

RESEARCH ARTICLE

Research on Technological Divisive Faultlines in Cliques: Evidence From China's Biomedical Industry Innovation Network

YAN ZHAO, ZHENG LI, LUYING LI, AND NIANNIAN QI

School of Management, Shanghai University, Shanghai 200444, China

Corresponding author: Luying Li (li_luying21@shu.edu.cn)


This work was supported by the Chinese National Natural Science Foundation under Grant 71673179.

ABSTRACT Social identity theory and self-classification theory provide theoretical supports for explaining the formation and action of the technological divisive faultlines. The purpose of this study is to explore the effects of technological divisive faultlines on a clique's innovation performance and the moderating effects of geographical proximity and closeness centrality. The data of 119 firm alliance and 351 firms in cliques are collected in China's biomedical industry from 2010-2017. Then, we perform the negative binomial regression by STATA software with these data as samples. The results show that there is an inverted U-shaped relationship between the technological divisive faultlines and clique's innovation performance; geographical proximity has no moderating effect on the inverted U-shaped relationship; closeness centrality has a significant negative moderating effect on the inverted U-shaped relationship between them. Besides, it suggests that the clique's innovation performance under high closeness centrality is higher than that under low closeness centrality, which provides a new perspective for the previous research that forming cliques could break the relational redundancy.

INDEX TERMS Innovation network, cliques, technological divisive faultlines, innovation performance.

I. INTRODUCTION

The innovative development of the biomedical industry provides an important guarantee for people's life safety [1], [2]. Since the outbreak of COVID-19, countries around the world have started to develop related vaccines, such as inactivated vaccines, subunit vaccines, adenovirus vector vaccines, and mRNA vaccines, which greatly challenge the biological medicine technology of a country. According to reality, developed countries such as the United States, Europe, and Japan are dominant in the biomedical industry, while developing countries like China are far behind [3], [4]. As a result, a large number of "life-saving drugs" in the biomedical industry in developing countries have to rely on imports. The biomedical industry in developing countries needs further innovated and developed.

The associate editor coordinating the review of this manuscript and approving it for publication was Justin Zhang .

At present, China's biomedical industry is in the dilemma of "strong production and weak innovation". To improve firm innovation ability and international competitiveness [5], Chinese biomedical firms have acquired knowledge and technology from developed countries through traditional means, including acquisitions, mergers and acquisitions, and joint ventures [6]. However, after the Section 301 investigation in 2017 and the China-US trade war in 2018, such alliances in which Chinese firms pay cash for foreign patents have been constrained. In this context, the establishment of multilateral alliances under the government's guidance has become the mainstream way to improve Chinese biomedical firms' innovation capability and competitiveness [7]. Such multilateral alliances correspond to the clique structures in innovation networks, i.e., fully connected subgraphs of at least three nodes [8].

There is technology similarity between the firms within a clique, but the similarity between each "firm pair" is discrepant. According to social identity theory and

self-classification theory [9], this phenomenon will result in the difference in knowledge and technology sharing among various “firm pairs” and lead to the uneven distribution of the inter-firm relationship strength among the firms within the cliques. In this case, the clique’s technological divisive faultlines occur, which promotes the clique to split into multiple sub-cliques or even disband completely [10]. Generally speaking, the firms within a clique prefer to carry out innovation activities within the sub-clique that they have a strong sense of belonging to, but this tendency will usually exacerbate the technical communication barriers between sub-cliques [11]. However, the effect of technological divisive faultlines within a clique on the clique’s innovation has been a largely under-explored domain.

In addition, in the field of innovation network research, previous scholars have conducted richer studies on geographical distance and network distance, but fewer scholars have conducted comparative studies on the two. This paper also plans to explore in this area. To this end, the purpose of this paper is to analyze the influence of technological divisive faultlines (TDF) on a clique’s innovation performance (CIP) and explore the moderating effects of geographical proximity (GP) and closeness centrality (CC). In this study, the network density (ND), average clustering coefficient (ACC), and patent accumulation (PA) are used as control variables. Our work extends fault theory to the domain of innovation networks of firm alliances, which enriches the research framework of fault theory and clique theory. Moreover, our work provides theoretical references in firms joining cliques and clique governance.

A. FAULTLINES

The term “fault”, which originally refers to the faults caused by the force of the earth’s crust, was introduced into the team level of organization management and defined as the invisible dividing line that divides a group into various groups according to the differences of member attributes [12]. Subsequently, Lawrence and Zyphur brought the concept of fault to the organizational level and defined organizational fault as the aggregation of attributes among members in a large population [9]. Over the years, some scholars in the field of organizational research have developed the fault theory from the perspective of individual attributes based on the organizational background such as executive team, board of directors, and others, which has extended the fault theory from the team level to the organizational level [13], [14]. Recent research by Chung *et al.* investigated the impact of innovation leaders’ network behavior on organizational innovation. They conceptualized faults as cross-job demographic dislocations and used data from a sample of 55 work units in a U.S. high-tech company to support a mediation model. In this model, the network behavior of senior leaders influenced innovativeness at the unit level through the network behavior of junior leaders [15].

In recent years, the focus of studies on fault has gradually shifted to the inter-organizational level, and the concept of

divisive faultlines has been proposed accordingly. A considerable literature has put forward that it is of great significance to carry out research and exploration of fault theory in the fields of the alliance, innovation network, and so on [16]. For instance, from the perspective of relationship embedding, Heidl *et al.* found that the divisive faultlines of multilateral alliances were caused by the difference in the degree of shared experience among firms [17]. Cheng *et al.* extended the theory of divisive faultlines to the technological innovation network constructed by joint patent applications. Their work proved that divisive faultlines within subgroups would lead to network polarization. Besides, there is an inverted u-shaped relationship between divisive faultlines and knowledge search breadth in technology innovation networks [18]. Accordingly, Cheng *et al.* took agricultural technology joint patent application and new energy vehicle patent construction cooperation network as samples, confirming that the location embedding had a significant positive moderating effect on the relationship between divisive faultlines and agricultural technological innovation, while the divisive faultlines negatively moderated the promoting effect between technological agglomeration and innovation [19]. Some scholars examined the relationship among divisive faultlines, knowledge stock, knowledge transfer efficiency, and situational embeddedness in firm alliances based on the questionnaire data provided by firm alliances [20]. Subsequently, Yu *et al.* collected data through questionnaires and found that relational divisive faultlines and innovation divisive faultlines partially mediated the negative correlation between psychological distance and intra-subgroup reciprocity [21].

However, subgroups proposed in these studies are broader than cliques, which exacerbates the difficulty of putting forward specific suggestions and strategies for the development of firms. Besides, a major problem with these questionnaires is that it has little consideration for network indicators. Above all, there are relatively few studies devoted to exploring the relationship between the TDF and the CIP, and our study fills the gap in the literature by empirical research.

B. CLIQUE’S TECHNOLOGICAL DIVISIVE FAULTLINES

The clique is a common structure in networks whose nodes are connected and closely related to each other. Various structures, including cliques in complex networks, were first presented in 2004 [22]. Subsequently, Palla *et al.* defined the clique as a fully connected subgraph composed of three or more nodes [8].

Previous scholars classified the divisive faultlines as organizational divisive faultlines, institutional divisive faultlines, and psychological divisive faultlines based on the degree of differences in organizational, institutional, and psychological factors between individual pairs within a community. In this paper, the TDF is defined as the invisible dividing lines that divide a clique into two or more sub-cliques due to differences in the technological similarity between firms that lead to uneven strength of inter-firm relationships. It characterizes the differences of all the firm pairs’ technological similarities

within a clique, and its value is defined as the intensity of the TDF [17], [18].

It has been suggested that the difference in technology similarity among clique members determines the intensity of the TDF. Specifically, the differences in the technological similarity between “firm pairs” within a clique promote the formation of cohesive sub-cliques. At the same time, the greater the difference in technology similarity between “firm pairs”, the more obvious the differences in technology overlap between them, and the stronger the intensity of the clique’s TDF. However, if all the firms within a clique are completely similar or different in technology, the possibility of TDF is immensely reduced because there is no obvious similarity distinction [23].

To sum up, several attempts have been made to explore the scale, trend, external firms, and the degree of cliques in the innovation network [24], [25], [26]. However, less attention has been paid to the TDF within a clique, which needs further exploration. In addition, from the fact perspective, the node-set divided by TDF within a clique is still a fully connected structure, and it is defined as a sub-clique.

C. GEOGRAPHICAL PROXIMITY AND CLOSENESS CENTRALITY

The geographical proximity (GP) and the closeness centrality (CC) are important indicators to measure the core position of a firm at the geographic and network levels [27], [28]. A short geographical distance between firms can promote the flow of knowledge and facilitate the cooperation between firms, but it may also accentuate the problem of knowledge homogenization and thus inhibit the firm’s innovation performance [29]. The proximity was summarized into five dimensions, including cognitive proximity, organizational proximity, social proximity, institutional proximity, and GP [30]. Among them, GP, as a measure of the geographical distance between the focal firm and its partners, has received great attention in innovation networks. For example, Buchmann and Pyka analyzed the cooperation behaviors of German automobile firms based on GP using the R&D project data from 1998 to 2007 and proved that firms with a closer geographical distance had a stronger willingness to cooperate [30]. Reuer and Lahiri addressed that a long geographical distance would hinder the formation of R&D cooperation among firms, but the negative effect of geographical distance would be significantly attenuated if the firms had historical cooperation experience in the same product market or had similar technical resources [31].

As for network distance research, a considerable amount of literature has been published on the position of a firm in the network. Several studies have documented that a firm with a core position in the network has more control over the resources [32]. It is worth mentioning that CC is an indicator to measure the network distance between the focal firm and partners in the network and calculates the reciprocal of the sum of the shortest paths from the focal node to all other nodes in the network. Existing research has found that

organizations with higher CC have more channels for imitation learning and knowledge absorbing [33]. In addition, some scholars also studied network distance from the perspective of embeddedness. For example, Cao *et al.* documented that proper network embedding is fast becoming a key instrument for firms to obtain network resources and promote innovation capacity [34]. Nevertheless, when a firm is over-embedded in the network, problems such as over-emphasis on network relationship maintenance will harm technology innovation.

In conclusion, previous research has recognized the critical role distance plays in the research of innovation networks [32], [33]. However, questions have been raised when there is TDF within a clique. The influence of TDF on CIP and the moderating effect of GP and CC on this effect have become urgent scientific issues to be explored, which also are the main research questions of this paper. Therefore, two research questions are proposed in this paper:

Q1: What is the impact of the TDF on CIP?

Q2: What are the moderating effects of GP and CC on the relationships between them?

II. THEORY AND HYPOTHESES

A. TECHNOLOGICAL DIVISIVE FAULTLINES AND CLIQUES’ INNOVATION PERFORMANCE

The intensification of TDF within a clique tends to foster the formation of cohesive sub-cliques, which will cause ownership issues for firms such as within the sub-clique or outside the sub-clique [17]. Social identity theory believes that similarity can promote knowledge flow between firms, and self-categorization theory presents that firms tend to develop closer alliances with similar firms [13], [14], which is the basis of the fault theory. When there are TDF within a clique, it will lead to the division of multiple sub-cliques within the clique. Firms within the clique are more willing to communicate with others with similar technologies to pursue greater knowledge flow [24] so that firms can solve their innovation problems within the sub-clique with a stronger sense of belonging. Therefore, it can be inferred that the TDF will make firms tend to complete innovation activities in the sub-clique with more technical similarity, weaken the unity of the clique and hinder the knowledge flow among the sub-cliques [18], [21].

Specifically speaking, when the intensity of TDF within the clique is inferior, firms can keep their innovation activities within the sub-clique they belong to and maintain communication with firms outside the sub-clique [17]. Firms are less embedded in the sub-clique where they are good at and trust while maintaining knowledge flows with firms outside the sub-clique [23]. As the intensity of TDF increases, clique members devote more energy to innovation activities in the sub-cliques to which they belong and reduce the maintenance of non-essential relationships with members outside the sub-cliques. Clique members develop innovations within sub-cliques where they feel a stronger sense of belonging, thus promoting CIP.

However, when the intensity of the TDF within the clique is high, the greater technological differences between the sub-cliques make firms with similar technology types form a closer sub-clique [17]. The sub-clique also becomes more closed and firms prefer to solve their innovation problems within the sub-clique and no longer engage in knowledge flow with firms outside the sub-clique, causing a decrease in clique knowledge flow and technology exchange [23]. As the intensity of the TDF increase, the closure of the sub-cliques is higher, and firms are more inclined to perform innovation activities within their own sub-clique instead of communicating with firms outside the sub-clique. This phenomenon results in the reduction of knowledge flow and technology exchange within the cliques, and adversely affects the CIP. Based on the above discussion, Hypothesis 1 is proposed:

Hypothesis 1: There is an inverted U-shaped relationship between the intensity of TDF and CIP.

B. THE MODERATING EFFECT OF GEOGRAPHICAL PROXIMITY

GP measures the geographic distance between the target firm and other firms in the network. A high GP of the target firm means that the sum of the geographic distances between the target firm and all firms in the network is low, indicating this firm is geographically close to other firms. This can be beneficial to the knowledge flow and technology exchange between the target firm and other firms in the network, but it can also lead to the problem of knowledge homogenization [35]. Therefore, the inverted U-shaped relationship between TDF and CIP could be moderated by GP.

In particular, if the firms belong to a clique with low intensity of TDF, they can conduct innovation activities within their sub-cliques and maintain the relationships with firms outside the sub-cliques simultaneously. As the intensity of TDF increase, firms within the clique can devote more effort to the inner part of the sub-cliques that they belong to, while appropriately reducing the knowledge flow with members outside the sub-cliques, which promotes CIP. This implies that there is a positive correlation between TDF and CIP [17]. Considering the moderating effect of GP, a short geographical distance between the firms within a clique and other firms contributes to the knowledge flow between them [37], [38]. At this point, as the intensity of TDF increases, the firms in the clique can devote more energy to conducting innovation in the sub-clique and share knowledge with clique partners outside the sub-clique. But this good situation is destroyed by GP because firms in cliques have to divert some of their efforts to maintain relationships with geographically proximate firms, which may result in relationship redundancy and even local knowledge homogenization [38], [39], thus impeding innovation. After all, GP weakens the positive correlation between low TDF and CIP. In other words, GP weakens the contribution of the low intensity of TDF to CIP. Therefore, the left tail of the inverted U-shaped curve that reflects the relationship between the intensity of TDF and CIP becomes flatter.

When the intensity of TDF within a clique is high, firms within the clique focus on confining their innovation activities to the sub-cliques they belong to and are less likely to communicate with other firms outside the sub-cliques, which is harmful to CIP [40]. As the intensity of TDF increases, the sub-clique becomes more closed and there is less knowledge flow within the clique, which is negative for innovation. It can be inferred that there is a negative correlation between the intensity of TDF and CIP [37], [38]. In combination with the influence of GP, the geographical closeness between firms within a clique and other firms reduces the cost of cooperation and promotes the flow of knowledge. At this point, as the intensity of TDF increases, the sub-cliques within the clique become more closed and the intra-clique knowledge flow becomes less, but this poor situation is ameliorated by GP. GP alleviates the situation where firms can only confine their innovation activities to be accomplished within sub-clique, and although it may cause knowledge homogenization [38], [39], it provides new knowledge intake paths for cliques and weakens the negative correlation between high intensity of TDF and CIP. In other words, GP weakens the inhibitory effect of high intensity of TDF on CIP. Compared with the previous, the right tail of the inverted U-shaped curve becomes flatter. Hypothesis 2 is proposed based on the above discussion:

Hypothesis 2: GP negatively moderates the inverted U-shaped relationship between the intensity of TDF and CIP.

C. THE MODERATING EFFECT OF CLOSENESS CENTRALITY

CC measures the network distance between the target firm and other firms in the network. A high CC of the target firm means that the target firm occupies a more central position in the network, and the network distance between the target firm and other firms is close [41]. This facilitates the flow of knowledge between it and the network members and the application of resources in the network [42]. CC has a moderating effect on the inverted U-shaped relationship between TDF and CIP.

Specifically, in the case that the intensity of TDF within a clique is low, firms within the clique can maintain relationships with other firms within the clique while carrying out innovation activities within the sub-cliques, which helps to improve the CIP. As the intensity of TDF increases, firms within the clique can devote more effort to the sub-cliques they belong to while appropriately reducing the knowledge flow with firms outside the sub-cliques, which contributes to CIP. We can speculate that there is a positive correlation between the intensity of TDF and CIP [17]. Combined with the influence of CC, firms within cliques are more centrally located in the network, which facilitates the flow of knowledge between them and other firms in the network [42], [43]. From the perspective of embeddedness, the firms within the clique belong to both the sub-clique caused by TDF and the existing clique. Moreover, they are also located in the center of the network. This leads to a situation where firms in the cliques are over-embedded and have to be distracted

TABLE 1. Descriptive statistics of samples.

Time windows	Network size	Clique members	Number of firms in cliques	Number of other organizations in cliques	Number of cliques	Maximum clique size	Minimum clique size
2010-2012	101	43	20	23	7	10	3
2011-2013	97	37	31	6	11	12	3
2012-2014	95	61	31	30	13	12	3
2013-2015	75	45	17	28	9	10	3
2014-2016	109	93	81	12	15	19	3
2015-2017	143	194	171	23	18	24	3
total	620	473	351	122	73		

from maintaining relationships with other firms rather than focusing on knowledge flow and R& D with clique partners, thus doing harm to innovation [44], [45]. CC weakens the positive correlation between the low intensity of TDF and CIP. That is to say, CC weakens the contribution of the low intensity of TDF to CIP. Compared to before, the left tail of the inverted U-shaped curve that reflects the relationship between the intensity of TDF and CIP becomes flatter.

In the other case that the intensity of TDF within a clique is high, firms within the clique can only confine their innovation activities to the sub-cliques they belong to and have less knowledge flow with other firms outside the sub-cliques, which is negative for the CIP. As the intensity of TDF increases, sub-cliques become more closed and there is less knowledge flow within the clique, going against innovation [23]. We can further infer that there is a negative correlation between TDF and CIP. Combined with the influence of CC, firms within a clique can carry out innovative activities within the sub-cliques to which they belong and develop collaborative relationships with other firms in the network, which promote the flow of knowledge [42], [43]. At this point, as the intensity of TDF increases, CC improves the situation where the objects of knowledge flow within the clique are limited to the sub-cliques. The sub-cliques within the clique become more closed and more detrimental to innovation, leading to the over-embedding of firms within cliques, but CC provides new ways of knowledge intake for cliques at the same time [42], from which CIP can benefit. CC weakens the negative correlation between the low intensity of TDF and CIP, namely CC weakens the inhibition effect of the high intensity of TDF to CIP. Compared to before, the right tail of the inverted U-shaped curve that reflects the relationship between the intensity of TDF and CIP becomes flatter. Hypothesis 3 is proposed accordingly:

Hypothesis 3: CC negatively moderates the inverted U-shaped relationship between the intensity of TDF and CIP.

According to these hypotheses mentioned above, the proposed research model of our study is as shown in FIGURE 1.

III. METHODOLOGY

A. DATA

The biomedical industry is a typical knowledge-intensive industry with high input, high risk, and high yields. As one

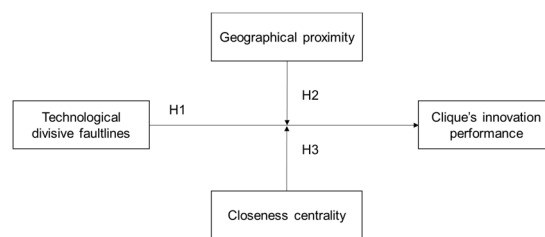


FIGURE 1. Research hypothesis framework.

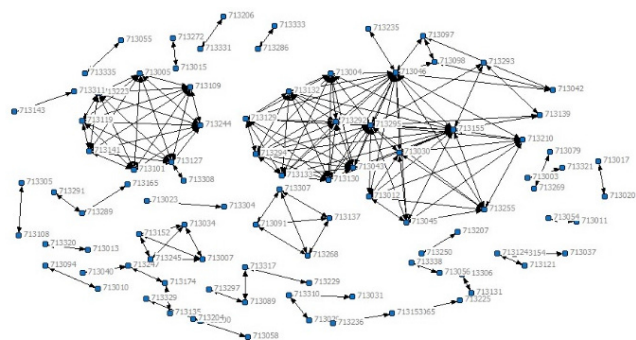


FIGURE 2. 2011-2013 alliance innovation network.

of the seven strategic emerging industries, the overall size of the biomedical market in China increased from RMB 183.6 billion to RMB 317.2 billion from 2016 to 2019, at a CAGR of 20%, much higher than other high-tech industries such as telecommunications equipment manufacturing, automobiles, and semiconductor industry (National Bureau of Statistic of China [NBSC] 2020) [4], [46]. As an emerging country committed to independent innovation, China is constantly confronted with trade and technical barriers with developed countries in the process of innovation and development. Especially after the trade war between China and the United States, this greatly restricted the development of China's biomedical industry. The study of the TDF in the innovation network of China's biomedical industry can provide a good reference for countries that are committed to independent innovation when facing the problem of technological matching within the alliance. Therefore, we chose the Chinese biomedical industry innovation network to conduct our study.

calculated according to formula (2):

$$D_{ij} = C \{ \text{arcCos}[\text{Sin}(\text{lat}_i)\text{Sin}(\text{lat}_j) + \text{Cos}(\text{lat}_i)\text{Cos}(\text{lat}_j)\text{Cos}(|\text{long}_i - \text{long}_j|)] \} \quad (2)$$

where j is a firm other than firm i in the innovation network, D_{ij} is the geographical distance between firm i and firm j , and $C=3437$ is a constant value between miles and latitude and longitude on earth. Then, the GP of focal firm i in t time window can be calculated by the formula (3). When the value is larger, it implies that the sum of geographical distances between the focal firm and other firms in the network is smaller, and the distance is closer. It is calculated as formula (3):

$$GP_{it} = \sum_j \frac{1}{(1 + D_{ij})} \quad (3)$$

where GP_{it} is the GP of firm i in the t time window, and D_{ij} is the geographical distance between firm i and firm j [52].

Closeness centrality (CC) describes the network distance between the focal firm and other firms in the network, and it is the reciprocal of the sum of the shortest paths between them. The larger the value is, the closer the network distance between the focal node and other nodes is, which also means the focal node is in a relatively central position in the network [42]. It is calculated as formula (4):

$$CC_{it} = 1 / (\sum_{i \neq j}^n d_{ij}) \quad (4)$$

where CC_{it} is the CC of firm i in time window t , and d_{ij} is the shortest path length between firm i and firm j , and n is the size of the network.

4) CONTROL VARIABLES

Network density (ND) is an indicator to measure the closeness of connections among members in a network, which describes the ratio of the actual number of connections in a network to the number of theoretical connections. Its value is from 0 and 1, and the closer it is to 1, the greater the ND is [42]. The calculation method is as formula (5):

$$\text{Density} = \frac{2L}{N(N - 1)} \quad (5)$$

where $Density$ is the ND, N is the network size, and L is the number of lines in the network.

The average clustering coefficient (ACC) reflects the clustering degree of network nodes, which is the proportion of closed triples to triples. Three nodes connected in a network are defined as closed triples, which is the basic structure of the network. The more closed triples are in the network, the higher the clustering degree of the network is [53]. And the calculation method is as formula (6):

$$ACC = 3N_{\Delta} / N_3 \quad (6)$$

where $N_{\Delta} = \sum_{k>j>i} a_{ij}a_{jk}a_{ki}$ is the number of closed triples and $N_3 = \sum_{k>j>i} (a_{ij}a_{jk} + a_{ji}a_{kj} + a_{ki}a_{kj})$ is the number of triples in the network.

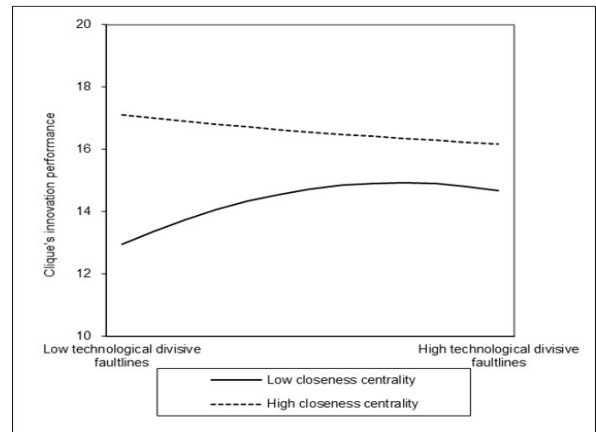


FIGURE 4. Moderating effect of closeness centrality (2D).

Patent accumulation (PA) can effectively measure the current technological reserve of the firms and is often used in the study of a firm's innovation performance [54]. In addition, the more technology patents a firm has, the higher innovation performance it is likely to create. In this paper, the total number of patents granted in the first five years of the observation period is used to measure the PA.

C. DESCRIPTIVE STATISTICS AND CORRELATIONS ANALYSIS

In this paper, the collected data of Chinese biomedical industry cliques were transferred into panel data, and descriptive statistics, correlation analysis, and negative binomial regression analysis were performed on 351 samples by STATA software. TABLE 2 shows the descriptive statistics and correlation analysis results of variables from where the correlation between variables is relatively low (the absolute value of the correlation coefficient is less than 0.7), meaning that there is no multicollinearity problem.

IV. RESULTS AND ROBUST ANALYSIS

A. RESULTS

The verification of the moderating effect is one of the research issues in this paper. To reduce the nonessential multicollinearity problem and ensure that the intercept of each variable has economic significance, the independent variables, moderating variables, and control variables in the research model were centralized. Moreover, according to the Hausmann test, $\text{Prob} > \text{Chi}^2 = 0.00$, indicating the model estimator of fixed effects is more effective. Considering that the patent data used to measure the CIP is the counting variable and relatively discrete, the panel negative binomial regression model with fixed effects was selected for analysis [55].

For Model 1 in TABLE 3, it can be seen that the control variables' coefficients are significant. Then, it can be concluded that the control variables are reasonable, and play a good control role in our research. Model 2 shows that the primary term of the TDF within a clique is positively significant

TABLE 2. Descriptive statistics and correlations analysis of variables.

Variable	Mean	S.D.	1	2	3	4	5	6	7
1. CIP	4150.22	11924.39	1						
2. TDF	0.22	0.15	0.030	1					
3. GP	0.58	0.27	-0.177	0.058***	1				
4. CC	1.16	0.22	0.217***	0.243***	-0.069	1			
5. ND	0.040	0.0055	-0.318***	0.283***	0.093***	0.101*	1		
6. ACC	0.82	0.055	-0.128**	-0.113**	0.083*	-0.048	-0.075	1	
7. PA	139.75	538.59	-0.013	0.061	0.093	0.094*	0.055	-0.005	1

Note: * p < 0.05, ** p < 0.01, *** p < 0.001

TABLE 3. Results of panel negative binomial regression models (obs=351).

Variable	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8
PA	0.0004** (2.63)	0.0004** (2.70)	0.0004* (2.42)	0.0004** (2.63)	0.0004* (2.46)	0.0003+ (1.81)	0.0003* (2.18)	0.0004* (2.30)
ND	-51.84* (-1.98)	-77.41** (-3.15)	-72.27** (-2.94)	-67.07** (-2.67)	-77.83** (-2.99)	-109.0*** (-4.83)	-99.96*** (-4.12)	-102.5*** (-3.69)
ACC	-5.50** (-2.93)	-4.91** (-2.65)	-4.36* (-2.36)	-3.90* (-2.09)	-4.57* (-2.41)	-2.92 (-1.56)	-4.60* (-2.37)	-5.15* (-2.32)
TDF		2.73** (3.22)	9.29*** (3.36)	8.62** (3.12)	1.68 (0.20)	6.09** (2.77)	43.03*** (3.94)	49.15** (3.17)
TDF ²			-16.10* (-2.52)	-14.54* (-2.28)	10.72 (0.51)	-10.89* (-2.03)	-61.50* (-2.37)	-64.44+ (-1.76)
GP				-0.91* (-2.30)	-0.50 (-0.45)			0.94 (1.06)
TDF×GP					10.87 (0.85)			-9.72 (-0.90)
TDF ² ×GP					-40.19 (-1.28)			10.79 (0.40)
CC						4.98*** (11.52)	9.21*** (11.12)	9.42*** (10.89)
TDF×CC							-33.30*** (-3.52)	-33.88*** (-3.30)
TDF ² ×CC							45.88* (2.04)	43.88+ (1.82)
constant	14.22*** (6.18)	14.06*** (6.72)	12.91*** (6.06)	12.92*** (5.93)	13.86*** (5.98)	8.31*** (4.40)	4.42* (2.15)	4.12+ (1.81)

Note: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001; the Z values are in parentheses

($\beta=2.73, Z=3.22$), meaning the main effect is significant and lays a foundation for the following test. For Model 3 in TABLE 3, it can be concluded the primary term of the TDF within a clique is positively significant ($\beta=9.29, Z=3.36$), and the quadratic term coefficient is negatively significant ($\beta = -16.10, Z=-2.25$). Thus, hypothesis 1 is verified and there is an inverted U-shaped relationship between the intensity of TDF and CIP [56].

As for Model 5, the primary term coefficient ($\beta = 10.87, Z=0.85$) and primary interaction term coefficient ($\beta=-40.19, Z=-1.28$) of GP in Model 5 are not significant. Besides, the GP's coefficient ($\beta=-0.50, Z=-0.45$), the primary interaction term coefficient ($\beta=10.87, Z=0.85$), and the quadratic interaction term coefficient ($\beta=-40.19, Z=-1.28$) are also not significant. It indicates that GP has no moderating effect on

the inverted U-shaped relationship between TDF and CIP, and hypothesis 2 has not been verified [56].

Model 7 shows the primary term coefficient of TDF is positively significant ($\beta=-43.03, Z=3.94$), and the quadratic term coefficient is negatively significant ($\beta=-61.50, Z=-2.37$). The CC's coefficient is positively significant ($\beta=9.21, Z=11.12$) while the primary interaction term coefficient is negatively significant ($\beta=-33.30, Z=-3.52$), and the quadratic interaction term coefficient is positive and significant ($\beta=45.88, Z=2.04$). Referring to the research of Haans et al., testing for flattening or steepening does not depend on any other coefficient than the coefficient of the quadratic interaction term. That is, testing for flattening or steepening is equivalent to testing whether the quadratic interaction term coefficient is significant. If the quadratic interaction term

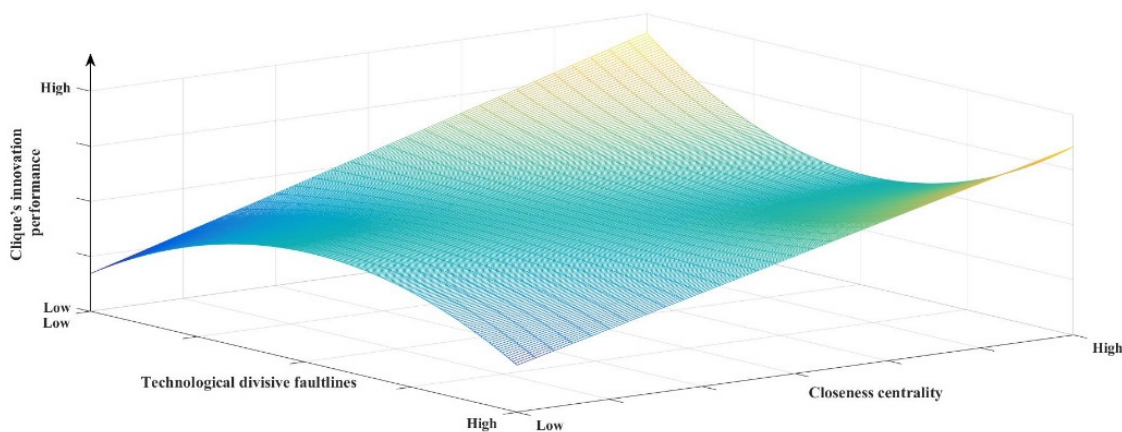


FIGURE 5. Moderating effect of closeness centrality (3D).

TABLE 4. Obust test of panel negative binomial regression models (obs=351).

Variable	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8
PA	0.0005** (2.85)	0.0005** (2.95)	0.0005** (2.67)	0.0005** (2.91)	0.0005** (2.73)	0.0004* (2.33)	0.0004** (2.82)	0.0005*** (3.45)
ND	-65.52* (-2.53)	-93.93*** (-3.72)	-89.38*** (-3.54)	-82.39** (-3.21)	-92.94*** (-3.51)	-114.30*** (-5.12)	-100.60*** (-4.14)	-87.64** (-3.05)
ACC	-5.99** (-3.08)	-5.36** (-2.77)	-4.72* (-2.45)	-4.15* (-2.14)	-4.87* (-2.46)	-4.048* (-2.17)	-6.11*** (-3.35)	-7.35*** (-4.37)
TDF		2.85** (3.12)	10.89*** (3.64)	10.30*** (3.46)	3.18 (0.37)	7.18** (3.14)	48.91*** (4.33)	62.96*** (4.51)
TDF ²			-19.47** (-2.87)	-18.05** (-2.66)	8.06 (0.38)	-13.57* (-2.48)	-75.42** (-2.78)	-95.44** (-2.81)
GP				-0.99* (-2.41)	(0.53) (-0.47)			1.70* (1.73)
TDF×GP					11.26 (0.88)			-18.12* (-1.70)
TDF ² ×GP					-41.92 (-1.32)			27.65 (1.11)
CC						5.32*** (12.41)	9.78*** (11.16)	10.12*** (12.38)
TDF×CC							-38.00*** (-3.93)	-40.74*** (-4.45)
TDF ² ×CC							56.84* (2.46)	60.38** (2.72)
constant	14.73*** (6.42)	14.62*** (6.87)	13.27*** (6.11)	13.11*** (5.95)	14.04*** (6.10)	7.95*** (4.17)	3.89* (1.82)	2.23 (0.84)

Note: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001; the Z values are in parentheses

coefficient is positive and significant, a flattening occurs for inverted U-shaped relationships. It can be concluded that the negative moderating effect of the inverted U-shaped relationship holds, and the moderating variable makes the opening of the previous inverted U-shaped curve larger or even the ends flip upward to form a U-shape. Model 7 indicates that the quadratic interaction term coefficient is 45.88, and it is significant as $Z = 2.04, p < 0.05$. Therefore, it can be concluded that CC negatively moderates the inverted U-shaped relationship between TDF and CIP, and hypothesis 3 is verified. In addition, comparing the regression coefficients of Model 8 with the previous models, it can be found that

the significance and positive and negative coefficients of the same index are basically consistent, indicating that the obtained results are consistent [56].

According to Model 7, we used EXCEL and MATLAB to draw 2D and 3D moderating effect diagrams (FIGURE 4 and FIGURE 5). In the case of low centrality, there is an inverted U-shaped relationship between TDF and CIP. With the increase of CC, the inverted U-shaped relationship between them goes from steepening to flattening, and the left and right tails become upward gradually. Finally, the curve the curve flips and becomes U-shaped. Thus, hypothesis 3 is verified again.

B. ROBUST ANALYSIS

To ensure the reliability of the empirical results, we changed the measurement method of dependent variables and used the total number of invention patent applications of all firms in the clique within the lag observation period of 3 years to measure the CIP [47]. As shown in Table 4, the robust test results are basically consistent with the above results (Table 3), which means the above results are robust.

V. DISCUSSION AND CONCLUSION

A. DISCUSSION

Based on the real data of China's biomedical industry, the impacts of TDF on CIP are explored. Specifically, in the biomedical industry in China, when the intensity of TDF is low, firms within the clique can conduct innovation activities within their sub-cliques while maintaining good relations with partners outside the sub-cliques. For this point, the coordination of cliques is beneficial to their innovation performance. On the other hand, when the intensity of TDF is high, intra-clique firms can only limit their innovation activities within sub-cliques. The relatively closed sub-cliques within a clique are detrimental to the overall innovation performance of the clique.

When choosing to participate in a clique, China's biomedical firms should take the clique's innovation ability into account and consider the technical similarity between themselves and their clique partners to achieve a harmonious relationship with the clique members. It is not advisable to simply pursue participating in a clique with strong innovation capability. The lack of consideration of technology similarity will often lead to rejection due to TDF, thus failing to solve their innovation problems effectively and even resulting in a decline in the innovation performance of the clique.

It is necessary to further explore the similarity problems at the technical level of firms and carefully select appropriate clique partners for biomedical cliques, only through which the TDF can be controlled. Based on the results of the study, we found no moderating effect of GP on the inverted U-shaped relationship between TDF and CIP. We believe this is because the strong development of communication industry and transportation industry has weakened the role of geographical factors. If we choose to use data from 20 years ago for our study, we believe that the role of GP will be significant. If the intensity of the TDF within a formed clique is too high, the network position of the clique should be considered, and some effective strategies can be adopted. For example, the cooperation and communication within the clique should be guided to weaken the inter-group bias and the inhibitory effect of the TDF on the CIP. Furthermore, cliques can absorb firms in a relatively core position in the network. With the help of these core firms, the network distance between clique members and other members in the network can be shortened, and the core position of clique members in the network can be improved. Such a practice will compensate for the high-intensity TDF within the clique and decrease its inhibitory effect on the CIP.

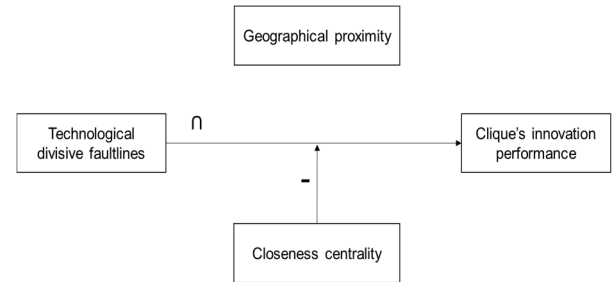


FIGURE 6. Results of research hypotheses test.

B. CONCLUSIONS

Based on China's Biomedical Industry Alliance data from 2010 to 2017, this paper explored the relationship between the TDF and the CIP. Further, it analyzed the moderating effect of GP and CC on the relationship. Our findings lead us to conclude that there is an inverted U-shaped relationship between the TDF and CIP. On this basis, the GP has no moderating effect on the inverted U-shaped relationship, while CC has a negative moderating effect on the inverted U-shaped relationship (FIGURE 6).

C. CONTRIBUTIONS

Based on the above conclusions, this paper also makes some contributions. Firstly, this paper sheds new light on the research framework of fault theory in the inter-organizational field. Existing studies on divisive faultlines mainly focus on subgroups in technology innovation networks constructed with patent co-applicants [18], [21]. As Cheng *et al.* proved that there is a positive correlation between split fault lines and the depth of knowledge search in technology innovation networks. Similarly, Yu *et al.* used a questionnaire to construct a technological innovation network, and their study found that faultlines partially mediated the relationship between psychological distance and intra-subgroup reciprocity. However, only a few works have been devoted to the relationship between divisive faultlines and innovation performance in the firm alliance innovation network. Our study examines the nonlinear relationship between TDF and CIP, filling a gap in the literature on innovation network fault theory, and providing new insights into the development of cliques in the biomedical industry.

Secondly, this study makes a major contribution to the research framework of cliques in innovation networks. Some studies focus on the individual innovation of clique members from the individual perspective [26], [58]. For example, Zhao *et al.* investigated the relationship between knowledge and firm innovation within factions, and it was found that there was an inverted U-shaped relationship between knowledge diversity and firm innovation in their study. However, the research on integral clique innovation has been a largely underexplored domain. In this context, our study provides a theoretical reference for the effective development of cliques by probing into the CIP.

Finally, geographical distance (GP) and network distance (CC) are taken as moderating variables in this study, and the mechanism of TDF within cliques on their innovation performance under the moderating effects of two kinds of distance are deeply revealed. It is beneficial to provide theoretical guidance for cliques' governance and further expand the study of fault theory on the innovation network.

According to Figure 4, the relationship between TDF and CIP showed an inverted U-shaped curve under low CC, while the relationship between TDF and CIP showed a U-shaped curve under high CC. This proves again that H3: CC negatively moderates the inverted U-shaped relationship between the intensity of TDF and CIP. Negative moderation is not a negative effect; the fact that a moderating variable displays a negative moderating effect does not mean that it is harmful to the dependent variable. In addition, an interesting finding of this paper is that the innovation performance of cliques under high CC is generally higher than that under low CC (FIGURE 4), which provides a new perspective for the study on the innovation network. At present, scholars in related fields have generally agreed that when an individual firm occupies an appropriate center position in the network, it is conducive to improving its innovation performance. But excessive closing to the center of the network is detrimental to its innovation performance (mainly due to information overload, relationship redundancy, excessive homogeneity, etc.) [43], [44], [58]. Broekel and Boschma suggested that a firm's excessive embedding in innovation networks may harm its innovation performance. Jiao *et al.* found an inverted U-shaped relationship between the number of a firm's alliance partners and its innovation performance. However, from the results, one can conclude that the feature of over-embedding will be weakened once the firm participates in a clique, and striving for occupying a more central position will help improve the innovation performance of the clique. Therefore, firms that join a clique can abandon the concerns of over-embedding to a considerable extent, and the cliques can actively carry out alliance activities to improve their network center position, which can promote the optimization of CIP. That is, forming cliques could break relational redundancy.

D. LIMITATIONS

There are some limitations in this paper. Firstly, the conclusion of this paper is based on the data from China's biomedical industry. Whether it can be applied to other industries such as the new energy industry, semiconductor industry, and communication equipment industry needs further exploration. Secondly, given that the paper is conceived in 2021, and the control variable PA is measured by the number of patents authorized within the five years before the formation of the cliques and the dependent variable CIP is measured by the number of patents applied in the third year after the formation of the clique. In order to ensure the integrity of data acquisition, the alliance data is selected from 2010 to 2017,

and the data from 2017 onwards will be followed up in the future. Finally, this paper is based on the TDF, and the positional divisive faultlines, organizational divisive faultlines and institutional divisive faultlines caused by other factors, such as the position, organization, and institution, need to be further explored, which can become the future research directions.

In addition, through literature review, we find that most existing studies focus on individual innovation performance and seldom consider the upstream and downstream relationship between alliance members. However, the cost of innovation is so high for individuals that they have to rely on alliances. The innovation performance of an alliance is a vital guarantee for the existence of the alliance and the sustainable innovation of enterprises. Therefore, we call on scholars to pay more attention to the overall innovation performance and the upstream and downstream matching of members within the alliance.

REFERENCES

- [1] S. Wu, "Progress and concept for COVID-19 vaccine development," *Biotechnol. J.*, vol. 15, no. 6, Jun. 2020, Art. no. 2000147.
- [2] T. M. Belete, "A review on promising vaccine development progress for COVID-19 disease," *Vacunas*, vol. 21, no. 2, pp. 121–128, Jul. 2020.
- [3] Q. Jiang and C. Luan, "Diffusion, convergence and influence of pharmaceutical innovations: A comparative study of Chinese and U.S. patents," *Globalization Health*, vol. 14, no. 1, pp. 1–9, Dec. 2018.
- [4] B. Liu, M. Lai, J.-L. Wu, C. Fu, and A. Binaykia, "Patent analysis and classification prediction of biomedicine industry: SOM-KPCA-SVM model," *Multimedia Tools Appl.*, vol. 79, nos. 15–16, pp. 10177–10197, Apr. 2020.
- [5] S. Elia, M. Kafourous, and P. J. Buckley, "The role of internationalization in enhancing the innovation performance of Chinese EMNEs: A geographic relational approach," *J. Int. Manag.*, vol. 26, no. 4, Dec. 2020, Art. no. 100801.
- [6] C. Zhou, J. Hong, Y. Wu, and D. Marinova, "Outward foreign direct investment and domestic innovation performance: Evidence from China," *Technol. Anal. Strategic Manag.*, vol. 31, no. 1, pp. 81–95, Jan. 2019.
- [7] J. Huang, H. Wang, J. Wu, Z. Yang, X. Hu, and M. Bao, "Exploring the key driving forces of the sustainable intergenerational evolution of the industrial alliance innovation ecosystem: Evidence from a case study of China's TDIA," *Sustainability*, vol. 12, no. 4, p. 1320, Feb. 2020.
- [8] G. Palla, I. Derényi, I. Farkas, and T. Vicsek, "Uncovering the overlapping community structure of complex networks in nature and society," *Nature*, vol. 435, no. 7043, pp. 814–818, Jun. 2005.
- [9] B. S. Lawrence and M. J. Zyphur, "Identifying organizational faultlines with latent class cluster analysis," *Org. Res. Methods*, vol. 14, no. 1, pp. 32–57, Jan. 2011.
- [10] J. N. Choi and T. Sy, "Group-level organizational citizenship behavior: Effects of demographic faultlines and conflict in small work groups," *J. Org. Behav.*, vol. 31, no. 7, pp. 1032–1054, 2010.
- [11] J. E. Perry-Smith and C. E. Shalley, "A social composition view of team creativity: The role of member nationality-heterogeneous ties outside of the team," *Org. Sci.*, vol. 25, no. 5, pp. 1434–1452, Oct. 2014.
- [12] D. C. Lau and J. K. Murnighan, "Demographic diversity and faultlines: The compositional dynamics of organizational groups," *Acad. Manag. Rev.*, vol. 23, no. 2, pp. 325–340, Apr. 1998.
- [13] S. M. Azin, "Evolution of the physician civil liability: An extreme return to the fault theory," *Contracts New Technol. Law*, vol. 1, no. 2, pp. 57–80, Feb. 2021.
- [14] Y. Lin, Y. Li, X. Yin, and Z. Dou, "Multisensor fault diagnosis modeling based on the evidence theory," *IEEE Trans. Rel.*, vol. 67, no. 2, pp. 513–521, Jun. 2018.
- [15] Y. Chung, Y. Jiang, J. R. Blasi, and D. L. Kruse, "Effects of leader networking behaviors and vertical faultlines on support for innovation," *Small Group Res.*, vol. 51, no. 5, pp. 616–650, Oct. 2020.

- [16] S. M. B. Thatcher and P. C. Patel, "Group faultlines: A review, integration, and guide to future research," *J. Manag.*, vol. 38, no. 4, pp. 969–1009, Jul. 2012.
- [17] R. A. Heidl, H. K. Steensma, and C. Phelps, "Divisive faultlines and the unplanned dissolutions of multipartner alliances," *Org. Sci.*, vol. 25, no. 5, pp. 1351–1371, Oct. 2014.
- [18] L. Cheng, M. Wang, X. Lou, Z. Chen, and Y. Yang, "Divisive faultlines and knowledge search in technological innovation network: An empirical study of global biopharmaceutical firms," *Int. J. Environ. Res. Public Health*, vol. 18, no. 11, p. 5614, May 2021.
- [19] L. Cheng, S. Zhang, X. Lou, J. Huang, F. Rao, and R. Bai, "How does tie strength dispersion within inter-organizational networks affect agricultural technological innovation? Evidence from China," *Land*, vol. 10, no. 7, p. 717, Jul. 2021.
- [20] L. Zhang and I. Guler, "How to join the club: Patterns of embeddedness and the addition of new members to interorganizational collaborations," *Administ. Sci. Quart.*, vol. 65, no. 1, pp. 112–150, Mar. 2020.
- [21] D. Yu, K. Deng, X. Gao, and Y. Liu, "Psychological distance impacts subgroup reciprocity in technological innovation networks: The mediating role of divisive faultlines," *Frontiers Psychol.*, vol. 13, Mar. 2022, Art. no. 857088.
- [22] A. Clauset, M. E. Newman, and C. Moore, "Finding community structure in very large networks," *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top.*, vol. 70, no. 6, 2004, Art. no. 066111.
- [23] H. A. Ndofor, D. G. Sirmon, and X. He, "Utilizing the firm's resources: How TMT heterogeneity and resulting faultlines affect TMT tasks," *Strategic Manag. J.*, vol. 36, no. 11, pp. 1656–1674, Nov. 2015.
- [24] K. M. Fargen, T. A. Wilson, R. de Leacy, A. P. Jadhav, and A. F. Ducruet, "Social media and JNIS: Expanding the digital clique," *J. Neuro Interventional Surgery*, vol. 9, no. 10, pp. 913–914, Oct. 2017.
- [25] E. Gregori, L. Lenzini, and S. Mainardi, "Parallel K-clique community detection on large-scale networks," *IEEE Trans. Parallel Distrib. Syst.*, vol. 24, no. 8, pp. 1651–1660, Aug. 2013.
- [26] Y. Zhao, X. Han, X. Yang, and Z. Li, "Interorganizational knowledge networks, R&D alliance networks, and innovation capability: A multilevel network perspective," *Complexity*, vol. 2021, pp. 1–22, Jun. 2021.
- [27] R. Zhang, Z. Wang, Y. Tang, and Y. Zhang, "Collaborative innovation for sustainable construction: The case of an industrial construction project network," *IEEE Access*, vol. 8, pp. 41403–41417, 2020.
- [28] L. Li, J. Xie, R. Wang, J. Su, and S. Sindakis, "The partner selection modes for knowledge-based innovation networks: A multiagent simulation," *IEEE Access*, vol. 7, pp. 140969–140979, 2019.
- [29] S. B. Letaifa and Y. Rabeau, "Too close to collaborate? How geographic proximity could impede entrepreneurship and innovation," *J. Bus. Res.*, vol. 66, no. 10, pp. 2071–2078, 2013.
- [30] T. Buchmann and A. Pyka, "The evolution of innovation networks: The case of a publicly funded German automotive network," *Econ. Innov. New Technol.*, vol. 24, nos. 1–2, pp. 114–139, Feb. 2015.
- [31] J. J. Reuer and N. Lahiri, "Searching for alliance partners: Effects of geographic distance on the formation of R&D collaborations," *Org. Sci.*, vol. 25, no. 1, pp. 283–298, Feb. 2014.
- [32] T. Wang, "Top managerial overseas social capital, firm network position and innovation: The mediating effect of prestige and power from firm network position," *J. Service Sci. Manag.*, vol. 14, no. 3, pp. 305–324, 2021.
- [33] J. Glückler, "Knowledge, networks and space: Connectivity and the problem of non-interactive learning," *Regional Stud.*, vol. 47, no. 6, pp. 880–894, Jun. 2013, doi: 10.1080/00343404.2013.779659.
- [34] H. Cao, L. Yang, and H. Zhu, "Novel node-ranking approach and multiple topology attributes-based embedding algorithm for single-domain virtual network embedding," *IEEE Internet Things J.*, vol. 5, no. 1, pp. 108–120, Feb. 2018.
- [35] C. Kapetanidou and S. H. Lee, "Geographical proximity and open innovation of SMEs in Cyprus," *Small Bus. Econ.*, vol. 52, no. 1, pp. 261–276, Jan. 2019.
- [36] M. J. Janssen and M. Abbasiharofteh, "Boundary spanning R&D collaboration: Key enabling technologies and missions as alleviators of proximity effects?" *Technol. Forecasting Social Change*, vol. 180, Jul. 2022, Art. no. 121689.
- [37] C. Forman and N. van Zeebroeck, "Digital technology adoption and knowledge flows within firms: Can the internet overcome geographic and technological distance?" *Res. Policy*, vol. 48, no. 8, Oct. 2019, Art. no. 103697.
- [38] P. Galaso and J. Kovářík, "Collaboration networks, geography and innovation: Local and national embeddedness," *Papers Regional Sci.*, vol. 100, no. 2, pp. 349–377, Apr. 2021.
- [39] M. Guo, N. Yang, J. Wang, and Y. Zhang, "Multi-dimensional proximity and network stability: The moderating role of network cohesion," *Scientometrics*, vol. 126, no. 4, pp. 3471–3499, Apr. 2021.
- [40] N. K. Steffens, K. A. Munt, D. van Knippenberg, M. J. Platow, and S. A. Haslam, "Advancing the social identity theory of leadership: A meta-analytic review of leader group prototypicality," *Org. Psychol. Rev.*, vol. 11, no. 1, pp. 35–72, Feb. 2021.
- [41] B. Wei and Y. Deng, "A cluster-growing dimension of complex networks: From the view of node closeness centrality," *Phys. A, Stat. Mech. Appl.*, vol. 522, pp. 80–87, May 2019.
- [42] D.-Y. Kim, "Closeness centrality: A social network perspective," *J. Int. Interdiscipl. Bus. Res.*, vol. 6, no. 1, pp. 115–122, 2019.
- [43] J. Jiao, Y. Xu, J. Li, and R. Yang, "The evolution of a collaboration network and its impact on innovation performance under the background of government-funded support: An empirical study in the Chinese wind power sector," *Environ. Sci. Pollut. Res.*, vol. 28, no. 1, pp. 915–935, Jan. 2021.
- [44] T. Broekel and R. Boschma, "Knowledge networks in the Dutch aviation industry: The proximity paradox," *J. Econ. Geography*, vol. 12, no. 2, pp. 409–433, Mar. 2012.
- [45] *China Statistical Yearbook on High Technology Industry*, Nat. Bur. Statistic China [NBSC], Beijing, China, 2020.
- [46] K. Riopelle and X. Wang, "Building a shared present and future: Learnings from Henry Ford and Albert Kahn's co-Wuity collaborative innovation network on the moving assembly line and mass production," in *Collaborative Innovation Networks* (Studies on Entrepreneurship, Structural Change and Industrial Dynamics). Cham, Switzerland: Springer, 2019, pp. 3–41.
- [47] M. Dziallas and K. Blind, "Innovation indicators throughout the innovation process: An extensive literature analysis," *Technovation*, vol. 80, pp. 3–29, Feb. 2019, doi: 10.1016/j.technovation.2018.05.005.
- [48] T. Teng, Y. Zhang, Y. Si, J. Chen, and X. Cao, "Government support and firm innovation performance in Chinese science and technology parks: The perspective of firm and sub-park heterogeneity," *Growth Change*, vol. 51, no. 2, pp. 749–770, Jun. 2020.
- [49] C. Wang, T. Chin, and J.-H. Lin, "Openness and firm innovation performance: The moderating effect of ambidextrous knowledge search strategy," *J. Knowl. Manag.*, vol. 24, no. 2, pp. 301–323, Jan. 2020.
- [50] S. Sinha and D. Vohora, "Drug discovery and development: An overview," *Pharmaceutical Med. Transl. Clin. Res.*, pp. 19–32, Jan. 2018.
- [51] L. Cheng, Y. Liu, X. Lou, Z. Chen, and Y. Yang, "Does technology conglomeration promote innovative outcomes of new energy vehicle enterprises? The moderating effect of divisive faultlines," *J. Cleaner Prod.*, vol. 324, Nov. 2021, Art. no. 129232.
- [52] X. Dang and H. Chang, (2013). *Network Position, Geographical Proximity, and Innovation Performance: An Interactive Effect Model*. Science Research Management. Accessed: May 9, 2022. [Online]. Available: http://en.cnki.com.cn/Article_en/CJFDTOTAL-KYGL201303001.htm
- [53] Y. Lyu, B. He, Y. Zhu, and L. Li, "Network embeddedness and inbound open innovation practice: The moderating role of technology cluster," *Technol. Forecasting Social Change*, vol. 144, pp. 12–24, Jul. 2019.
- [54] T. Iwasako and K. Futagami, "Patent protection, capital accumulation, and economic growth," *Econ. Theory*, vol. 52, no. 2, pp. 631–668, Mar. 2013.
- [55] C. J. Sroka and H. N. Nagaraja, "Odds ratios from logistic, geometric, Poisson, and negative binomial regression models," *BMC Med. Res. Methodol.*, vol. 18, no. 1, pp. 1–11, Dec. 2018.
- [56] R. F. J. Haans, C. Pieters, and Z.-L. He, "Thinking about U: Theorizing and testing U- and inverted U-shaped relationships in strategy research," *Strategic Manag. J.*, vol. 37, no. 7, pp. 1177–1195, Jul. 2016.
- [57] M. Gómez-Solórzano, M. Tortoriello, and G. Soda, "Instrumental and affective ties within the laboratory: The impact of informal cliques on innovative productivity," *Strategic Manag. J.*, vol. 40, no. 10, pp. 1593–1609, Oct. 2019.
- [58] M. Gebreyesus and P. Mohnen, "Innovation performance and embeddedness in networks: Evidence from the Ethiopian footwear cluster," *World Develop.*, vol. 41, pp. 302–316, Jan. 2013.



YAN ZHAO received the B.S. degree in biology from the School of Life Science and the Ph.D. degree in management science and engineering from the School of Business, University of Science and Technology of China, Anhui, China, in 1999 and 2004, respectively.

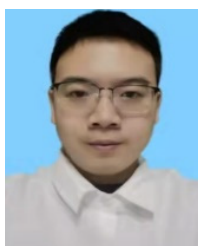
From 2004 to 2008, he was a Lecturer and an Associate Professor at the Sydney Institute of Language and Commerce (SILC), Shanghai University, Shanghai, China, where he has been an

Associate Professor and a Professor with the School of Management, since 2008. His research interests include frontier research on innovation strategies, knowledge-intensive service industries, industrial clusters and technology parks, innovation alliances and inter-enterprise networks, and venture capital. His awards and honors include the Outstanding Achievement Award from the Chinese Society of Technological Economics, the Outstanding Youth Award from the Chinese Association for Science of Science and S&T Policy, the Outstanding Theoretical Prize, and the Best Paper Prize.



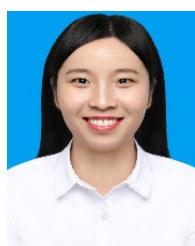
LUYING LI is currently pursuing the doctoral degree with the School of Management, Shanghai University, Shanghai, China.

Her current research interests include innovation systems, innovation networks, and knowledge management.



ZHENG LI is currently pursuing the doctoral degree with the School of Management, Shanghai University, Shanghai, China.

His research interests include innovation systems, innovation networks, and knowledge management.



NIANNIAN QI is currently pursuing the doctoral degree with the School of Management, Shanghai University, Shanghai, China.

Her current research interests include innovation networks and firm alliances.

...