external knowledge.

Ostas (2003) and Boschma and Ter Wal (2007) also stress the importance of sharing common technological elements when attempting to absorb new technologies to reduce communication costs. In line with the above arguments, we propose Hypothesis 6:

Hypothesis 6. The technological proximity between firms and PRIs has a positive influence on technology transfer between them.

3. Data and methods

3.1. Empirical context and data

To test our hypotheses, we conducted this study in China's S&T innovation system. The sample of institutions comprised research institutes affiliated with Chinese Academy of Science (CAS) and "Project 985" universities. These are universities that receive special government support for their research activities under the banner of Project 985's goal for China to cultivate world-class universities in the 21st century.

We chose China as a context for three reasons. First, this is an innovation ecosystem in which both universities and public research institutes play important role (Chen et al., 2017; Liu and White, 2001). In many national innovation systems, universities are the dominant driving force behind technological advancement. However, while the same is true of China, the Chinese government only began to undertake serious investment in university research in the late 1980s. Since then, government funding for university research has increased at a compound annual growth rate of 15%–a sustained rate rivaled only by the US in the post-Sputnik era (Chen et al., 2016). Consequently, public research institutes like CAS have played, and continue to play, a stronger role in technological progress than perhaps in other countries. According to the China Statistical Yearbook on Science and Technology 2017,[1] public research institutes in number and their scientific outputs in share accounted for more than 50% of China's innovation system. However, compared to universities, public research institutes have attracted rather limited attention by innovation scholars, with many studies on technology transfer excluding PRIs from their analysis (Decter et al., 2007; Intarakumnerd and Goto, 2018; Povoa and Rapini, 2010; Theodorakopoulos et al., 2012; Villani et al., 2017; Zhang et al., 2016). Hence, to explore the transfer of all types of public research into private knowledge, we must examine both universities and public research institutes.

Second, Project 985 universities are particularly strong in scientific research and are counted among the highest technology transferors in the world (Chen et al., 2016). Moreover, they work closely with private enterprise and use their scientific research achievements to help industrial development (Zhang et al., 2013). Funded and implemented by the government of the People's Republic of China, Project 985 was launched on May 4th, 1998 (Jiang et al., 2020) with seed funding for a set of 39 universities to expand their research footprint and impact on the world. Today, 985 universities are listed in the program as comprehensive universities focusing on basic and applied research. According to the Yearbook, 60% of all invention patents held by Chinese universities are held by Project 985 universities. As shown in Fig. 1, Project 985 universities have sustained rapid growth in granted patents for over a decade, and their total number of technology transfers has also remained at a high level.

Third, CAS is one the largest and most prominent public research institutes in the world. It maintains close relationships with industry through joint research and commercializing their technologies (Chen et al., 2017). CAS was established on November 1, 1949 and has since contributed substantially to the country's drive to explore and harness advanced technologies and the natural sciences for the benefit of China. Today, it houses 104 research institutes, bringing together every scientific discipline, including physics, chemistry, materials science, mathematics, environment and ecology, earth sciences, and beyond. Within CAS, there are 39 technology transfer/incubation centers and more than 250 joint research entities that together have participated in more than 10,000 technology transfers. As Fig. 1 shows, CAS has also sustained rapid growth in granted patents for over a decade. The trends for growth in technology transfers, though, may be misleading. Although the data shows that transfers for CAS peaked between 2008 and 2013, this is a process that takes some time. So, an analysis of the period post-2014 conducted in years to come may show a very different picture.

Another reason for choosing China and CAS is that CAS has a self-developed professional intellectual property information platform called the CAS intellectual property database, which includes information on all patents invented by CAS researchers.[2] This database records complete and detailed transfer history of patents, making it an ideal data source to study. For these reasons, CAS provides its own sufficient sample size and is an excellent subject for this study.

In line with previous studies (Brennecke and Rank, 2017; Wang et al., 2019; Yayavaram and Ahuja, 2008), we used patent data for our analysis. Not only are patents a mainstay for both firms and PRIs to protect their technology stocks, they are already classified into technical fields via International Patent Classification codes (IPC codes). Moreover, patents are the main means of technology transfer for PRIs (Bosworth and Yang, 2000). This is known because, according to China's patent law, patent documents must include a detailed history of transferred patents.

Our collection process began with patents listed in China's State Intellectual Property Office (SIPO)[3] and the CAS intellectual property database and followed four steps to result in three different datasets. The stepwise results of the collection and cleaning process and the configuration of the three different datasets is outlined in Table 1a and 1b.

3.2. Variables and measures

To begin trying to understand the relationships in the sample, we loaded all the variables into a network analysis model. The full transfer network was the dependent variable, and the four technological attributes were the independent variables. We controlled for research strength, age of organization, geographic proximity, collaborations, and endogenous effects. Fig. 2 presents a schematic representation of the model. Explanations of the measurement of the variables follow.

3.2.1. Dependent variable

The transfer network: This technology transfer network is a two-mode network with two types of nodes: PRIs and firms. Each connection represents one transfer of a patent from a PRI to a firm; thus, technology transfers are represented as directed edges from a specific PRI to a specific firm. Each edge was recorded dichotomously and arranged in a 76×367 binary adjacency matrix $X = \{x_{ij}\}$, in which cell x_{ij} corresponds to the relation of PRI i to firm j. If j acquired a patent from i, cell x_{ij} was coded as 1, and 0 otherwise.

3.2.2. Independent variables

The four independent variables we wish to test the influence of are diversity, uniqueness, combinative power, and proximity, i.e., our selected set of technological attributes. However, not only do the nodes represent different entities, but there are no connections from PRI to PRI or firm to firm; the only connections are between PRIs and firms. We therefore applied a two-mode exponential random graph model (ERGM) to conduct the analysis. We also constructed a knowledge network charting the combinative history of the knowledge elements. The

[1] http://www.stats.gov.cn/tjsj/tjcbw/201810/t20181024_1629501.html Hereafter, referred to as "the Yearbook".

[2] http://www.casip.ac.cn/.

[3] http://english.cnipa.gov.cn/.

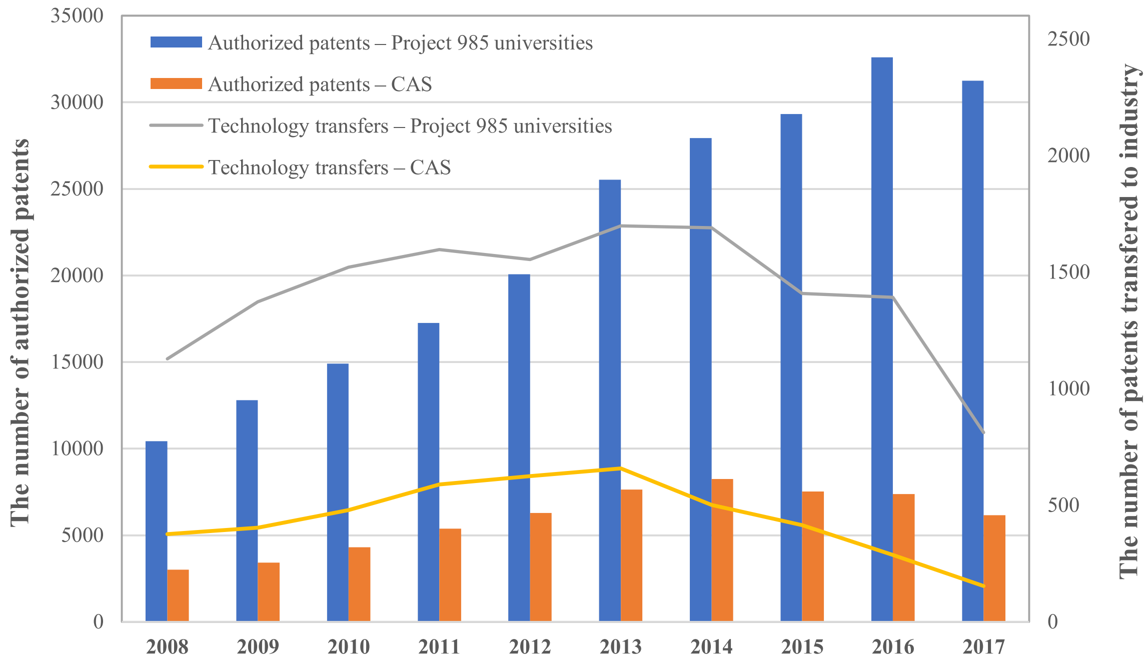


Fig. 1. The number of patents and patents transfers to industry (2008–2017).

Table 1a
Stepwise data collection.

	No.	Dataset
No. patents granted to Project 985 universities/CAS institutes 2008–2017	281,478	
No. patents subsequently transferred to another entity	21,063	
No. patents transferred to private enterprise	19,331	Dataset 1
No. of entities in Dataset 1 (33 universities, 43 CAS, 367 firms)	443	
No. patents in SIPO held by these 443 entities	365,058	Dataset 2
No patents held by these entities that have not been transferred	345,727	Dataset 3

attributes were then calculated for each firm, PRI, and pair. Diversity, uniqueness, and combinative power were treated as attributes of the entity, i.e., continuous variables, while proximity was treated as a dyadic covariate.

The knowledge network was constructed following Brennecke and Rank (2017). The industry coding system used was the 4-digit IPC (IPC4) codes (610 in total), with a link connecting two industry codes assigned to the same patent. Organizations and industry codes were connected if an entity had ever held a patent with that code.

The next step was to calculate the values of the four attributes. Most of the calculation methods were informed by Brennecke and Rank (2017).

Diversity. Technological diversity was measured using the *Herfindahl–Hirschman Index* (*HHI*), which essentially estimates an organization's diversity according to the number of IPCs attached to their patents. However, because a simple count does not reflect the importance of each technology to an organization, the index includes a weight that takes into account the proportion of one IPC4 to all of the other IPC4s in the organization.

HHI is commonly used to measure market concentration and is calculated by squaring the market share of each firm competing in a market and then adding the results (Kvålseth, 2018). Wang et al. (2019), however, found that applying the reciprocal of the *HHI* to patent portfolios gives a better reflection of an organization's technological diversity. Unlike the method used by Brennecke and Rank (2017), the reciprocal of *HHI* considers the share of each IPC4. Hence, the technological diversity of organization i (TD_i) is defined as follows:

$$TD_i = 1 \Big/ HHI = 1 \Big/ \sum_{j=1}^{n} \left(\frac{p_j}{p}\right)^2 \tag{1}$$

where n is the total number of IPC4s for organization i, p_j is the number of patents held by organization i belonging to IPC4 j, and p is the total number of patents held by organization i. The higher the TD_i, the more technologically diverse the organization.

Uniqueness. An organization's technological uniqueness depends on the frequency with which each organization connects to an IPC4. By deduction, it then holds that a technology's uniqueness can be measured by how many organizations connect to an IPC4. In line with Brennecke and Rank (2017), the uniqueness of IPC j (UTE_j) is defined as follows:

Table 1b
Dataset statistics.

	No. of firms involved in patent transfers with the sample institutes	Total no. of patents held by these firms *(Dataset 2)*	No. of patents transferred from the sample to industry *(Dataset 1)*	Dataset 3 = Dataset 2 - Dataset 1
CAS	43	59,357	19,331	345,727
985 university	33	222,121		
Industry	367	83,580		
Total	443	365,058		

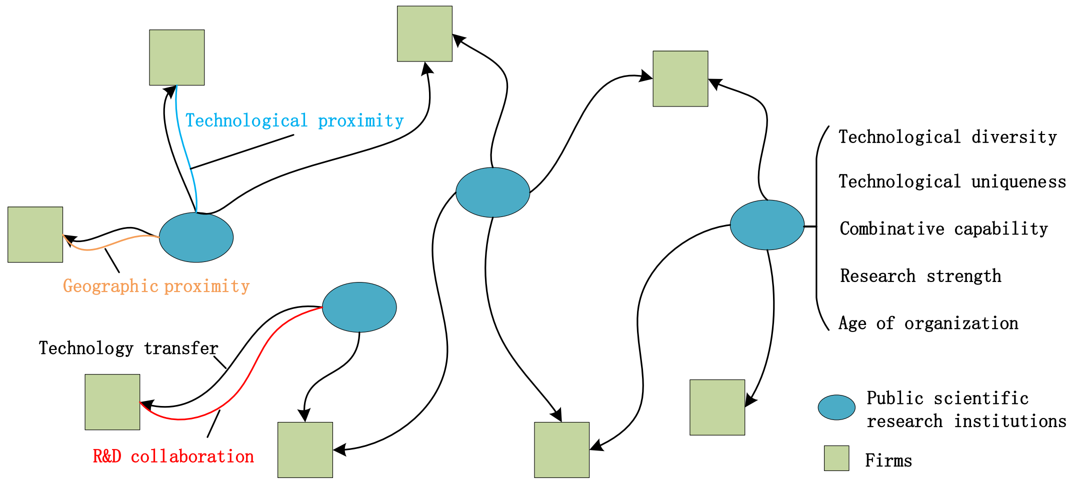


Fig. 2. Schematic representation of the network analysis model.

$$UTE_j = \frac{1}{\sum_{1}^{n=443} x_i} \tag{2}$$

where $n = 443$ is the total number of organizations (76 PRIs and 367 firms). If organization i is connected to IPC4 $j, x_i = 1$, and 0 otherwise. In other words, UTE_j is the reciprocal of the number of firms and PRIs with an interest in IPC4 j. The technological uniqueness of organization i (TU_i) is then calculated from the average uniqueness of all IPC4s related to organization i as per Eq. (3):

$$UT_i = \frac{\sum_{j=1}^{m} UTE_j}{m} \tag{3}$$

where m is the total number of IPC4s connected to organization i. The higher the UT_i, the more unique the organization's technology i.

Combinative power. Similar to uniqueness, the combinative power of an organization is based on the combinative power of its IPC4s. Hence, this indicator is calculated by combining the weighted degree centrality (*WDC*) and structural holes (*SH*) filled by the IPC4 *j*. *WDC* reflects both the number of co-occurring IPC4s in the organization's knowledge stocks plus the number of times those combinations have been made (Brennecke and Rank, 2017). An IPC4 spans a structural hole if it links two elements that are not directly connected, i.e., if it acts as a bridge between two technologies. Thus, the combinative power of IPC4 *j*, i.e., $CPTE_j$, is calculated as follows:

$$CPTE_j = WDC_j + SH_j = \sum_{k=1}^{p} l_{jk} + 2 - c_j \tag{4}$$

where p is the total number of IPC4s connected to IPC4 j in the knowledge network, and l_{jk} represents the weight of the edge between nodes i and j, i.e., the number of times these two IPC4s co-occur in different patents. c_j is a constraint proposed by Burt (1992) that reflects the control advantages j creates by spanning structural holes. Following Wang et al. (2019) and Guan and Liu (2016), c_j is calculated by 2 min a count of the structural holes bridged.

With the combinative power of each IPC4 calculated, the combinative power of the organization's full knowledge stocks is taken as the average:

$$CP_i = \frac{\sum_{j=1}^{m} CPTE_j}{m} \tag{5}$$

where m is the total number of IPC4s connected to organization i. The higher the CP_i, the greater the combinative power of organization i's technologies.

Proximity. Prior studies have tended to measure technological proximity by the number of shared IPC4s (Brennecke and Rank, 2017). However, this method does not account for differences in the importance of specific IPC4s to each organization. Consider, for example, an IPC4 shared by a PRI and a firm. For the PRI, this is its primary technology area covering dozens of patents while, for the firm, that technology is counted in only one of the many patents it holds. To better understand this problem, we examined the distribution of patents held by firms across different technology areas. Taking one example, Semiconductor Manufacturing International Corporation (Beijing) holds patents across 51 IPC4 codes. But 81.6% of its patents are concentrated in one technological area and the remaining 18.4% are scattered across the other 50. To avoid problems in this respect, we used the cosine similarity method to calculate the technological proximity between PRI i and firm j (Kryszkiewicz, 2014; Lahitani et al., 2016):

$$TP_{ij} = \cos(X, Y) = \frac{X \cdot Y}{|X| \cdot |Y|} \tag{6}$$

where $X_i = (x_1, x_2, \ldots, x_{n=610})$ and $Y_j = (x_1, x_2, \ldots, x_{m=610})$ are two vectors of 610 dimensions that respectively represent the IPC4 distributions of the knowledge stocks of PRI i and firm j. Each dimension x_n in vector X is the number of patents held by PRI i that belong to IPC4 n, and likewise for y_n and firm j. The resulting values, falling into the range of 0–1, were then converted into either 0 or 1–1 if TP_{ij} was ≥ 0.5 and 0 otherwise, where 1 means the PRI and firm have proximity and 0 means they do not. This conversion is necessary because, when using ERGM to analyze a dyadic covariate, one cannot use continuous values directly. Instead, the values must be binary and drawn from a matrix (Park et al., 2009).

3.3. Control variables

We included four control variables in the analysis as follows.

Age of organization (*AO*): We hypothesize that the age of an organization may affect their decisions and behavior in technology transfer. Old PRIs are better known, so they have more appeal as a transferor. However, a mature firm may have enough capital and researchers to develop new technologies by themselves, so they are less inclined to buy technologies.

Research strength (*RS*): Research strength has been shown to be a key factor in technology transfer and may also positively influence an organization's appeal as a transferor/transferee (Caldera and Debande, 2010). We used the logarithm of the number of patents to measure this indicator for both types of organizations.

Geographic proximity (*GP*): Our results support the argument that if a PRI and a firm are located in the same province, they are more likely to meet. Also, they will face less political resistance to transferring technology than if they are in different provinces (O'Shea et al., 2005; Wu, 2013). Belonging to the same province is a dyadic attribute of an organization pair.

Research and development collaboration (*R&D C*): Santoro and Chakrabarti (2002) and Lai (2011) propose that R&D collaboration is both complementary and a "bridging industry" where universities/PRIs transform knowledge into new technologies. In turn, these technologies flow to industry. Thus, PRIs may be more likely to transfer their patents to firms with which they have previously collaborated. We controlled for R&D collaboration by considering the co-inventors listed on previous patents as a dyadic attribute.

In addition, the technology transfer network analyzed violates the assumption of sample independence conventional to traditional regression analysis. In testing for the interdependencies between relations, we controlled for the simplest form of dyadic dependency (edges), which is the general tendency of organizations to transfer technologies and, hence, create a connection in our network (Brennecke and Rank, 2017). Further, to better understand the degree centralization in the network, we added 2-star, 3-star, and Alternating-star parameters into the model. These effects reflect the fact that the ties in this network are rarely evenly distributed and so control for the degree of imbalance (Brennecke and Rank, 2017; Robins et al., 2009).

3.4. ERGM analysis

We selected ERGM as the analysis model because it provides good results with two-mode networks, (Dubnjakovic, 2016; Jiao et al., 2017; Robins et al., 2007; Wang et al., 2009). Formerly known as p* models, ERGMs were first proposed by Wasserman and Pattison (1996) as a means of analyzing networks with more than one type of node or relationship, such as ours where some nodes represent public transferors and other nodes represent private transferees (Robins et al., 2009; Wang et al., 2009; Wang et al., 2013). They can be used to analyze many different types of networks, such as directed and nondirected networks, bipartite and multiplex networks, etc. To date, ERGMs have been empirically applied to social networks (Lazega and Pattison, 1999; Lubbers and Snijders, 2007), citation networks (Gondal, 2011), multicultural research collaborations (Sayogo et al., 2011), organizational information seeking (Johnson et al., 2012; Su and Contractor, 2011), and medical innovation (Zappa and Mariani, 2011).

ERGMs treat the entire network as the dependent variable and model the network structure in terms of both endogenous effects, i.e., combinations of structural ties, and exogeneous effects, i.e., the attributes of the nodes and edges (Lusher et al., 2013). In our case, analyzing the influence of the four characteristics and determining how the network was originally formed are one in the same task. This is because ERGMs reveal which attributes increase the probability of creating an edge, i.e., which attributes increase the likelihood of a technology transfer. They also reveal how appealing the PRI becomes to a firm or how likely a firm is to want to participate in technology transfers with PRIs. In addition, because diversity, uniqueness, and combinative power are continuous variables, but attributes of ties such as proximity and collaboration are dyadic covariate, ERGMs allow us to more intuitively examine the interactions between them. Table 2 summarizes the effects included in this study.

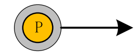
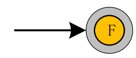
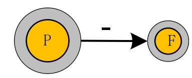
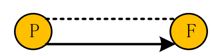
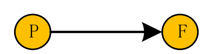
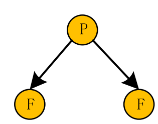
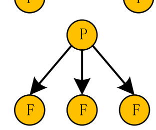
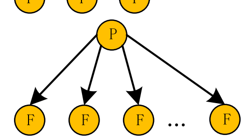
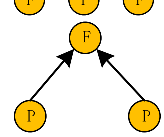
Following the general form of ERGMs (Robins et al., 2007), we constructed our model as follows:

$$\Pr\ (X = x) = \frac{1}{k}\exp\left\{\sum_{A}\eta_A g_A(x)\right\} \tag{7}$$

where X denotes the transfer network, $g_A(x)$is a network statistic counting the number of network effects of type A, η_A is the parameter corresponding to the network statistic $g_A(x)$, and k is a normalizing quantity to ensure that $Pr\ (X = x)$ has an appropriate probability distribution.

With this formulation, if parameter η_A of effect A is significant and positive, the characteristics/controls influence over the formations of technology transfer network is positive. To estimate our model, we followed Snijders et al. (2006) and Brennecke and Rank (2017) and used Markov Chain Monte Carlo Maximum Likelihood (MCMCML) estimation, implementing the model in MPNet (http://www.melnet.org.au/pnet), a statistical analysis program for ERGMs (Wang et al., 2009).

Table 2
Effects included in our ERGM.

Types of variables	Variables	Effects and visualization	Interpretation
Entity attributes	Diversity	 Attribute_P_sender	The tendency for a PRI with a high/low value of a particular attribute to be popular as a technology transferor.
		 Attribute_F_receiver	
	Uniqueness		The tendency for a firm with a high/low value of a particular attribute to be popular as a technology transferee.
	Combinative power Age of organization Research strength	 Attribute_Difference	Technology transfer is more likely to occur between PRIs and firms that have a different degree of a particular attribute.
Exogenous contextual factors	Proximity Geographic proximity R&D collaboration	 Attribute_edge	The tendency for technology transfers to co-occur between PRIs and firms connected in another network.
Endogenous effects	Edge		Basic propensity toward technology transfers.
	2-star-P		The tendency for PRIs that have already transferred many technologies to transfer more technologies.
	3-star-P		
	Alternating-star-P		
	2-star-F		The tendency for firms that have already purchased many technologies to purchase more technologies.

Note. P = PRIs and universities; *F* = firms.

4. Empirical analysis and results

4.1. Descriptive results

Table 3 presents the descriptive statistics and the correlations between variables. As shown in Fig. 3, the average number of patents held across all organizations is of 660.49 with 1.76 average collaborations between firms and PRIs. From the two distinct regions in the figure, PRIs clearly hold many more patents in many more IPC4 codes than firms. Fig. 4 presents the three network diagrams used as the basis of our analysis, i.e., knowledge, transfer, and IPC4-organizations network.

4.2. ERGM results

Table 4 reports the ERGM results of the transfer network analysis. Conditional on all other patterns in the model, a positive (negative) parameter indicates that a pattern is observed more (less) often than we would expect if the ties emerged randomly (Brennecke and Rank, 2017).

Regarding Hypotheses 1 and 2 and the impact of diversity on technology transfers, the results show that diversity has a significant positive affect on the appeal of PRIs as transferors (exp (8.2682) = 3897), but not on firms as transferees (exp (11.7808) = 130,718). Hence, Hypothesis 1 is supported, but Hypothesis 2 is rejected. Concerning Hypothesis 3 and technological uniqueness, again, the results were significant and positive for PRIs (exp (-10.6401) = 0.0000239) but not for firms (exp (-10.6401) = 0.020). Thus, Hypothesis 3 is supported. The results for combinative power (Hypotheses 4 and 5) show neither to be significant. Thus, the generalizability of a technology holds little appeal, and Hypotheses 4 and 5 are rejected. Finally, regarding Hypothesis 6, technological proximity was significant and positive (exp (0.9791) = 2.662), which suggests that technological proximity is a necessary condition for technology transfer. Hence, Hypothesis 6 is supported.

Some of the control variables also had a significant influence. Initially, we expected that the age of a firm may have significant negative influence on its tendency to become a transferee. Our reasoning was that, to compete in the market, firms would need to rely more on external existing technologies at the beginning of the entrepreneurial journey, but this reliance would gradually lessen as the enterprise grew with age. However, the results were not significant. This led us to explore research strength as a better fit for this thinking, and the results bear this out. Research strength was significant and positive for PRIs (exp (0.0001) = 1.000), while research strength was significant and negative for firms (exp (-0.0004) = 0.999). This shows that a PRI with good research strength is more likely to be selected as a transferor, while firms with low research capacity are more likely to import external technologies. The results for collaborations and geographic proximity were also significant and positive (R&D C _Edge = exp (4.9814) = 145.678; GP_Edge = exp (2.2091) = 9.108) indicating that previous R&D partnerships and being located in the same province can each increase the probability of technology transfer. Finally, we find that the endogenous network effects (2-star-PRIs, 2-star-firms, 3-star-PRIs and Alternating-star-PRIs) all have a significant influence on the formation of the transfer network.

4.3. Goodness of fit

From 5,000,000 simulated networks, we randomly sampled 3000 graphs to conduct goodness of fit tests with. The graph statistics used for the tests were drawn from Wang et al. (2013), the implementation software was MPNet (Wang et al., 2009), and the method followed Hunter et al. (2008) where sample networks and observed networks are compared using t-ratios. A small t-ratio indicates and adequate fit for that statistic. Generally, for the statistics modeled with an ERGM, the absolute value of the t-ratios should be less than 0.1 to demonstrate that the model has converged. For other network statistics, t-ratios of less than 2.0 indicate an acceptable fit (Robins et al., 2009; Wang et al., 2009).

As presented in Table 5, the results for all effects estimated in the model show a good fit with two exceptions, these being 3-star-Firms and Alternating-stars-Firms. Hence, the degree distribution of the firms (stddev_degreeX_F) is poorly fit. However, the model also failed to reproduce the basic four cycles (4-Cycle), hence the clustering coefficients of transfer network didn't fit well. Further, when the parameters for the 3- and Alternating-star-Firms were included, the model would not converge. Nor would it converge with 4-Cycle included. From this we can only conclude that our model performs poorly overall with the connections to firms. Acknowledging that the model has limitations, we still feel it is serviceable enough to use for interpretation (Wang et al., 2009).

4.4. Robustness check

Recognizing that our method for measuring technological proximity accounts for differences in the importance of IPC4s to each organization, whereas Brennecke and Rank's (2017) method does not, provided a good opportunity to conduct a robustness test of our results. The results appear in Table 6, noting that TP Brennecke and Rank's (2017)_edge is a count of the IPC4s shared between PRI-firm pairs. The effect is still significant and positive (exp (0.577) = 1.781) but weaker with the Brennecke and Rank (2017) method.

5. Discussion and conclusion

5.1. Main findings

The aim of this paper was to explore which characteristics of an organization's knowledge stocks influence technology transfers from the public sector to industry. To this end, we conceptualized the relationship between technological attributes and technology transfer as a network model and analyzed how diversity, uniqueness, combinative power, and proximity influence the formation of a technology transfer network. Using patent data from China, we find that diversity and proximity have a significant positive influence; uniqueness has a significant negative influence; and combinative power has little to no influence.

First, we find that technological diversity in makes PRIs more appealing to firms as a source of technology. The more diverse a PRI's technology stocks, the more likely they are to be selected as a transferer. We also find that a firm's technological diversity has no affect on its motivation to acquire new technologies. Hence, our results are not

Table 3
Descriptive statistics and correlations.

Variables	Mean	Std. dev.	1	2	3	4	5	6
1. Research strength	660.49	1943.11	1					
2. Diversity	48.89	92.26	0.89**	1				
3. Uniqueness	1.22	2.97	0.92**	0.97**	1			
4. Combinative power	13.06	5.17	0.65**	0.80**	0.69**	1		
5. Age of organization	20.55	27.1	0.66**	0.80**	0.74**	0.70**	1	
6. R&D Collaboration	1.76	4.13	0.78**	0.74**	0.77**	0.56**	0.54**	1

$N = 443$. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

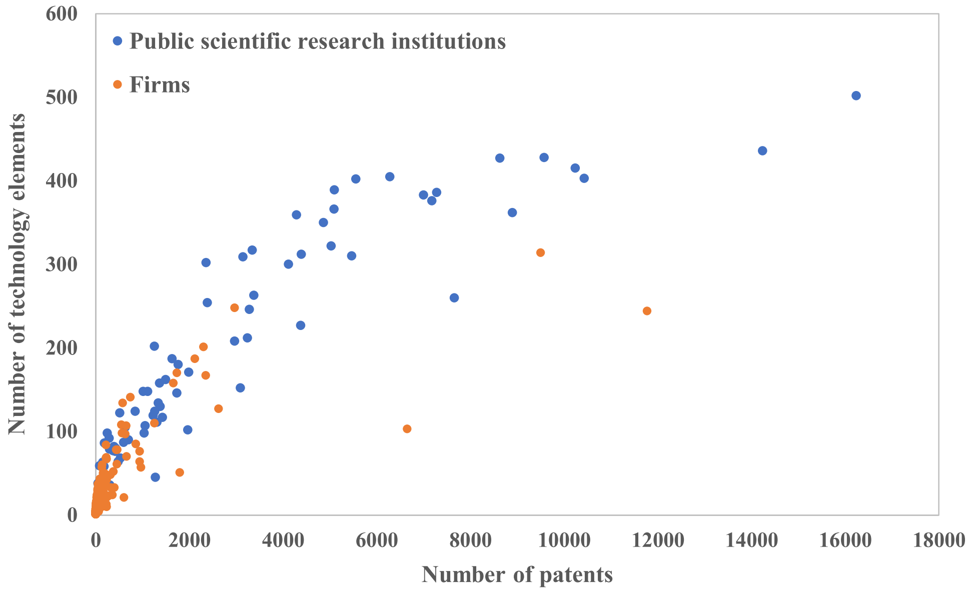


Fig. 3. The number of patents and IPC4s by entity.

consistent with the proposition of Sampson (2004, 2007) that high technological diversity might increase the difficulty of finding suitable new technologies from PRIs or that small firms cannot afford the greater search costs. However, the results are consistent with Liu et al. (2015) and Yu (2013), who argue that diversity is vital for the re-innovation of firms and that firms need to continuously acquire diverse technologies, combining them in new and different ways, to maintain market advantage.

Moreover, this finding appears to link to two further findings – one, that combinative power has little effect on transfers for either PRIs or firms and, two, that most transferees are small firms with limited R&D capability. It therefore makes sense that generalizability would not be a factor as they have no capacity to absorb and re-apply new technologies. In a similar vein, the underlying appeal of diversity must not lie its ability to drive re-innovation. Brennecke and Rank (2017) assert that diverse knowledge can help increase an inventor's relevance to many audiences. Our results lead us to a similar conclusion – that diversity may be merely a way to win the numbers game. In other words, the more technologies one has in its stable, the greater the probability someone will find something they want. Overall, given a network containing many small firms, diversity will promote technology transfer so, if most of the PRIs in the transfer network have high diversity, the network should turn out to be dense with transfers.

Second, uniqueness reduces the likelihood of transferor for PRIs. This finding contradicts Granovetter (1973) and Schulz (2001), who contend that uniqueness is a symbol of value, i.e., the more unique the knowledge, the stronger its appeal. Rather, the other side of the debate appears to win the day, i.e., that uniqueness is a sign that a technology holds little value (Brennecke and Rank, 2017; Yayavaram and Ahuja, 2008; Zhang et al., 2016). Unique technologies may benefit the daily research activities of PRIs, but, from a market perspective, unique technologies carry a high degree of uncertainty, which is a detractor for profit-oriented enterprises. Therefore, PRI's technological uniqueness is a negative factor for the technology transfer network. The density of a technology transfer network with many PRIs with low technological uniqueness may be greater than a technology transfer network with many PRIs with high technological uniqueness. Within a technology transfer network, the in-degree distribution of PRIs is negatively influenced by their technological uniqueness.

Third, combinative power does not play a key role in technology transfers. We, and other researchers in the field, expected PRIs with high combinative power to be more popular as transferors given their popularity as cooperators and advisors in this regard (Brennecke and Rank, 2017; Guan and Liu, 2016; Li and Tan, 2019). Similarly, we expected firms with low combinative power to be active transferees. However, our results do not support these expectations. A possible explanation is that most firms participating in technology transfers are small and therefore, as mentioned above, they have limited ability to re-apply the technologies they acquire.

Fourth, technological proximity is a significant factor. Our analysis shows that the greater the crossover in shared technology, the more likely it is for firms and PRIs to engage in transfers with each other. This finding is consistent with that of several research teams (e.g., Boschma and Ter Wal 2007, Martin 2012 and Ostas 2003) who demonstrate that greater proximity means firms can more easily apply the technologies they acquire without additional capital investment or equipment. Some studies suggest that heterogeneous technological elements may be a catalyst for innovation (Crescenzi et al., 2016). However, our results do not support this idea. As discussed above, small enterprises are more careful about the cost of acquiring, learning, and using new technologies and aim to make them productive as quickly as possible. Therefore, a certain technological proximity between PRIs and firms is necessary for technology transfer between them.

Among the control variables, R&D collaborations were a significant factor. R&D collaboration is an effective approach to accelerate technology transfer from PRIs to industry. This stands to reason because R&D collaboration can help firms to identify the right technologies for their production. It can also increase trust between PRIs and firms, which is a necessary external condition for technology transfer. More importantly, reducing the technological distance between PRIs and firms through R&D collaboration makes it more likely that they will develop the trio of synergies where governments fund R&D for specialized and fully-equipped centers, which leads to sales for commercialization, resulting in further advancements, and the cycle continues. Thus, transfers are more likely to occur between firms and PRIs that already work together.

5.2. Contributions

Our findings have theoretical and practical implications for future research. First, this study complements previous studies on technology transfer by extending our understanding of the factors that influence the process. Prior studies have explored the effects of geographic proximity, collaboration, and intermediary organizations, but, as yet, few studies

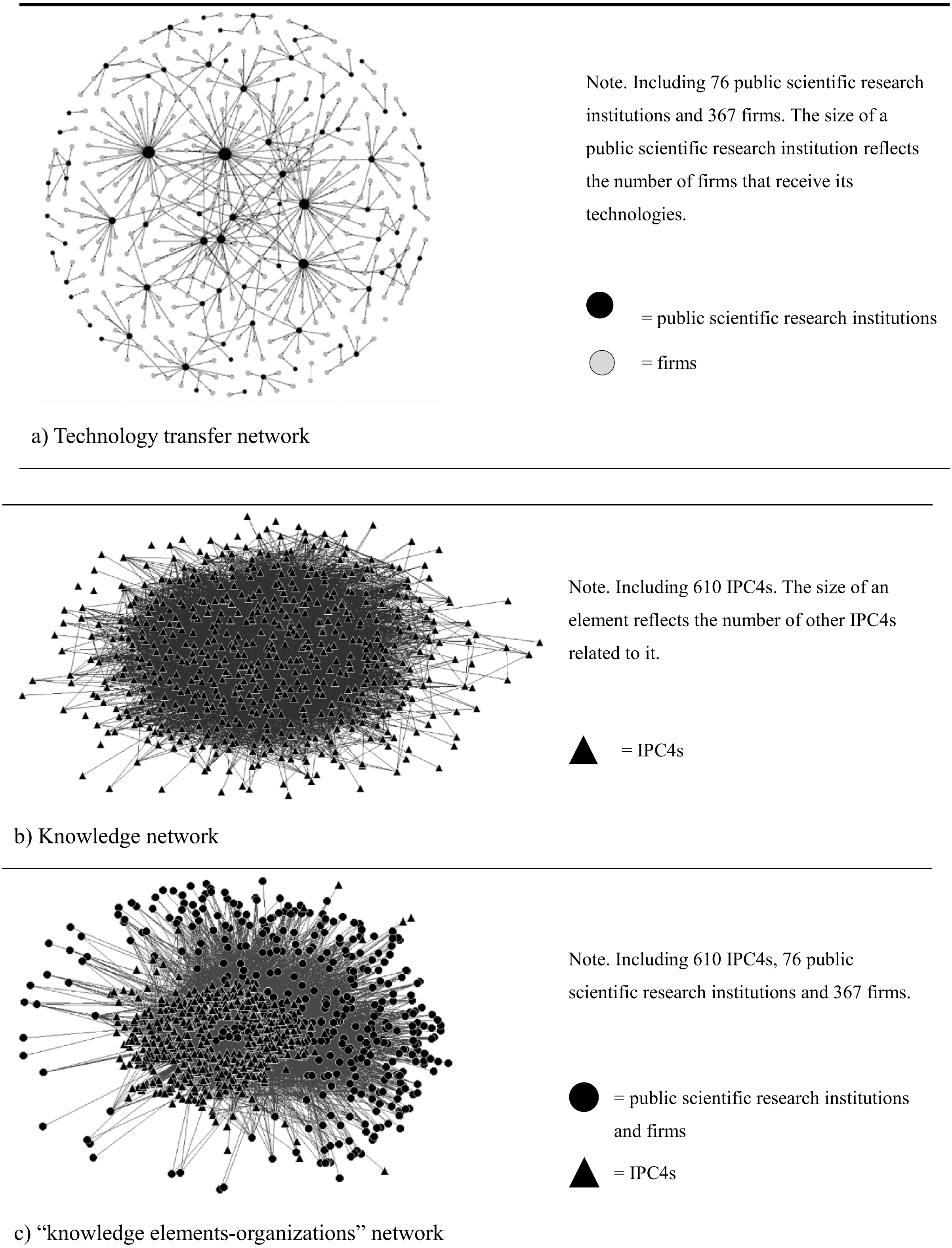


Fig. 4. Visualization of the observed network, the knowledge network, and “knowledge elements-organizations” network.

have examined the characteristics of an organization’s knowledge stocks (Algieri et al., 2013; Steruska et al., 2019; Theodorakopoulos et al., 2012; Villani et al., 2017). We followed the propositions of Brennecke and Rank (2017), Guan and Liu (2016), Guan et al. (2017), and Wang et al. (2019), and built three different kinds of networks to test their contentions. By taking the technological attributes of PRIs and firms into account, our analysis provides a new perspective through which to understand the technology transfer process.

Our results show that the technological attributes of a firm and who it selects to acquire its technology from are closely related. Diversity and uniqueness play particularly important roles due to the size of the firms most involved in transfers. In practical terms, this has significant

Table 4
ERGM results for the technology transfer network.

Effects	Parameter	Std. dev.	*t*-ratio
Edge	-5.1520*	0.874	-0.023
2-Stars-*P*	0.1004*	0.025	0.085
2-Star-*F*	-1.8638*	0.176	0.012
3-Stars-*P*	-0.0039*	0.001	0.094
Alternating-Stars-*P*	-0.7041*	0.318	-0.010
RS_P_sender	0.0001*	0.000	0.049
RS_F_receiver	-0.0004*	0.000	0.084
TD_P_sender	8.2682*	4.111	0.024
TD_ F_receiver	11.7808	6.865	0.035
TD_Difference	-7.4863	4.015	0.028
UT_P_sender	-10.6401*	3.734	0.066
UT_F_receiver	-3.9129	7.947	0.042
UT_Difference	9.1555*	3.635	0.071
CP_P_sender	3.5885	3.032	-0.013
CP_F_receiver	-3.3232	3.103	0.009
CP_Difference	-1.4319	2.953	-0.016
AO_P	0.0006	0.002	0.049
AO_F	0.0148	0.012	-0.011
R&D C _Edge	4.9814*	0.246	0.091
TP_Edge	0.9791*	0.156	0.045
GP_Edge	2.2091*	0.146	0.000

* indicates that the estimated value is at least twice the standard error, so the corresponding variable is significant.

implications for developing countries like China, where many enterprises are small, lack capital, and have a limited ability to re-innovate. Providing a variety of valuable technologies that can be absorbed by small firms quickly and easily is something PRIs should consider (Sampson, 2007; Brennecke and Rank, 2017; Martin, 2012). Efforts should also be made to develop platforms and databases of research results to help firms to quickly find the technologies they need.

Second, this study enriches the literature on public to private technology transfers – an area that remains to be fully explored (Park et al., 2018; Povoa and Rapini, 2010). Taking both universities and PRIs into consideration, we demonstrate some of the differences between their knowledge stocks. For example, compared to universities, the knowledge stocks of PRIs are typically less diverse (Martino, 1996). Sampson (2004, 2007) claims that overly diversified technology stocks pose significant challenges for technology transfer. However, our findings show that, whether for universities or PRIs, a diverse technology portfolio is the key to facilitating technology transfer.

In terms of technological uniqueness, Martin (2012) finds that high uniqueness translates to low technological value for universities that offer the full range of disciplines. As such, universities tend not to invest a great many resources into unique technologies and, in turn, they can be more difficult to commercialize. PRIs usually focus on narrower technology areas. As a result, their technological uniqueness is higher and fluctuates less than that of universities (Martino, 1996). Overall, our analysis shows that highly unique technology stocks reduce the likelihood of transfer.

With respect to technological proximity, our conclusions support the results of Daghfous (2004) and Martin (2012). Both universities and PRIs need to "talk the same language" for firms to be able to commercialize technologies easily. The positive relationship between proximity and transfer suggests that, if a searchable technology transfer platform were to be created, PRIs should be divided into technical areas to help firms quickly locate the right partners with the right technologies.

Third, this paper enriches technology transfer theory in developing countries. Many studies have examined technology transfers in the US and the major countries of Europe (Decter et al., 2007; Kirchherr and Matthews, 2018). However, little research focuses on technology transfer in developing countries, with their backward technologies and low transfer rates. As the largest developing country, China actively promotes public R&D and technology transfer to private enterprise at all levels of government (Chen et al., 2016). In recent years, the number of patent applications in China has skyrocketed, to the point that China is now the world's leader in patent applications. However, this increase has also raised many doubts about whether quality is being lost in the pursuit of quantity (Chen et al., 2017; Zhang et al., 2016). Interestingly, some of the conclusions drawn in the developed world do hold for China; others do not. For instance, according to Daghfous (2004), technological diversity increases opportunities for transfer from academic institutions in the US because the high quality of patents and the diversity of technologies offered better meets the needs of enterprises. Yet, although the low quality of patents in China may cause firms some difficulties, diversity still seems to be an appealing attribute. Except for differences in patent quality, the differences in the size of firms as technology transferee lead different conclusion in the effect of combinative power. As a converse example, Ayşe (2015) notes that the combinative power of technologies is a valuable asset in Western Europe and the US. However, we did not find the same to be true of China for two reasons. First, most transferees are small firms that lack the capacity for re-innovation and, second, it is more difficult for firms to accurately judge the combinative power of an academic institution's technologies in China due to lax patent quality controls. Overall, we advise readers to consider the differences in both innovation strength and the innovation environment between developed and developing countries when generalizing our findings.

Finally, this study enriches our understanding of the technological attributes of organizations. Of the few studies that have considered these features, most only focus on diversity and proximity (Martin, 2012; Moreira et al., 2018). Combinative power and uniqueness are less studied (Brennecke and Rank, 2017; Guan et al., 2017) and, to the best of our knowledge, no study has tested all four on one sample.

Table 5
Poorly fit statistics.

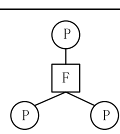
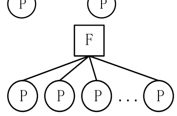
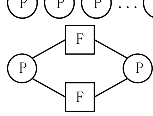
Statistics	Visualization	Observed	Mean	Standard deviation	*t*-ratio
3-Stars-*F*		134.000	56.955	9.581	8.042
Alternating-Stars-*F*		158.343	182.411	10.666	-2.256
4-Cycle		137.000	79.694	17.232	3.326
stddev_degree_F		-0.865	-1.179	0.022	14.378
clustering coefficients		0.070	0.043	0.007	4.141

Table 6
ERGM results for the technology transfer network based on the technological proximity measurement method used in Brennecke and Rank (2017).

Effects	Parameter	Standard Error	t-ratio
Edge	-4.5731*	1.007	0.028
2-Stars-P	0.1027*	0.026	0.004
2-Star-F	-1.7661*	0.176	0.066
3-Stars-P	-0.0040*	0.001	0.002
Alternating-Stars-P	-0.6381*	0.281	0.017
RS_P_sender	0.0001*	0.000	0.029
RS_F_receiver	-0.0003*	0.000	0.045
TD_P_sender	8.7546*	4.202	0.041
TD_ F_receiver	8.3855	7.071	0.067
TD_Difference	-7.4704	4.089	0.03
UT_P_sender	-10.4830*	3.826	0.059
UT_F_receiver	-1.8460	8.217	0.064
UT_Difference	8.7651*	3.726	0.052
CC_P_sender	2.4637	3.051	0.031
CC_F_receiver	-2.9227	2.916	0.042
CC_Difference	-1.1072	2.841	0.019
AO_P	0.0009	0.002	0.050
AO_F	0.0083	0.013	0.034
R&D C _Edge	5.2063*	0.223	0.021
TP Brennecke and Rank's (2017)_Edge	0.5770*	0.241	0.059
GP_Edge	2.2357*	0.13	-0.038

Note. * indicates that the estimated value is at least twice the standard error, so the corresponding variable is significant.

5.3. Limitations and future research

This study has some limitations that should be addressed in future research. First, our analysis was based exclusively on technology transfer from Project 985 universities and CAS. These are unique entities with many advantages to support technology transfers, such as abundant resources for innovation and a high administrative ranking that no other PRI in China could possibly match (Zhang et al., 2016). Thus, generalizing our findings should be done with care. Moreover, future studies on this topic might expand the sample to consider other Chinese PRIs. Second, although our findings may be applicable to other developing countries, such as Vietnam and Cambodia, many developed countries are ahead of China in terms of technology transfer, and their innovation systems are different. Therefore, future research could extend our analysis to these countries. Third, measuring technology transfer by simply referring to the number of patents is a limitation that needs to be addressed. Technology transfer involves different types of collaboration between public bodies and firms. Patents are only one of the outcomes of such collaborations. Therefore, future studies should consider other types of technology transfer. Fourth, in this study, we limited our scope to technology transfer from PRIs to firms. However, technology transfer between firms, from firms to PRIs, and from firms or PRIs to universities may also be influenced by technological attributes. This is a more general theory that should be investigated in the future. Last, most firms in our empirical analysis were small, new, and unlisted, so some information, such as their registered capital and R&D spending, could not be collected as control variables.

CRediT authorship contribution statement

Xiangpeng Lian: Methodology, Software, Data curation, Writing – original draft, Visualization, Validation, Formal analysis. **Ying Guo:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Investigation. **Jun Su:** Supervision, Conceptualization, Methodology.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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