sustainability

MDPI

Article

Toward a more Efficient Knowledge Network in Innovation Ecosystems: A Simulated Study on Knowledge Management

Houxing Tang [1], Zhenzhong Ma [2,3], Jiuling Xiao [4] and Lei Xiao [5,*]

1 School of Business Administration, Nanchang Institute of Technology, Nanchang 330099, China; tanghouxing1982@nit.edu.cn
2 Center for Israeli Studies of UESTC, University of Electronic Science and Technology of China, Chengdu 611731, China; maz@uwindsor.ca
3 Odette School of Business, University of Windsor, Windsor, ON N9B 3P4, Canada
4 School of Business, Nanjing Audit University, Nanjing 211815, China; xjl@nau.edu.cn
5 School of Economics and Management, University of Electronic Science and Technology of China, Chengdu 611731, China
* Correspondence: xiaolei@uestc.edu.cn

Received: 3 July 2020; Accepted: 4 August 2020; Published: 6 August 2020

Abstract: Knowledge management has become increasingly important in the era of knowledge economy. This study explores what is an optimal knowledge network for more efficient knowledge diffusion among strategic partners in order to provide insights on sustainable enterprises and a more knowledge-efficient innovation ecosystem. Based on simulated analyses of the efficiency of knowledge network models, including regular network, random network, and small world network, this study shows that a random knowledge network is more efficient for knowledge diffusion when a mixture knowledge trade rule is used. This study thus helps identify which knowledge networks facilitate knowledge exchange among collaborative partners for sustainable knowledge management. Management practitioners and policymakers can use the findings to design more appropriate knowledge exchange networks to improve the efficiency of knowledge diffusion in an innovation ecosystem.

Keywords: knowledge network; knowledge management; network structure; innovation ecosystem

1. Introduction

Knowledge and knowledge management have become a new driving force of economic development in the era of knowledge economy [1–8]. More firms have recognized the importance of knowledge and knowledge diffusion in obtaining sustainable advantages [4,8–11]. As the global market becomes more competitive, only those firms that can continuously create, transmit, and absorb new knowledge are able to achieve sustainable success in an increasingly turbulent environment [12]. Knowledge has thus become a critical factor for firms to innovate and compete with domestic and international counterparts for sustainable development [8,10,13,14].

Interfirm networks in a variety of forms (such as strategic alliances and industry clusters) have become increasingly important in helping firms improve their competitive positions through enhanced access to knowledge, innovation, and resources otherwise not available to them [6,7,15–17] In response to the increased performance pressure from unforeseeable challenges in the global market, firms have formed various networks and moved fast from competitors to collaborators and value cocreators in order to build knowledge efficient innovation ecosystems [17,18], a coopetition view of modern business activities. It has been widely accepted that knowledge networks in an ecosystem affect the diffusion of new ideas and practices and further innovation performance [13,19–21]. Consequently, changes in knowledge networks have a great impact on the level of knowledge diffusion [13,22]. Therefore, a better understanding of knowledge networks and further knowledge diffusion becomes essential for sustainable growth. There is still a lack of convincing evidence, however, on which knowledge networks are optimal for efficient knowledge diffusion. Cowan and Jonard [20] and other scholars used the "barter trade" rule to explore the impact of knowledge networks on knowledge diffusion efficiency. They compared the knowledge diffusion efficiency of different knowledge networks and claimed that a small world network is the optimal structure for knowledge diffusion, which has been widely accepted in many studies on knowledge management and innovation research [11,20,23–25].

However, while knowledge exchange using the barter trade rule is mutually beneficial, it is not always a good fit with the newly emerged interfirm structures, such as strategic partner alliances or clustered interfirm networks in industrial parks. An interfirm network among strategic partners provides an efficient channel for information, resources, and knowledge exchange among firms, and every firm acts as an information sender and receiver in the network to facilitate organizational learning among strategic partners [10,26,27]. Within such a network, knowledge diffusion may not expect returns from exchange partners but has an intention to help a partner grow or simply foster a partner relationship [28]. Thus, the knowledge exchange is not always a barter exchange, but could be a unilateral gift-giving—a gift knowledge trade. In addition, at the early stage of network development in the increasingly popular industrial parks and strategic partnership [2,29–31], some network partners may have no unique knowledge to offer to knowledge providers. Therefore, the barter trade rule is not always consistent with the purpose of strategic partnership or industrial parks [30]. Instead, a mixture rule, including both the barter trade rule and the gift trade rule is more conducive to increasing the overall knowledge diffusion efficiency among networked members. As a result, research on knowledge networks and knowledge diffusion often draws different, sometimes conflicting, conclusions on the impact of knowledge networks due to different assumptions, models and data [23]. There still lacks a consensus on what is the optimal knowledge network for efficient knowledge diffusion among clustered firm partners. It is also practically important for practitioners and policymakers to better understand what kind of knowledge network should be adopted to facilitate knowledge diffusion and further sustainability in an innovation ecosystem [31–33].

This study aims to bridge this research gap in order to help determine which structure will facilitate efficient knowledge diffusion among clustered firms in an innovation ecosystem. This question is very important when more firms are forming strategic partners and many governments are building industrial parks to bolster their economic development [30,31]. Finding an efficient knowledge network to facilitate knowledge diffusion among strategic partners becomes a determining factor on whether an innovation ecosystem can really help clustered firms' learning. Based on the work of Cowan and Jonard [23] and a contingency view, this study first explores how the evolution of a knowledge network affects knowledge diffusion efficiencies. Firm networks' structure ranges from a regular graph to a mixture graph, and then to a completely random graph, and knowledge diffusion efficiency is assessed with average knowledge stock (*AKS*), speed of knowledge diffusion (*SKD*), and average knowledge disparity (*AKD*), respectively. Simulated analyses are then conducted to examine the impact of knowledge networks on knowledge diffusion efficiency. A sensitive analysis is also conducted to compare the results with those of Cowan and Jonard [23] in order to explore those seemingly conflicting conclusions. Potential implications are then discussed based on the findings. The results show that when a mixture rule is used for knowledge diffusion among strategic partners, random knowledge network is optimal, and when a barter trade rule is used, the small world knowledge network is optimal, a more contingent finding on the impact of knowledge network on knowledge diffusion efficiency.

The value of this study lies in that a contingency approach is adopted to explore a different but more realistic knowledge diffusion rule than the one used in previous research [23]. According to the contingency view [33], different knowledge trade rules should be considered in firm networks depending on the knowledge management stages: in the early stage of knowledge diffusion among clustered firms, a mixture trade rule including both gift trade and barter trade of knowledge may be better in helping increase the knowledge level of all members. The results of this study show that under the new trade rule—the mixture trade rule, the optimal knowledge network for efficient knowledge diffusion among strategic partners is no longer the small world network; instead, a random network is more efficient when the new trade rule is used. As a result, this study adds an important piece to the literature on knowledge networks and knowledge diffusion efficiency: According to Cowan and Jonard [20,23], the small world network is optimal for knowledge diffusion, but their research somehow fails to consider the important condition under which the barter trade rule is used in knowledge diffusion process, namely the benevolent nature of the partnership among strategic partners or the early stage of network development in industrial parks. This study shows that a static view used in previous research is defective. Using a contingency perspective, it is argued that the mixture rule of knowledge diffusion (i.e., barter trade plus gift trade for knowledge exchange) may be more realistic and thus more suited to strategic partnerships or industrial parks. Consequently, the random network is more optimal for efficient knowledge diffusion.

The rest of this paper is structured as follows. We first present a brief review of relevant studies in the literature, and then network models are conducted to simulate the process of knowledge diffusion, including setting a mixture knowledge trade rule, constructing different knowledge networks and measuring the efficiencies of knowledge diffusion. We then report the simulated results and a sensitive analysis to compare our models and those of Cowan and Jonard [23]. The last section discusses the findings and provides implications for management practitioners and policymakers.

2. Literature Review

In response to the emerging challenges in the dynamic and interconnected market, firms have formed strategic partnerships such as joint ventures, alliances, and interfirm clusters to obtain enhanced access to innovation, knowledge, complementary resources, and capabilities not available to them otherwise [2]. Governments in different countries have also created a large number of industrial parks in order to take advantage of the synthesis effect of innovation ecosystems on economic development [34]. Strategic alliances lead to clustered firms, which can use both market and non-market interactions. Firms can exploit, participate, and position themselves in the interfirm network to respond to radical changes in the global market [10,35]. When firms form and maintain strategic alliances with each other, they are actually weaving a relationship network, and firms embedded in the network are able to gain access to knowledge and technologies from their network partners [36]. Interfirm networks provide each firm with rapid and flexible access to resources embedded in other firms or related industries [2,24,30,31].

2.1. The Impact of Network Characteristics on Knowledge Diffusion

Network characteristics affect knowledge diffusion among network members [37–40]. Network density is one of the most important characteristics, reflecting the proportion of possible ties that are actualized among network members. Research has shown that network density can promote group communication and mutual trust in collective behaviors. Further, it can promote the recognition and coordination of group members and facilitate knowledge diffusion among network members, especially for invisible resources and tacit knowledge [37–44]. A dense network can increase the probability of forming strong ties, which is not only conducive to the transfer and diffusion of tacit knowledge, but also has a positive effect on innovation performance [22,45]. The speed of knowledge accumulation for a single firm also heavily depends on the density of its social network connections with other firms [46].

Another important network characteristic is network centrality, a network node's location in the network, and it is closely related to its social capital. Studies on organizations' network positions have shown that individual firms can obtain and use more diverse resources through their social network ties [35]. Such network embeddedness is conducive to the flow of information and acquisition of knowledge. For example, firms located in the center of the network or with many strong ties usually have access to abundant information, have strong influences on others, and can increase the others' dependence [47]. The central firms have access to more sources of knowledge and can foster innovation by successfully combining knowledge acquired from different sources [48]. Similarly, firms located in strategic positions in the network can spread more valuable resources, thus exerting a greater influence on decision makers [49].

2.2. The Impact of Knowledge Networks on Knowledge Diffusion

Network structure is another important network characteristic that affects knowledge diffusion among network members [20,23]. Knowledge networks can be grouped into random networks, small world networks, regular networks, scale-free networks, and complex networks, among others. There is an ongoing debate in the literature about which structure facilitates efficient knowledge diffusion and how different knowledge networks promote a fast diffusion of knowledge and collective innovation [14]. For instance, the speed of knowledge diffusion may change along with the change of network randomness, that is, the transmission speed in a regular network is much slower but it becomes much faster in a small world network [50]. The small world network can make knowledge diffusion much more comprehensive because of its high cohesion and shorter average path length and thus is widely considered the optimal structure for knowledge diffusion [20].

However, the small world network is not always efficient [11]. When there are great knowledge disparities between network members, the small world network is not an optimal knowledge diffusion structure, and it can only achieve a moderate level of performance: The higher the diversity among individual network members, the more likely it is that the small world network will widen the gap between network members' acquired knowledge [51], because the argument that the small world network is optimal is based on the condition that a barter knowledge trade rule should be used in the knowledge diffusion process, i.e., knowledge diffusion can only occur when both trade partners have something needed by the other side, and knowledge diffusion stops when one or both sides exhaust the resources needed by the other side. In addition, the small world knowledge network may not benefit every network member: network members may face longer search paths when locating knowledge in an organization, and their world may be large [52]. In fact, the ideation of innovation is better communicated by a knowledge network with a "complete graph", which maximizes the number of parallel communications and encourages people to dynamically stir through a large set of conversational partners [53].

In sum, a knowledge network has an important impact on knowledge diffusion efficiency among clustered firms, but which structure is optimal for knowledge diffusion is to be further examined. For example, a random network may be better in a knowledge diffusion process without creating new knowledge, while a regular network may be better in a knowledge diffusion process which creates new knowledge [20]. For a long-term knowledge accumulation, a small world network may be the best [20]. In addition, if the knowledge is scarce, the network with structural holes is better. If the knowledge is abundant, a high-density network is better [26]. Moreover, a star node, which is often treated as an important information center of knowledge distribution in the network, makes the highly asymmetric network more conducive to rapid knowledge diffusion. If the star node withdraws from the network, it will lead to severe destruction in the network distribution. Consequently, a flat knowledge network will be favored when there are increasing cases of withdrawing [54]. Furthermore, Nieves and Osorio [55] argue that the knowledge search strategy should also be considered in the search for the most suitable knowledge network. As a result, past studies have created a lot of confusions, and it is critical to further explore the impact of knowledge networks on knowledge diffusion performance, in particular for the increasingly popular strategic partnerships and industrial parks, in order to help management practitioners and policymakers to create more appropriate interfirm networks to facilitate knowledge creation and exchange.

3. Modeling the Process of Knowledge Diffusion among Clustered Firms

In order to further explore the impact of interfirm knowledge networks on knowledge diffusion efficiency for more sustainable development, we decided to use computer simulations to compare the efficiency of different knowledge networks in knowledge exchange. Computer simulations provide a cost-efficient tool to compare different interfirm networks and their performance. Several models were thus constructed in this study to analyze the relationship between knowledge networks and knowledge diffusion efficiency with different knowledge exchange rules that are more consistent with the purpose of strategic partnership and industrial parks.

3.1. Rules of Knowledge Interactions/Diffusion

Scholars have used different trade rules in their studies on knowledge network and knowledge diffusion [20,23]. For example, the oft-used "barter trade" rule assumes that an individual network member transfers part of his/her knowledge to another and is paid back with a different knowledge, and both members consider knowledge trade as mutually beneficial [20,23]. This is also the condition used in the studies by Cowan and Jonard [23] and many other scholars [25], who consequently contend that a small world network is the optimal structure for knowledge diffusion and the barter trade rule should be used in knowledge diffusion. Contrary to this assumption, the "gift trade" rule does not expect returns from exchange partners, but has an intention to develop or maintain a social relationship between exchange parties [28], and this rule is largely ignored in the mainstream studies on knowledge diffusion [20,25]. In this study, a contingency view is used [33], and it is argued that both knowledge trade rules should be considered in clustered firms depending on the knowledge management stages: in the early stage of knowledge diffusion among clustered firms, policymakers hope to increase the knowledge level of all members through a variety of knowledge trade activities. While it is beneficial to have barter trade of knowledge between partners, some network partners often have no definite return to knowledge providers—those firms with more knowledge endowment. Therefore, a mixture rule, rather than a barter trade rule, is more consistent with the policy reality at the early stage of interfirm alliances and benevolent strategic partners. A barter trade rule is more appropriate at the mature stage of knowledge management, when both partners have developed some knowledge needed by the other. Therefore, this study will model the knowledge diffusion process using a mixture rule, a more realistic knowledge diffusion rule for clustered firms in an innovation ecosystem. When two firms meet, they make either a bilateral or unilateral knowledge trade. That is, if Firm A has knowledge Firm B does not have and Firm B also has knowledge Firm A does not have, then the trade occurs, a bilaterally profitable trade (i.e., barter trade). On the other side, if Firm A has knowledge Firm B does not have, but Firm B has no knowledge Firm A needs, the trade also occurs, on a unilaterally profitable trade (i.e., gift trade), and vice versa. Using a different but also more realistic knowledge trade rule is the major difference between this study and those of Cowan and Jonard [20,23,24,54]. Further, this study also assumes that knowledge exchange can take place only with those to whom firms have direct links (edges). This process is repeated and forms the foundation on which knowledge spreads through the interfirm network for overall knowledge increase.

3.2. Constructing a Knowledge Network

3.2.1. Basic Assumptions

We consider a population $N = \{1, 2, \cdots, n\}$ of firms in a networked partnership. Each firm is treated as a node, and the relationship between two firms is treated as an edge. The undirected graph associated with this social network is written as $G(V, E)$, where the correspondence $V = \{V_i, i \in N\}$ represents the set of nodes to which each node is connected. The l_{ij} is defined as the length of the shortest path from node i to node j, that is $V_i = \left\{ j \middle| l_{ij} = 1, j \in N \right\}$. The $l_{ij} = 1$ indicates that node i and node j are directly connected. It is assumed in this study that two nodes can interact only when they are directly connected. Indirect exchange is not considered in our study.

3.2.2. Constructing Different Knowledge Networks

In order to model different knowledge networks, a re-wiring algorithm is used in this study—the same as the one used in similar studies [23]. According to the algorithm, we begin with a regular graph: a circular lattice with n nodes, and each node has some edges connected only to its m nearest neighbors (m is even). We operate on each edge of the nodes sequentially, but in a particular order: we first begin with node one, and the edge connects to its nearest neighbor clockwise. With probability p ($0 \leq p \leq 1$), we cut the connection to the neighbor and re-connect the edge to a code selected randomly over the entire graph. With probability 1—p, the edge remains unchanged. The progress is around the lattice clockwise, considering one edge per node and avoiding duplicated edges. After one complete round, the procedure is repeated, and the second nearest clockwise neighbor is considered. We repeat the procedure and consider progressively more distant neighbors, until every structure is considered, ranging from a perfect regular ($p = 0$), periodic lattice ($0 < p < 1$) to a completely random graph ($p = 1$).

3.3. Measuring Knowledge Diffusion Efficiency

This study aims to understand how a knowledge network affects the efficiency of knowledge diffusion between partnered firms to identify optimal knowledge networks for efficient knowledge diffusion in clustered firms. The key question is to measure the efficiency of knowledge diffusion. Scholars have used the efficiency of networks to measure the efficiency of *knowledge* diffusion with un-weighted networks [56,57] and weighted networks [58]. In particular, the mean μ and variance σ^2 are used in past studies to measure the accumulation and dispersion of knowledge over the agents [23]. However, the absolute variance σ^2 may not be suitable for measuring the dispersion. For example, at the beginning, the knowledge stock of firms i and j are $S_i(0) = 1$ and $S_j(0) = 2$, respectively, and at the end the knowledge stock of firms i and j are $S_i(t) = 4$ and $S_j(t) = 8$, respectively. If we use absolute variance, the dispersion increases, because it does not take into account the total knowledge stock in the whole network. In other words, a relative *measure* index may be more suitable. Therefore, we considered three indexes to measure knowledge diffusion efficiency in order to address the concerns mentioned above.

First, a structure will be better than others if it helps clustered firms reach a high overall knowledge level, which is often the purpose of strategic partnerships and industrial parks [20]. Therefore, we used the average knowledge stock (i.e., $AKS(t)$) to measure the mean of the whole network's knowledge stock. It is denoted as follows:

$$AKS(t) = \frac{1}{n}\sum_{i=1}^{n} S_i(t) \tag{1}$$

Second, the speed of knowledge diffusion (i.e., $SKD(t)$) is another major concern, and therefore, the faster the knowledge diffusion, the better the knowledge diffusion in clustered firms. The $SKD(t)$, the slope of the curve of $AKS(t)$, was thus used in our study.

$$SKD(t) = \frac{1}{n}\sum_{i=1}^{n} S_i(t+1) - \frac{1}{n}\sum_{i=1}^{n} S_i(t) \tag{2}$$

Third, the goal of knowledge diffusion in clustered firms is to help every network member get more knowledge and improve their performance. In particular, the studied network should help backward firms catch up with more advanced firms. From this perspective, the desired level of disparity in the distribution of knowledge in interfirm alliance should be lowest. So, we used $AKD(t)$ to denote the level of average knowledge disparity, and it is written as follows:

$$AKD(t) = \frac{\sum_{i=1}^{n} \left| S_i(t) - AKS(t) \right|}{\sum_{i=1}^{n} S_i(t)} \tag{3}$$

4. Simulation and Results

4.1. Setting of Parameters

The parameters used in the experiment were set as follows. Assume that the interfirm *network* for knowledge exchange has a total population of $n = 1000$ firms. Each of them holds $m = 6$ links, similar to the parameters used in previous studies [23]. There are $k = 50$ possible types of knowledge. Initially, each firm $i \in N$ holds one type of knowledge with independent identical probability $q = 0.15$. Experiments with different sets of knowledge, $k = 10$, 20, and 30, were also conducted and showed similar results (which did not affect the trend of evolution, but only the specific numerical size and the time-cost to the steady state). Moreover, initializing firms' knowledge endowments differently—by changing the amount of knowledge held on average by individual firms—produces little variation. We also set $q = 0.05$, 0.1, 0.3, and 0.5, respectively, which did not affect the trend of evolution, but only the specific numerical size and the time-cost to the steady state. The evolution of the knowledge network was tested by assigning the re-wiring probability p different values between 0 and 1—here $p = 0$, 0.1, 0.5, and 1, respectively, which represents knowledge networks different from a regular network ($p = 0$), a mixture network ($0 < p < 1$), and a completely random network ($p = 1$). The procedure was simply repeated and stopped when the interaction possibilities had been exhausted, or the output had reached a steady state. All the simulations were conducted on platform MATLAB R2014b.

4.2. Methodological Procedures

We used procedures similar to those of previous studies [23] to create different knowledge network structures for comparison. As described in Section 3.2.2, we first constructed a regular network with the symmetric connection matrix. If the matrix elements in location (i, j) is 1, it means that nodes i and j are connected. Then, based on the re-wiring algorithm in Section 3.2.2, with the increasing of p, the network structure changed from a regular network to a small world network and to a random network. For the initial knowledge endowment of each node, i.e., $S_i(0)$, we used the rand function rand (1) to calculate its value. If the parameter q, as in Section 4.1, is greater than rand (1), then $S_i(0) = 1$, which mean that node i has the knowledge. After that, we calculated the knowledge accumulation and disparity of the whole network using the knowledge interaction rule and formula as set in Equations (1)–(3), and then plotted the results in different figures.

4.3. The Accumulation of Knowledge in Clustered Firms

In this section, the goal is to find the optimal knowledge network based on the amount and speed of knowledge accumulation. Let p be equal to 0, 0.1, 0.5, and 1, respectively, *representing* different structure forms from a regular network, a mixture network to a completely random network. The results are shown in Figure 1.

As seen in Figure 1, the amount of average knowledge stock (i.e., *AKS*) will reach the maximum value of 50, which indicates that the diffusion is completed for all kinds of knowledge network. However, the cost-time reaching the maximum decreases with the increase of the value of p, which implies that the diffusion speed is the fastest for $p = 1$. As discussed before, for the indexes *AKS* and *SKD*, the more the better. Therefore, when the accumulation of knowledge is considered under the mixture trade rule, the completely random network (i.e., $p = 1$) is the optimal. Similar results were obtained when different values of p were tested, as in Figure 1.

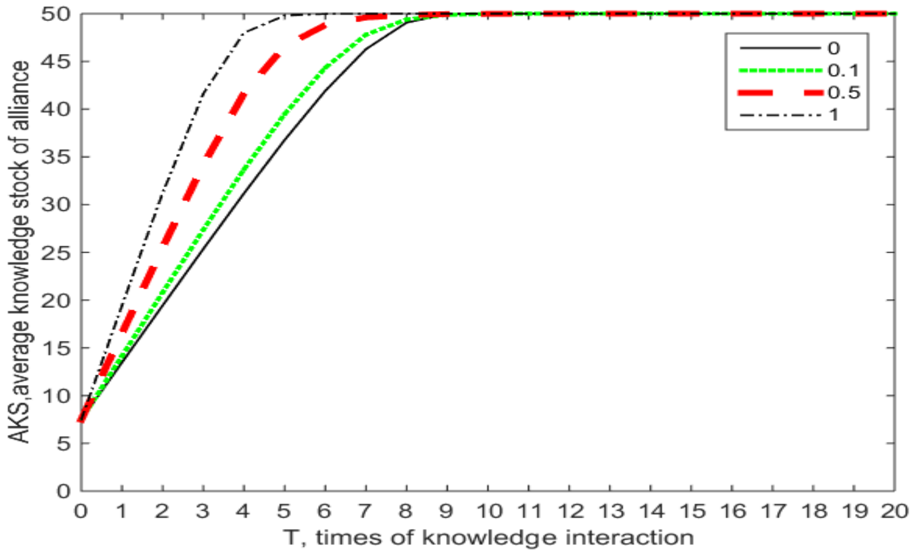

Figure 1. Average knowledge stock held by firms with different values of *p*.

4.4. The Dispersion of Knowledge in Clustered Firms

In this section, the goal is to find the optimal knowledge network based on knowledge disparity among clustered firms. Let *p* equal to 0, 0.1, 0.5, and 1, respectively, representing different structure forms from a regular network, a mixture network, to a completely random network. The results are shown in Figure 2.

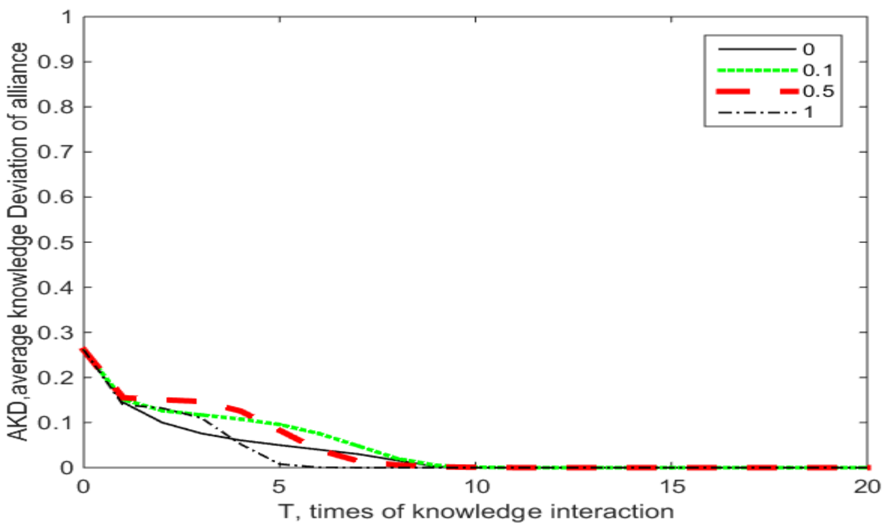

Figure 2. Average knowledge disparity between firms with different values of *p*.

We can see from Figure 2 that the amount of average knowledge deviation (i.e., *AKD*) will reach the minimum (i.e., 0), meaning that all firms have the same knowledge level. However, the cost-time reaching the steady state decreases with the increase of value of *p*. In other words, the speed of knowledge diffusion (*SKD*) increases with the increase of the value of *p*. As discussed before, for the index of *AKD*, the less the better; and for the index of *SKD*, the bigger the better. Therefore, when the knowledge disparity and the speed of knowledge diffusion are considered under the mixture knowledge trade rule, the completely random network (i.e., *p* = 1) is still the optimal structure. Results are very similar when we use different values of *p* as in Figure 2.

5. Sensitivity Analysis

This study shows that under a mixture trade rule, the random knowledge network is optimal for knowledge diffusion among strategic partners, which is different from the argument that a small world network is the optimal structure for knowledge diffusion [23]. To validate our result, a sensitivity analysis is conducted in this section to explore why our result is different from that of previous works.

5.1. Analysis of the Reliability of the Method

Using the interaction rule and performance indexes provided by Cowan and Jonard [23]—that is, a barter trade as the interaction rule, with μ and σ^2 as the performance indexes—a simulation is conducted to test whether our procedure is reliable by using our algorithm with their parameters to see whether we would get the same results. Note that all the parameters used in this test are set as theirs, that is, $n = 500$, $m = 10$, $k = 20$, and $q = 0.25$. The results are as follows.

Figure 3 shows the average knowledge stock held by firms and the speed of diffusion with different values of p, and Figure 4 shows the average knowledge disparity between firms with different values of p. It is expected that the more the better for μ but the less the better for σ^2 when the curves reach a steady state. These two results also indicate that the small world network is the best (i.e., $p = 0.1$), which is consistent with the finding of Cowan and Jonard [23]. Therefore, it can be concluded with confidence that our models and the algorithm/calculation procedure used in this study are valid: when the barter trade rule is used, our study also shows that a small world network is optimal, but it is argued in our study that a different rule should be used to explore knowledge diffusion among strategic partners or firms in industrial parks which often have a more benevolent relationship among network members, and thus a strict barter rule for knowledge trade may not be appropriate.

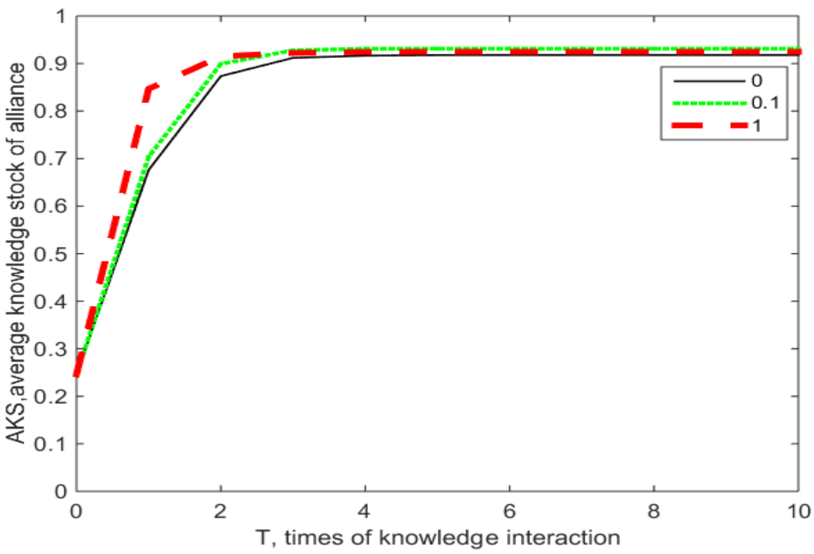

Figure 3. Average knowledge stock held by firms with different values of p based on the barter rule and μ.

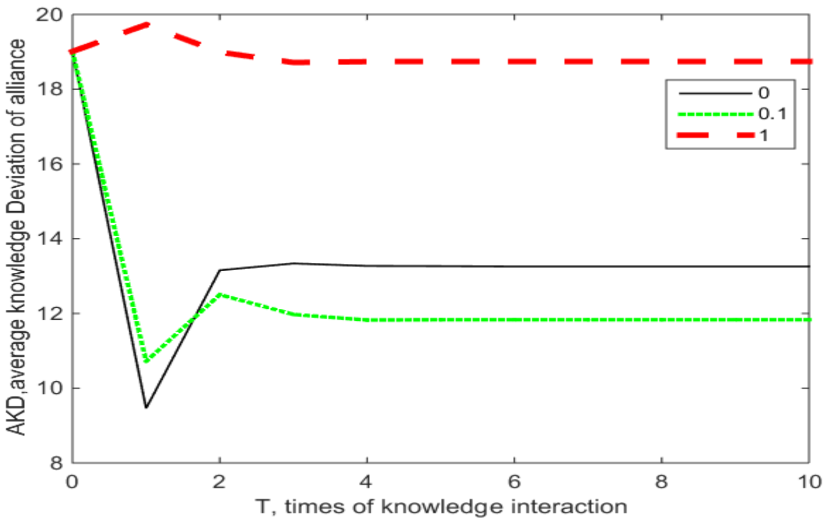

Figure 4. Average knowledge disparity with different values of p based on the barter rule and σ^2.

5.2. Effect of the Degree of Node

Among all parameters, the degree of node m seems to be arbitrary. Intuitively, if only considering the efficiency of knowledge diffusion, a shorter path length and a faster knowledge diffusion are better for knowledge accumulation. Thus, it seems that the largest degree of node (i.e., $m = n - 1$) would be best. In other words, the knowledge network with complete connections should be the optimal one, and it makes less sense to search for the so-called optimal network. However, while there is already a consensus that highly dense networks and sparse networks are not good for network knowledge diffusion, which implies that there should be an optimal degree of node between 0 and $n - 1$, the degree of mode has received limited attention in the literature on how to prove that the optimal level actually exists. Therefore, an important question to be solved is whether an optimal value of m indeed exists, in order to confirm the reliability of our simulation experiment.

In this study, we also test the marginal effect of the degree of node to measure knowledge accumulation with the increase of m. In this simulation, the parameters are set as follows: $n = 1001$, m increasing from 2 to 1000 with intervals 2 (i.e., from minimum value to maximum value, note that m is even), $k = 50$, $q = 0.15$. The result is shown in Figure 5.

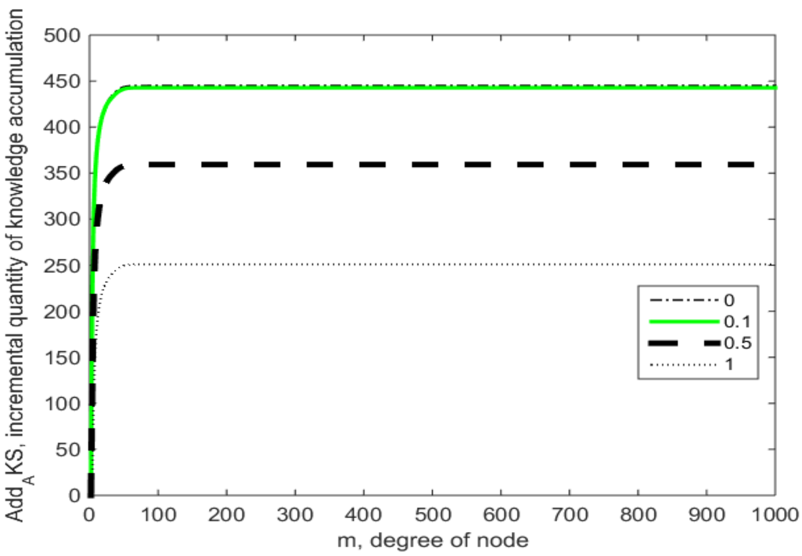

Figure 5. Marginal effect of the degree of node.

Figure 5 shows that knowledge accumulation has increased rapidly with the increase of m at the beginning, which indicates that more links are favorable. However, the increase of m makes decreasing difference when it reaches a steady state, indicating that too many links are not always more favorable, and they may even bring negative effects considering the cost. This result suggests that a moderate intensive network is more favorable, which is consistent with the current literature. This also confirms that a knowledge network with complete connections is not optimal. In other words, based on a given m, there is indeed an optimal knowledge network to be discovered, rather than simply adopting a completely connected structure to increase knowledge diffusion.

5.3. Effect of Knowledge Interaction Rules

In this section, we want to test whether the choice of the knowledge trade rule does lead to different conclusions. Thus, we use the mixture rule as the interaction rule and keep the performance index the same as used in similar studies (i.e., μ, and σ^2). The simulation results are shown in Figures 6 and 7.

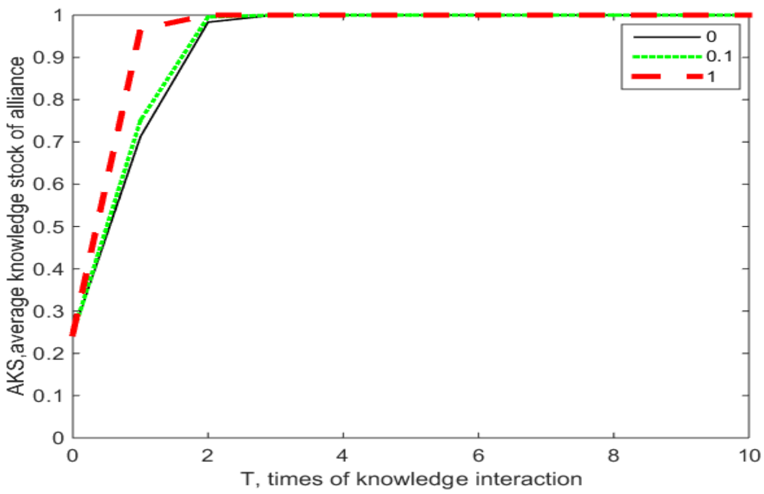

Figure 6. Average knowledge stock with different values of p based on a mixture rule and μ.

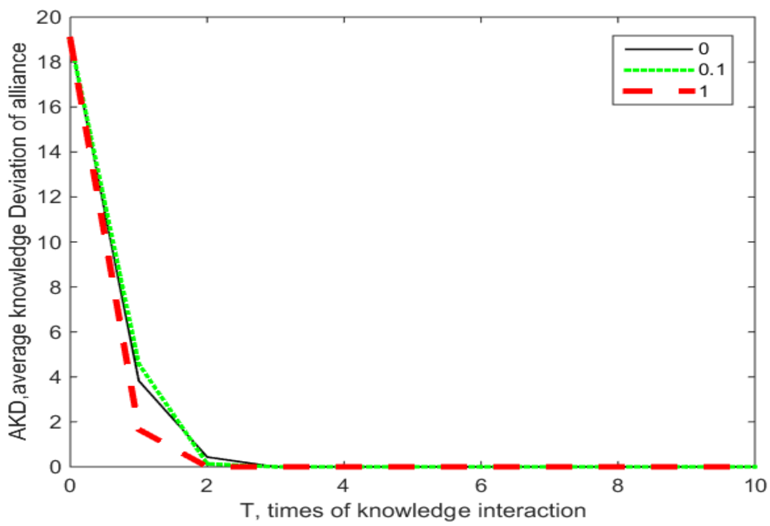

Figure 7. Average knowledge disparity with different values of p based on a mixture rule and σ^2.

As seen in Figures 6 and 7, the completely random network (i.e., $p = 1$) is the best when using the mixture trade rule. Therefore, it can be concluded that the use of different interaction rules leads to a different result from what Cowan and Jonard [23] have found. Furthermore, since the barter trade represents a bilateral profitable trade, the knowledge trade may be terminated if there is no mutual benefit opportunity in the network. As a result, the knowledge diffusion may be incomplete, as shown in Cowan and Jonard [23], which is against the goal of strategic partnership. By contrast, a mixture rule including the barter trade and gift trade is more likely to promote knowledge diffusion among network members. Even though Cowan and Jonard [23] argue that knowledge exchange is not a gift grade but a barter trade when competitors are involved, we argue that there is much more cooperation than competition among strategic partners or networked firms in strategic alliances, and therefore a gift rule cannot be ruled out. In other words, the gift trade should also be considered for knowledge diffusion in strategic alliances. Of course, the most important task is to determine how policymakers can create a *fair environment* in order to make the mixture rule (mainly the gift trade rule) work well.

5.4. Effect of Performance Indexes

To further examine the validity of our study, we also tested whether the choice of performance index leads to different conclusions. We used the same interaction rule as in previous studies (i.e., the barter trade rule) and our indexes *AKS*, *SKD*, and *AKD* as the performance indexes, respectively. The simulation results are shown in Figures 8 and 9.

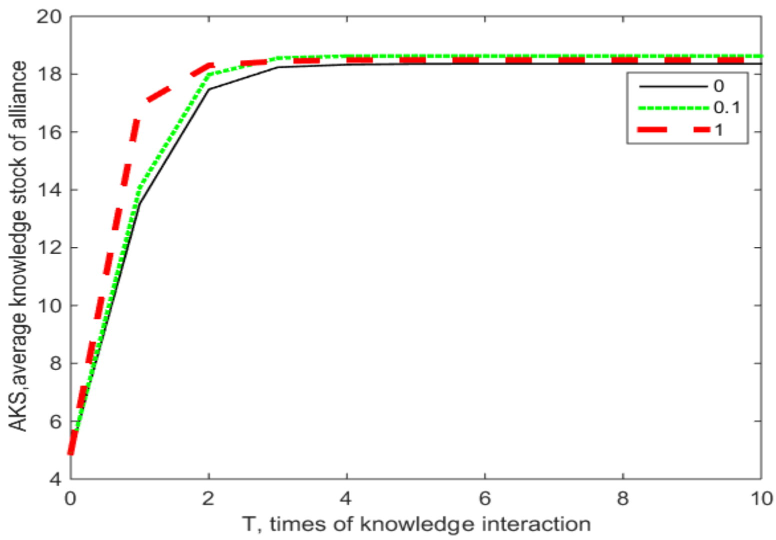

Figure 8. Average knowledge stock with different values of p based on the barter rule and *AKS*.

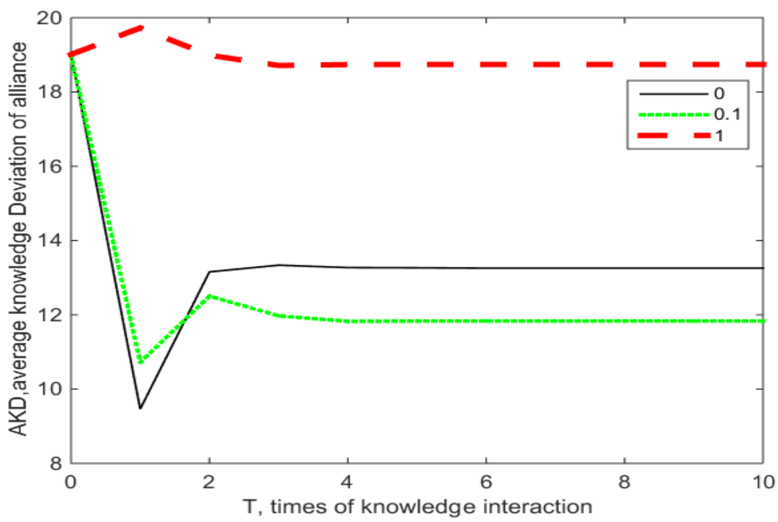

Figure 9. Average knowledge disparity with different values of p based on the barter rule and *AKD*.

As seen in Figures 8 and 9, the small world network (i.e., $p = 0.1$) proves to be the best. Thus, we can confirm that the change of index performance does not result in different conclusions between our study and those of Cowan and Jonard [23]. Furthermore, it confirms that the interaction rule is the determining factor if more average knowledge stock and less average knowledge disparity is preferred.

6. Discussion and Conclusions

6.1. Discussion

In this study we searched for an optimal knowledge network for knowledge diffusion in networked firms among strategic partners. Based on a mixture rule of knowledge interaction (i.e., a combination of barter trade and gift trade) and using different performance indexes (more average knowledge stock, faster speed of knowledge diffusion, and less knowledge disparity), a set of knowledge diffusion models were constructed and tested with a computer simulation. The simulation results show that a random network, rather than a small world network, is the optimal structure when a mixture knowledge trade rule is used. In other words, our study shows that the efficiency of knowledge diffusion increases along with the increase in the degree of randomness if both the barter trade rule and the gift trade rule are used.

Our finding contradicts the previous view that a small world network is the best for knowledge diffusion [20,23–25]. To validate our result, sensitive analyses were conducted to test whether our method is reliable and why our study generated a different result. The comparative analysis suggests that our method is reliable and valid, and the key difference between our study and previous studies is that our study used a different knowledge trade rule—the mixture rule. We argue that different knowledge interaction rules reflect different environment conditions, and thus a contingency view better reflects the reality of interfirm alliances [33]. More specifically, the barter trade represents a formal relationship among firms based on market exchange, and therefore knowledge diffusion must be a bilaterally profitable trade. The knowledge trade will be terminated if there is no mutual profit, and consequently knowledge diffusion based on the barter trade rule tends to be slow and incomplete. The gift trade rule represents a committed relationship among firms based on friendship and sometimes mutual obligations, and thus it may also be used to form a unilaterally profitable trade. Therefore, we argue that the appropriate knowledge interaction rule should be a mixture rule including barter trade and gift trade among strategic partners and in the early stage of industrial parks, because policymakers or government agents often require faster and complete knowledge diffusion with less disparity, and consequently may request more advanced firms to unilaterally help backward firms in a strategic alliance.

Our findings are consistent with those of many other scholars, who contend that a small world network may not be the optimal structure under conditions such as an uncertain environment or abundant resources [13,52,53,59]. Our findings, together with others, show that whether a knowledge network is optimal should be contingent upon whether it fits with environmental conditions rather than the pure static topology in knowledge networks. Put in another way, when you have the option to design a firm-based network for strategic alliances, what is an optimal structure really depends on whether it fits in with the contextual requirements. Therefore, this study adopts a contingent view to consider a more realistic knowledge trade rule, different from the static view which contends that a small world network is the only optimal structure [33].

6.2. Managerial Implications

Recent years have seen increasing interests in clustering, innovation ecosystems, and localization because the underlying assumption is that knowledge transmission and recombination are easier among agents of a geographically localized area, where industrial R&D and knowledgeable workforce abound. However, research also shows that there may be too much or too dense clustering in an innovation ecosystem [2,22,60]. At the same time, it is also important that cluster members maintain close links with members located outside the cluster. In this case, unlike the traditional viewpoint that a small world network is the best, our study shows that a random network is the best for efficient knowledge diffusion for network members within an innovation ecosystem when a more realistic knowledge trade rule is used.

The findings of this study thus have important implications for policymakers and management practitioners. First, policymakers of industrial parks and government agents should encourage and create policies to facilitate firms to develop new partnerships across the border of local clusters in order to obtain more efficient knowledge diffusion and innovation ecosystems. Policymakers can also encourage firms to carry out extensive technical cooperation through joint R&D projects as a form of linking clustered firms—a random network—to promote knowledge diffusion among clustered members. Third, strategic alliances should promote informal communication between firms using methods such as technical cooperation forums, entrepreneur salons, firm associations, and industry forums of technological consulting. Of course, the type of communications is not only important for local firms, but also for those in different geographic locations, in order to create more opportunities for different firms to facilitate knowledge diffusion and a more efficient ecosystem. Finally, policymakers can promote the mixture rule of knowledge diffusion through enhancing mutual trust and a cooperative atmosphere, which ultimately helps implement a fully random network to improve the efficiency of knowledge diffusion among firms in interfirm alliances. This is even more important because many firms are not willing to share knowledge using the gift rule in the market economy, but the findings of this study show that certain unilaterally beneficial policies may be better for the collective good.

More specifically, the findings of this study can help policymakers understand and identify efficient knowledge networks to facilitate knowledge diffusion in different stages in clustered firms in order to build more efficient innovation ecosystems. Based on the findings of our study, the mixture interaction rule (i.e., barter trade plus gift trade) may be more realistic and thus should be adopted in the initial stage of interfirm alliances, when a lot of network partners still do not possess the knowledge desired by their partners and consequently a random network is optimal for knowledge diffusion. The barter trade rule may be more feasible in the mature stage of interfirm alliances, when a small world network should be used. This is particularly important when an increasing number of high-tech parks and interfirm alliances are created in many countries to recreate the success of Silicon Valley. In the early stage of high-tech interfirm alliances, there often exist several core firms with sufficient knowledge and a lot of non-core firms with less knowledge. It is expected that the core firms will help non-core firms increase their knowledge stock as soon and as much as possible. Under such a situation, a barter trade is not feasible because the non-core firms may have little or no knowledge for the core firms, and thus the small world network is not a proper structure for knowledge diffusion. Instead, the mixture rule (i.e., barter trade plus gift trade) is much more realistic, and the random network will be optimal. However, the gift trade rule may not be sustainable because it only benefits one side of the exchange relationship. When the non-core firms obtain and create unique knowledge needed by other firms, the barter trade is more desirable than the mixture rule. In this situation, a small world network should be the preferred structure to facilitate knowledge diffusion in the mature stage of interfirm alliances.

6.3. Contributions

This study makes important contributions to the literature in several aspects. Firstly, there is an ongoing debate on what is the optimal structure for knowledge diffusion in networked firms, and whether more links between nodes would be better for knowledge diffusion in networked firms [11]. Some arguments based on the structural hole theory and the social capital theory are proposed to examine the advantages or disadvantages of relevant structures, but there is no consensus. In this study, our simulation results show that an optimal structure for knowledge diffusion is possible.

Secondly, based on a mixture rule of knowledge interaction and with a contingency view [33], our results show the possibility that a random network, rather than an intuitively attractive small world network, is likely to be the optimal structure for efficient knowledge diffusion. On the one hand, this suggests that the optimal knowledge network depends on environments of interfirm alliance, as discussed in the literature. On the other hand, it provides a feasible method for policymakers to achieve efficient knowledge interaction through enhancing mutual trust or creating a cooperative atmosphere in order to adopt the completely random network, which ultimately improves the efficiency of knowledge diffusion among networked firms in a strategic partnership.

6.4. Limitations and Future Research

This study has its limitations. Caution should be exercised when applying the findings of this study to other contexts. In our model, the degree of node (i.e., m) is fixed for each node, but a network with high degree-heterogeneity is likely to be suitable for knowledge diffusion [61]. Furthermore, the network often evolves over time. For example, a novel mechanism of network change, namely "node collapse", is proposed by Hernandez and Menon [62], which shows that node collapses directly affect the performance of the acquirer and indirectly that of other actors, and that the direction of network evolution hinges on the degree to which firms pursue internal versus network synergies through node collapses. Moreover, the peer effect may also influence the selection of partners and consequently influence the forming of a network. For instance, exogenous factors beyond individual agency, i.e., random peers, can shape a knowledge network [63]. Therefore, future research is called on to test whether a random network is still the optimal knowledge network if the degree of node m is not fixed.

In addition, we have assumed a static knowledge diffusion process, as in other studies [20,23,24,54]. In other words, it was assumed that no new knowledge has been added to the knowledge network, an assumption used for both our model and that of Cowan and Jonard [23], and thus no consideration was given to the scenario where the stock of new knowledge keeps growing. Future research is urged to consider the situation when more new knowledge is added to the knowledge diffusion process, a dynamic view of knowledge diffusion, in order to better capture the nature of knowledge diffusion among clustered firms in strategic partnerships. Another limitation embedded in this study is that, comparing with the studies by Cowan and Jonard [20,23,24,54], our study is based on simulated models. We do not have industrial data from different firms for a more in-depth analysis, and thus this study may not be *practical* enough, which could limit its generalizability. Future research is thus needed to collect more industrial data to validate the findings of this study. That being said, given that nothing is more practical than a good theory [64], this study will be able to provide important insights for future practical research.

Author Contributions: Conceptualization, Z.M.; data curation, H.T.; formal analysis, L.X.; investigation, H.T., J.X. and L.X.; methodology, H.T.; project administration, Z.M.; resources, Z.M., H.T., J.X. and L.X.; supervision, Z.M.; validation, L.X.; visualization, H.T. and J.X.; writing—original draft, H.T.; writing—review & editing, Z.M. All authors have read and agreed to the published version of the manuscript.

Funding: This study was partially supported by grants from the National Natural Science Foundation of China (Grant#: 71572027, 71661022, 71772088) and a grant from the Centre for Asia-Pacific Studies (Grant #816058), University of Windsor, Canada.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Drucker, P.F. *Post-Capitalist Society*; Harper Collins: New York, NY, USA, 1993.
2. Lai, Y.; Hsu, M.; Lin, F.; Chen, Y.; Lin, Y. The effects of industry cluster knowledge management on innovation performance. *J. Bus. Res.* **2014**, *67*, 734–739. [CrossRef]
3. Ma, Z.; Yu, K. Research paradigms of contemporary knowledge management studies: 1998–2007. *J. Knowl. Manag.* **2010**, *14*, 175–189. [CrossRef]
4. Nonaka, I. The knowledge creating company. *Harv. Bus. Rev.* **1991**, *69*, 96–104.
5. Nowacki, R.; Bachnik, K. Innovations within knowledge management. *J. Bus. Res.* **2016**, *69*, 1577–1581. [CrossRef]

6. Yin, J.; Ma, Z.; Yu, H.; Jia, M.; Liao, G. Transformational leadership and employee knowledge sharing: Explore the mediating roles of psychological safety and team efficacy. *J. Knowl. Manag.* **2020**, *24*, 150–171.
7. Yu, H.; Shang, Y.; Wang, N.; Ma, Z. The mediating effect of decision quality on knowledge management and firm performance for Chinese entrepreneurs: An empirical study. *Sustainability* **2019**, *11*, 3660. [CrossRef]
8. Grimaldi, M.; Rippa, P.; Ruffolo, M. A methodology to evaluate the organizational impact of IT on knowledge management: An Italian case study. *J. Inf. Technol. Case Appl. Res.* **2008**, *10*, 8–24. [CrossRef]
9. Grant, R.M. Toward a knowledge-based theory of the firm. *Strateg. Manag. J.* **1996**, *17*, 109–122. [CrossRef]
10. Ma, Z.; Huang, Y.; Wu, J.; Dong, W.; Qi, L. What matters for knowledge sharing in collectivistic cultures? Empirical evidence from China. *J. Knowl. Manag.* **2014**, *18*, 1004–1019.
11. Ma, Z.; Tang, H. Network structure and knowledge sharing efficiency in industrial alliances: Where is the fit? In Proceedings of the Annual Meeting of the Administrative Sciences Association of Canada, Toronto, CA, Canada, 27–29 May 2018.
12. Nonaka, I.; Takeuchi, H. *The Knowledge-Creating Company: How Japanese Companies Create the Dynamics of Innovation*; Oxford University Press: New York, NY, USA, 1995.
13. Abrahamson, E.; Rosenkopf, L. Social network effects on the extent of innovation diffusion: A computer simulation. *Organ. Sci.* **1997**, *8*, 289–309. [CrossRef]
14. Mueller, M.; Bogner, K.; Buchmann, T.; Kudic, M. The effect of structural disparities on knowledge diffusion in networks: An agent-based simulation model. *J. Econ. Interact. Coord.* **2017**, *12*, 613–634. [CrossRef]
15. Koch, T.; Windsperger, J. Seeing through the network: Competitive advantage in the digital economy. *J. Organ. Des.* **2017**, *6*. [CrossRef]
16. Ma, Z.; Jin, Q. Success factors for product innovation in China's manufacturing sector: Strategic choice and environment constraints. *Int. Stud. Manag. Organ.* **2019**, *49*, 213–231. [CrossRef]
17. Lusch, R.F.; Vargo, S.I.; Gustafsson, A. Fostering a trans-disciplinary perspective of service ecosystems. *J. Bus. Res.* **2016**, *69*, 2957–2963. [CrossRef]
18. Ma, Z.; Lee, Y. Patent application and technological collaboration in inventive activities: 1980–2005. *Technovation* **2008**, *28*, 379–390. [CrossRef]
19. Burt, R.S. Social contagion and innovation: Cohesion versus structural equivalence. *Am. J. Sociol.* **1987**, *92*, 1287–1335. [CrossRef]
20. Cowan, R.; Jonard, N. Network structure and the diffusion of knowledge. *J. Econ. Dyn. Control* **2004**, *28*, 1557–1575. [CrossRef]
21. Lin, C.; Wu, J.-C.; Yen, D.C. Explore barriers to knowledge flow at different knowledge management maturity stages. *Inf. Manag.* **2012**, *49*, 10–23. [CrossRef]
22. Capaldo, A. Network structure and innovation: The leveraging of a dual network as a distinctive relational capability. *Strateg. Manag. J.* **2007**, *28*, 585–608. [CrossRef]
23. Cowan, R.; Jonard, N. Network architecture, barter exchange and the diffusion of ideas. *Int. J. Agric. Res. Gov. Ecol.* **2007**, *6*, 165–178. [CrossRef]
24. Cowan, R.; Jonard, N. Structural holes, innovation and the distribution of ideas. *J. Econ. Interact. Coord.* **2017**, *2*, 93–110. [CrossRef]
25. Schilling, M.A.; Phelps, C.C. Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. *Manag. Sci.* **2007**, *53*, 1113–1126. [CrossRef]
26. Ahuja, G. Collaboration networks, structural holes, and innovation: A longitudinal study. *Adm. Sci. Q.* **2000**, *45*, 425–455. [CrossRef]
27. Owen-Smith, J.; Powell, W.W. Knowledge networks as channels and conduits: The effects of spillovers in the Boston biotechnology community. *Organ. Sci.* **2004**, *15*, 5–21. [CrossRef]
28. Bell, D. Modes of exchange: Gift and commodity. *J. Socio-Econ.* **1991**, *20*, 155–167. [CrossRef]
29. Wright, M.; Liu, X.; Buck, T.; Filatotchev, I. Returnee entrepreneurs, science park location and performance: An analysis of high-technology SMEs in China. *Entrep. Theory Pract.* **2008**, *32*, 131–155. [CrossRef]
30. Iandoli, L.; Ponsiglione, C.; Marchione, E.; Zollo, G. Knowledge exchange processes in industrial districts and the emergence of networks. *Cent. Eur. J. Oper. Res.* **2012**, *20*, 231–250. [CrossRef]
31. Ponsiglione, C.; Quinto, I.; Zollo, G. Regional innovation systems as complex adaptive systems: The case of lagging European regions. *Sustainability* **2018**, *10*, 2862. [CrossRef]
32. Van Egeraat, C.; Curran, D. Social networks and actual knowledge flow in the Irish bio-tech industry. *Eur. Plan. Stud.* **2014**, *22*, 1109–1126. [CrossRef]

33. Kim, T.H.; Lee, J.-N.; Chun, J.U.; Benbasat, I. Understanding the effect of knowledge management strategies on knowledge management performance: A contingency perspective. *Inf. Manag.* **2014**, *51*, 398–416. [CrossRef]
34. Powell, W. Neither market nor hierarchy. *Res. Organ. Behav.* **1990**, *12*, 295–336.
35. Gay, B.; Dousset, B. Innovation and network structural dynamics: Study of the alliance network of a major sector of the biotechnology industry. *Res. Policy* **2005**, *34*, 1457–1475. [CrossRef]
36. Zheng, X.; Zhao, Y. The impact of alliance network structure on firm innovation capability: An empirical study of ten high-tech industries in China. *J. Sci. Technol. Policy China* **2013**, *4*, 4–19. [CrossRef]
37. Collins, C.J.; Smith, K.G. Knowledge exchange and combination: The role of human resource practices in the performance of high-technology firms. *Acad. Manag. J.* **2006**, *49*, 544–560. [CrossRef]
38. Dyer, J.H.; Singh, H. The relational view: Cooperative strategy and sources of inter-organizational competitive advantage. *Acad. Manag. Rev.* **1998**, *23*, 660–679. [CrossRef]
39. Granovetter, M. Economic action and social structure: The problem of embeddedness. *Am. J. Sociol.* **1985**, *91*, 481–510. [CrossRef]
40. Hansen, M.T. The search-transfer problem: The role of weak ties in sharing knowledge across organization subunits. *Adm. Sci. Q.* **1999**, *44*, 82–111. [CrossRef]
41. McFadyen, M.A.; Cannella, A.A. Social capital and knowledge creation: Diminishing returns of the number and strength of exchange relationships. *Acad. Manag. J.* **2004**, *47*, 735–746.
42. Moran, P. Structural vs. relational embeddedness: Social capital and managerial performance. *Strateg. Manag. J.* **2005**, *26*, 1129–1151. [CrossRef]
43. Uzzi, B. Social structure and competition in interfirm networks: The paradox of embeddedness. *Adm. Sci. Q.* **1997**, *42*, 35–67. [CrossRef]
44. Zander, U.; Kogut, B. Knowledge and the speed of the transfer and imitation of organizational capabilities: An empirical test. *Organ. Sci.* **1995**, *6*, 76–92. [CrossRef]
45. Koka, B.R.; Prescott, J.E. Designing alliance networks: The influence of network position, environmental change, and strategy on firm performance. *Strateg. Manag. J.* **2008**, *29*, 639–661. [CrossRef]
46. Henning, C.; Saggau, V. Networks, knowledge spillovers and technological progress of firms: Simulations in an evolutionary framework. *Int. J. Innov. Technol. Manag.* **2013**, *10*, 1340018. [CrossRef]
47. Burt, R.S. Attachment, decay, and social network. *J. Organ. Behav.* **2001**, *22*, 619–643. [CrossRef]
48. Belso-Martinez, J.A.; Diez-Vial, I. Firm's strategic choices and network knowledge dynamics: How do they affect innovation? *J. Knowl. Manag.* **2018**, *22*, 1–20.
49. Martin, R. Differentiated knowledge bases and the nature of innovation networks. *Eur. Plan. Stud.* **2013**, *21*, 1418–1436. [CrossRef]
50. Delre, S.A.; Jager, W.; Janssen, M.A. Diffusion dynamics in small-world networks with heterogeneous consumers. *Comput. Math. Organ. Theory* **2007**, *13*, 185–202. [CrossRef]
51. Morone, P.; Taylor, R. Knowledge diffusion dynamics and network properties of face-to-face interactions. *J. Evol. Econ.* **2004**, *14*, 327–351. [CrossRef]
52. Singh, J.; Hansen, M.T.; Podolny, J.M. The world is not small for everyone: Inequity in searching for knowledge in organizations. *Manag. Sci.* **2010**, *56*, 1415–1438. [CrossRef]
53. Lovejoy, W.S.; Sinha, A. Efficient structures for innovative social networks. *Manag. Sci.* **2010**, *56*, 1127–1145. [CrossRef]
54. Cowan, R.; Jonard, N. Knowledge portfolios and the organization of innovation networks. *Acad. Manag. Rev.* **2009**, *34*, 320–342.
55. Nieves, J.; Osorio, J. The role of social networks in knowledge creation. *Knowl. Manag. Res. Pract.* **2013**, *11*, 62–77. [CrossRef]
56. Baggio, R.; Cooper, C. Knowledge transfer in a tourism destination: The effects of a network structure. *Serv. Ind. J.* **2010**, *30*, 1757–1771. [CrossRef]
57. Vragović, I.; Louis, E.; Díaz-Guilera, A. Efficiency of informational transfer in regular and complex networks. *Phys. Rev. E* **2005**, *71*, 036122. [CrossRef]
58. Latora, V.; Marchiori, M. Efficient behavior of small-world networks. *Phys. Rev. Lett.* **2001**, *87*, 198701. [CrossRef] [PubMed]
59. Wang, C.C.; Sung, H.Y.; Chen, D.Z.; Huang, M.H. Strong ties and weak ties of the knowledge spillover network in the semiconductor industry. *Technol. Forecast. Soc. Chang.* **2017**, *118*, 114–127. [CrossRef]

60. Molina-Morales, F.X.; Martínez-Fernández, M.T. Social networks: Effects of social capital on firm innovation. *J. Small Bus. Manag.* **2010**, *48*, 258–279. [CrossRef]
61. Zhang, Y.; Li, X.; Aziz-alaoui, M.A.; Bertelle, C.; Guan, J.; Zhou, S. Knowledge diffusion in complex networks. *Concurr. Comput. Pract. Exp.* **2017**, *29*, 1–13. [CrossRef]
62. Hernandez, E.; Menon, A. Acquisitions, Node Collapse, and Network Revolution. Available online: https://faculty.wharton.upenn.edu/wp-content/uploads/2016/10/hernandez-menon-ms.pdf (accessed on 5 August 2020).
63. Hasan 2017, S.; Bagde, S. Peers and network growth: Evidence from a natural experiment. *Manag. Sci.* **2015**, *61*, 2536–2547. [CrossRef]
64. Lewin, K. *Field Theory in Social Science: Selected Theoretical Papers by Kurt Lewin*; Harper & Brothers: New York, NY, USA, 1951.