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The impact of university–industry collaboration networks on innovation in nanobiopharmaceuticals

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ABSTRACT

This paper investigates the effects of multiplicative interaction between clustering and reach on members' knowledge creation and patent value based on complex network analysis in nanobiopharmaceuticals field. In order to avoid the high skew of patent value among patents, we use the weighted patent value as a proxy index of the invention's innovation performance rather than simple patent counts. The university–industry collaboration networks in the emerging and rapidly evolving interdisciplinary field are examined at firm-level. We further detect the impact of small world properties as well as the size of largest component on patent value and find that small-world structure has parabolical effect on patent value at firm-level. We add new evidence to the literature on this topic with an empirical investigation for the university–industry patent collaboration in the nanobiopharmaceutical field. The findings broaden and enrich the existing literature and can contribute to policy makers and relevant managers when making decisions for university and firm locality as well as the choices of the collaborators.

1. Introduction

In today's highly competitive environment, a firm's ability to catch up with technological progress and continuously innovate is crucial for its survival and growth. However, it is increasingly difficult for firms to explore new technologies completely on their own as a result of limited expertise and resources. There has been a universal recognition that collaboration between industry and research universities should be enhanced in order to satisfy the growing demand for industrial innovation in the global market place. The linkages among universities and industry comprise significant parts of regional as well as national innovation systems [1]. Therefore, enhanced collaboration between them is crucial for the competitiveness of a country. University–industry knowledge transfer is nowadays a key research subject both in economics and management studies, as well as a top entry in the science and technology policy agenda of a number of developed and developing countries [2].

It has been certified that collaboration between industry and universities is useful in reducing the cost of R&D, decentralizing risks, and promoting these organizations to share resources and attain complementary capability [3]. Such cooperation has become increasingly crucial to the success of industrial innovation for most countries. For example, Canadian industry doubled its collaboration with universities from 1980 to 1995 [4]. The modes of innovative cooperation between industry and universities are largely of informal communication of skills and knowledge, technology trade or technology transfer, formal R&D collaboration (e.g., R&D alliance, R&D outsourcing), training of innovative personnel, and provision of skilled workforce and graduates with knowledge and skills and so on [5].

Furthermore, social network analysis (SNA) is a hopeful method for comprehending the complex relations between

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various actors, such as industry and universities, inventors within organizations, organizations with regions, and so forth [6]. It can be utilized for discriminating the structures in social systems according to the relations among the system's components rather than the attributes of individual cases [7]. Networking can be a complementary factor in situations where cooperation and networking are required to attain economies of scale and/or to integrate diverse skills, technologies and competencies [8]. To our knowledge, there are several empirical researches that have examined the impact of the collaboration network characteristic on knowledge creation. Some researchers suggested that network cooperation or using a wide range of external actors and sources had a positive influence on innovation performance of firms [9]. Becker and Dietz [10] explicitly acknowledged that cooperation with different partners on research and development (R&D) had a positive effect on innovation achievement. Similarly, Brioschi et al. [9] noticed that social interactions based on trust and cooperation took a major role in coordination of the activities among different small- and medium-sized enterprises (SMEs). Uzzi and Spiro [11] pondered the network structure of the creative artists who made Broadway Musicals from 1945 to 1989, and inferred a conclusion that the large-scale structure of the artists' collaboration network notably affected on their creativity, and the financial and artistic performance of their musicals. Schilling and Phelps [12] worked over the impact of large-scale network properties on the innovative output of members of the network. Chen and Guan [13] investigated the impact of small world properties on innovation at national level with an empirical investigation for the patent collaboration networks of 16 main innovative countries during 1975–2006. Despite the recognized importance of university–industry collaboration across various S&T fields, relatively few studies [14–16] have examined the impact of network topologies of the university–industry collaboration on member innovation, especially in interdisciplinary field.

As for interdisciplinary field, of which we just spoke, in this article, nanobiopharmaceutical technology, as an emerging and rapidly evolving field with the interdisciplinary nature, is chosen. Nanobiopharmaceutical technology connotes the technology which can be used in production or consumption for applications of nano and biotech in drug discovery [17]. The challenge of nanotechnology is to exploit nanoparticles for biomedical and biotechnology applications to deliver the pharmaceutical in the right place at the right time. Nanobiotechnology, which is currently being used to explore the pathomechanism of disease, refine molecular diagnostics, and aid in the discovery, development and delivery of drugs [18], involving biological systems manufactured at the molecular level, is a multidisciplinary field that has cultivated the development of nanoscaled pharmaceutical delivery devices [19]. Nanobiopharmaceutical technology represents recent globally significant innovation trends at the intersection of pharmaceutical technology and nanobiotechnology [17], was firstly introduced by Jain in 2008 [18,20]. This field is chosen for three reasons. First, carefully checking nanotechnology research demonstrates a large increase in research activity in nanobiopharmaceutical field since 2000. Since 2000, we have enjoyed a profusion of success producing bionano research findings while taking the fancy of a great deal of investment from pharmaceutical corporations setting up advanced drug discovery operations. This field is a promising research domain from latest scientific advances with potential and enormous economic value. Nanobiopharmaceuticals is emerging from recent scientific advances to which marketers and investors attribute enormous commercial potential [17]. Second, nanobiopharmaceuticals is a generic and radical technology that is of high interest owing to its potential for value creation across an extensive range of industries and applications. As a generic technology, nanobiopharmaceuticals offers the potential for value creation across a broad range of industries and applications, which will get access to benefits for a wide range of sectors of the economy and/or society [21]. Recently, many areas of nanobiopharmaceuticals have witnessed a speedy increase in the number of patents filed [22]. Therefore, we are interested in development and application of bionanotechnology within the domain of pharmaceutical research. Third, it is widely acknowledged that nanobiopharmaceuticals, as an emerging and rapidly evolving field with the multidisciplinary nature, is perceived not only by scientist and technology developers but also by policy-makers as one of crucial technologies of this century. New interdisciplinary research areas often develop in the interstices of established fields, through fusion or integration of some topics across the existing parent fields [23]. It has great prospect to lead the world into next new industrial revolution. Little is implemented bibliometric analyses, however, about nanobiopharmaceuticals. Lenoir and Herron [17] combine citation analysis, text mining, mapping, and data visualization to gauge the development and application of nanotechnology in China, particularly in nanobiopharmaceuticals, and to estimate the impact of Chinese policy on nanotechnology research production. Zhao and Guan [24] studied the International collaboration of three “giants” with the G7 countries in emerging nanobiopharmaceuticals.

Preceding argument brings about the following questions: how does the structure of a university–industry collaboration network (the definition and details of the structure of a university–industry collaboration network are described below in Section 4.2) in the field of nanobiopharmaceuticals influences the rate of knowledge creation among firms and universities in the network? In particular, the network method provides a systematic analytical tool to uncover the hidden structure and to monitor the effectiveness of knowledge exchange among researchers across industry and university. The goals of the paper are two-fold: first, we study the impact of following two key network properties, clustering and reach, on the innovative output of members of the network. Second, we generate network to detect the impact of small world properties as well as the size of largest component on patent value of innovation performance at firm level.

This study broadens the existing literature in several ways. First, one of the challenges with using patents to measure innovation is that the propensity to patent may vary with industry, resulting in a potential source of bias. Previous quantitative studies have merely emphasized the patent counts yet have considered little about the difference of patent value. We use weighted patent value (WPV, the definition and its details are described below in Section 4.3) as a measure of the invention's innovation performance rather than simple patent counts. Second, Schilling and Phelps [12] proposed that firms embedded in alliance networks that exhibited both high clustering and high reach (short average path lengths to a wide range of firms) will have greater innovative output than firms in networks that do not exhibit these characteristics. They find support for this proposition in a longitudinal study of the patent performance of 1,106 firms in 11 industry-level alliance networks. We broaden this proposition to firm-level university–industry collaboration networks in an emerging interdisciplinary field other than only alliances between firms. Third, despite the several empirical studies of small world network and innovation at national, industrial, discipline or regional level [12,13,25,26], in this study, we develop and exploit a novel database on university–industry patent collaboration for the field of nanobiopharmaceuticals to investigate the impacts of small world networks on the patent value of innovation output at firm-level. Fourth, the study is relevant, as nanobiopharmaceuticals is quite a new technology and there are not many works that analyze this field under a quantitative approach.

The remaining parts of the paper are organized as follows. The next section discusses that the impact of clustering and reach on weighted patent value (WPV) of the innovative output of members, and develops the hypotheses to be tested. The third section discusses the impact of small worlds on WPV of the innovative output of members, and develops the hypotheses to be tested. The fourth section presents our data, methods for network generation, variables, small world measures and model specification. The fifth section presents the results of the empirical analysis, whose main implications are discussed in the last section.

2. The impact of clustering and reach on WPV of the innovative output

2.1. Clustering

The clustering coefficient (CC) is a measure of the local graph structure. Co-authorship networks are liable to be characterized by local clusters of individuals who are tied to most of the others [27]. The actual CC is on a scale from zero to one. Zero stands for no clustering, and one stands for full clustering. For example, it is the probability of co-operation if both have worked together a third author for coauthor networks. If a network has a clustering coefficient of 0.6, it signifies that there is 60% of a probability that two authors both collaborating with a third author would also work together each other. Clustering enhances the information transmission capacity of a network.

2.2. Reach

The size of a network and its average path length (i.e., the average number of links that separates each pair of members in the network) also influences information diffusion and novel recombination. A member's distance-weighted reach is the sum of the reciprocal distances to every member that is reachable from a given member, i.e., $\sum_j 1/d_{mj}$, where d_{mj} is defined as the minimum distance (geodesic), d, from a focal member m to partner j, where $m \neq j$. A network's average distance-weighted reach is this gauge averaged across all members in the network, $\left(\sum_n \sum_j 1/d_{mj}\right)/n$, where n is the number of member in the network using distance-weighted reach. It provides a significant gauge of the overall size and connectivity of a network, even when that network has manifold components, and/or component structure is changing over time [12].

Recent research has revealed that even sparse, highly clustered networks can have high reach if there are a few links generating bridges between clusters [28,29]. As Uzzi and Spiro [11] noticed, bridges between clusters increase the likelihood that different ideas and routines will come into contact, facilitating recombinations that integrate both previous conventions and novel approaches while reducing the average path length and increasing reach. The combination of clustering and reach enables an extensive range of information to be interchanged and integrated rapidly, bringing about greater knowledge creation [12]. In sum, we forecast a multiplicative interaction between clustering and reach in their impact on member knowledge creation. Consistent with the symmetrical nature of such interactions [30], we have argued and anticipate that the effect of clustering on members' knowledge creation and patent value will be increasingly positive as reach increases, while the effect of reach on patent value will be more and more positive as clustering increases.

Hypothesis 1. Members going in for alliance networks that combine a high degree of clustering and reach will exhibit more patent value than members in networks without these characteristics.

3. The impact of small worlds on WPV of the innovative output of members

In today's highly competitive society, a firm's performance relies on how it can acquire resources within a network of relationships [31]. Strategic research has been made to study how network topology molds the evolution of competition in various industries [32]. One type of social organization that has obtained a great deal of attention for its possible ability to impact creativity and performance is the small world network.

We focus our study at the firm level, allowing us to explore the relationship between small world collaboration network and WPV of the innovation output. It is argued that small worlds can enhance the level of creativity and innovation. The effects can be organized into three aspects, clustering, path length and their interaction. When the clustering increases, the more connected and cohesive nature should cultivate innovation through the sharing of ideas, soft information and other resources. Besides the more easy diffusion of creative material, the greater level of repeated and third party links can also bring about greater risk sharing and trust in a community [33]. High clustering facilitates sanctions that make it less risky for people in the network to trust one another. Over the long haul, repetitive ties can reduce innovation cost by spreading the risk of experimentation. Both the effects on creative material diffusion and trust enhancement reveal that increased clustering can enhance the performance of the global network. While on the other side, high clustering may bring about too much common perspectives and unnecessary information, which may harm innovation performance because inventors need to think differently in order to break existing prototypes [13]. As Uzzi and Spiro [11] point, small world's effect may be parabolic. As the level of small world adds, separate clusters change into more interlinked and linked by persons who understand each other. These processes contribute creative material among teams and help to establish a cohesive social organization within teams that encourage risky collaboration around good ideas. However, these benefits may rise only up to a marginal value after which point they shift negative [34]. Past a certain threshold, these same processes can be a hindrance for collaboration. Excessive structural connectivity decreases some of the creative distinctiveness of clusters, which can make similar pool of creative material. The ideas most probably flowing ideas can be traditional rather than fresh opinions due to the common information effect, and because newcomers discover it difficult to have their ideas understood and accepted.

How can these opposing points of view work together? We put forward that when the clustering is at a relative low level, there are few links between friends of friends and the global networks do not get necessary information, so increasing clustering should enhance innovation performance because it brings more effective creative material diffusion and risk sharing. However, past a certain threshold, the positive aspect becomes neglectable while negative aspect begins to work noticeably to whittle down the innovation output.

These drivers all give rise to the expectation of a parabolic relationship between network clustering coefficient and WPV of innovation performance. Hence, our second hypothesis is:

Hypothesis 2. The relationship between network clustering coefficient and WPV is parabolical. Specially, below a medium level, clustering coefficient will correlate positively with increased future WPV, while the correlation will turn negatively when overtaking the medium level.

Independent of the medium clustering coefficient, the shorter path length should also enhance inventor's innovation performance for its ability of easier information transfer, diverse ideas interaction and heterogeneous creative resource diffusion [13,26]. We anticipate a positive relationship between decreased path length and WPV of innovation performance. Thus we come to our third hypothesis:

Hypothesis 3. Decreased average path length of the university–industry collaboration network will have a positive effect on the future WPV for its member.

As discussed above, we suggest that higher clustering can bring more positive effect when it is under the threshold and more negative effect when the threshold is overtaken, while shorter path length always has positive effects; thus it is rational to put forward another parabolic relationship between small world Quotient and WPV of innovation output. Thus we come to our fourth hypothesis:

Hypothesis 4. The relationship between small world Quotient and WPV of innovation performance is parabolical. Specially, below a medium level, small world Quotient will correlate positively with increased future WPV, while the correlation will turn negatively when overtaking the medium level.

A component is a subset of vertices in the graph each of which is reachable from the others by some path through the network. The largest component is the component with largest sum of vertices belonging to that component [35]. In this study, we discover that at the beginning of the network evolution, the global networks are made up of numerous small components, and then collaborations among these components connect them together to shape one dominant large component. The so-called largest component of a network measures the collection of actors that are linked to each other by at least one path of intermediaries [36]. The eroding components result in the small-world network becoming increasingly isolated from the greater outer network and this trend manifests in the decreased formation of bridging ties between the occupants [37]. As aggregation of members boosts information flow and knowledge transfer, we imagine that the aggregation of isolates and small clusters should correlate positively with WPV of innovation performance [13]. Thus we come to our fifth hypothesis:

Hypothesis 5. The size of largest connected component will correlate positively with increased future WPV of the members.

4. Data and methods

4.1. Data collection

We chose nanobiopharmaceutical field, which is characterized by a strong reliance on scientific developments and, therefore (at least potentially) involves high levels of interaction among the universities and firms involved in science and those involved in industrial research. The empirical analyses presented in this study draw on the Derwent Innovation Index database (DII) because it is the most comprehensive database covering the data of the main leading patent-issuing authorities including USPTO, JPO, EPO, World Intellectual Property Organization (WIPO) and Sino Intellectual Patent Office (SIPO).

In carrying out a bibliometric analysis of nanotechnology science, Hullmann and Meyer [38] used “nano*” as the query to identify nanotechnology where * means wildcard, and mentioned that this is a pragmatic approach when the domain is interdisciplinary and difficult to identify [39]. Similarly, nanobiotechnology documents are retrieved by using nano* and bio* as the query [40]. The nanobiopharmaceuticals is the application of nanotechnology and biotechnology to pharmaceuticals [18]. This means that, dissimilar from the interdisciplinarity of two domains (e.g., nanobiotechnology, biopharmaceutics and nanopharmaceutical), the multidisciplinary domain incarnates more comprehensive intellectual information of nanotechnology, biotechnology and pharmaceuticals, and is more difficult to identify.

We utilize the search strategy recommended by Lenoir and Herron [17] in order to search and select the relevant nanobiopharmaceutical patents for investigating our research questions. Lenoir and Herron [17] estimated a series of search efforts and provide a search strategy to select nanobiopharmaceutical patents. This method uses the set of 32 bio- and pharma-relevant Keywords Plus® terms including titles, abstracts, key words identifying nanotech research publication production for the purpose of formulating a high-precision query for bio- and pharma-nanotechnology documents. This search strategy has empirically tested by Lenoir and Herron [17] through a series of search efforts and the search results are almost always deeply relevant to bio- and pharma-nanotech.

Furthermore, we also carefully check the front pages of the patent documents retrieved by the queries to examine and filter their relevance to nanobiopharmaceuticals, trying to eliminate the false and retain the true.

The empirical analyses presented in this study draw on the Derwent Innovation Index database (DII) because it is the most comprehensive database covering the data of the main leading patent-issuing authorities. More importantly, DII provides the descriptive titles and concise front pages rewritten by subject experts, which easily highlight information about the domain of a patent and are used to help exactly distinguishing if the samples we selected are relevant for our research questions.

The query, written in SQL, searching for all records whose KeyWords Plus® field matched any of the 32 terms is performed by Lenoir and Herron [17] as follows:

mysql $>$ select $*$ from nano_IDs

- where ID like "cytotoxicity" or ID like "immunoassay" or ID like "glucose" or ID like "antibody" or ID like "single molecule" or ID like "layered double hydroxides" or ID like "Ascorbic acid" or ID like "alpha-cyclodextrin" or ID like "assay" or ID like "expression" or ID like "amplification" or ID like "poly(acrylic acid)" or ID like "titanium-dioxide films" or ID like "cadmium-sulfide" or ID like "block copolymers" or ID like "glucose-oxidase" or ID like "anatase TiO2" or ID like "beta-cyclodextrin" or ID like "recombination" or ID like "micellization" or ID like "Solgel" or ID like "TiO2 films" or ID like "nanocrystalline tio2" or ID like "acrylamide" or ID like "fluorescence probes" or ID like "paste electrodes" or ID like "triton x-100" or ID like "oxidase" or ID like "horseradish-peroxidase" or ID like "binding" or ID like "photodegradation" or ID like "DNA hybridization".

Therefore, we use the 32 bio- and pharma-relevant topic terms and nano* together as the query to collect the patents. In addition, we add to three prefixes, nano*, bio* and pharm*, as the query to more completely collect the patents. Besides, we use nanobio* (or bionano*) and pharm*, biopharm* and nano*, nanopharm* and bio*, as well as nanobiopharm* (or bionanopharm*) as four complementary queries [20]. Next, we check carefully the abstracts of patents retrieved by the queries to examine and sieve their relevance to nanobiopharmaceuticals. This approach has identified more than 11,000 records in the DII database in the time frame of 1982–2009. The total number of patents obtained by universities in the world is 2,624.

Throughout this study, patents only refer to the ones pertaining to the field of nanobiopharmaceuticals unless otherwise stated. Here we only think about last 10 years (2000–2009), with speedy development of patents in nanobiopharmaceutical research unless otherwise stated. Here, university–industry collaboration patent refers to the patent that is co-invented by at least one university and one firm. The data comprise a panel data set containing 640 firms and universities participating in university–industry collaboration patents in the field from the global nanobiopharmaceutical sector.

4.2. Alliance network

Network structure is defined as the pattern of direct and indirect ties between actors. A general proposition is that actors' differential positioning within a network structure has an important impact on resource flows, and hence, on entrepreneurial outcomes [41]. Network structure is a significant source of insight into network performance [42]. We apply a rule to guide our construction of the university–industry collaboration networks used in this study. Each alliance includes at least one firm and a university that collaborate on at least a patent in the field of nanobiopharmaceuticals. Any member in each alliance is a firm or a university which has participated in at least one university–industry collaboration patent in the field. Thus, we set up a patent-member database about university–industry collaboration, which is made up of patent and their corresponding members of university–industry collaboration. The patent-member database about university–industry collaboration permits us to construct a unipartite network, where actors in the network are individual firms or universities which has participated in at least one university–industry collaboration patent in the field of nanobiopharmaceuticals, based upon patent data from Derwent Innovation Index database in the field. Each pair of actors is "linked" to each other by such university–industry patent collaboration.

4.3. Dependent variable: Weighted patent value

One way that knowledge creation is instantiated is in the form of inventions [43]. Knowledge embedded in artifacts such as inventions stands for the "empirical knowledge" of organizations [44]. Inventions thus offer a trace of an organization's knowledge creation. Patents offer a measure of novel invention that is externally validated through the patent examination process [45]. Patents mirror the inventive and innovative evolution in modern technology, while scientific publications mirror the state-of-the-art of science [46]. While patents are the output of inventive activity, it is also widely acknowledged that patents offer a trustworthy, though not ideal, measure of innovative activity [47].

Economists for several decades have tried to apply patent statistics to measure the returns to innovative activity and the value of patent protection, as patent records are one of the only quantifiable and publicly available products of research and development. The use of patent statistics as measures of economic value, however, has been confronted with a lot of hurdles. Patent value is defined as the economic benefit that the patent can bestow upon its owner. The proxy of patent value should have a close relevance to an economic reward or cost associated with ownership of the patent [48]. Simple patent counts are not very revealing indicators of economic value, as patents are very noisy measures of innovative output with the distribution of patent value highly skew and much of the incentive for innovation resting in the very tail of the value distribution [49]. The use of patent counts weighted by forward patent citations (that is, references to a patent by later patents) and by other attributes of the patent (for example, the number of claims) have been verified to be better measures of patent value [50]. This method has had only limited success in identifying appropriate indicators of patent value. For example, Harhoff et al. [51] discovered that even within the relatively select cohort of full-term patents, citation frequency only augments noisily with reported economic value.

An alternative approach has been to apply patent renewal data, since many countries require the payment of a fee so as to keep the patent in force [52]. The motivation for filing an application in multiple countries is that a patent will bestow its owner monopoly only in the application country. Patent family size can be defined as the number of countries in which the patent is taken out [53]. It may be used as the basis to establish more refined patent indicators, to research different proxies for patent value or to explore the motivations and strategies of patent applicants. Five uses of patent family data can be put forward: (i) to avoid double counting; (ii) to neutralize home advantage; (iii) to predict applications; (iv) to analyze the internationalization of technology; and (v) to evaluate patent value [54]. Generally speaking, the more valuable the application to the applicant is, the more broadly the application will be filed [55]. If the applicant has filed or obtained patents in many different patenting authorities on the same invention, it is a good bet that this patent endows with value to the applicant or his/her company. Based on this point, Mogee et al. [56] recommended taking patent family size as a gauge of the invention's private value. There is some evidence that, patent family size is a better gauge of patent value than patent citations [57]. Therefore, the patent value is estimated by weighting patent family size in this study, which is referred to as weighted patent value (WPV), where patent family size is the weight associated with the patent. WPV can go a long way toward removing the noise in simple patent counts and might be just the sort of complimentary information needed so as to enhance the precision of measures of innovation derived from renewal and application data [58]. The more numbers a patent has in its patent family, the higher is its weighted patent value.

One of the challenges for using patents to gauge innovation is that the propensity to patent may vary with industry, resulting in a potential source of bias [59]. We address this potential bias in three ways. First, we sample only one high-tech field: the field of nanobiopharmaceuticals. Innovation was emphasized in this field. Second, the propensity to patent may also differ due to firm characteristics [45]. We endeavor to control for such sources of heterogeneity by using covariate, Presample Patents (described below), and fixed and random effects in our estimations. Third, we use patent family size instead of simple patent counts as a measure of the invention's patent value. Granted the use of patent value, the next issue is how to go about conceiving a sensible weighting scheme. A straightforward possibility is to weight each patent i by the actual number of patent value in year t, denoted by V_{it}. Thus, if we want to compute an index of weighted patent value (WPV) for, say, the field of nanobiopharmaceuticals in a given year, t, we will have,

$$\mathrm{WPV}_{it} = \sum_{I} V_{it}$$

Here I is the set of patents issued by member m during year t in the field. This linear weighting scheme then assigns a value regarded as dependent variable. Therefore, we use the weighted patent value as a proxy index of the invention's innovation performance and effective measurement, rather than a direct reflection of economic value (market value). The reasons are as follows. The size of the patent family indicates how widely an innovation is used [60]. The more numbers a patent has in its patent family, the higher is its weighted patent value. Therefore, the weighted patent value, where patent family size is the weight associated with the patent, is a better indicator of innovation performance than those traditional indicators, such as simple patent counts, which have been considered to be a proxy index of the innovation performance in the mainstream in innovation management. Putnam [53] and subsequently a number of authors have argued out that information on patent family size may be particularly well suited as an indicator of patent value [61]. Therefore, the proposed WPV concept in the present study seems fit to be able to contribute to the literature of innovation management.

4.4. Small world measures

The most recent efforts in this tradition draw extensively on graph theory and social network analysis techniques, to show that the scientific co-authorship network is characterized by the structural properties of small world networks [62]. Broadly speaking, a small world is a network configuration that is both highly locally clustered and has a short path length, two network characteristics that are normally dissimilative [28]. This type of structure is thought to be particularly important for both the generation and the diffusion of knowledge.

To infer whether a network is a small world, Watts's model [28] compares the actual network's characteristic path length L_{actual} and clustering coefficient C_{actual} to a random graph of the same size, where random graphs have both very low characteristic path lengths and low clustering. In particular, the closer the PL ratio (PL of the actual network/PL of a random graph comparison) is to 1.0 and the more the CC ratio exceeds 1.0 (CC of the actual network/CCof the random graph comparison), or simply the bigger the small world quotient (Q), which is CC ratio/PL ratio, the larger the network's small world nature. In random connected networks with large n (the number of nodes) and k (the nearest neighbors of node), the characteristic path length L_{random} can be defined as [28]:

$$L_{\mathrm{random}} \sim \frac{\ln(n)}{\ln(k)}$$

The clustering coefficient of a node reflects the degree to which a node's partners are also buddies with each other. In a random network with n nodes and an average connection number of k, the clustering coefficient can be reckoned according to Watts [28]:

$$C_{\mathrm{random}} \sim \frac{k}{n}$$

4.5. Model specification 1

4.5.1. Independent variables

4.5.1.1. Clustering coefficient. To calculate the actual CC, we decide how many pairs of artists have a shared associate, or how many triads are "closed" [27,63]. Three different configurations can yield a triad: person A is connected to person B who is connected to person C, both persons A and B are connected to person C or both persons B and C are connected to person A. Three links among persons A, B, and C consist of a closed triad (i.e., a triangle). Thus, Clustering coefficient is a standard way to make out how clustered these networks are [64]:

$$C = \frac{3 \times (\text{number of triangles on the graph})}{(\text{number of connected triples of vertices})}$$

4.5.1.2. Reach. To capture the reach of each network for each time period, we employ a gauge of average distance-weighted reach [65]. This measure is calculated as

$$\text{Average distance weighted reach} = \left(\sum_{n}\sum_{j} 1/d_{mj}\right)/n$$

where n is the number of nodes in the network, and d_{mj} is defined as the minimum distance (geodesic), d, from a focal node m to partner j, where $m \neq j$. Average distance-weighted reach can range from $0 - n$, with larger values indicating higher reach. This is a compound measure that takes into account both the number of members that can be reached by any path from a given member, and the path length it takes to get to them. It shuns the infinite path length problem typically associated with disconnected networks by measuring only the path length between connected pairs of nodes, and it offers a more significant measure than the simple average path length between connected pairs by factoring in the size of connected components [12].

4.5.1.3. Clustering × Reach. Mentioned above, we forecast that the combination of clustering and reach will have a positive impact on members' WPV of innovation, and thus include the interaction term, Clustering × Reach.

4.5.2. Firm-level control variables

4.5.2.1. Presample Patents. To control for unobserved heterogeneity in member's patenting, we follow the presample information approach of Blundell et al. [66] and reckon the variable Presample Patents as the totality of patents acquired by a member in the 5 years prior to its entry into the sample.

4.5.3. Betweenness centrality

Betweenness centrality is on the basis of the number of shortest paths passing through a vertex. Vertices with a high betweenness play the role of linking different groups. In the following formula [67], g_{jmk} is all geodesics linking node j and node k which pass through node m; g_{jk} is the geodesic distance between the vertices of j and k. The term g_{jmk}/g_{jk} captures the probability that member m is involved in the shortest path between j and k.

$$C_B(m) = \sum_{j,k \neq m} \frac{g_{jmk}}{g_{jk}}$$

In social networks, vertices with high betweenness are "pivot points of knowledge flow in the network" [68]. Betweenness centrality can reflect the transmission of technological knowledge, which may promote the emergence of new technology [69]. Betweenness centrality is the total of these evaluated probabilities over all pairs of members (excluding the mth member) in the network. It has a minimum of zero, obtained when m falls on no links. Its maximum is $(g-1)(g-2)/2$, which is the number of pairs of nodes not including m, we can normalize it as:

$$C'_B(m) = \frac{2C_B(m)}{(g-1)(g-2)}$$

to make the gauge comparable across time and networks.

4.5.3.1. Degree. Network nodes (actors) which directly connected to a specific node are in the neighborhood of that specific node. The number of neighbors is defined as nodal degree, or degree of connection. Granovetter [70] proposed that nodal degree is proportional to probability of obtaining resource.

4.5.4. Network control variables

4.5.4.1. Network density. We control for the overall density of the network with the variable network density, calculated for each network and time period. We do so because the rate and extent to which information diffuses increases with density [71].

4.5.4.2. Centralization. The centralization of a network is higher if it contains very central vertices as well as very peripheral vertices. To control for network centralization, we make use of Freeman's index of group betweenness centralization [67], computed for each network and time period. Group betweenness centralization for network j in year t is calculated as follows:

$$\text{Betweenness centralization}_{jt} = \left(\sum_{m=1}^{g}\left[C_B{}'(n*) - C_B{}'(n_m)\right]\right)/g-1$$

Here $C_B{}'(n*)$ is the largest realized normalized betweenness centrality for the set of members in network j in year t, $C_B{}'(n_m)$ is the normalized betweenness centrality for member m (in network j for year t), and g is the number of members. This variable is expressed as a percentage and can range from zero, where all members have the same individual betweenness centrality, to 1, where one member links to all other members [12].

4.5.4.3. Firm R&D intensity. Because R&D expenditures are not available for members, in investigating the robustness of our results, we utilize a control variable (stock of patents obtained in the past 4 years) that has been demonstrated to be highly correlated with annual firm-level R&D expenditures [12].

The dependent variable in this study, WPV, is a count variable and takes on only nonnegative integer values. The linear regression model is inadequate for modeling such variables because the distribution of residuals will be heteroscedastic nonnormal. A Poisson regression approach is appropriate to model count data. However, the Poisson distribution includes the strong assumption that the mean and variance are equal. Patent data often exhibit overdispersion, where the variance exceeds the mean. In the presence of overdispersion, coefficients will be evaluated consistently, but their standard errors will generally be underestimated, giving rise to spuriously high levels of significance. A generally utilized alternative to the Poisson regression model is the negative binomial model. The negative binomial model is a generalization of the Poisson model and allows for overdispersion by incorporating an individual, unobserved effect into the conditional mean [72]. The panel data performance of the negative binomial model accommodates explicit control of persistent individual unnoticed effects through both fixed and random effects.

A final estimation issue concerns the suitable lag structure of the independent variables. Based on previous research that investigates the relationship between interfirm alliances and innovation [12,73], we make use of alternative lags of our independent variables relative to our dependent variable. We evaluate models using one-year, two-year, and three-year lags. We do so to seek after the robustness of our findings across alternative specifications. All models are estimated with Stata 10.0. The model we evaluate takes the general form provided below. Variables are indexed across members (m), and time (t):

$$
\begin{aligned}
&WPV_{mt+1(2,3)}\\
&= f(Clustering_t,\ \mathrm{Reach}_t,\ \mathrm{Cluster} * \mathrm{Reach}_t,\ \mathrm{Centrality}_{mt},\ \mathrm{Degree}_{mt},\\
&\mathrm{Centralization}_t,\ \mathrm{Density}_t,\ \mathrm{Presample\,Patents}_{mt},\ 2003,\ 2004,\\
&2005,\ 2006,\ 2007)
\end{aligned}
$$

4.6. Model specification 2

In order to explore the relationship between small world nature in university–industry collaboration network and WPV of innovation output, the conditional mean of the negative binomial patent function for member m in year $t+1$ is described in Eq. (1):

$$
\begin{aligned}
\gamma_{m,t+1} = {}& E\Big(\mathrm{WPV}_{m,t+1}\Big|\mathrm{Intensity},\ \mathrm{Inventors},\ \mathrm{Corp},\ \mathrm{LC},\\
&\mathrm{CCration},\ \mathrm{CCration2},\ \mathrm{PLration},\ Q,\ Q^2\Big)\\
= {}& \exp(\alpha_0 + \alpha_1 \mathrm{Intensity}_{m,t-4-t-1}\\
&+\alpha_2 \mathrm{Inventors}_{m,t-4-t} + \alpha_3 \mathrm{Corp}_{m,t-4-t}\\
&+\alpha_4 \mathrm{LC}_{m,t-4-t} \mathrm{CC\,ration}_{m,t-4-t} + \alpha_6 \mathrm{CC\,ration2}_{m,t-4-t}\\
&+\alpha_7\,\mathrm{PL\,ration}_{m,t-4-t} + \alpha_8 Q_{m,t-4-t} + \alpha_9 Q^2{}_{m,t-4-t})
\end{aligned}
$$

where $\gamma_{m,t+1}$ represents the conditional expected number of WPV of the patents granted to member m in year $t+1$, and it is decided primarily by R&D expenditures, personnel, cross-border corporation and small-world structure in previous years. However, because R&D expenditures are not available for most of members, we make use of a control variable-intensity (stock of patents obtained in the past 4 years) that has been shown to be highly correlated with annual firm-level R&D expenditures [12]. In order to evaluate the impact of small world and the size of largest component during five-year moving windows on the next year patent output, dependent variable is calculated in year $t+1$ while all independent variables with an exception of intensity are calculated from years $t-4$ to t.[1] Dependent variable $\mathrm{WPV}_{m,t+1}$ is WPV of patents granted to member m in year $t+1$. There are six explanatory variables. The size of the largest component (LC) is counted as the proportion of members included in the largest connected component of the network. Clustering coefficient is gauged by CC ration and its squared term CC ration2, while path length is gauged by PL ration. Small world nature is gauged both as linear (Q) and squared terms ($Q2$), too. All these network indexes mentioned above are calculated for the network formed for member m during year $t-4$ to t.

The model specification 2 also contains control variables for R&D expenses, personnel and cross-border co-patents, as these factors are imperative for patent output. We use R&D intensity mentioned above to control the expenditure input for member. The personnel are controlled by the number of inventors for member m to account for the number of people engaged in invention. The cross-border collaborations (Corp) are controlled by the number of institutions in the five-year networks with at least one other member [13].

5. Results

5.1. Development trend of university–industry collaboration

In order to more completely seek for the development trend of university–industry collaboration and predict this development trend in the field, the collected data are then preprocessed as follows. The online Loglet Lab curve fitting system[2] is adopted to fit the collected data during 1982–2009. The following three parameters are provided by automatic computation of the curve fitting system and can be made a choice by operator's own judgment: (1) ceiling value; (2) growth time; (3) midpoint [74].

In Fig. 1 we present the development trend forecast using the Loglet Lab S-curve model for the amount of university–industry collaboration patent. As shown by Fig. 1, the development tend has the growth time of 9.4 years, and the inflection point of the development trend occurs at year 2005 if the development trend analyzed is set to begin at year 1991 when first university–industry patent was invented in the field of nanobiopharmaceuticals. According to Fig. 1 and the idea of bibliometrics [75], university–industry collaboration patent would continue to grow about 9.4 years after the inflection point, 2005 and will then reach the predicted saturation time in the field. University–industry collaboration patent will be invented about 91.4 cases, the ceiling value, pertinent to nanobiopharmaceuticals per year after it reaches the predicted saturation time.

Similarly, in Fig. 2 we present the development trend forecast using the Loglet Lab S-curve model for the amount of corresponding member of university–industry collaboration patent. Firms and universities are gradually linking together over time.

According to Figs. 1–2, we find that although nanobiopharmaceuticals has witnessed a sharp increase in the number of patents, university–industry collaboration research develops at a relative slow pace, indicating that they lack the ability to work hard together to exploit the potential economic value of their patents in the field. There may be following three reasons for this

[1] Different lags and window sizes did not demonstrate substantively different results.

[2] http://phe.rockefeller.edu/LogletLab/.

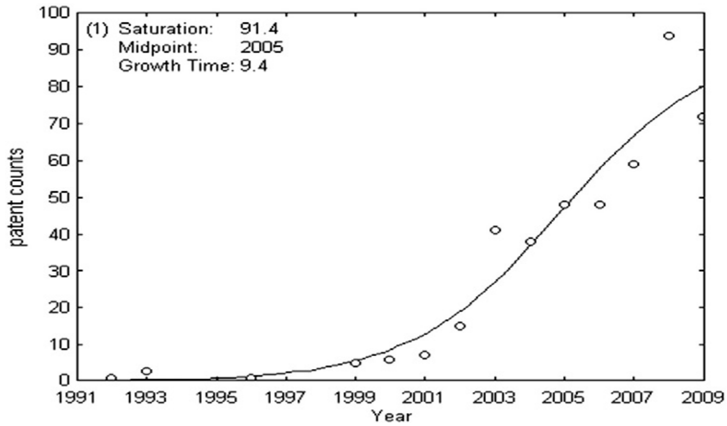

Fig. 1. Development trend forecast for the amount of university–industry collaboration patent.

relatively slow pace. First, in terms of the supply and demand, according to level of technology development and stage in the product cycle, the scope of industry networks maybe are sufficient at this stage and they do not need to interact with universities. Second, some firms prefer not to collaborate with universities because: (i) lack of efficient communication channels for the research results; (ii) the research results are difficult to commercialize; (iii) the research results are immature; (iv) the research results have high uncertainty from the market place perspective; and (v) unsupportive corporate culture and confidentiality issue considering the high competition in this industry. Third, in terms of mission orientation of universities, most of the research activities of universities are not market oriented and mainly focus on knowledge generation and accumulation. The researchers of these institutions often pursue the technology novelty and seldom consider the market prospects of their research work [1].

5.2. Has the interaction of Clustering and Reach a positive effect on member's patent value?

The preliminary bibliometric investigations and analyses above lead readers to grasp the general development profiles for the university–industry collaboration in the field. In next analysis, we test our hypothesis that predicts a positive effect of the interaction of Clustering and Reach on WPV of member's innovation. The interaction term, Clustering × Reach, does not gain statistical significance at conventional levels in the model specified with a three-year lag, using either fixed or random firm effects (model 9). The coefficient for Clustering × Reach is positive and statistically significant in models using both one- and two-year lags (models 3 and 6). This result is suitable for models using both fixed and random firm effects. Thus, our hypothesis obtains strong support in models using one- and two-year lags. Our results are similar with the results obtained

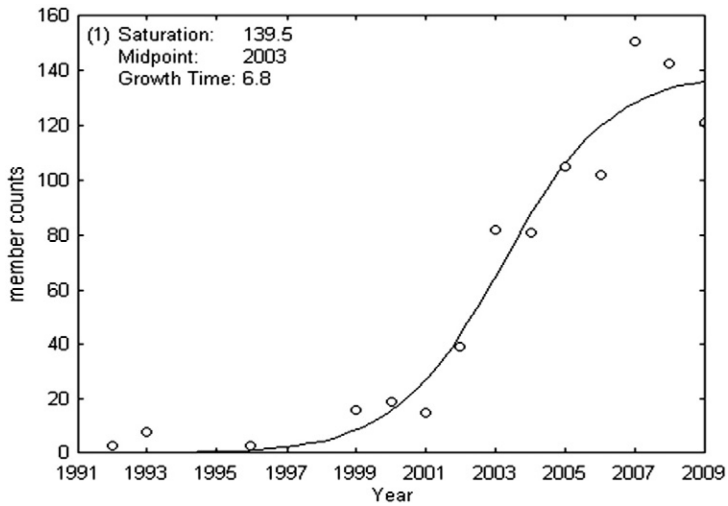

Fig. 2. Development trend forecast for the amount of members of university–industry collaboration patent.

Table 1
Panel negative binomial regression models with fixed effects ($N = 640$; obs = 6219).

	WPV_{mt+1}			WPV_{mt+2}			WPV_{mt+3}		
	1	2	3	4	5	6	7	8	9
Fixed effects									
Constant	-6.865^{***}	-9.847^{***}	-2.686	-6.239^{***}	-6.307^{***}	11.967^{***}	-1.511^{**}	-1.105^{*}	1.788
	(0.571)	(0.673)	(1.932)	(0.583)	(0.617)	(2.087)	(0.591)	(0.584)	(1.955)
Density	4.927^{***}	-3.926^{***}	-12.486^{***}	9.073^{***}	10.804^{***}	-12.543^{***}	4.131^{***}	5.896^{***}	2.106
	(0.995)	(1.260)	(2.476)	(0.898)	(1.048)	(2.683)	(0.853)	(0.961)	(2.615)
Average distance	-4.172^{***}	-7.190^{***}	-3.350^{***}	-3.518^{***}	-3.250^{***}	-6.371^{***}	-0.566	-0.549	-2.065^{*}
	(0.507)	(0.606)	(1.139)	(0.523)	(0.540)	(1.176)	(0.541)	(0.536)	(1.114)
Centralization	-267.208^{***}	-429.266^{***}	-197.016^{***}	-292.035^{***}	-290.393^{***}	-300.117^{***}	-147.672^{***}	-120.046^{***}	-29.800
	(33.907)	(38.851)	(70.487)	(33.665)	(38.040)	(75.242)	(42.430)	(41.563)	(71.670)
Centrality	1.237^{***}	1.248^{***}	1.218^{***}	1.020^{**}	1.061^{**}	0.999^{**}	1.589^{***}	1.540^{***}	1.523^{***}
	(0.432)	(0.422)	(0.422)	(0.473)	(0.480)	(0.475)	(0.477)	(0.477)	(0.476)
Degree	0.022^{***}	0.040^{***}	0.041^{***}	0.004^{***}	0.005^{***}	0.011^{***}	0.079^{**}	0.059^{*}	0.059^{*}
	(0.029)	(0.030)	(0.029)	(0.030)	(0.031)	(0.031)	(0.034)	(0.035)	(0.035)
Intensity	0.261^{***}	0.254^{***}	0.244^{***}	0.224^{***}	0.224^{***}	0.205^{***}	0.159^{***}	0.167^{***}	0.162^{***}
	(0.035)	(0.035)	(0.035)	(0.038)	(0.038)	(0.038)	(0.042)	(0.042)	(0.042)
Presample	0.190^{***}	0.183^{***}	0.174^{***}	0.156^{***}	0.155^{***}	0.140^{***}	0.091^{***}	0.100^{***}	0.096^{***}
	(0.032)	(0.031)	(0.031)	(0.034)	(0.034)	(0.034)	(0.038)	(0.038)	(0.038)
Clustering		3.351^{***}	-3.410^{**}		-0.770^{***}	-17.669^{***}		-0.239	-2.973^{*}
		(0.335)	(1.737)		(0.190)	(1.850)		(0.179)	(1.772)
Reach		-0.822^{***}	-2.220^{***}		0.334^{***}	-3.415^{***}		-0.203^{*}	-0.793^{**}
		(0.127)	(0.377)		(0.113)	(0.425)		(0.118)	(0.399)
Clustering × Reach			3.252^{***}			8.340^{***}			1.344
			(0.823)			(0.909)			(0.867)
Log likelihood	-6443.515	-6360.593	-6352.573	-6427.564	-6419.503	-6373.840	-6367.519	-6357.421	-6356.211

Notes: $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.
Standard errors are in parentheses.

by Schilling and Phelps [12], and the coefficient for Clustering × Reach is positive and statistically significant in models using both two- and three-year lags in their results.

In order to deeply understand the implication of the interaction effect, we should understand the nature of the coefficients for Clustering and Reach in Models 3 and 6 in Tables 1 and 2, using model specification 1. The estimated coefficients for Clustering and Reach in these models are simple effects rather than true main effects owing to the significance of the interaction term [30]. Consequently, the effect of each on WPV is conditioned on the other variable taking on the value of zero. For example, the coefficient estimate of −17.563 for Clustering in Model 6 (random effects) supposes that the value of Reach is equal to zero (thus removing the interaction effect with Reach). Thus, the negative sign of the coefficient for Clustering cannot be interpreted as a negative (main) effect of Reach on WPV [12]. While the impact of Clustering is indeed negative when Reach is equal to zero, the effect becomes positive when values of Reach exceed some value (the range of Reach is 1.470–2.638).

Similarly, the effect of Reach is negative (although not statistically significant) when Clustering is zero, but becomes positive for values of Clustering greater than some value (the range of Clustering is 0–1). Our hypothesis is underpinned by the fact that the impact of Clustering or Reach will be positive when the other takes a relatively small value, and augments its positive effects as the other increases. These mutually reinforcing impacts are in conformity with the symmetrical nature of multiplicative interaction effects [30].

The results connected with the control variables are also worthy of discussion. The effect of betweenness centrality on subsequent members' WPV achieves statistical significance in any of the estimated models. However, the effect of betweenness centralization on subsequent members' WPV achieves significant negative effect in almost all of the estimated models. One elucidation of this maybe is following reasons. On the one hand, betweenness centrality represents an actor's position within the shortest path between two other actors, which implies that the actor can control the interactions between the two nonadjacent actors and function as a point of control in the communication [67]. One the other hand, if a network has a high level of betweenness centralization, the emerging core–periphery structure may result in preferential attachment. This results in excessively dependence on center nodes, and leaves peripheral nodes relatively detached.

The intensity variable has positive and significant effect on members' WPV in all models. R&D expenditures investment is the main input in the innovation system, which is a direct result of the push for advancement in science and technology. However, Presample patents haven a statistically significant positive effect on members' (WPV) in all models. It indicates its importance as a control for firm-level unobserved heterogeneity [12]. Degree has positive and significant effect on members' WPV in all models as we expected. The diffusion of knowledge is vital for collaboration researchers in a large, intricate, and fast changing society. The firms can offer the universities with market information and user feedback; while universities play vital roles not only as

Table 2
Panel negative binomial regression models with random effects ($N=640$; obs $=6219$).

	WPV_{mt+1}			WPV_{mt+2}			WPV_{mt+3}		
	1	2	3	4	5	6	7	8	9
Random effects									
Constant	-6.581^{***}	-9.658^{***}	-2.62	-5.959^{***}	-6.073^{***}	12.071^{***}	-1.357^{**}	-0.982^{*}	2.029
	(0.569)	(0.672)	(1.922)	(0.582)	(0.617)	(2.078)	(0.588)	(0.583)	(1.944)
Density	4.507^{***}	-4.361^{***}	-12.748^{***}	8.649^{***}	10.271^{***}	-12.871^{***}	3.781^{***}	5.432^{***}	1.490
	(0.994)	(1.258)	(2.459)	(0.898)	(1.047)	(2.6680)	(0.854)	(0.961)	(2.599)
Average distance	-3.918^{***}	-6.981^{***}	-3.211^{***}	-3.256^{***}	-2.985^{***}	-6.557^{***}	-0.723	-0.726	-2.301^{**}
	(0.505)	(0.606)	(1.134)	(0.522)	(0.542)	(1.171)	(0.538)	(0.536)	(1.108)
Centralization	-250.790^{***}	-417.167^{***}	-188.936^{***}	-275.123^{***}	-276.016^{***}	-310.431^{***}	-137.699^{***}	-111.978^{***}	-18.100
	(33.778)	(38.792)	(70.167)	(36.572)	(38.045)	(74.965)	(42.216)	(41.477)	(71.310)
Centrality	1.486^{***}	1.487^{***}	1.460^{***}	1.292^{***}	1.338^{***}	1.248^{***}	1.841^{***}	1.805^{***}	1.786^{***}
	(0.387)	(0.375)	(0.375)	(0.426)	(0.433)	(0.4290)	(0.426)	(0.427)	(0.426)
Degree	0.005^{***}	0.011^{***}	0.012^{***}	0.025^{***}	0.022^{***}	0.018^{***}	0.046^{***}	0.029^{***}	0.030^{***}
	(0.029)	(0.029)	(0.029)	(0.030)	(0.030)	(0.030)	(0.034)	(0.034)	(0.034)
Intensity	0.298^{***}	0.293^{***}	0.283^{***}	0.257^{***}	0.257^{***}	0.238^{***}	0.194^{***}	0.199^{***}	0.194^{***}
	(0.034)	(0.034)	(0.034)	(0.038)	(0.038)	(0.038)	(0.046)	(0.046)	(0.046)
Presample	0.220^{***}	0.214^{***}	0.206^{***}	0.182^{***}	0.182^{***}	0.167^{***}	0.120^{***}	0.126^{***}	0.122^{***}
	(0.031)	(0.031)	(0.031)	(0.034)	(0.034)	(0.034)	(0.041)	(0.041)	(0.041)
Clustering		3.358^{***}	-3.292^{*}		-0.773^{***}	-17.563^{***}		-0.247	-3.096^{*}
		(0.335)	(1.730)		(0.190)	(1.843)		(0.179)	(1.763)
Reach		-0.803^{***}	-2.179^{***}		0.364^{***}	-3.369^{***}		-0.171	-0.787^{**}
		(0.127)	(0.375)		(0.112)	(0.424)		(0.118)	(0.398)
Clustering × Reach			3.197^{***}			8.288^{***}			1.400
			(0.819)			(0.905)			(0.862)
Log likelihood	-9031.821	-8947.154	-8939.319	-9054.095	-9045.965	-9000.464	-9012.409	-9003.792	-9002.465

Notes: $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.
Standard errors are in parentheses.

the creators of new technology but also as the suppliers of the much desired capable personnel. Therefore, the R&D capability of them can be improved through such kind of cooperation.

Among the other variables in the models, most were not consistent in terms of sign and significance. This might be partly owing to the moderate-to-large correlations among the network measures (i.e., Centralization, Density, Reach, Clustering, and Clustering × Reach) [12]. This multicollinearity may impact on the robustness of our main finding because parameter estimates are unstable to very small changes in the data when a good deal of collinearity is present, sometimes leading to the signs on estimated coefficients to flip (known as the “wrong sign” problem) [76]. To study the impact of multicollinearity on our main result, we rerun each of the models in Tables 1 and 2 with centralization, density and degree removed, respectively (not reported here). The results for Reach, Clustering, and Clustering × Reach keep substantively unchanged across all models.

5.3. Has small world collaboration network properties a positive effect on member's patent value?

The panel data implementation of the negative binomial model during the reference period (2000–2009) accommodates explicit control of persistent individual unobserved effects through both fixed and random effects. The fixed-effects negative binomial model is favored. A Hausman test refuses random effects specification at the 0.1% level. Table 3 lists summary statistics average per year using model specification 2. The mean of small world Q is 516.649, which verifies the existence of small world characters.

Table 4 presents our regression analysis of WPV using model specification 2. At the beginning model 1 takes into account the control variables. Then we consider the size of the largest component measure in model 2 and small world measures in models 3 and 4. Here we utilize two specifications of the small world model as previous study [11,13]. We first separately embrace the PLration and CCration along with its square in model 3. Then we look into their interaction term Q and its square in model 4. The intensity variable is positive and significant effect on members' WPV in all models. It indicates that R&D expenditures have significant positive relationships with WPV. It is generally convinced that more R&D capital can bring more innovation output. Both personnel and the cross-border corporations have positive relationships with WPV of patent output but they fail to reach a 10% level significance in some of the models. As mentioned above, one explanation for the results could be that lack of efficient communication channel between firms and universities is an important barrier. Lack of skilled persons and lack of innovation-relevant information (including technology and market information) could be other important barriers on innovation as nanobiopharmaceuticals is quite a new technology.

The size of largest component shows strong influence on members' subsequent WPV, which is consistent with the results obtained by Fleming [26] and contradictory to the results obtained by Chen and Guan [13]. Isolates and small components that did not have been involved in the largest component would be left without access to new ideas and

Table 3
Summary statistics ($n=640$).

Variable	Mean	Std. dev.	Min	Max
WPV	2.731	5.701	0.100	63.600
Intensity	1.520	3.266	0.001	40.100
No. of inventors	2.616	3.917	0.200	41.100
No. of cross-border corporations	3.993	6.232	0.100	64.200
Largest component size	0.098	0.059	0.052	0.235
Clustering coefficient ratio	128.854	79.703	21.636	239.326
Path length ratio	0.260	0.052	0.207	0.376
Small world Q	516.649	305.206	57.557	831.254

results and thus their creativity would be hampered. In this condition, as the creativity materials are limited, if they do not enter into the largest component, there would be less opportunities to access new ideas and information [26].

We forecast a parabolical relationship between our network's level of small world nature and the subsequent WPV of patent output. Results of models 3 and 4 are both consistent with our prediction. The linear term of clustering coefficient ratio is positive and significant, and the quadratic term is negative and significant, which together display an overturned U-shaped relationship between clustering and WPV of patent output. As expected, path length has a negative and significant contribution to WPV, implying thatshorter path length can bring more WPV. Their interaction term, i.e., the small world Q is positive and significant, and the squared term Q^2 is negative and significant, which together display an overturned U-shaped relationship between small world nature and WPV of patent output, implying that an intermediate level of small world nature would better enhance WPV of innovation performance, while low and high levels of it may get in the way of WPV of innovation [13].

In sum, the results of the empirical study verify our hypothesis of positive and statistically significant impact between Clustering×Reach and innovation output using one- and two-year lags. While it failed to confirm statistical significance at conventional level with a three-year lag. The results of the empirical study also verify our hypotheses of the parabolic relationship between clustering coefficient and WPV of innovation performance, the negative relationship between path length and WPV of innovation performance, the parabolic relationship between small world quotient and WPV of innovation performance, and the positive relationship between the size of largest component and WPV of innovation performance, as described in Hypotheses 2–5.

6. Concluding remarks

This research makes up the existing literature by providing an empirical investigation of the impact of network property for university–industry collaboration network on WPV of the innovative output at firm level. This paper illustrates members taking a part in alliance networks that combine a high degree of clustering and reach will display more WPV of knowledge creation than members in networks without these characteristics. This study also shows that small world structure does profit WPV of innovation but it is limited to a special scope after which the impacts reverse. Our results offer suggestions to policy makers and managers. They can take account of social networks when making decisions for technology, industry or firm location. Their decisions impact on the formation of social networks and then social networks influence their performance. When the networks they participated in are small world networks, they would have more chances to acquire fresh and unfamiliar information easily. Therefore, when managers select positions to locate their firms and universities, the social networks should be thought over.

The firm agglomeration should be maintained at moderate level rather than too dispersed or too gathered together. If too scattered, the communications within industry and university would be hard; if too converged, it would induce much repetitive and redundant information and then newcomers would discover it difficult to have their ideas understood and accepted. Both too high and too low agglomeration would hold back innovation activities. Therefore, policy makers should consider both conditions to develop the social networks to appropriate small world characteristic [13,77].

While at the firm level, knowledge diffusion is a two-edged sword. On the one hand, the participation in the network can make their technology spillover and contribute to others. On the other hand, they can also obtain spillover and retribution from others [78]. Firms can go into the networks by employing employees from competitors, universities, suppliers or partnering with them. The policy makers can motivate the network formation and the knowledge diffusion by encouraging

Table 4
Conditional fixed-effect negative binomial models of patent value in year $t+1$.

Variable	Model 1	Model 2	Model 3	Model 4
Intensity	0.026^{***} (0.003)	0.024^{***} (0.004)	0.028^{***} (0.003)	0.025^{***} (0.004)
No. of inventors	0.002 (0.003)	0.001^{**} (0.005)	0.001^{**} (0.003)	0.002^{*} (0.003)
No. of cross-border collaborations	0.003^{**} (0.005)	0.011^{**} (0.003)	0.010^{*} (0.005)	0.009 (0.006)
Largest component size		6.757^{*} (0.577)		
Clustering coefficient ratio			0.021^{***} (0.002)	
Clustering coefficient ratio squared			-0.001^{***} (0.001)	
Path length ratio			-2.814^{***} (0.806)	
Small world Q				0.005^{***} (0.012)
Small world Q^2				-0.001^{***} (0.001)
Constant	-2.189^{***} (0.040)	-1.504^{***} (0.067)	-2.374^{***} (0.285)	-3.331^{***} (0.107)
Log likelihood	−6683.453	−6599.182	−6564.724	−6585.773

Notes: $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.
Standard errors are in parentheses.

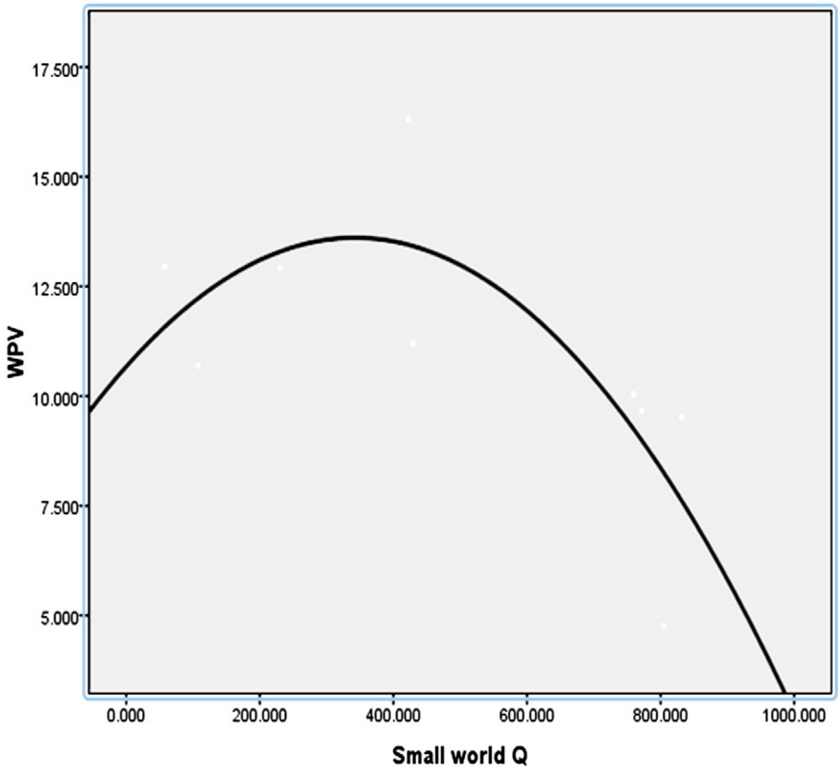

Fig. 3. The relationship between the small world Q and WPV artistic success.

personnel mobility and industry–university cooperation. In order to promote university–industry interaction and explore how to balance the too dispersed or too aggregated, we explore what are the optimal levels of small world. Fig. 3 shows the magnitude of the effect of Q on WPV. The results signify that at the predicted bliss point of Q (about 400). Consistent with the results [13,37], the benefit of small world may rise only up to a marginal value after which point they shift negative. Excessive structural connectivity and small world decrease some of the creative distinctiveness of clusters, which can homogenize the pool of creative material. A small world is a network configuration that is both highly locally clustered and has a short path length, while reach is closely related to path length. Therefore, we can appropriately adjust reach and clustering to get to this optimal level. According to this optimal level, policy makers should place greater emphasis on creating effective network structure arrangements to promote creativity and performance.

Collaboration between university and industries mainly relies on performance itself, but governance or policy makers should create better environment and platform to promote university–industry collaboration at the same time. Collaboration ties are key tools through which companies acquire external knowledge, including technical breakthroughs and new insights to problems and failures (e.g. Powell et al. [79]). However, the collaboration is still far from efficient in terms of performance indicators such as WPV, to measure innovation in the field. Lack of efficient communication channel to the research results of universities and uncertainty of market perspective of the research results may be important factors to hinder commercializing research results produced by universities. Lack of skilled persons and lack of innovation-relevant information (including technology and market information) may be also crucial barriers on innovation as nanobiopharmaceuticals is quite a new technology. It is necessary to exploit an effective information platform among the collaboration partners through combining the network with their intranets. Policymakers and university leaders should have a clear mind in raising a positive cycle of commercializing activities and research publication of universities. Academic research commercialization inspires the faculty members to make their research agenda more basic- and applied-orientation integrated [80].

From a policy perspective, policy makers should place greater emphasis on creating effective institutional arrangements or policies to promote university–industry cooperation network, and constitute a stable platform for cooperation to attain mutual learning between U-I linkages. For example, science parks (SPs) and business incubators (BIs) are believed to offer an effective tool for university and industry to interact [81] and we should give full play to their abilities and role. From a viewpoint of policy, more polices contributing to the linkages with universities for firms should be made. Under this model, the firms can offer the universities with market information and user feedback; the R&D capability of the enterprises can be improved through such kind of cooperation. Universities play vital roles not only as the creators of new technology but also as the suppliers of the much desired capable personnel, and as the media players who match the economic changes with the changes in society. So, we focus our analysis on UI collaborations, which take an irreplaceable role in contrast to alliances between firms. From a managerial viewpoint, it shows that cooperation between U-I linkages is an effective approach to enhancing their innovation performance. Thus, it is necessary for firms to apply various cooperation networks (formal or informal relationships, such as cooperative alliances and personal networks) to acquire external knowledge and resources. Furthermore, we should shall establish a sound management mechanism of U-I cooperation. Suitability of management offers three underlying determinants: management profile, services provided and innovative ideas [82]. Aernoudt [83] validated the role of management as critical for the success of SPs and BIs.

Furthermore, the Triple Helix thesis of university–industry–government relations states that the university can play an enhanced role in innovation in increasingly knowledge-based societies [84]. The Triple Helix offers a flexible frame-work to conduct knowledge-based economic and social development. Innovation thus becomes an endless transition, an endogenous series of initiatives among university, industry and government [85]. Frequently it is a matter of combining complementary innovations in an attempt to create a solution to a customer problem. The open innovation model of Chesbrough [86] also acknowledges the benefits of depending on a distributed model of innovation where the enterprise reaches out beyond its own boundaries to obtain and integrate technology developed by others [87]. The open innovation is the use of purposive inflows and outflows of knowledge to speed up internal innovation, and broaden the markets for external use of innovation, respectively [86]. Open innovation indicates that the company requires to open up its solid boundaries to let valuable knowledge flow in from the outside so as to create opportunities for co-operative innovation processes with universities, government, customers and/or suppliers [88]. On the other hand, close innovation is a view that says successful innovation requires control. This paradigm counsels firms to be strongly self-reliant, because one cannot be sure of quality, availability and capability of others' ideas [89]. Therefore, we should further constitute effective platform for university–industry–government cooperation to really shift innovation paradigm from “close innovation” to “open innovation.”

The results we achieved are linked to our research sample, but also not limited to our research sample. The most of results we achieved are suited for the topics related. We explore the relationship between network properties and innovation at firm level. Many results we achieved are similar to the previous research results in this aspect at industrial, discipline, regional or even national level, but not identical (Chen & Guan, 2010; Schilling & Phelps, 2007; Guimera et al., 2005; Fleming et al., 2007). This also reflects that the results we achieved are not limited to our research sample and can be extended to other sectors and fields at various levels. First, the results can contribute to policy makers and relevant managers in other sectors when making decisions for firm locality as well as the choices of the collaborators. Second, the quantitative analysis and empirical investigation of the impact of network property on the innovative output about the emerging interdisciplinary subject-nanobiopharmaceuticals has important reference meaning for other sectors in terms of constructing reasonable and effective cooperation network and exploring the development of other sectors, especially those that involves emerging interdisciplinary subjects. Third, our research method, hypotheses and some of the results we achieved can be easily generalized and extended to some alliance networks among firms in other sectors or other fields. For example, the firm agglomeration should be maintained at moderate level rather than too dispersed or too gathered together. Both too high and too low agglomeration would deter innovation activities. This is true for our alliance networks based on our research sample and other alliance networks among firms in other sectors at the same time. Fourth, some of our policy suggestions can be extended to other sectors as an effective way to increase the innovation performance. At the very least, our research method based on our research sample is suited for examining the impact of the collaboration network characteristic on knowledge creation and other research for the topics related.

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