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The evolution of government sponsored collaboration network and its impact on innovation: A bibliometric analysis in the Chinese solar PV sector

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ABSTRACT

This study explores the dynamics of a government sponsored collaboration network concerning the development of solar photovoltaics (PV) technologies in China, and investigates the effect of network evolution on the subsequent innovation performance of network actors. Network structure characteristics and attribute proximity variables are jointly examined through a bibliometric methodology based on scientific publication and patent data. In addressing the evolution of the government sponsored collaboration network, this study has identified that actors are more likely to engage in collaboration with prior partners, partners of direct & indirect partners, and partners with similar attributes. These collaboration patterns, in turn, negatively impact direct ties and network efficiency, and increase the attribute proximity of an actor's network. On the other hand, the estimation results indicate that direct ties have an inverted U-shaped effect on innovation performance, while indirect ties are found to be positively related to innovation performance. As expected, a positive effect of network efficiency is found on innovation performance. The results of attribute proximity variables suggest geographical proximity is negatively related to innovation performance. Taken together, the collaboration patterns in the government sponsored network might have a negative impact on innovation performance of network actors. The empirical findings extend the network literature that collaboration network matters differently in different research contexts, and it is no longer appropriate to simply assume that collaboration is purely a good thing. As such, special attention should be paid to the network structure and composition in further policy design.

1. Introduction

Government agencies, particularly in the OECD countries, have increasingly positioned collaboration activities between the knowledge-based organizations at the core of innovation policy with the aim to facilitate the creation, diffusion and utilization of scientific knowledge and, ultimately, to boost technology development and economic growth (Autio et al., 2008; Heinze and Kuhlmann, 2008; Poirier et al., 2016). In line with this objective, an increasing amount of government funding is provided for collaborations of knowledge-based organizations – usually enterprises, universities and research institutes (Fier et al., 2006; Protogerou et al., 2013). Hence, it is important to understand how government sponsored collaboration networks influence innovation performance to provide empirical evidence of how the commitment of public money has resulted in significant and tangible outcomes (Clarysse et al., 2009).

Previous network and innovation studies reveal that network structure and partners composition (in terms of different dimensions of attribute proximity) are highly relevant in influencing the development of collaboration networks and their subsequent innovation performance (e.g., Ahuja, 2000; Broekel and Boschma, 2012; Phelps, 2010). In analyses of collaboration network evolution, scholars have adopted either a static approach at a single time point or taking a period as a whole to explain the totality of network changes (Powell et al., 2005; Rosenkopf and Padula, 2008). Less attention has been devoted to the changing nature of network formation over time (Balland et al., 2013; Ter Wal, 2014). Moreover, the question of whether innovators should occupy densely interconnected "closed" network positions, or sparsely connected "open" network positions, has yielded conflicting answers providing support for both views (e.g., Ahuja, 2000; Baum et al., 2000; Schilling and Phelps, 2007).

To address these gaps, this study develops a bibliometric methodology based on scientific publications and patent data to analyze: (a) the evolution of government sponsored collaboration networks in terms of their changes in network structural effects and attributes proximity effects from 2003 to 2013 in the Chinese solar PV sector, and (b) the impact of those changes (in network structural effects and attributes proximity effects) on the subsequent innovation performance of

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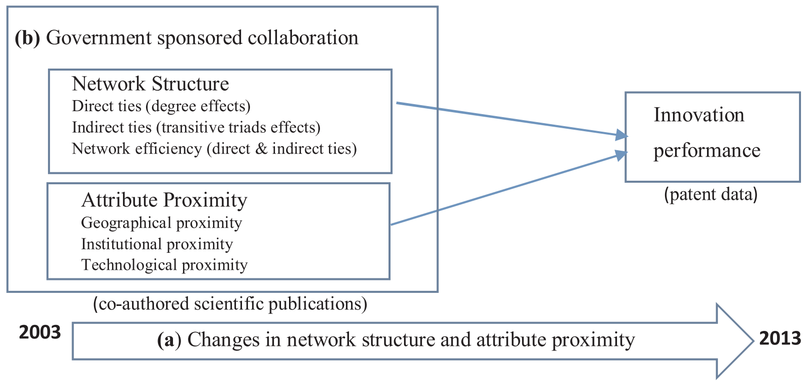

Fig. 1. Research framework of this study.

network actors. The research framework is presented in Fig. 1.

This study, first, examines network evolution of government sponsored collaboration in research; therefore, in contrast to the predominant focus on industrial actors in past literature, the focus is on the science community (universities and public research institutes) when addressing the impact of government funding on network collaboration. Second, instead of the predominant focus on network structure, the effects of both network structure and attributes proximity are included. Finally, similar studies have not been done in the emerging energy technologies sector; the predominant focuses of network evolution have been in the fields of biotechnology, chemicals, and semiconductors.

2. Scientific collaboration and innovation

Scientific collaboration, also referred as research collaboration (Katz and Martin, 1997; Lee and Bozeman, 2005) or R&D collaboration (Bjerregaard, 2010), is defined in many ways. Following previous research (Lee and Bozeman, 2005; Ynalvez and Shrum, 2011), scientific collaboration is viewed as the process through which scientists work together in a research project with one or more specific goals, including the common goal of producing new scientific knowledge. As public and private research funding agencies increasingly require inter-organizational collaboration for funding and research (Lee and Bozeman, 2005), this study focuses on inter-organizational scientific collaborations concerning government funded research involving two or more organizations in the solar PV sector in China.

The solar PV sector is a suitable research setting for three reasons. *First*, the solar PV sector is a high technology industry, where knowledge and innovation are fundamental to the pursuit of competitive advantage (Schilling and Phelps, 2007; Wu and Mathews, 2012). *Second*, due to its nascent and science-based nature, the solar PV sector has been characterized by a wealth of inter-organizational collaboration networks for innovation activities (Cattani and Rotolo, 2013). *Third*, there is a large consensus in the international community that government R&D investments are the key to foster technological improvements in solar PV technologies. The Chinese government has set up multiple national science and technology plans to support the R&D of PV technologies (Sun et al., 2014). *Additionally*, as previous scholars argued that innovative competence is strongly sector-specific, and the knowledge base and learning processes related to innovation differ across sectoral systems of innovation (Quintana-García and Benavides-Velasco, 2008), a single industry study is preferred.

The evolution of collaboration networks, in terms of ties establishment and termination between different network members (e.g., Balland et al., 2013; Gulati and Gargiulo, 1999), is driven by a series of endogenous effects, such as the search for repeated ties, or the tendency of actors to form closed networks (friends of friends become friends), and exogenous effects which depend on external attributes (e.g., various attribute proximity dimensions). These collaboration patterns, in turn, determine directly a number of network structural variables and attributes proximity-related variables.

Several dimensions of attribute proximity, such as geographic, organizational, cognitive, social, cultural, institutional, and technological proximity, have been considered as relevant in the development of collaboration networks and the subsequent innovation performance (e.g., Balland, 2012; Broekel and Boschma, 2012), but the proliferation has generated conceptual ambiguity and overlap that may dilute the significance of the proximity notion (Capaldo and Petruzzelli, 2014; Knoben and Oerlemans, 2006). Three fundamental dimensions of proximity, namely, geographical proximity, technological proximity and institutional proximity, are highlighted in the literature and, thus, are considered in this study together with three network structure variables − direct ties, indirect ties and network efficiency (or non-redundant ties). The changes of these network structural and attribute proximity variables in the network collaboration patterns of the solar PV sector from 2005 to 2013 and their effects on innovation performance are examined.

3. Method

This study considers co-authored scientific publications from government funded research projects (co-authored by scientists affiliated to different organizations) as proxy indicators of network properties to derive structural and proximity variables. Patent data is considered as proxy indicator of innovation performance. The visualization of the network evolution patterns are created by Ucinet 6 and the network pattern changes examined by SIENA.

To analyze the impact of the changes in network structural effects and attributes proximity effects on the subsequent innovation performance of network actors, hypotheses relating to the influence of each structural and proximity variable on innovation performance are developed and tested by binomial regression. The hypotheses of the network structure and attribute proximity variables are discussed next.

3.1. Direct ties

The variable of direct ties in collaboration networks refers to the number of direct partners maintained by the focal actor, providing three substantive benefits. First, direct ties provide potential access to other organization's knowledge elements (Wang et al., 2014) and the number of direct ties indicates its combinatorial potential with other knowledge elements (Guan and Liu, 2016). Second, collaborations enable the newly created knowledge to become available to all actors involved and, thus, enhance knowledge sharing (Ahuja, 2000). Third, most knowledge is subject to economies of scale and scope, especially for explicit knowledge which, once created, can be deployed in additional applications at lower marginal cost (Grant, 1997). Therefore, the number of direct ties in an organization's collaboration network is considered to be relevant for its innovation performance.

However, too many direct ties have an adverse effect on innovation (Guan and Liu, 2016) because of management burden (Gilsing et al., 2008; Vanhaverbeke et al., 2007) and other issues. For instance, Ahuja and Katila (2001) argue that a large network portfolio creates a risk of dealing with many unfamiliar streams of knowledge that are increasingly difficult to integrate. Also, Wang et al. (2014) indicate that combinatorial potentials are probably low when there are too many direct ties in an organization's collaboration network, because the combinatorial potential of any knowledge element has an upper limit. Subsequently, the variable of direct ties in an innovator's collaboration network is expected to have an inverted-U shape effect on its innovation performance (e.g., Gilsing et al., 2008; Guan and Liu, 2016; Vanhaverbeke et al., 2007), thus generating the following hypothesis:

Hypothesis 1. Direct ties have an inverted-U shaped effect on innovation performance.

3.2. Indirect ties

Indirect ties in the collaboration network refer to the actors that the focal actor can reach in the network through its partners and their partners (Gulati and Gargiulo, 1999). It can be visualized as: (A) partners with (B), and (B) allies with (C). The focal actor (A) and the third partner (C) have no direct linkage, but are connected indirectly through the common partner (B). The focal actor's partners can bring knowledge and information on relevant technological developments in different parts of the network through indirect ties that extend far beyond its direct reach (Ahuja, 2000). In general, the more indirect ties a focal actor has, the more knowledge and information the focal actor can search (Guan and Liu, 2016) to enhance innovation performance. Meanwhile, unlike direct ties, indirect ties entail relatively low or no maintenance costs for the focal actor and, thus, benefits of indirect ties are extremely welcome (Ahuja, 2000), which posits the following:

Hypothesis 2. Indirect ties have a positive effect on innovation performance.

3.3. Network efficiency

Structural holes, a concept often used to measure the network efficiency of actors in a collaboration network, refers to gaps in information flows between actors linked to the same focal actor but not linked to each other (Burt, 1992). From the perspective of structural holes theory, ego networks, in which an actor's partners have no link with each other, are preferred to densely tied networks; because ego networks are rich in structural holes, and so, usually implies access to mutually unconnected partners and consequently to many distinct information flows, therefore, leading to higher network efficiency (Ahuja, 2000). In addition, an actor network rich in structural holes has few constraints in exploring new ideas because it is rarely affected by knowledge inertia, which is a common phenomenon in redundant network structures (Guan and Liu, 2016). Thus, minimizing redundancy between partners provides higher network efficiency and has a positive effect on innovation performance. Thus,

Hypothesis 3a. Network efficiency has a positive effect on innovation performance.

However, Vanhaverbeke et al. (2007) argue that while accessing complementary knowledge and information is one issue, understanding, assimilating and applying it is another. Redundant ties between partners can foster the development of shared norms of behavior and explicit inter-organizational knowledge sharing routines (Uzzi, 1997) and, thus, could help organizations to understand, assimilate and, eventually, acquire different knowledge elements (Guan and Liu, 2016; Kogut, 2000). Furthermore, dense ties between partners are also likely to spur the creation of inter-organizational trust that may prevent opportunistic behavior (Ahuja, 2000; Vanhaverbeke et al., 2007). Without trust and shared norms of behavior, sharing knowledge and combining skills are likely to be difficult and unproductive in any context (Coleman, 1990). In short, the lower network efficiency associated with dense, embedded networks can maximize the benefits from collaboration, and thus, may enhance innovation performance. Hence,

Hypothesis 3b. Network efficiency has a negative effect on innovation performance.

As discussed, both views above may be valid in view of the effects of collaboration for technological innovation, therefore prompting two different hypotheses. On one hand, accessing novel and complementary knowledge and information requires an emphasis on diversity and disintegrated network structures; on the other, assimilation and application of such novel knowledge may favor more redundant network structures for integrating the diverse inputs.

3.4. Geographical proximity

Geographical proximity, which is denoted as territorial, spatial, local or physical proximity (Knoben and Oerlemans, 2006), can be measured in distance unit, such as kilometres (Villani et al., 2017), or expressed as the actor's perception of the spatial area according to the boundaries of the country or regions (Balland, 2012). This study adopts the latter view, namely the geographical co-location, so that two actors who are from the same province are considered as similar on this dimension.

The core idea behind increasing the geographical proximity is that shorter physical distance between actors facilitates easier interaction (Capaldo and Petruzzelli, 2014; Villani et al., 2017), and provides a more direct access to information and knowledge, especially when knowledge is tacit, complex and sticky (Knoben and Oerlemans, 2006). Interactive learning is made easier when interactions are facilitated and, thus, the innovation performance may also be increased. Therefore,

Hypothesis 4a. Geographical proximity has a positive effect on innovation performance.

However, Boschma (2005) argues that interactive learning may not necessarily be due to geographical proximity. Scholars have put forward the notion of temporary geographical proximity (Torre, 2008), implying that actors need not be in constant geographical proximity when collaborating. Meetings, short visits and temporary co-location might be sufficient for actors to build other forms of proximity which, subsequently, allow collaboration over large geographical distances. In this case, geographical proximity may be harmful for interactive learning and innovation when actors in a region become too inward looking, and so, the learning ability of local actors may be weakened (Boschma, 2005). In these situations, when co-located actors are cognitively too close, geographical proximity gives rise to unintended knowledge spillovers and creates a climate of mistrust as a result of localized competition pressure (Carrincazeaux et al., 2008). Hence,

Hypothesis 4b. Geographical proximity has a negative effect on innovation performance.

3.5. Institutional proximity

In the literature, institutional proximity is studied on national and organizational levels. At the organizational level, institutions are related to the norms and routines presented in an organization. In this way, organizational and institutional forms of proximity may be strongly interconnected (Boschma, 2005). Usually, institution proximity at this level refers to the institutional kind of organizations in the triple helix model, where the companies, universities and public research institutes are distinguished (Angelini, 2014; Etzkowitz and Leydesdorff, 2000). This study follows the organizational level of institutional proximity, and two universities, for example, are considered as similar institutions.

The literature on knowledge and proximity identifies an association between institutional proximity and the presence of knowledge transfer, interactive learning and innovation (Boschma, 2005; Ponds et al., 2007). Institutional proximity is believed to be beneficial for learning and innovation. New knowledge creation and innovation go along with uncertainty and opportunism, and so, institutions function as a sort of 'glue' for collective action because they reduce uncertainty and lower transaction costs (Boschma, 2005). Institutional proximity facilitates collective learning and innovation by allowing free knowledge transfer among agents based on a common language, shared habits, a law system securing ownership and intellectual property rights, etc. (Balland, 2012), particularly in respect of tacit knowledge thanks to a mutually understandable language including shared routines and practices (Angelini, 2014).

Conversely, institutional proximity could be unfavorable for new ideas and innovations due to institutional lock-in, providing no opportunities whatsoever for newcomers. Furthermore, Boschma (2005) argues that institutional proximity may lead to institutional inertia, hindering the development of new innovations that require the build-up of new, or the restructuring of old, institutional structures. Further, institutional proximity also could give rise to unintended knowledge spillovers and a climate of mistrust as a result of competition pressure for limited resources (such as funding), while a culture of shared trust is often regarded as a capability that supports learning and innovation. Thus,

Hypothesis 5a. Institutional proximity has a positive effect on innovation performance.

Hypothesis 5b. Institutional proximity has a negative effect on innovation performance.

3.6. Technological proximity

The concept of technological proximity, sometimes denoted as cognitive proximity (Angelini, 2014), is defined as the similarity among actors in terms of technological knowledge bases. Knoben and Oerlemans (2006) argue that the fundamental difference is that cognitive proximity can be considered as a broader concept referring to "how" actors interact, whereas technological proximity refers to "what" they exchange and the potential value of these exchanges. This study identifies PV-related inventors based on publication and patents data, so, technological proximity occurs when both actors are PV-related inventors, given that PV-related inventors develop the same kind of knowledge base.

The importance of technological proximity is based on the concept of absorptive capacity (Cohen and Levinthal, 1990), which concerns acquisition of external knowledge by an organization and the capability to recognize it, decode it, and elaborate it − particularly when knowledge is tacit (Angelini, 2014). The similarity of the knowledge bases is emphasized because it could greatly help the process of knowledge exchange between organizations.

However, knowledge production and innovative processes often require dissimilar, complementary bodies of knowledge possessed by heterogeneous agents, and a limited technological distance hardly triggers this kind of processes (Oerlemans et al., 2013). In other words, technological proximity could hinder the exposure of novel knowledge and information of network actors. Boschma, (2005) also argues that technological proximity may be detrimental to interactive learning as it not only decreases the potential for learning, but also increases the risk of lock-in and the problem of involuntary spillovers to competitors.

Similar to the effects of network efficiency, there are two contradictory effects of attribute proximities between a focal actor and its partners in innovation and, thus, prompts two competing predictions with respect to the relationship between each proximity and innovation:

Hypothesis 6a. Technological proximity has a positive effect on innovation performance.

Hypothesis 6b. Technological proximity has a negative effect on innovation performance.

4. Evolution of government sponsored collaboration network

4.1. Scientific co-publication data collection

Although co-authored publication is by no means a perfect indicator of a scientific collaboration network because not all collaborative research projects eventuate in a co-authored paper (Katz and Martin, 1997) and a publication may be co-authored where, in fact, no significant collaboration has taken place (Wong and Singh, 2013), co-publications have many advantages for analyzing scientific collaborations, including objectivity, specificity, publicly availability and large sample size (Ubfal and Maffioli, 2011), thus making it the most commonly used approach for analyzing scientific collaboration (Glänzel and Schubert, 2005). In China, the number of scientific publications is one of the most important evaluation indicators of government sponsored research, and publications must acknowledge the specific funding sources. Hence, it is assumed that publications with government funding acknowledgements are the output of government sponsored R&D activities, and co-publications that have government funding acknowledgements imply government sponsored scientific collaborations.

This study has extracted the publication data on solar PV in China by interrogating the database of Web of Science (WoS); specifically, the following databases therein: a) Web of Science TM Core Collection (the Science Citation Index Expanded part, SCI), specializing in science and medicine, and b) China Science Citation Database SM, specializing in Chinese scientific papers (CSCD). To collect all the publications related to solar PV technologies, this research has adopted the keyword search strategy, which also presents two main limitations. First, many highly related publications do not contain expected keywords, while some publications containing them are not really relevant (Cattani and Rotolo, 2013). Second, the solar PV technologies are evolving rapidly, making it difficult to search all the related data by one or a few keywords. To minimize these limitations and increase the reliability of data; this study has conducted an extensive review of previous research and solar PV technologies itself; and identified a series of core terms for filtering the large number of publications (see Appendix A). Since the Chinese government support in R&D was negligible before 2003 (De La Tour et al., 2011); publications data are collected from 2003. As a result; an initial sample of 13,686 publications is obtained; from 2003 to 2013. Furthermore; this study excludes publications in which the first affiliation is international organizations based on the assumption that research activities are dominated by the researchers of the first affiliation; yielding a new sample of 10,366 publications. It is believed that this approach assures a higher degree of coherence with the phenomenon under investigation. Of the 10,366 publications; 9327 publications are sponsored by government.

4.2. Patent data collection

Patent data are subject to limitations; for instance, part of the technical knowledge may remain unpatented either because it is unpatentable or because an organization may choose not to patent (to keep in secrecy), and the propensity to patent may differ widely across industries and organizations (Nelson, 2009). These limitations notwithstanding, a large body of research has demonstrated the validity of patents as proxies to measure innovative activities (e.g., Gilsing et al., 2008; Guan and Liu, 2016; Petruzzelli, 2011).

The patents data were extracted from the patent databases of the State Intellectual Property Office (SIPO) of the People's Republic of China, selecting all patents with photovoltaic IPC (International Patent Classification) codes. These IPC codes tag all patents concerning inventions related to solar photovoltaic technologies (see Appendix B). Only applicants based in Mainland China is considered. The initial sample consists of 21,108 solar PV patents from 1985 to 2013. Because a few patents are assigned to subsidiaries, this study carefully aggregates patents to the organization level (e.g., universities, public research institutes, enterprises). For the purpose of this research, applicants who are not listed in the publication database are excluded, resulting a revised sample of 8, 846 patents.

It should be noticed that, the patent data used in this study are patent applications, rather than patents granted. According to previous scholars (e.g., Belderbos et al., 2010; Crosby, 2000), patent applications reflect actual innovation activities in a given year and granted patents are more reliable for innovation qualities. The patenting process has several formal and informal steps that must occur before a patent is granted, and it usually takes 4–5years on average for a patent to be granted from its date of application (Belderbos et al., 2010; Liegsalz and Wagner, 2013), making patents granted a poor indicator of recent innovation activities. Additionally, many patent applications do not lead to patents granted due to issues relating to examiners, fees and policy, rather than that they are not novel and useful. Furthermore, this study investigates the impact of a collaboration network on the innovation performance of collaborating organizations based on a longitudinal data set (2003–2013), and not all patents applied for during this period are granted. Therefore, patent applications are used in this research as a proxy measure of innovation performance.

There are some simplifications and assumptions. *First*, international partners are excluded because information of the organizational attributes of international partners is unavailable. *Second*, collaboration relationships, typically, last for more than one year, and, generally, government grants are awarded for a number of years (Schilling and Phelps, 2007). In the literature, the duration of collaborative networks vary from one year (Stuart, 2000) to five years (Gulati and Gargiulo, 1999). Following Schilling and Phelps (2007), a conservative approach is taken by assuming research relationships to last for three years. *Third*, inventing authors are distinguished from non-inventing authors, and it is assumed that there are sparse, if any, interactions between inventing authors and non-inventing authors within the same organization.[1] In this research, inventing actor refers to all solar PV-related inventing authors in an organization, whereas non-inventing actor includes all non-inventing researchers in an organization. Therefore, scientific collaboration in this study refers to inter-organizational collaboration at the actor level, which is similar to Katz and Martin' (1997) 'group level' and 'inter-organizational' collaboration.

4.3. Network visualization

Based on a 3-year moving window (e.g., 2003–2005), nine snapshots of government sponsored collaboration network are created using Ucinet 6 (see Borgatti et al., 2002) which measures the structural properties and attribute proximities of networks (see Table 1). Each network snapshot is constructed as an undirected binary adjacency matrix, and repeated collaboration between the same pair of actors in a time window is treated as one link. The nine snapshots (i.e., 2003–2005, 2004–2006 … 2011–2013) are labelled as Network 2005, Network 2006, …, Network 2013 respectively, i.e. Network 2005 is based on the co-authored publications data during 2003–2005.

NetDraw (Borgatti, 2002) was used to generate diagrams of the networks for the representation of network dynamics over time. Following Powell et al. (2005), this study scales the size of nodes to represent the number of ties an organization has, and uses the color and shape of nodes to represent the attributes of actors. As such, if the proximity mechanism drives collaboration, the images would display a preponderance of nodes of the same color or shape. Moreover, if new partners are chosen on the basis of their common partners, the images depict more and more triangles or other closed figures. Two snapshots of the government sponsored networks (Network 2008 and Network 2013) are selected to contrast network collaboration patterns.[2] The coding of colors, size, and shapes of nodes and lines for the interpretation of the network patterns are given in Figs. 2 and 3.

Several key features stand out for Network 2008 in Fig. 2. (1) The most active participants in the collaboration network are public research institutes (rounded square) and universities (circle) which indicates that government sponsored research collaboration in the early years of solar PV mainly concentrated in the science community. While public research institutes primarily refers to institutes of the Chinese Academy of Sciences (CAS), such as the Institute of Physics, Institute of Chemistry, and Institute of Semiconductors, universities actors mainly include top ranking universities in China, such as Nankai University, Fudan University, Peking University and Tsinghua University. (2) Orange ties, which denote regional collaboration, are prevalent particularly for large nodes, providing evidence that most actors are likely to collaborate with partners within the same region. (3) Only large nodes have a wide variety of partners, while some of the smaller nodes have little diversity in their partners.

Network 2013 (Fig. 3) reflects the growing network complexity and a number of noticeable features are present. (1)The green square node holds a dominant position in the network, reflecting that most active members are inventing actors, with the CAS at the centre of the network connected to a number of inventing actors which are notably universities (circle). (2) Besides the traditional leading universities in previous years, a large number of actors, such as Zhejiang University, South China University of Technology, Harbin Institute of Technology and Jilin University, play an increasingly important role in the network. (3) The organizational composition of the network has shifted as industrial actors have increased considerably in number, and other actors, such as industrial associations, government departments are also engaged directly in the network. (4) The large amount of orange color ties are evident outside the centre of the network, reflecting that most nodes at the periphery are linked with nodes within the same region.

In short, the overall picture has shifted from one in which public research institutes and universities were the dominant actors to one in which industrial actors are also important. This reflects evidence that innovation policy is changing in the solar PV sector with increased amounts of government funding for enterprises' R&D activities.

4.4. Statistical examination of network evolution

As a supplement to the visualizations, this study undertakes a statistical examination of network dynamics and assesses the collaboration patterns, using the stochastic actor-based model in the SIENA.[3] software (Snijders et al., 2010), which is part of the network software package STOCNET[4]

[1] From the data on patents and publications, it is found that researchers in an organization often conduct research in research group (s) and work together in co-publications and patents applications. Usually, inventing authors and non-inventing authors of the same organization come from different departments and rarely interact with each other.

[2] To simplify the presentations, this study includes only those actors in the main component of each network snapshot, thereby removing the isolates. Most network measures are based on the main component, which is a connected graph for which measures can be generated.

[3] SIENA stands for 'Simulation Investigation for Empirical Network Analysis'. For more details, please refer to https://www.stats.ox.ac.uk/~snijders/siena/.

[4] STOCNET is a software system for the advanced statistical analysis of social networks, focusing on probabilistic (stochastic) models. See http://www.gmw.rug.nl/~stocnet/StOCNET.htm.

Table 1
Structural properties and attribute proximities of the government sponsored collaboration networks.

Network	Number of Actors	Average Direct Ties	Average Indirect Ties	Average Network Efficiency[a]	Average Geographical Proximity[a]	Average Institutional Proximity[a]	Average Technological Proximity[a]
Network 2005	155	2.065	17.665	0.840	0.400	0.640	0.520
Network 2006	171	2.234	21.642	0.846	0.396	0.552	0.487
Network 2007	223	2.143	24.440	0.854	0.371	0.543	0.532
Network 2008	282	2.284	31.676	0.835	0.408	0.545	0.522
Network 2009	351	2.416	44.288	0.841	0.453	0.576	0.554
Network 2010	442	2.683	64.072	0.854	0.475	0.601	0.543
Network 2011	552	3.065	89.998	0.868	0.467	0.606	0.523
Network 2012	690	3.670	128.129	0.861	0.471	0.586	0.530
Network 2013	811	4.298	173.663	0.843	0.449	0.569	0.528

Note:
[a] Means the isolates are excluded.

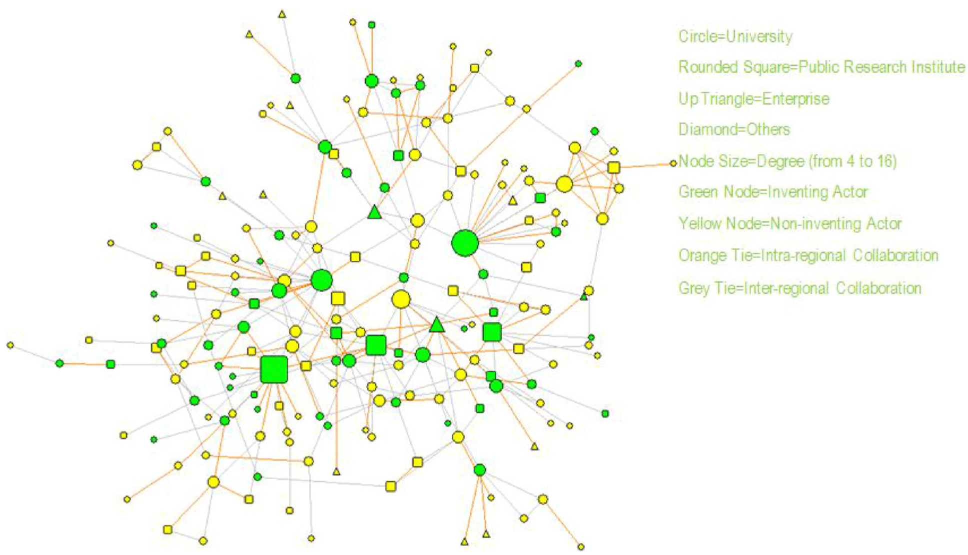

Fig. 2. Government sponsored research collaboration network 2008, main components.

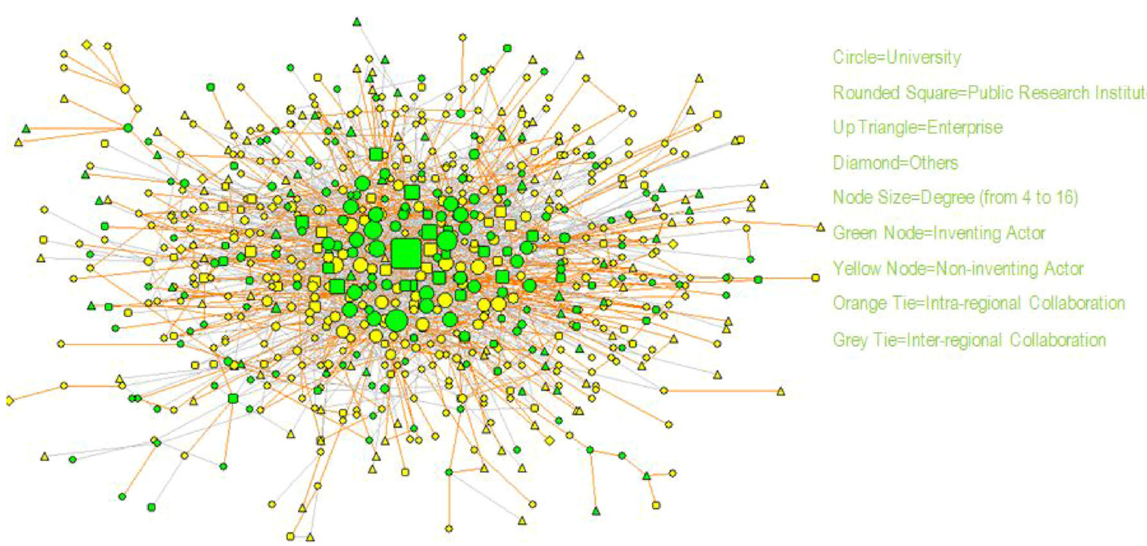

Fig. 3. Government sponsored research collaboration network 2013, main components.

Following previous scholars (e.g., Balland et al., 2013; Van de Bunt and Groenewegen, 2007), the creation of linkages employs the *unilateral initiative and reciprocal confirmation model*, which is built through specifying the 'effects' that drive the evolution of the collaboration network (see Snijders et al., 2009 for more detail). This study specifies the effects in the model to be (a) three structural effects – degree effect, transitive triplets effect and transitive ties effect; and (b) three proximity effects that describe the role of individual attributes of actors, namely, geographical, institutional and technological proximity.

According to Snijders et al. (2010), the degree effect, also called density effect, considers the number of relations of each actor; the transitive triplets effect is the classical representation of network closure by calculating the number of transitive triplets to determine the likelihood for partners of partners to become partners; transitive ties effect (earlier called direct and indirect ties effect) is defined by the number of actors to whom an actor is tied directly and indirectly.

The influence of proximity-based mechanisms on the evolution of a network can be evaluated by means of the 'same covariate effect' (Angelini, 2014). Technological proximity occurs when actors develop the same kind of knowledge. Geographical proximity is determined according to the co-location within the same spatial area. In this study, province is taken as the analysis unit, and thirty-one spatial areas in China are distinguished. In line with previous scholars (e.g., Balland, 2012; Ponds et al., 2007), institutional proximity appears when organizations have the same institutional form according to the triple helix model (Etzkowitz and Leydesdorff, 2000).

The t-value of convergence indicates the goodness-of-fit of the simulated model (Snijders et al., 2010) and the t-ratios for all parameters in all observations are less than 0.1 in this study, indicating the model estimation converges to stable outcomes (Ter Wal, 2014). To confirm a stable result of the estimation algorithm, the estimation processes are repeated until the estimation results obtained in consecutive trials are very similar (Snijders et al., 2010). Results of parameter estimations of the changes in collaboration network from 2003 to 2013 is modeled in 8 waves based on 1000 simulation runs (the default). The shift between two consecutive snaphsots of network, say, from Network 2005 to Network 2006, is labelled as a wave in Table 2.

As shown in Table 2, the degree effect is negative and significant during the whole period, suggesting that researchers are more likely to collaborate with prior partners. The effect of transitive triads, namely collaboration with actors of partners, is positive and significant in wave 4, then wanes in wave 5, and emerges stably in the last three waves. Regarding the direct and indirect ties, a positive and significant effect in the whole period is found, implying that actors are more likely to collaborate with partners of partners, or indirect partners.

Turning to the attribute proximity effects, geographical proximity is positive and significant in the whole period, suggesting that actors prefer to collaborate with actors who are located in the same region. The effect of institutional proximity is negative and significant in wave 2, but positive and significant in the last four waves, and not significant in other waves. Interestingly, the direction has changed from negative in the first three waves to positive in the last five waves. This suggests that actors are more likely to engage in inter-institutional collaboration before 2009, but tend to collaborate with partners with a similar institutional context thereafter.

Taken together, the results of the network structural effects and the attribute proximity effects indicate that actors are more likely to collaborate with familiar partners (i.e., prior partners, partners of direct & indirect partners) and partners with similar attributes (geographical & institutional proximity). These collaboration patterns, in turn, determine directly a series of network structural and partner composition variables, and eventually impact the innovation performance of network actors. Specifically, selecting cooperation partners among those with whom they have cooperated already in the past hinders the increase of direct ties of the focal actor, and collaborating with partners of direct and indirect partners reduces network efficiency. Clearly, collaborating with partners of similar attribute increases the attribute proximity.

5. Impact of collaboration network on innovation performance

5.1. Measurement of variables

5.1.1. Dependent variables

In line with previous scholars who use patent count directly as the proxy of innovation performance (e.g., Ahuja, 2000; Demirkan and Deeds, 2013), this study measures the dependent variable as the number of patent applications by the actors in a year.

5.1.2. Independent variables

The independent variables in this study are direct ties, indirect ties, network efficiency and three dimensions of attribute proximities. This study calculates all these variables using UCINET 6 for Windows–Version 6.556.

5.1.2.1. Direct ties. This variable is measured by the number of collaborations to whom the focal actor is connected directly (i.e., the size of the ego-network or the degree centrality), namely, the number direct partners of the focal actor. Since this study proposes an inverted U-shaped relationship between innovation performance and the number of direct ties, the squared term of the number of direct partners is also used.

5.1.2.2. Indirect ties. This variable comprises the number of partners the focal actor can reach indirectly. There are different possibilities to operationalize indirect ties. In line with prior researchers (e.g., Ahuja,

Table 2
Estimation results for network evolution in SIENA.

Parameter estimates	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5	Wave 6	Wave 7	Wave 8
Rate of change	2.6074* (0.2952)	2.9778* (0.3052)	5.0210* (0.4228)	4.1292* (0.2942)	3.8625* (0.2376)	6.1077* (0.2710)	6.1509* (0.2075)	6.7088* (0.1775)
Degree	−2.2352* (0.4461)	−2.0801* (0.3299)	−2.6716* (0.3314)	−3.2403* (0.2727)	−3.3513* (0.2030)	−3.1107* (0.1717)	−3.1035* (0.1277)	−3.1161* (0.1105)
Transitive triads	0.0841 (0.3386)	0.2724 (0.2685)	0.1141 (0.2871)	0.4703† (0.2474)	0.1243 (0.1793)	0.7355* (0.0590)	0.2427* (0.0871)	0.2748* (0.0853)
Direct & indirect ties	0.7496* (0.2500)	0.7152* (0.2128)	0.9021* (0.2095)	0.5936* (0.1672)	0.7523* (0.1468)	0.7047* (0.0932)	0.7737* (0.0726)	0.7035* (0.0725)
Geographical Proximity	1.6997* (0.2963)	1.5655* (0.2922)	1.9932* (0.1920)	2.3690* (0.1732)	2.4689* (0.1425)	1.9382* (0.1227)	2.0090* (0.1070)	1.7548* (0.1037)
Institutional Proximity	−0.4330 (0.3894)	−0.6551* (0.2992)	−0.2221 (0.3229)	0.0727 (0.2583)	0.3518† (0.1900)	0.3968* (0.1338)	0.2425† (0.1377)	0.2700* (0.1003)
Technological Proximity	−0.0491 (0.2595)	0.1222 (0.2122)	0.0791 (0.1809)	0.2871 (0.1806)	0.1105 (0.1382)	0.0469 (0.1058)	0.0917 (0.0933)	0.1027 (0.0786)

Standard errors in parentheses, beneath regression coefficients.
Wave 1 = from Network 2005 to Network 2006.
Wave 2 = from Network 2006 to Network 2007.
....
Wave 8 = from Network 2012 to Network 2013.
* $P < 0.05$.
† $P < 0.10$.

2000; Guan and Liu, 2016; Vanhaverbeke et al., 2007), this study chooses a variable that measures the impact of indirect ties while taking into account the decline in tie strength of more distant ties. This study operationalizes the variable using 'distance weighted centrality' measure – Everett and Borgatti (1999). This variable is calculated by summing all ties at several distances weighted by their path distances, namely, the sum of the number of actors that can be reached in k steps divided by k. For k = 1, this is equivalent to degree centrality, namely the direct ties, and thus indirect ties only calculates the number of other actors in the network that the focal actor can reach at path distances of two or greater (k ≥ 2) which, thus, excludes direct ties. The result is that collaboration partners receive smaller weights the longer the path distance to the focal actor.

5.1.2.3. Network efficiency. The variable of network efficiency has been used extensively in prior research (e.g., Ahuja, 2000; Phelps, 2010). The network efficiency of actor *i* is obtained by using the following formula:

$$\text{Network efficiency}_i = \left[\sum_j \left(1 - \sum_q p_{iq} m_{jq}\right)\right] / N,\ j \neq q \tag{1}$$

where P_{iq} is the proportion of ties invested by actor *i* in the relationship with *q*, m_{jq} is the marginal strength of the relationship between actor *j* and actor *q* (as this study uses binary data, all values of m_{iq} are set to 1 if a tie exists and 0 otherwise), and *N* represents the number of partners to which focal actor *i* is connected. This measure ranges from a maximum of 1, indicating that every contact of the focal actor is non-redundant, down to a minimum approaching 0, indicating high contact redundancy and, therefore, low efficiency. If all of an actor's partners were unconnected to each other, the value of the measure would be 1. Connections between an actor's partners imply a higher $\sum_q P_{iq} m_{jq}$ and, consequently, a lower value indicative of lower efficiency and fewer structural holes.

5.1.2.4. Attribute proximity measures. The attribute proximity-based measures refer to three dimensions of attribute proximities, namely geographical proximity, technological proximity and institutional proximity. Proximity refers to correlation between ego attributes and its partners' attributes, and is measured by being in the same category. The value of this measure is the proportion of direct ties between focal actor and partners in the same attribute category to focal actor's total number of direct ties. Proximity-based measures range from a maximum of 1, indicating that all partners are of same attribute category as the focal actor, down to a minimum 0, indicating no partner is of the same attribute category as the focal actor.

5.1.3. Control variables

To minimize alternative explanations and isolate the marginal effects of the independent variables, this study controlled for several variables whose influence on innovation performance might be confounded with the independent variables.

5.1.3.1. The number of publications. The number of publications in the year observed was controlled. The number of publications is assumed to proxy the size of an organization, given that larger organizations may result in more papers. The size of an organization could impact the results heavily, as big organizations with more researchers can handle more direct ties and, thus, increase the upper limit of beneficial direct ties. As discussed above, too many direct ties can have a negative impact on the innovation performance. Additionally, the number of scientific publication could to some extent be used to proxy the variable of research intensity, which is a common control variable in the innovation literature (Ahuja, 2000; Benner and Tushman, 2003). Actors that invest heavily in R&D are expected to have a higher rate of innovation, and R&D investments may also play a role in enhancing the ability to recognize, value and assimilate external knowledge (Phelps, 2010; Vanhaverbeke et al., 2007). This study argues that the number of scientific publications is more appropriate to proxy the research intensity of university and public research institutes than traditional R&D expenditure-related measures, as scientific publications are the important output indicators of scholars in universities and public research institutes. In fact, the number of scientific publications has been used to measure scientific and technological strengths of a region (Van Noorden, 2014).

5.1.3.2. Technological diversity. Technological diversity is another important factor that can affect the innovativeness of a focal actor. Actors with high technological diversity may be more innovative due to greater internal knowledge flows (Garcia-Vega, 2006), and more able to absorb extramural knowledge (Phelps, 2010). In this study, the variable technological diversity is constructed based on the inverted Herfindahl index, which, conventionally, is used to indicate industry concentration and, now, is becoming a popular measure of technological diversification (e.g., Chiu et al., 2008; Garcia-Vega, 2006; Phelps, 2010). The Herfindahl index of diversification can be expressed as follows:

$$\text{Technological Diversity}_{it} = \left[1 - \sum_{J}^{j=1} \left(\frac{N_{jit}}{N_{it}}\right)^2\right] \tag{2}$$

where N_{it} is the total number of patents obtained by actor *i* in the five years prior to year *t*. N_{jit} is the number of patents in technology class (IPC symbols) *j* in actor *i*'s five year patent stock. This variable may take on values between 0–1. A higher value implies that an actor invests more resources into technological diversification whereas a low value suggests that the scope of technology is relatively narrow (Chiu et al., 2008). In this research, the technological diversity ranges between 0 and 0.9787.

An additional control for actor-level unobserved heterogeneity is lagged dependent variables, which are frequently used to control for unobserved heterogeneity in actor patenting propensity (e.g., Ahuja and Katila, 2001; Guan and Liu, 2016; Schilling and Phelps, 2007; Vanhaverbeke et al., 2007). Moreover, actors in different regions may have different propensities to apply for patents, a dummy variable is introduced to indicate if the actor is located in Beijing or Shanghai, since it is posited that actors located in Beijing or Shanghai may have a different propensity to patent. Furthermore, to control the heterogeneity between university and public research institutes, this study also includes a dummy variable to indicate whether an actor is a university. Finally, this study includes year dummy variables to control for changes in patenting over time due to systematic period effects such as differences in macroeconomic conditions or technological opportunity. Accordingly, eight year dummy variables are created, and the reference year is 2013. Table 3 presents descriptions of the variables.

5.2. Model specification and estimation

The dependent variable, namely the number of patents of a focal actor, is a non-negative, integer count variable. Under this condition, the Poisson regression approach or negative binominal regression models are appropriate (Demirkan and Deeds, 2013). The Poisson model assumes that the conditional mean and variance of the dependent variable are equal, but patent data often present over-dispersion (Vanhaverbeke et al., 2007). In the presence of over-dispersion, standard errors of coefficients will, generally, be underestimated, leading to spuriously high levels of significance (Schilling and Phelps, 2007). Negative binominal regression models, as extensions of the Poisson estimation, correct for over-dispersion and, thus, have been used extensively in studies of over-dispersed dependent variables (e.g., Ahuja 2000; Capaldo and Petruzzelli, 2014; Guan and Liu, 2016). That is the case for this study and, thus, the negative binomial regression that

Table 3
Definitions and operationalization of variables.

Variables	Operationalization and Measurement
Dependent variable	
Innovation performance	The number of patents, an actor applied for in a given year t
Network structural variables	
Direct ties	Degree centrality: the number of collaborations to whom the focal actor is directly connected to
Indirect ties	Weighted distance reach centrality: the sum of the number of actors that can be reached in k steps divided by k, $k \geq 2$
Structural hole	Network efficiency: the ratio of non-redundant ties to total ties for the focal actor
Attribute proximity variables	
Geographical Proximity	The proportion of direct ties between focal actor and partners in the same province to focal actor's total number of direct ties.
Institutional Proximity	The proportion of direct ties between focal actor and partners of the same organizational type (e.g., university, enterprise) to focal actor's total number of direct ties.
Technological proximity	The proportion of direct ties between focal actor and partners of the same knowledge base (PV-related inventor) to focal actor's total number of direct ties.
Control variables	
The number of publications	The number of publications of the focal actor in year t
Technological diversity	Inverted Herfindahl index measures IPC symbols in the previous 5 years
Lagged innovation performance	Innovation performance is lagged for one year
Beijing or Shanghai	Dummy variable: 1 if the first affiliation of this publication is located in Beijing or Shanghai, and 0 otherwise
University	Dummy variable set to one if the actor is a university (public research institute is the reference)
Year dummy	Dummy variable: 1 indicating a particular year (2005–2012), 2013 is 0 for the reference

allows for over-dispersion by incorporating an individual, unobserved effect into the conditional mean is employed.[5]

Since this study uses unbalanced panel data with several observations on the same actor at different points in time, the individual actor effects to control for unobserved heterogeneity across actors is employed. Moreover, the panel data implementation of the negative binomial model accommodates explicit control of individual unobserved effects through two widely used methods: fixed effects and random effects (Clark and Linzer, 2015; Gilsing et al., 2008). The Hausman test is regularly deployed as a test for whether random effects can be used, or whether fixed estimation should be used instead (e.g., Gilsing et al., 2008; Phelps, 2010; Vanhaverbeke et al., 2007). However, researchers have recently criticized the commonly-used Hausman test as neither a necessary nor a sufficient statistic for deciding between fixed and random effects (e.g., Bell and Jones, 2015; Clark and Linzer, 2015). They argue that a random effects model that properly specifies the within and between effects will provide identical results to fixed effects, regardless of the result of a Hausman test. Moreover, one side effect of the features of fixed-effects models is that they cannot be used to investigate time-invariant causes of the dependent variables (Torres-Reyna, 2011). In line with previous researchers who study the role of networks within the context of innovation, and considering patent count as the dependent variable (e.g., Ahuja, 2000; Gilsing et al., 2008; Guan and Liu, 2016), this study chooses a random-effects specification of the negative binomial regression to control for unobserved heterogeneity.

5.3. Regression results

Table 4 provides the descriptive statistics and correlations for all variables. As shown, there is substantial variation across actors in most of the key variables. The variance exceeds the mean for the variable of innovation performance, and indicates that the dependent variable suffers from over-dispersion.[6] To assess the potential threat of multicollinearity, this study estimates the variance inflation factors (VIF) for each independent variable. The results show that the maximum variance inflation factor is 5.40, below the recommended threshold level of 10 (Powers and McDougall, 2005), indicating that multicollinearity should not be a problem in this study.

Table 5 represents the results of the regression analysis using random-effects negative binomial estimation, with robust standard errors; all significance levels are for two-tailed tests. Model 1 presents the base model with only control variables included. Model 2 adds the four structural variables and model 3 adds the three attributes proximity variables to the specification. Model 4 is the complete specification, namely the full model. The Wald statistics at the bottom of Table 5 indicate models 2–4 provide significant improvement in fit relative to model 1. Moreover, the coefficients and significance of most independent variables are relatively stable over all the models (except the variable of *network efficiency*), indicating the robustness of the results. The full model is (i.e., Model 4) used to produce the results.

5.3.1. Structural variables

Hypothesis 1 predicts direct ties have an inverted-U shaped effect on innovation performance. As Table 5 shows, the coefficient of direct ties is positive and significant ($b = 0.0233$, $p < 0.05$), while the coefficient of direct ties squared is negative and significant ($b = -0.0005$, $p < 0.01$). This indicates that direct ties have an inverted-U shaped effect on innovation performance, supporting Hypothesis 1. In other words, direct ties are beneficial for innovation; however, with the increase in the number of direct partners after a specific point, diminishing returns start to dominate. Hypothesis 2 argues that indirect ties have a positive effect on innovation performance. As expected, the regression result of indirect ties in Table 5 is positive and significant ($b = 0.0033$, $p < 0.05$), supporting Hypothesis 2.

Hypothesis 3 presents two competing predictions for the effect of network efficiency on focal actor' innovation performance. Hypothesis 3a, predicting network efficiency has a positive effect on innovation performance, is supported by the result in Model 4 in Table 5. Interestingly, the estimated coefficient of the variable network efficiency is enhanced in terms of the magnitude and the significance level from Model 2 (i.e., without three attributes proximity variables, $b = 0.4733$, $p < 0.05$) to Model 4 (i.e., the full model in which the attributes variables are introduced, $b = 0.5878$, $p < 0.05$). This implies that

[5] A likelihood-ratio test provides strong evidence of over-dispersion in the data suggesting that negative binomial models are more appropriate over Poisson regression to predict the variable of innovation performance.

[6] This study also conducted supplementary analyses to evaluate the presence of over-dispersion in the dependent variable using generalized negative binomial regression. The LR-test of alpha = 0 show that the negative binomial model is preferred to the Poisson regression model.

Table 4
Descriptive statistics and correlation matrix.

Variable	Mean	Std. Dev.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12
1. Innovation performance	3.697	5.382	0	50												
2. Direct ties	5.194	6.444	1	73	0.569											
3. Direct ties squared	68.460	257.127	1	5329	0.385	0.853										
4. Indirect ties	102.294	71.008	1	260.547	0.260	0.464	0.302									
5. Network efficiency	0.872	0.174	0.250	1	0.150	0.077	0.086	−0.069								
6. Geographical proximity	0.427	0.346	0	1	−0.103	−0.065	−0.034	−0.072	0.101							
7. Institutional proximity	0.593	0.362	0	1	−0.073	−0.063	−0.061	0.027	0.033	−0.021						
8. Technological proximity	0.494	0.345	0	1	−0.043	−0.071	−0.029	−0.025	0.059	0.031	−0.124					
9. Innovation performance lagged	3.087	4.702	0	33	0.746	0.609	0.412	0.302	0.163	−0.074	−0.070	−0.026				
10. Technological diversity	0.674	0.376	0	0.979	0.388	0.353	0.179	0.273	0.133	−0.016	−0.137	−0.126	0.437			
11. The number of publications	8.073	12.270	0	122	0.588	0.877	0.758	0.379	0.161	−0.092	−0.037	−0.081	0.616	0.369		
12. Universities	0.771	0.420	0	1	−0.103	−0.094	−0.090	−0.037	0.012	−0.166	0.530	−0.079	−0.122	−0.055	−0.026	
13. Beijing or Shanghai	0.299	0.458	0	1	0.170	0.201	0.137	0.010	−0.008	0.172	−0.238	0.142	0.212	0.144	0.101	−0.303

Notes: Based on 940 observations. Correlations for year dummies are suppressed.

interaction might exist between network efficiency and attribute proximity variables.[7]

5.3.2. Attribute proximity variables

Hypotheses 4–6 proposed contradictory effects of attribute proximities on focal actor's innovation performance. The results in Table 5 show that the coefficient of geographical proximity is negative and significant (b = 0.3588, $p < 0.01$), providing strong support to Hypothesis 4b. Moreover, the results indicate that the variables of institutional and technological proximities have negative sign on innovation performance, but they do not reach the lowest significance level. Therefore, Hypotheses 5 and 6 are not supported.

5.3.3. Control variables

The coefficients of some control variables are also significant. Specifically, prior innovation performance (i.e., innovation performance lagged) has a positive effect on current innovation performance, albeit only at the 10% significance level in the full Model. As expected, technological diversity is positive and significant in all models, which confirms the previous researchers' argument that actors with high technological diversity may be more innovative due to greater internal knowledge flows and more able to absorb extramural knowledge (e.g., Garcia-Vega, 2006; Phelps, 2010). In line with previous researchers (e.g., Vanhaverbeke et al., 2007; Gilsing et al., 2008; Quintana-García and Benavides-Velasco, 2008), a significant and positive effect is found in the number of publications coefficient on innovation performance. However, the effect of organizational type is not significant, indicating that researchers in universities and public research institutes are no different in terms of innovation performance. Finally, the coefficient of Beijing or Shanghai is positive and significant in all models, indicating researchers in Beijing or Shanghai might be more innovative or/and have greater propensity to patent.

6. Discussion

6.1. Main findings

The main purpose of this study is to explore a) the evolution of the government sponsored collaboration network; and b) its effect on collaborating actors' innovation performance. In addressing the evolution of the government sponsored collaboration network, the SIENA model confirms the three structural effects (degree, transitive triads, direct/indirect ties) and two proximity effects (geographic and institutional) to be significant parameters in modeling 8 waves of innovation in the solar PV industry from 2003 to 2013. The results of the network structural effects and the attribute proximity effects indicate that actors are more likely to engage in collaboration with prior partners, partners of direct & indirect partners, and partners with similar attributes (geographical & institutional proximity). These collaboration patterns, in turn, will hinder the increase of direct ties, reduce network efficiency, and increase the attribute proximity of an actor's network. While collaboration network is only a tool, the real concern is the effect on innovation performance. In other words, what is needed is to understand what these types of networking really mean for the innovation performance of the collaborating actors.

Regarding the role of direct ties, an inverted-U shaped effect is found on innovation performance, confirming the findings of pervious researchers (e.g., Demirkan and Deeds, 2013; Vanhaverbeke et al., 2007). It indicates actors benefit from collaboration directly with other actors, however, up to a certain point. Guan and Liu (2016) argue that

[7] To specify the interaction between network efficiency and attribute proximity variables, this study reran the model 2 in Table 5 with three attribute proximity variables added respectively. The result showed that the network efficiency coefficient became positive and significant when geographical proximity or technological proximity was controlled, while the result was unchanged when institutional proximity was controlled.

Table 5
Random effects negative binomial regression for innovation performance.

Variables	Model 1	Model 2	Model 3	Model 4
Structural Variables				
Direct Ties		0.0244*(0.0118)		0.0233*(0.0118)
Direct Ties Squared		−0.0005**(0.0002)		−0.0005**(0.0002)
Indirect Ties		0.0036*(0.0015)		0.0033*(0.0015)
Network efficiency		0.4733†(0.2607)		0.5878*(0.2623)
Attribute Variables				
Geographical Proximity			−0.3734**(0.1281)	−0.3588**(0.1277)
Institutional Proximity			−0.0959(0.1388)	−0.1299(0.1377)
Technological Proximity			−0.1285(0.1197)	−0.1583(0.1204)
Control Variables				
Innovation performance lagged	0.0173*(0.0075)	0.0145†(0.0076)	0.0172*(0.0074)	0.0145†(0.0075)
Technological diversity	1.468***(0.168)	1.4397***(0.1619)	1.4399***(0.1694)	1.3929***(0.1638)
The number of publications	0.0165***(0.0026)	0.015***(0.0038)	0.0162***(0.0026)	0.0151***(0.0038)
Universities	0.0352(0.1424)	0.0436(0.1309)	0.0344(0.155)	0.0615(0.1451)
Beijing or Shanghai	0.4187**(0.1333)	0.3272**(0.1239)	0.4674***(0.1323)	0.3876**(0.124)
Year dummy variables	Included	Included	Included	Included
Constant	−0.4461†(0.2603)	−1.7666***(0.4578)	−0.1555(0.2828)	−1.4911**(0.4619)
Number of actors	200	200	200	200
Number of actors-years (obs.)	940	940	940	940
Wald chi-squared (d.f.)	339.96***(13)	390.67***(17)	352.32***(16)	404.11***(20)
Log-likelihood	−1864.3356	−1852.7928	−1859.1769	−1847.5596
Likelihood-ratio test vs. pooled	87.11***	63.05**	83.2***	59.17**

Notes: Year dummy variables were included in the models but their coefficients were not reported in the table.
Standard errors in brackets.
† $P < 0.10$.
* $P < 0.05$.
** $P < 0.01$.
*** $P < 0.001$.

further increases in direct ties hinder the organization's ability to innovate by reusing its extant knowledge elements, as combinatorial potentials of these knowledge elements are exhausted. Demirkan and Deeds (2013) argue that adding a large proportion of new members to the ego-network aggravates the complexities and uncertainties associated with the management of the network. Therefore, to facilitate innovations, the ego-network size of an organization in a collaboration network should be maintained at a moderate level, which might be expected to depend on combination of factors, notably, the size of organization and age structure of team members.

By contrast, indirect ties are found to be positively related to innovation performance. In other words, being well connected to the rest of the collaboration network through indirect ties is advantageous for inventing-actors, adding empirical evidence to the network literature. Therefore, when seeking innovation opportunities, an organization should conduct not only a local search around its ego-networks but also a distant search, namely collaborate with actors who already have more partners.

Regarding the role of network efficiency in the collaboration network, the results suggest non-redundant network structure has a positive effect on innovation performance, which is in contrast with Ahuja (2000) who demonstrated that structural holes were negatively related to innovation output. While Ahuja's finding supports Coleman's (1990) proposition that network actors benefit most from cohesive (or redundant) ties, the finding of this study confirms Burt's (1992) argument that ego networks rich in structural holes (high network efficiency) imply access to mutually unconnected partners and, consequently, many distinct information flows. Guan and Liu (2016), similarly, suggest that an organization should be embedded in open collaboration networks to benefit its innovation performance.

Another main contribution of this study is that network structure and attributes proximities are jointly considered in assessing their effect on innovation performance. The results show that all proximity-based variables have negative effects on innovation performance, although most of the coefficients are not significant. Moreover, this study finds that the impact of network structure variables on innovation performance changes in terms of the magnitude and significance level of coefficients, when proximity-based variables are introduced. In particular, the effect of network efficiency on innovation performance is enhanced. This reflects the potential interaction effects between network structural variables and attribute variables on actors' innovation performance, providing important implications for further research.

Furthermore, it should be noted that this study focused on the government sponsored collaboration network, namely collaboration networks generated by policy instruments, which might differ from the emerging networks without external stimulus. The government sponsored collaboration network could be viewed as the outcome of the interaction between government agencies and a set of knowledge-based organizations, making it different from self-organizing networks as there is a wide range of organizations that exert influence on network evolution and subsequent innovation performance. To this end, an additional analysis of the whole collaboration network (including collaborations without government funding support) has been conducted.[8] Except that the magnitude and the significance level of the estimated coefficients change, the signs of the estimated coefficients for the variables concerned are similar to the regression results for the government sponsored collaboration network. It seems that the government sponsored collaboration network is not different in terms of the specific effects of collaboration network on innovation performance. One possible explanation is that in the vast majority of research collaborations, the public research organizations in particular, are supported by government funding.

6.2. Implications

6.2.1. Theoretical implications

As previously discussed, our understanding of network evolution is

[8] As the additional analysis did not yield significant results, it is not included in this paper.

still preliminary as the network evolution is a very complex process in the light of actors' different priorities, environments and mindsets. Relying on the emerging network evolution model-SIENA, this study adds to the growing literature on network dynamics through considering network structural effects and organizational attributes-related effects jointly. The empirical results indicate that both network structural effects and organizational attributes-related effects are relevant for collaboration network formation.

The findings on direct ties and indirect ties confirm the prescription in the literature to use indirect ties as an efficient and effective way of maximizing network benefits (Ahuja, 2000; Burt, 1992, Powell et al., 1996). Further, indirect ties can act as information channels and facilitators of knowledge exchange between network actors, but need to bear relatively low or no maintenance costs for direct partners. As such, it seems reasonable to assert that it is beneficial for the focal actor to keep its indirect ties as extensive as possible. However, this study argues that indirect ties do not guarantee that the focal actor can achieve the desired innovation performance. Ahuja (2000) argues that direct ties and indirect ties can differ significantly in the nature and/or content of benefits that they provide to the focal actor, and that, even when direct ties and indirect ties provide the same kind of benefit, the magnitude and the level of benefits provided by indirect ties may be significantly different from those provided by direct ties. The difference between direct ties and indirect ties may have different effects on different innovation activities. This indicates that further studies examining collaboration networks and innovation should be designed to reflect the potential differences.

Regarding another ongoing debate in the network literature on whether innovators should occupy "closed" or "open" networks, the finding of this study supports the latter. It should be noticed that this conclusion is unlikely to be true universally. Ahuja (2000), for instance, has demonstrated that open networks (higher network efficiency) were negatively related to innovation output. Coleman (1990) acknowledges that social relationships that constitute social capital for one kind of productive activity may be impediments for another. Ahuja (2000) similarly argues that the optimal structure of inter-organizational networks depends on the objectives of the network members. Burt (2005) further argues that different forms of network structure may play different roles for different populations or goals. This study also has no intention to indicate that closed networks are inferior to open network or vice versa. Rather, this study argues that whether open networks are more productive than closed network depends on the context being studied or, more precisely, the different innovation activities conducted.

Taken together, it is reasonable to argue that direct ties and indirect ties, open and closed networks may differ in the nature or content of benefits that they provide to the focal actor, and these differences, in turn, will affect the focal actor's innovation performance differently. Accordingly, a distinction of innovation activities is expected to be helpful in better understanding how collaboration networks influence innovation. In fact, scholars have attempted to differentiate innovation performance in terms of exploratory and exploitative innovations in investigating the effect of collaboration networks on innovation performance. However, existing studies distinguishing exploratory and exploitative innovations also yielded inconsistent findings. By distinguishing exploratory and exploitative innovations, Vanhaverbeke et al. (2007) found that indirect ties have a positive effect on both exploratory and exploitative innovations, whereas Guan and Liu (2016) demonstrated that indirect ties have only a negative effect on exploratory innovation. Moreover, Vanhaverbeke et al. (2007) found that network efficiency has a negative effect on exploitative innovation, whereas Guan and Liu (2016) demonstrated that network efficiency has a positive effect on exploitative innovation. One possible explanation is that there is no clear distinction between exploratory and exploitative innovations, which have been operationalized in different ways in the literature, as authors adapt them to their research needs with various interpretations. Identifying different innovation activities properly is, therefore, likely to be critical to better understand the relationship between collaboration network and innovation performance, although there is probably no simple, universal answer.

6.2.2. Policy implications

This study focuses on government sponsored collaboration networks and, thus, provides important implications for policy makers. As discussed, an increasing amount of government funding is provided for collaborations of enterprises, universities and public research institutes as a means to strengthen their innovative capabilities. A collaboration network is widely assumed to be "a good thing" and should be encouraged (Katz and Martin, 1997). However, the findings of this study indicate that collaboration is not always "a good thing". On the one hand, this study identifies that actors are more likely to engage in collaboration with prior partners, partners of direct and indirect partners, and partners with similar attributes in the government sponsored collaboration network. On the other hand, these collaboration patterns might be harmful to innovation performance of network actors. Specifically, collaborating with partners of direct and indirect partners reduces network efficiency, which is found to be conductive to innovation performance. Moreover, collaborating with partners of similar attributes increases the attribute proximity and, thus, might not be conducive to innovation. Furthermore, too many direct ties impede innovation performance, and appropriate direct ties can enhance innovation performance; the threshold point might depend on the actor-specific capabilities, which is an area that demands further study. In short, it is no longer appropriate to simply assume that more partners are better and that all network actors will benefit equally from similar collaboration networks. These findings convey important implications for policy-makers that more attention must be paid to the network structure and composition in future policy design.

6.2.3. Practical implications

The findings of this study also provide important implications for practitioners on how collaboration networks might be structured to enhance their innovation performance. For instance, they should collaborate directly with partners who are well connected, but the direct partners should be maintained at a moderate level as their innovation performance could suffer from having too many partners at the same time. Moreover, their innovation performance will be better off when their direct partners are not connected with each other. Furthermore, collaboration across regional boundaries will benefit their innovation performance.

6.3. Limitations and future research

The study is subject to some limitations, which also open perspectives for future research. First, the government sponsored collaboration network is constructed based on co-authored scientific publications with government funding acknowledgement. Although extensively used in the literature for analyzing scientific collaborations, co-authored publications is only a rough proxy as it cannot capture "hidden" scientific collaboration and can be overrepresented by the 'honorary' collaboration (Katz and Martin, 1997). Moreover, researchers in enterprises are not motivated to publish their findings like scientists within universities and public research institutes. Hence, the network in this study is incomplete. Future research could extend our understanding of the collaboration network by using a more exhaustive database. Second, this study measures innovation performance based on patent applications of an organization. It should be noticed that a patent is not necessarily an innovation as, usually, commercialized patents are regarded as innovations in the literature (e.g., Dodgson et al., 2008; Jaffe and Stavins, 1994). Moreover, the measure may not capture all of an organization's innovations as part of technical knowledge may remain unpatented either because it is unpatentable or because an organization may choose not to patent for secrecy. Third, this empirical study is limited to only one industrial context, namely the emerging solar PV sector. The results cannot be simply generalized to other industrial contexts. However, the methodology in this paper could be replicated. Further corroboratory evidence using data from different samples and industry contexts is encouraged to validate this study's findings and, especially, to test the hypotheses of the present research further.

7. Conclusion

While the literature highlights the importance of a collaboration network in promoting innovation, empirical investigation of network evolution and its effect on network actor's innovation performance is very recent, particularly the government sponsored collaboration network. This study is exploratory and an early attempt to analyze the dynamics of a government sponsored collaboration network along the development of an emerging high-tech sector in the Chinese context, and investigates the effect of network evolution on the subsequent innovation performance by considering the network structural effects and attribute proximity-based effects.

The results indicate that the evolution of the government sponsored collaboration network indeed follows some patterns. These collaboration patterns could lead to a high ratio of geographical proximity and a low ratio of network efficiency of the collaboration network, both of which impact innovation negatively. The empirical findings also extend the network literature that, direct ties and indirect ties, open network and closed network might differ in the nature or content of benefits that they provide to the focal actor. Taken together, such findings should lead to a better understanding of the ways in which government R&D funding interacts with the collaboration behaviors of knowledge-based organizations, and the consequent impact on innovation. This understanding, therefore, could ultimately lead to the improved design and implementation of innovation policy instruments, which are of particular importance to the emerging energy-saving technologies.

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Appendix A

The search terms with boolean operator for solar PV scientific publications: Silicon OR "Si" OR Thin film* OR Cadmium Telluride OR CdTe OR Copper Indium Selenide OR CIS OR CuInSe* OR Copper Gallium Diselenide OR CGS OR Copper Indium Gallium Diselenide OR CIGS OR Copper Zinc Tin OR CZTS OR "Organic photovoltaic*" OR 'Organic PV*" OR "Organic solar cell*" OR OPV OR Polymer OR Dye sensiti* OR DSSC* OR "Quantum dot" OR "Concentrat* photovoltaic*" OR 'Concentrat* PV' OR "Concentrat* solar cell*" OR CPV OR junction OR III–V OR Gallium indium OR GaInP OR InGaP OR GaInAs OR InGaAs OR Germanium OR Ge OR Gallium arsenide OR GaAs OR 'Photovoltaic* effect' OR "Photovoltaic* material' OR 'photovoltaic* Propert*" OR "Photoelectric Conversion' OR (Photovoltaic* same soliton*) AND 'Solar cell*" OR "Photovoltaic*" OR "PV cell*" ***in the Topic*** OR "Photovoltaic* effect" OR 'Photovoltaic* material' OR "photovoltaic* propert*" OR 'Solar Cell*" OR "Photovoltaic Cell*' OR "PV Cell*' ***in the Title***, and the address is ***China***.

Appendix B

IPC green inventory (The photovoltaics part)	
Photovoltaics (PV)	International Patent Classification (IPC)
Devices adapted for the conversion of radiation energy into electrical energy	H01L27/142, 31/00-31/078 H01G 9/20 H02N 6/00
Using organic materials as the active part	H01L 27/30, 51/42-51/48
Assemblies of a plurality of solar cells	H01L 25/00, 25/03, 25/16, 25/18, 31/042
Silicon; single-crystal growth	C01B 33/02 C23C 14/14, 16/24 C30B 29/06
Regulating to the maximum power available from solar cells	G05F 1/67
Electric lighting devices with, or rechargeable with, solar cells	F21L 4/00 F21S 9/03
Charging batteries	H02J 7/35
Dye-sensitised solar cells (DSSC)	H01G 9/20 H01M 14/00

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