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DIFFUSION OF INNOVATIVE KNOWLEDGE: A PERSPECTIVE FROM INNOVATOR COOPERATIVE NETWORK

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Abstract

Understanding the knowledge-diffusion network can help government and businesses effectively use their investment to stimulate science and technology development. We are interested in the roles that innovators play in the cooperative network and how the structural characteristics of innovator cooperative network affect innovative knowledge diffusion in terms of patent citation frequency. We propose an improved model for innovative knowledge diffusion by incorporating the innovator cooperative network with Jaffe's double exponential model, which has been verified as effective, to evaluate the relationship between the innovator cooperative network and innovative knowledge diffusion. We conduct empirical analysis with the proposed model using patent data from the Derwent database, and discover a positive correlation between the innovator cooperative network and innovative knowledge diffusion. Our results also reveal several interesting patterns of innovative knowledge diffusion in the field of nanostructures. We also discuss the practical implications in knowledge management that analyzing patents, as a form of innovative knowledge, can unveil knowledge diffusion patterns and urge organizations to learn the technology development trend and advance their technology progress.

Keywords

Knowledge Diffusion, Innovative Knowledge, Innovator Cooperative Network, Patent Citations, Social Network Analysis

1. Introduction

Innovation is considered an interactive learning process involving the creation of novel combinations of existing knowledge domains and the pursuit of new knowledge elements (Jin *et al.*, 2022). This process contributes to social and economic value derived from knowledge (Hamdoun *et al.*, 2018). Innovative knowledge, distinguished by its novelty, rareness, and difficulty of imitation and substitution, has long been regarded as a strategic resource for achieving significant international competitiveness (e.g., Hu, 2009; Dasgupta, 2012; Ogundeinde and Ejohwomu, 2016; Veréb and Ferreira, 2018). Innovation and innovative knowledge diffusion (IKD) have become integral components of investments aimed at maximizing the value of knowledge (Gao *et al.*, 2020). Therefore, nations are driven to understand the factors influencing and driving IKD performance (Pylypenko *et al.*, 2023; Yang *et al.*, 2015), scholars are prompted to extensively investigate this topic (Fang *et al.*, 2017).

Emerging as a significant field, complex network theory, encompassing static and dynamic networks analysis (Moosavi *et al.*, 2021), has garnered increasing attention from scholars (Kumar and Ahmad, 2022), particularly in the study of network distribution and community characteristics (Qiu and Huang, 2021). The network structure provides a framework for facilitating the adoption and diffusion of innovative knowledge, thereby serving as a pivotal avenue for enterprises and governments to improve their sustainable development level (Yin *et al.*, 2022). Scholars usually investigate network determinants by methodological approaches, and have found that the efficiency of innovation diffusion is positively correlated with the density and sharing degree of a network (Ma *et al*., 2021). Therefore, innovation capabilities exhibit a strong association with the network structure (Xiang *et al*., 2021; Han *et al*., 2022).

A mounting body of evidence underscores the value of patent citations in revealing latent knowledge diffusion patterns (Hu and Jaffe, 2003; Eaton and Kortum, 2007; Roach and Cohen, 2013; Sharma and Tripathi, 2017; Chen, 2017). Patent citation can be modeled as networks (Jaffe and Trajtenberg, 2002; Park *et al.*, 2017). Consequently, prior literature has predominantly examined IKD using network theory to explore underlying mechanisms and the evolution of network structures (Cowan and Jonard, 2004; Ribeiro *et al*., 2011; Luo *et al*., 2014; Yang *et al.*, 2015). However, existing studies in this area often focus on the patent citation network (Ribeiro *et al*., 2011; Park *et al.*, 2017), inadvertently neglecting the influence of the innovator cooperative network (ICN) on knowledge diffusion.

To address these gaps and underscore the significance of social network factors in IKD, our study examines the importance of increasing collaborations among innovators during patent creation. We develop an improved model for knowledge diffusion incorporating ICN and reveal IKD patterns in the field of nanostructures using the Derwent Database. Consequently, this paper aims to investigate IKD patterns with respect to the ICN and assess the scientific impact of introducing an improved model based on patent citations with ICN. Specifically, we focus on the following research questions:

i. What roles do innovators in the cooperative network play, and how do the structural characteristics of the ICN impact on IKD in terms of patent citation frequency?
ii. Can we enhance the model of IKD by integrating ICN, and if so, does it prove effective?
iii. What insights do the IKD patterns in the nanostructures field (from Derwent Database) reveal?

The rest of this paper is organized as follows. Section 2 presents a comprehensive literature review on knowledge diffusion, cooperative networks, and patent citations. Section 3 introduces an improved model for knowledge diffusion. Section 4 describes the data specifications and some pre-analysis on the data. In Section 5, we investigate the relationship between ICN and IKD, fit the model and discusses the patterns of IKD in the field of nanostructures. Finally, Section 6 concludes the paper, highlighting future research directions.

2. Literature review

2.1 Innovative Knowledge Diffusion

In the midst of the intensive global competition, knowledge is widely recognized as a core asset (Davenport and Prusak, 1998; Hao *et al*., 2022). According to Zhu and Ma (2018), the value of knowledge usually expands during the diffusion process. Knowledge diffusion, as a significant aspect of knowledge management (Su *et al*., 2017) and a key component of innovation (Hamdoun *et al.*, 2018), plays an increasingly important role in modern organizations (Fleming *et al.*, 2007; Nilsen and Anelli, 2016) and various industries (Guan and Chen, 2012). Effective knowledge diffusion can stimulate the new knowledge creation and the generation of innovation (Huang and Zhuang, 2012; Kun, 2018), making it a vital method for enhancing a firm's innovation capacity (Hamdoun *et al.*, 2018) and evaluating the degree of social development (Zhu and Ma, 2018).

According to Lee *et al*. (2014), innovative knowledge can be underlined by its distinctiveness from existing technologically innovative concepts and prototypes in the knowledge reservoir. Novel knowledge tends to be unique and substantially dissimilar from existing unrelated technologies. Wu *et al*. (2019) defined innovative knowledge assets as a firm's distinctive knowledge stocks, essential for creating competitive advantages. In this paper, we consider innovative knowledge as both reshaped from existing knowledge and newly created knowledge that enhances competence.

Different types of knowledge, simple or complex, explicit or tacit, can all be diffused through various channels, and the process of knowledge diffusion is influenced by various external factors (Evans *et al.*, 2009; Sorenson *et al.*, 2006), such as geographical distance (e.g., Fadly and Fontes, 2019), technology similarity (e.g., Chen and Guan, 2010), language (e.g., Hu, 2009), time (e.g., MacGarvie, 2005) and social network (e.g., Sorenson *et al.*, 2006).

2.2 Innovator Cooperative Network

It is believed that networks factors, especially formal cooperative networks, contribute significantly to IKD (Han *et al*., 2022; Hertzum, 2008; Yin *et al*., 2006). Cowan and Jonard (2004) modeled knowledge diffusion as a barter process, where agents exchange different types of knowledge. They examined the relationship between network architecture and diffusion performance, finding that the performance exhibits clear "small world" properties. These properties include higher cohesion and shorter average path length txhan regular and random networks, which are beneficial to knowledge diffusion.

According to Cantner *et al.* (2010), knowledge diffusion can be identified and quantitatively analyzed by network theory, i.e., the regional innovator cooperative network relate to presumed knowledge diffusion among innovators. Based on social network structure, Maythu *et al*. (2024) suggested that it is possible to understand how and under what circumstances potential adopters can attain innovative knowledge. They argued that even minor changes in network structure characteristics may greatly influence the degree of innovation knowledge diffusion. However, most studies employing this approach overlook the impact of the ICN of patents on knowledge diffusion.

Fleming *et al*. (2007) discovered that co-invented experience among innovators is an important type of social linkage that facilitates technology diffusion by shaping dense and clustered informal local networks. Xiang *et al*. (2013) proposed a method for the construction of international knowledge diffusion networks by incorporating patent citations with co-innovators information. This approach detected changes in network structure induced by social ties among co-innovators and reflects both explicit and tacit knowledge diffusions across national borders.

2.3 Patent Citation and Knowledge Diffusion

Over the past two decades, the utilization of patent citation data in science research has seen exponential growth. It is believed that patents, which can be categorized into specific technical domains, reflect the output of the innovation process and provide extensive information about the attributes of innovations and applications (Ma *et al*., 2022). What also makes citations potentially useful is that those provided by the applicant are termed as ‘prior art’ and are known as ‘applicant citation’, while the cited material has some links to the idea(s) being patented and its claims (Sharma and Tripathi, 2017). Inheritance from existing technology can be manifested through a patent’s references to previous literature, and can be studied quantitatively to reveal its characteristics and inherent laws (Zhang, 2003). Although the analogy with the broader field of bibliometrics may seem obvious, patent citations differ from scientific citations in substantial ways (Meyer, 2000). Hence, patent data can be harnessed for our research on innovation.

The widespread use of patent citations in social science research can be traced to the availability of patent statistics in digitally readable form in the late 1970s, when Griliches (1979), in his important manifesto for research on R&D and productivity growth, suggested that the frequency with which patents from different industries cite each other could be used as a measure of the technological proximity of industries (Jaffe and de Rassenfosse, 2017). In general, patent citation analysis contributes significantly not only to leveraging the wealth of knowledge but also to discovering new knowledge. Practices can be derived using these data to: i) Assess technological trajectory and measure attributes of innovations; ii) Measuring knowledge diffusion across individuals, institutions, and regions; iii) Map knowledge or innovation networks (Jaffe and de Rassenfosse, 2017; Sharma and Tripathi, 2017). Here we mainly focus on the second aspect.

It is noteworthy that Jaffe and Trajtenberg (1996) stand as pioneers who took initiative to introduce the idea of utilizing patent citation to approximate knowledge flow and then transform the process of intangible knowledge flow into an observable process. They suggested that patent citations could be used as a kind of “article trail” that allows knowledge flows to be measured and tracked. It might have opened a new door for scholars to subsequently use patent reference relationship to study the flow, dissemination and diffusion of knowledge. From then on, as elaborated in the ‘Introduction’ section, patent citation has become extensively employed as a proxy for knowledge diffusion in current research on IKD.

In summary, we assume that IKD will be inevitably diffused among innovators, no matter whether within an innovation or in different innovations. The cooperative network among innovators provides increased opportunities for interpersonal contact. People tend to share knowledge and resources with whom they had developed a close relationship according to the social capital theory (Swanson et al., 2020). In another word, the stronger connected ICN, the more innovative knowledge diffuses. Therefore, we speculate the following central hypothesis of this study:

Hypothesis: *The degree of innovative knowledge diffusion is positively related to the degree of innovator cooperative network.*

3. An Improved Model for Knowledge Diffusion

3.1 Jaffe’s models on Patent Citation

In 1993, Caballero and Jaffe (1993) proposed a double exponential model to discuss knowledge diffusion based on the economic growth theory. The model is shown in Formula (1):

$$p(T,t)=\alpha e^{-\beta(T-t)}\left(1-e^{-\gamma(T-t)}\right) \qquad \text{where } T\ge t, 0\le\alpha\le 1,\ \gamma\ge 0,\ \beta\ge 0 \tag{1}$$

In this model, $p(T,t)$ represents the frequency of a patent of year *t* being cited in the year T, while $1-e^{-\gamma(T-t)}$ represents the probability of a patent of year *t* being cited in the year T. At the same time, since old knowledge will be gradually replaced by new knowledge, its usefulness will reduce slowly as time goes by. Therefore, another exponential form $\alpha e^{-\beta(T-t)}$ stands for corruption of knowledge.

In 1999 and 2003, Jaffe and colleagues have improved their model by considering factors of technology similarity, geography, language and time (Hu and Jaffe, 2003; Jaffe and Trajtenberg, 1999), as shown in Formula (2). However, their model neglects the contributions of ICN.

$$CF_{iT,jtg} = \left(1 + \gamma Prox_{iT,jtg}\right)\alpha(i,j,g,T)e^{(-\beta_{1ij}(T-t))}\left[1 - e^{(-\beta_2(T-t))}\right] + \varepsilon_{iT,jtg} \qquad (2)$$

3.2 An improved model based on Jaffe's models

After we confirm the significant correlation between the diffusion of innovative knowledge and innovator cooperative network, in this section, we attempt to improve Jaffe's model for knowledge diffusion (Caballero and Jaffe, 1993; Hu and Jaffe, 2003) by considering the impact of ICN at the collective level.

According to the social network theory, the degree of ICN at the collective level can be measured by the several structural measures of the underlying ICN, such as the network degree distribution, average (shortest) path and clustering coefficient (Ribeiro *et al*., 2011). Among these parameters, clustering coefficient is a coefficient that measures the degree to which nodes in a graph tend to cluster together. Evidence shows that in real-world networks, especially in social networks, nodes tend to establish tightly knit groups characterized by a relatively high density of connections (Said *et al*., 2018). Clustering coefficient at the collective level can well describe such density of the entire network and accordingly can well represent the degree of cooperative relationships among innovators.

Therefore, we propose an improved model for IKD by incorporating the factor of ICN with the Jaffe's double exponential model, as shown in Formula (3).

$$CF_{tlsT} = \alpha_{tlT}\left(1+\delta NC_T\right)\left(1+\gamma\, Prox_{ltTs}\right)e^{-\beta_1(T-t)}\left[1-e^{-\beta_2(T-t)}\right]$$
$$\text{where } T > t,\ \alpha_{tlT} > 0,\ 0<\delta<1,\ 0<\gamma<1,\ 0<\beta_1<1,\ 0<\beta_2<1 \qquad (3)$$

In this model, CF_{tlsT} (the citation frequency of patent under International Patent Classification category s of year t in the country l in the year *T*) is affected by NC_T (degree of ICN of year T), $Prox_{ltT}$ (technical similarity degree of the cited patent) and $T-t$ (time difference between the citing patent and cited patent). Other parameters of this model are explained as follows:

CF_{tlsT}: In the year *T*, the citation frequency of patents under IPC category *s* of year *t* in the country *l*.
α_{tlT}: A parameter which depends on the innovative knowledge embodied in the citing and cited patents in the country *l*.
δ: The coefficient measuring how much effect of innovator cooperative network on the frequency of patent citation.
γ: The growth of patent citation frequency when the citing patent and cited patent has similar technology.
$Prox_{ltT}$: Technology similarity degree of the cited patent of country *l* in the years *t* and *T*;
β_1: The rate at which a piece of innovative knowledge embodied in a patent becomes obsolete.
β_2: The rate of innovative knowledge diffusion, i.e., how fast a piece of innovative knowledge travels.
NC_T: The degree of aggregation coefficient for the entire innovator cooperative network in the year T.

In this model, we keep the meaning of $1-e^{-\beta_2(T-t)}$, $\alpha_{tlT}e^{-\beta_1(T-t)}$ and $(1+\gamma\, Prox_{ltT})$ unchanged with Jaffe's original model. $1+\delta NC_T$ stands for the positive influence of ICN on the citation frequency, where δ is used to measure the overall increase of citation frequency with the degree increase of ICN. Since the citation frequency in the model works at the collective level instead of the individual level, we choose the variable $Prox_{ltT}$, as shown in Formula (4), to represent the technology similarity degree of the two categories s and S in these collections according to Hu and Jaffe (2003),

$$Prox_{ltT} = \sum_s f_{lts} * f_{TS} = \sum_s \frac{N_{lts}}{N_{lt}} * \frac{N_{TS}}{N_T}, \qquad (4)$$

where

$Prox_{ltT}$: Technology similarity degree of the cited patent of country l in the years t and T;
f_{lts}: Fraction of potential cited patents in patent class s;
f_{TS} Fraction of potential citing patents in patent class S;
N_{lt}: The sum total of cited patents in country l in the year t;
N_{lts}: The number of cited patents in category s of country l in the year t;

N_T: The number of potential citations in year T mentioned in N_{lt};
N_{TS}: The number of potential citations of category S in year T mentioned in N_{lts}.

4. Data

4.1 Data collection

Unlike other emerging fields, nanostructure has undergone a relatively mature development process (Liu et al., 2011; Liu et al., 2015; Robinson et al., 2007; Tang and Hu, 2013). According to Wang and Shapira (2011), nanostructures can be recognized as a fundamental technology for the economy and society. In this paper, considering data availability and data representativeness, we chose the Derwent database as our primary data source. Specifically, to control the data volume to be a reasonable scope, we retrieved the database using International Patent Classification (IPC) category classification number B82B (nanostructures formed by manipulation of individual atoms, molecules, or limited collections of atoms or molecules as discrete units; manufacture or treatment thereof) and its sub-category to study the diffusion of innovative knowledge.

We chose the study period from 1991 to 2023 for the following reasons. The first International Conference on Nano-scale Science and Technology, which marked the inception of nano science and technology, took place in Baltimore, USA, in July 1990. From then on, nanostructures have been formally introduced as a new branch of materials science, and nanostructures-related patents represent tangible outcomes of nanostructures innovation (Jiang *et al*., 2014; Roco *et al*., 2011), and have experienced fast development over the subsequent decades (Thirugnanasambandan *et al*., 2024; Zikalala *et al*., 2024). Besides, the 30 years' time length is enough for a sufficient research cycle (Chen *et al.*, 2013).

Articles take an average of three or five years to be steadily cited (Van Raan, 2006; Wang, 2016). Accordingly, considering time lag between citing patents and cited patents, we decided to focus on the cited patents from the period of 1991 to 2020, and the citing patents from the period of 1992 to 2023.

4.2 Data pre-analysis

Our approach builds on the similar dataset used by Ji and Wang (2011), who researched the determinants of knowledge diffusion. In this research, we identified a total of 25,874 patents, associated with 214,590 citations (means been cited). It was found by Criscuolo and Verspagen (2008) that increasing geographical distance reduces the likelihood of technology spillovers, based on the study of patent applications and citation data from the European Patent Office database from 1985 to 2000. During the data collection, we were also interested in whether there is any difference in different regions. Seven countries or organizations or regions, including US, Japan, Korea, Russia, China, World Intellectual Property Organization and European Patent Office, contributed the majority of nanostructures patents, accounting for 93.57% of all retrieved patents and 84.26% of the total citations. Therefore, this study focuses on the patents and their citations from these seven countries or organizations. This decision helps mitigate analysis bias arising from dominant sources, form different samples and facilitate effective comparisons among countries or organizations. The distribution of retrieved patents and their citing patents is shown in Table 1.

To test the above hypothesis, we need to operationalize the degree of diffusion of innovative knowledge, as well as the degree of ICN. Since there are increasing support of patent citation as a proxy of knowledge diffusion (MacGarvie, 2005; Büttner *et al*., 2022), the degree of innovative knowledge diffusion is measured by patent citation frequency in this study.

Country	Number of patents	Percentage	Cumulative percentage	Number of citations	Percentage	Cumulative percentage
US	6545	25.30%	25.30%	100354	46.77%	46.77%
Japan	4295	16.60%	41.90%	44372	20.68%	67.45%
South Korea	4046	15.64%	57.53%	13071	6.09%	73.53%
Russia	3911	15.12%	72.65%	11660	5.43%	78.96%
China	2608	10.08%	82.73%	4839	2.25%	81.22%
World Intellectual Property Organization	1548	5.98%	88.71%	2991	1.39%	82.61%
European Patent Office	1257	4.86%	93.57%	3528	1.64%	84.26%
Others	1664	6.43%	100.00%	33775	15.74%	100.00%
Total	**25874**	**-**	**-**	**214,590**	**-**	**-**

Table 1 The distribution of cited patents and citing frequency among countries or organizations

According to the social capital theory, relationships between people are captured by social capital resided by people. Among many facets of social capital, the structural capital, which describes the impersonal configuration of linkages among a social group of people (Wasko and Faraj, 2005), can be measured by structural properties of social network (Yu *et al.*, 2013). Consequently, in this study we measure the degree of ICN by structural properties.

We use the Pajek tool (Dabkowski *et al.*, 2015) to build the ICN. Pajek is a large and complex network analysis tool, which is used to study the various complex nonlinear networks. Pajek runs in the Windows environment, and can be used for analysis and visualization of large networks of millions of nodes. By using Pajek, we can identify clusters in a network (composition, neighbor of important nodes, cores, *et al*.), extract nodes belonging to the same cluster (show them separately), map the connection of nodes, contract nodes into clusters and illustrate the relationships between clusters.

To build the ICN, we first add the innovators of patents to the innovator cooperative network by connecting the authorship relations and create a two-mode ICN. In order to have a clearer view of the network structure, we then delete nodes with no more than one neighbors to simplify the network graph. From the graph, we can find out that those innovators participating in more than one patent help connect the entire network and finally provide channels for knowledge diffusion.

We also calculate the coefficient of aggregation network, namely degree of ICN, using Pajek tool. We observed that those inventors who had participated in multiple inventions have become a “bridge” for knowledge diffusion among different patents, that is to say, those innovators participating in more than one patent can help connect the entire network and finally provide channels for knowledge diffusion. We are convinced that these outward channels represent knowledge diffusion from the focal inventor, and the degree centrality of each originating inventor can be calculated by the number of these channels. Then the average clustering coefficient of all nodes in the ICN, namely the clustering coefficient of the network, reflects the clustering situation of innovators in the network.

In addition, during the data collection, we found that those citations were not limited to nanostructures category, which necessitating the coefficient of proximity, to measure the technology similarity degree among these patents.

5. Results and Discussion

5.1 Correlation analysis of innovator cooperative network on innovative knowledge diffusion

In this section, we firstly examine the correlation between ICN and IKD. In order to test our hypothesis, we conduct a relevance analysis based on the whole data of 25,874 patents, the result of which can be seen in Table 2. Results shown in the table indicate that there exists a significant positive correlation (r = 0.644, $p = 0.004 < 0.01$) between citing frequencies, namely CF_{tlsT}, and degrees of ICN of the studied patents, namely NC_T.This indicates a remarkable correlation between ICN and IKD, when controlling other factors, and a strong support to our hypothesis. In other words, we believe that there is a positive relationship between the degree of innovator cooperative network and innovative knowledge diffusion.

Item	Value
Adjusted R square	0.657011
Correlation coefficient	0.643848
F value	11.39279
F value obtained from table-lookup	4.543
Significance	0.00416

Table 2 Regression analysis results and correlation coefficients

Our result is coinciding with the conclusion from Jiang, *et al*. (2014) that knowledge diffusion is likely to occur between two innovators with high degree centrality, and high authority innovators are also likely to collaborate and share knowledge with each other.

Meanwhile, the value of adjusted R-squared also indicates that ICN as an explanatory variable can only explain part of dependent variables. It means that although the frequency of cited patents is influenced by the structural characteristics of the inventor's cooperative network, it is also influenced by more other factors. This phenomime might be interpreted as previous studies by scholars on the impact of factors such as geography, language, and time on the process of knowledge diffusion.

5.2 Model Fitting

Before the model fitting, we process the data into patent groups. The form of a patent group looks like $CF_{1991,US,1992}$, which represents the citation frequency in 1992 for patents registered in 1991 in the US. During the model fitting process, in order to ensure the sample size contains enough data with little variation, cited patents from all seven countries or organizations (i.e., US, Korea, Japan, Russia, World Intellectual Property Organization, China and European Patent Office) are selected. Particularly, the period for cited patent ranges from 1991 to 2020, and the period for citing patent ranges from 1992 to 2023. Altogether, there are altogether 3,675 patent groups, 525 for each country, after data processing.

Estimation of the parameters of a nonlinear sum of exponentials model is an important and well-studied problem in time series analysis, and the nonlinear least-squares (NLS) method finds application in modeling various physical phenomena in a wide variety of real-life applications (Mitra and Mitra, 2012). Our proposed model in Formula (3) was estimated with the NLS method, similar to Hu and Jaffe (2003). We use the Matlab model fitting tool. The fitting results are shown in Table 3. The adjusted R^2 of the model, ranging from 0.66 to 0.839, suggests that the model fits the data reasonably well, in all of the seven countries or organizations. And all parameters estimated are highly statistically significant, far above conventional confidence levels. Particularly, the significant positive value of the parameter δ further supports the central hypothesis of this study, indicating the degree of ICN positively related to patent citations.

Country	α_{tlT}	δ	γ	β_1	β_2	***adjusted R^2***
US	2433	0.1001	0.7017	0.2573	0.075	0.839
Japan	1664	0.1319	0.7109	0.4998	0.069	0.749
South Korea	1529	0.1001	0.723	0.3698	0.028	0.803
Russia	1472	0.1002	0.8	0.46	0.024	0.787
China	990.5	0.1025	0.8	0.3135	0.005	0.66
World Intellectual Property Organization	672.3	0.1087	0.7998	0.4213	0.009	0.758
European Patent Office	502.6	0.1014	0.7994	0.3296	0.009	0.688

Table 3 Results of model estimations

α_{tlT} is related to the nature of citing patents and cited patents, and is approximately proportional to the total number of cited patents in various countries or organizations. δ is the promoting effect of network aggregation coefficient on citation frequency, and we found an interesting result that Japan has much higher value of δ, which means that the effect of ICN on IDK is much more obvious in Japan. We considered the reason to be the language barriers.

In addition, γ is the promoting effect of technological similarity on the frequency of citations, and we found that those citing patents are not limited to nanostructures category, which confirming the necessity of the coefficient $Prox_{ltT}$, to measure the technology similarity degree among these patents.

β_1 is the corruption rate of a single country's patents. And a higher corruption rate indicates that a country's patent can be cited faster, with a shorter citation delay and a faster decrease to 0. β_2 is the diffusion rate, which indicates the effectiveness of knowledge diffusion in a country and can be used as a comparison of diffusion situations in different countries or organizations.

5.3 Patterns of Innovative Knowledge Diffusion in the field of Nanostructures

We are also interested in the patterns of IKD in the field of nanostructures. In this section, we try to discuss them. A significant difference in the results can be found in the value of β_2. It leads us to analyze the practical experience in the nanostructures. As shown in Table 3, after controlling the effect of ICN, technology similarity, in the field of nanostructures, the seven countries or organizations can be divided into three groups in terms of the diffusion rate β_2.

Figures 1 plot the patent citation frequency distribution across these countries. In this figure, the vertical axis is set as the citation frequency, while the horizontal axis is set as the time lag. We discover that the cited patents peak about two to four years later, and the citation frequency drops off to 0 in eleven to fourteen years. Comparing with previous study by Jaffe and colleagues (Hu and Jaffe, 2003), the corruption rate of patents in the field of nanostructures is higher than those in other fields, which implies that their citations come earlier and the citation frequency drops faster. This phenomenon also indicates that nanostructures has developed rapidly, and knowledge in this area diffused quickly.

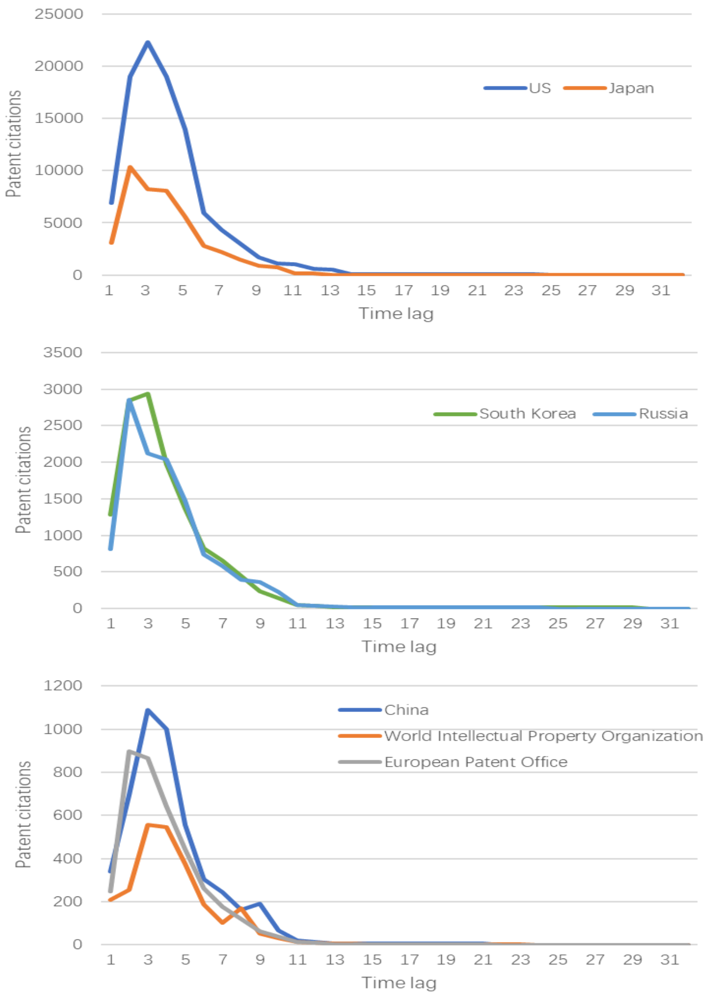

Fig. 1 Citation frequency distribution in the seven countries

According to Jaffe and Trajtenberg (1996), the citation lag of cited patents reaching a peak approximately equals to the reciprocal of the corruption rate of a country, that is $1/\beta_1$.The citation lag of the US patent peaks in about 4 years, matching the corruption rate of the US, which is around 0.25. Also, we find that the diffusion rate β_2 is relatively high for the US. It may be caused by the leading position of the US in the area of nanostructures, and lots of innovators tend to apply for the same patent again in the US as well as registering in their own country. Similar findings can be observed for Japan. Japanese patents reach the citation peak in two years after registration, which matches their corruption rate is nearly 0.5. Compared with the US patents, the corruption rate of Japanese patents is higher, resulting in those Japanese citations reach their peak earlier and drop off to 0 in about eleven years. It is also noteworthy that the diffusion rate β_2 of Japan is also quite high, indicating that Japan is also in a dominant position in the nanostructures area.

The citation pattern of Korea is similar to that of the US and Japan. However, compared with them, the diffusion rate of Korea is significantly lower. In addition, the diffusion rate of Russia is almost the same as that of Korea, maybe because their technical position and superiority are very similar.

The World Intellectual Property Organization and European Patent Office have a very close number of patents and citations. Although their patents and citations are relatively small, their citation peak time is basically consistent with its corruption rate. Meanwhile, diffusion rates of the World Intellectual Property Organization and European Patent Office are relatively small. For Chinese patents and their citations, although the number of patents is larger than that of the World Intellectual Property Organization and European Patent Office, the diffusion rate is much lower, which to some extent revealing that Chinese scientists' research in the field of nano-material do not attract more attentions from other countries or organizations in the same industry. We may attribute such phenomenon to the geographical and language barriers.

6. Conclusions and Implications

In this study, we examine the impact of ICN on IKD embodied in patent citation frequency, proposed an improved model for knowledge diffusion integrating ICN with Jaffe's double exponential model and revealed the patterns of IKD among different countries or organizations in the field of nanostructures. We have the following findings:

i. Innovative knowledge is influenced by several factors, we have proposed and verified a positive correlation between ICN and IKD.
ii. We introduced an enhanced model for IKD by incorporating ICN with Jaffe's double exponential model. The results of our NLS estimation demonstrate a good fit of our model to patent citation data.
iii. Our empirical analysis revealed several interesting patterns of IKD in the field of nanostructures. The peak of IKD, measured by patent citations, typically occurs within two to four years, while the decay of nanostructures knowledge spans from eleven to fourteen years. The rate of IKD varies among the studied countries or organizations, categorizing them into three groups: Group 1 (US and Japan), Group 2 (Korea and Russia), and Group 3 (China, World Intellectual Property Organization and European Patent Office). Notably, innovative knowledge tends to spread more readily in the same geographic region.

The theoretical and managerial implications drawn from this study are significant. Our results validate the substantial positive correlation between ICN and IKD in terms of patent citations. This emphasizes the importance of social network factors in patent citation and knowledge management analyses. Moreover, our study proposes an enhanced model for knowledge diffusion that effectively captures the patterns of knowledge diffusion across countries or organizations. This model not only aids researchers in studying similar topics in related knowledge domains but also provides valuable insights for practical applications.

Understanding the pattern of knowledge-diffusion networks among innovators can help governments and businesses effectively use their investment to stimulate commercial science and technology development. First, in the era of knowledge economy, patents as a form of innovative knowledge should be given more attention by governments and enterprises. By analyzing cited and citing patents in a certain field, it is possible to discover the leading countries or organizations or regions of the latest technology in the field. The revealed knowledge diffusion patterns can be used for organizations to learn the technology development trend and to advance their technology knowledge. Second, our findings suggest that ICN plays a crucial role in IKD. Therefore, organizing projects of cooperation and exchange can encourage innovators to make full use of the opportunities and create more new knowledge. Besides, it is necessary to focus on key innovators who hold higher degree of ICN can facilitate knowledge diffusion within specific technology fields.

While this study contributes valuable insights, there are limitations that suggest avenues for promising future research. For instance, our data focuses solely on the same IPC category, potentially underestimating the convergence of technology similarity during the early stages of knowledge diffusion. Additionally, considering data from diverse technology fields could provide a more comprehensive understanding of field-specific characteristics and offer generalized conclusions for various industries. Furthermore, while we employed patent citation as a proxy for knowledge diffusion, exploring alternative surrogates, such as user-generated content over the Internet or academic papers and references citation, could offer new perspectives in future studies.

In conclusion, while this study is inevitably with limitations, it paves the way for future research endeavors. Our comprehensive analysis sheds light on the role of ICN in knowledge diffusion, offering valuable insights for both academia and practical applications.

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