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How virtual clusters affect innovation performance: Evidence from global hydropower industry

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ABSTRACT

With the fast development of information communication technologies, firms break through geographic restrictions and form into virtual clusters for innovation. Existing studies mostly explore the innovation ecosystem by applying either a macro-level perspective or a micro-level perspective, which cannot answer how firms establish connections in their virtual clusters to promote innovation. Therefore, using large-scale patent data and topological clustering algorithms, this study explores the impacts of firms' characteristics within the virtual cluster on their innovation in the global hydropower industry from 1987 to 2019. The findings suggest that firms have better innovation performance with higher degree centrality and more structural holes within the virtual cluster. Moreover, small firms benefit more from degree centrality within the virtual cluster than big firms. This paper makes up for the lack of recent research on virtual clusters and provides implications for managers and policymakers.

1. Introduction

Innovation is a collective activity. With the increasing complexity of technological innovation, diversified organizations need to be embedded in the innovation ecosystem for collaborative innovation (Bogers et al., 2019; Jacobides et al., 2018). Moreover, the fast development of information communication technologies also promotes organizations to break through geographical boundaries to form virtual clusters in the innovation ecosystem.

But only a few studies pay attention to virtual clusters. Prior research has generally applied two complementary perspectives to explore the impacts of innovation ecosystem on innovation performance. The macro-level studies explore how the network structure formed by all members of the ecosystem affects the members' innovation performance (Panetti et al., 2019; Schilling and Phelps, 2007). The micro-level studies believe that the network connections among firms and their partners will affect innovation performance (Ahuja, 2000; Zaheer et al., 2010; Zhou et al., 2020b). But the two above perspectives risk providing a complete picture of the innovation ecosystem. Although some studies have been discussed at the meso level, most of them focus on industry clusters identified according to geographical proximity (Bell, 2005; Lee, 2018). Research on virtual clusters breaking through geographical restrictions needs to be strengthened.

Further, the effects of virtual clusters on innovation have not been fully discussed. Most of the studies discuss the concept or causes of virtual clusters using qualitative methods (Chen et al., 2021; Passiante and Secundo, 2002). Only a few scholars explore how virtual clusters' characteristics affect firms' innovation performance, such as cluster size (Ruiqian et al., 2021). But different firms in the virtual cluster may have different network relationships, which has heterogeneous impacts on firms' behaviors and performance. So, the influence mechanism of virtual clusters on innovation performance needs to be further explored by quantitative methods.

This study takes the hydropower industry as an example to analyze virtual clusters further. There are two main reasons. On the one hand, the hydropower industry has been developed rapidly over the past two decades for providing essential power and climate mitigation services (Sun et al., 2021). This can help us explore the evolution of virtual clusters and their impacts on innovation performance better. On the other hand, the hydropower industry is characterized by sophisticated operations and intensive service (Zhou et al., 2020a). Contractors, suppliers, and service providers along the value chain from all over the world collaborate closely for innovation (Gabrielsson et al., 2018). For example, China Sinohydro Corporation cooperates with European

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consultants, global manufacturers (like Alstom), and operators from Ghana for the building of the Bui Dam in Ghana (Han and Webber, 2020). China Gezhouba Group also has established close relations with General Electric Company, Prysmian Group (Italy), Korea Water Resources Corporation, and Nur-MOHHeliothermal (Greece). It can be found that firms around the world begin to break through the geographical boundaries for collaboration. Closely-related firms form into virtual clusters for innovation gradually.

To explore the relationship between firms' characteristics within the virtual cluster and innovation performance, this study tracks the hydropower industry over the period from 1987 to 2019. Based on the large-scale collaboration network of co-patenting relationships among 7429 organizations, we employ topological clustering algorithms to identify virtual clusters in the innovation ecosystem. Then, we analyze the 121 focal firms by negative binomial regression to test the hypotheses. The findings suggest that firms have better innovation performance with higher degree centrality and more structural holes within the virtual cluster. Moreover, small firms benefit more from degree centrality within the virtual cluster than big firms.

This paper has three main contributions. First of all, this paper makes up for the lack of existing research on virtual clusters. By emphasizing the role of virtual clusters in promoting innovation, this study enriches the innovation ecosystem from the meso-level. Second, this research contributes to opening the black box of the impact mechanism of virtual clusters by investigating how innovation is affected by degree centrality and structural holes within the virtual cluster empirically. This paper also explains whether this relationship is contingent on firm size. Third, this study also provides an effective quantitative method to explore virtual clusters in the ecosystem. Based on large-scale patent data, this study utilizes topological clustering algorithms to identify virtual clusters, which provides a valuable method for revealing the mechanism of virtual clusters. Our findings guide both managers and policymakers on how to improve innovation performance through virtual clusters.

This paper is organized as follows. The following section illustrates the theoretical background of this study. Then, we developed a conceptual model and several hypotheses about the mechanism of virtual clusters in Section 3. Section 4 describes the data and methods used for the empirical study. The successive section presents the main results and robustness checks. Section 6 describes the discussion and conclusions, including some limitations.

2. Theoretical background

2.1. Virtual clusters in the innovation ecosystem

Existing research relates to the impacts of the ecosystem on innovation performance mostly explores global network at the macro-level or ego network at the micro-level. On the one hand, the macro-level perspectives explore how the inter-organizational network structure formed by members of the innovation ecosystem affects innovation performance, such as network diversity (Reagans and Zuckerman, 2001), network density (Reagans and Mcevily, 2003), and small-world structure (Brian Uzzi and Jarrett Spiro, 2005). On the other hand, the micro-level perspectives focus on the ego network. They emphasize the relationships or structures among firms and their partners will affect innovation performance (Zaheer and Bell, 2005), such as the number of direct or indirect ties (Ahuja, 2000), ties' strength or stability (Baum et al., 2012; Kumar and Zaheer, 2019), and firms' positions (Zaheer and Bell, 2005; Zhou et al., 2021). However, neither of these two perspectives risks providing a complete picture of the innovation ecosystem. As the sub-environment in the innovation ecosystem, virtual clusters at the meso-level should also be studied.

Some scholars have explored from the meso-level, such as the industry cluster. Industry clusters are groups of geographically proximate firms in the same industry (Bell, 2005; Pouder and St. John, 1996). Like Silicon Valley, regions gathered with firms catalyze innovation by increasing interaction among members, facilitating information flow, and allowing firms to imitate (Fleming et al., 2007; Funk, 2014; Lee, 2018).

But virtual clusters identified by actual cooperative relationships-not geographical proximity-are also meaningful for the hydropower industry. Virtual clusters can be defined as a group of closely-related organizations across geographic boundaries, aiming at innovation. The complex and sophisticated large-scale projects related to innovation in the hydropower industry require the participation of consultants, suppliers, and operators from all over the world (Han and Webber, 2020). These members are not geographically closed. Furthermore, these actual relationships are most likely to reflect the flow of knowledge, information, and resources among members (Sytch and Tatarynowicz, 2014; Sytch et al., 2012), which has impacts on innovation performance.

The discussions on virtual clusters are still inadequate. Most of the studies discuss the concept and causes of virtual clusters using qualitative methods. Virtual clusters are defined as a community in which suppliers, distributors, service providers, and customers can cooperate or compete based on technological business networks (Passiante and Secundo, 2002). Some scholars also construct a driving-force model for virtual agglomeration in the creative industry (Chen et al., 2021). Regarding the research on the impact of virtual clusters on firms' performance, some scholars use network analysis to explore the influence mechanism of virtual clusters' characteristics, such as cluster size and cluster connectivity (Ruiqian et al., 2021). But existing studies ignore the heterogenous of firms' network relationships within virtual clusters, which may have different impacts on firms' behaviors and performance. Therefore, it is necessary to explore the impacts of firms' network relationships within the virtual cluster on innovation performance.

2.2. Virtual clusters and innovation performance

Virtual clusters will have impacts on the firms' innovation performance from two aspects. On the one hand, the closer connections and shorter distances among members within the virtual cluster make it easier for firms to communicate with each other and access the resources of their cluster (Sytch and Tatarynowicz, 2014). Meanwhile, the cost of obtaining resources of other virtual clusters is higher because of the sparse structure and long distance (Gulati et al., 2012; Sytch and Tatarynowicz, 2014). As a consequence, knowledge other critical resources, which are considered to be the original material of innovation, are likely to be more homophily within the virtual cluster. On the other hand, exchanging innovation materials is more effective within virtual clusters because the higher degree of interconnectedness better enables members to collectively monitor and sanction deviant behavior (Rowley et al., 2005; Walker et al., 1997). The intensive interactions also lead firms within the virtual cluster to share a sense of identity and positive mutual sentiments, such as trust and reciprocity (Clement et al., 2018). In this case, it is reasonable to expect that firms' innovation performance will be affected by firms' characteristics within the virtual cluster in the innovation ecosystem.

At the same time, the relationship between virtual clusters and innovation performance may also be moderated by the feature of firms. As for the hydropower industry, firms range in size from less than 1 MW–22,500 MW, which varies greatly (IHA, 2021). And also, firms of different sizes have different innovation capabilities (Rogers, 2004). In this case, we explore the moderating effects of firm size on the relationship between within-cluster characteristics and innovation performance.

3. Conceptual model and hypothesis

Based on the literature of innovation ecosystem and virtual clusters, we develop a conceptual framework (see Fig. 1) and hypotheses to explore the effects of firms' characteristics within the virtual cluster on innovation performance. As the existing studies explained, network

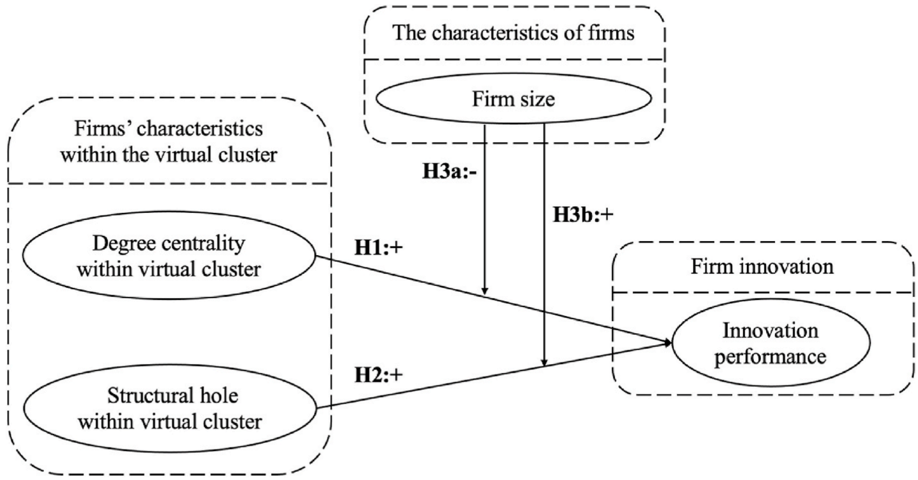

Fig. 1. Conceptual model.

relationships provide potential opportunities for innovation improvement (Adler and Kwon, 2002; Soda et al., 2019). And whether these opportunities can be realized or not also depends on the characteristics of individual firms (Shipilov, 2006) and other moderators. As an organizational factor, firm size is an important moderator in the field of innovation and management research (Ahuja et al., 2008; Cohen and Levin, 1989; Lee and Kim, 2016). Firm size can reflect the financial and technical resources owned by organizations, which may have effects on the relationship between firms' network and innovation performance (Rogers, 2004). In this case, we explore the mechanisms underpinning returns to relationships within the virtual cluster by considering the role of firm size.

3.1. The effects of virtual cluster

Firms' innovation performance benefits more from numerous connections within a virtual cluster. First, firms with more connections have significant advantages in resource acquisition, which can enhance their knowledge base and thereby promote innovation performance (Ahuja, 2000). In this case, firms with plenty of within-cluster connections can easily exchange abundant information, knowledge, and other critical resources with other members of the same virtual cluster, which is critical to innovation. Besides, the interpretation of information and knowledge is eased for more details are provided by the increased within-cluster degree centrality (Zhou et al., 2020b), which is positive for innovation. Second, a firm with higher within-cluster degree centrality has a more extraordinary ability to rely on reputation effects to attract deep cooperation, which brings high-quality resources critical to innovation (Rowley et al., 2005). Additionally, such firms can also rely on their reputation to gather cluster members together, which can help them solve the negotiation issues more efficiently and accrue innovation resources they cannot gain individually (Carton and Cummings, 2012).

Accordingly, hypothesis 1 is proposed: the degree centrality within the virtual cluster has positive impacts on firms' innovation in the network.

Firms' innovation performance benefits more from numerous structural holes within a virtual cluster. On the one hand, firms occupying structural holes enjoy information benefits (Burt, 1992). By connecting disconnected alter firms in the same virtual cluster, the broker firms can receive a great variety of non-redundant knowledge as the original material of innovation (Yang et al., 2010). A similar knowledge background also makes resources absorbed and integrated into innovation more efficiently (Balachandran and Hernandez, 2018). In addition, by comparing and contrasting the veracity of knowledge provided by different alter firms, broker firms can distinguish redundant information and improve the quality of key resources (Clement et al., 2018), which is helpful to improve innovation performance. On the other hand, firms located in the structural hole achieve control benefits because they obtain necessary information access channels (Vasudeva et al., 2013). The broker firm also plays an intermediary role in the exchange of resources and shared knowledge between the alter firms. In this case, broker firms can control the way and speed of information transformation, which is conducive to innovation performance (Soda et al., 2018).

Accordingly, hypothesis 2 is proposed: structural holes within the virtual cluster have positive impacts on firms' innovation in the network.

3.2. The moderating effects of firm size

Firm size plays a negative role in the impact of degree centrality within the virtual cluster on innovation performance. The advantages generated by within-cluster degree centrality are mainly due to obtaining abundant knowledge from similar fields — this is the raw material of innovation. Large firms are likely to have enough available resources already (Rogers, 2004). Thus, establishing connections within the virtual cluster will become less critical as a means for large firms to gain resources to promote their innovation performance. At the same time, the costs of maintaining many inter-organizational relationships are high and may even exceed their information benefits (Fleming and Waguespack, 2007; Sytch et al., 2012). In this case, positive impacts of degree centrality within the virtual cluster on innovation performance diminish. Besides, the knowledge obtained by degree centrality within virtual cluster needs additional novelty to be integrated into innovation (Zhou et al., 2020b). Compared with large firms, small firms are more likely to recombine knowledge in creative ways (Nieto and Santamaría, 2010; Tether, 1998), which expands the positive effects of degree centrality within the virtual cluster on innovation performance.

Accordingly, hypothesis 3a is proposed: the relationship between degree centrality within the virtual cluster and firms' innovation performance is negatively moderated by firm size.

Firm size amplifies the impacts of structural holes within the virtual cluster on innovation performance. One of the advantages generated by structural holes within the virtual cluster is to bring non-redundant resources from disconnected partners (Burt, 2009), which requires additional integration costs to be translated into innovation. Big firms can benefit more because they have abundant financial resources and more specialized researchers to invest in R&D activities, while small firms face several constraints in carrying out their innovation activities (Feller et al., 2002; Fontana et al., 2006). Both of the differences lead to higher efficiency in the transformation of diverse resources into innovation for big firms. Another advantage of structural holes within the virtual cluster is control power (Burt, 1992). Firms with more structural holes are more innovative when trust develops between firms and alters (Kwon et al., 2020). In this case, larger firms combined with a reputation among the specialized field can be more productive in innovation than small firms when occupying structural hole positions.

Accordingly, hypothesis 3b is proposed: The relationship between structural hole within virtual cluster and firms' innovation performance is positively moderated by firm size.

4. Data and methods

4.1. Data

We conducted an empirical study in the global hydropower industry from 1987 to 2019 to test the hypotheses. Fig. 2 shows the dynamic evolution of hydropower patents granted every five years. As indicated by this figure, the number of patents was stable in the 1990s. But a considerable growth was observed during the 2000s and 2010s (see Fig. 3).

We retrieved worldwide patent data from the Derwent World Patents Index (DWPI) through the Derwent Innovation (DI) search engine. Derwent Innovation Index database is a complete patent database worldwide, covering patent information issued by more than 40 authorities, including USPTO, EPO, and so on. Therefore, hydropower patents obtained from this database can reflect the global development trend of the industry.

To accurately identify and capture hydropower patents from the DI database, we followed the searching strategy utilized by Jiang (Jiang et al., 2016). And then, we performed the extracting processes in August 2020. After data cleaning, we got 19,917 pieces of patent data related to the hydropower industry from 1987 to 2019, which were used to construct the inter-organizational network in the innovation ecosystem.

Besides, to avoid the limitations of patent data, we also retrieved financial data from the Osiris database. By matching the names of the top 800 firms in the patent number in the OSIRIS database, we finally got 121 key firms as sample firms for further regression analysis. And 3388 pieces of 121 firms' basic longitudinal information were also obtained, including the number of employees, return on assets, expenses on research and development, sales, etc.

4.2. Network construction

Network construction is based on the inter-organizational co-patenting relationship from patent data. Since the year of patent publication does not accurately indicate that the collaborative relationships between firms only exist in this year, they can still exist for several years before and after the application of patents. Following prior literature (Guan and Liu, 2016; Sytch and Tatarynowicz, 2014), we constructed inter-organizational networks of 7429 organizations based on the inter-organizational co-patenting relationship with a 5-year window. For the collaboration network in year t, it includes the inter-organizational co-patenting relationships that occurred in year *t-4* to year *t*. Using 1991 as the first year, we constructed 28 yearly observations of the evolving collaboration network until 2018. Although using patent data to construct the network has certain limitations, a large body of research has demonstrated the validity to measure innovative activities in a single industry (Belenzon and Patacconi, 2013; Guan et al., 2015; Wang and Lu, 2021). It is rational to explore the mechanism of virtual clusters using patent data.

4.3. Virtual cluster detection

We use topological clustering algorithms to detect virtual clusters. Following prior literature (Sytch and Tatarynowicz, 2014; Wang and Lu, 2021; Xu et al., 2020), the method proposed by Louvain (Blondel et al., 2008) is one of the most robust methods of cluster or community identification. Unlike traditional clustering based on similarities in firms' attribute data, this method can divide a large network into multiple clusters according to the aggregation degree of nodes in the network (Newman, 2004; Sytch and Tatarynowicz, 2014). Since it is difficult for networks in reality to provide prior information, this method is more effective in identifying communities in the innovation networks. The optimization strategy of the Louvain clustering algorithm is to maximize the modularity Q of the divided network. The larger the Q, the better the division effect. Its definition is as follows (Clauset et al., 2004):

$$Q = \frac{1}{2m}\sum_{ij}\left(A_{ij} - \frac{k_i k_j}{2m}\right)^2 \delta(c_i, c_j) \tag{1}$$

M represents the sum of the weights of all connections in the network. A_{ij} represents the weight of the connection between node *i* and node *j*. $A_{ij} = 0$ if there is no connection between the two nodes.

4.4. Variables and measures

4.4.1. Dependent variables

Innovation Performance (IP) : We captured the *innovation performance* of firms using the counts of their patent applications. Patent applications provide an externally validated measure of innovation

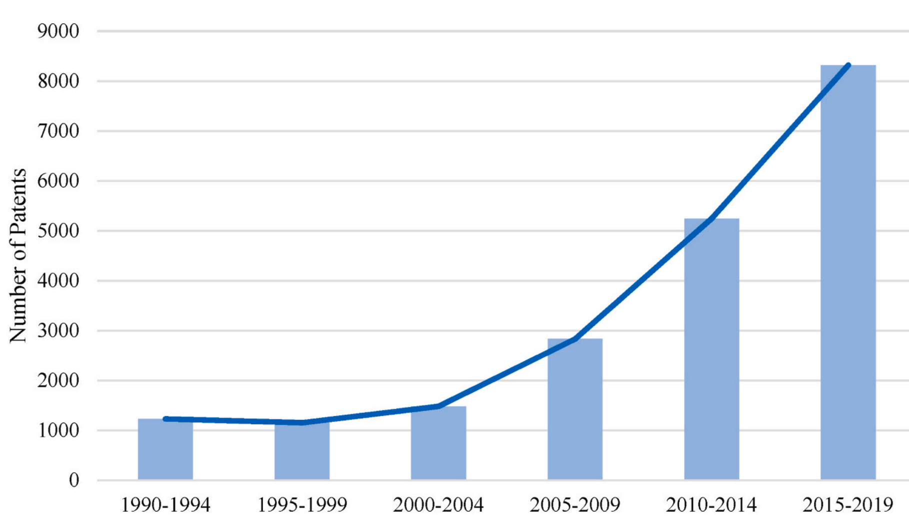

Fig. 2. The number of hydropower patents per five-year, 1990–2019.

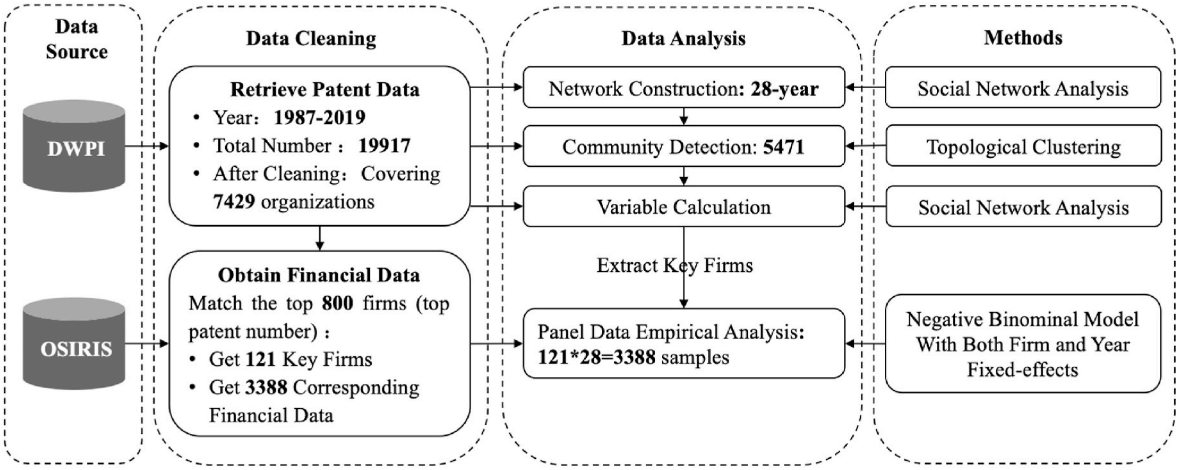

Fig. 3. Data acquisition and analysis process.

(Griliches, 1990).

4.4.2. Independent variables

*Degree Centrality Within Virtual Cluster (**$DCentrality_{WVC}$**)*: Referring to Freeman (1991), we defined the $DCentrality_{WVC}$ of firm i as follows to test Hypothesis 1a:

$$DCentrality_{WVC} = n_i/(Cluster\ Size_i - 1) \tag{2}$$

where n_i is the number of ties that connect firm i and other firms within the virtual cluster. $Cluster\ Size_i$ is the total number of firms that are members of the firm i's virtual cluster.

*Structural Hole Within Virtual Cluster (**$Structural\ Hole_{WVC}$**)*: Referring to Burt (1992), we defined the $Structural\ Hole_{WVC}$ as follows to test Hypothesis 1b:

$$Structural\ Holes_{WVC} = 1 - \sum_{j=1}\left(p_{ij} + \sum_{q=1} p_{iq}p_{qj}\right)^2 \tag{3}$$

where firm i、j、q belong to the same cluster, and $q \neq i,j$. While firm i and firm j are both connected with firm q directly, firm i and firm j are not connected directly. p_{ij} is the proportion of firm i's ego network spent directly with firm j in their cluster. $\sum_{j=1}\left(p_{ij} + \sum_{q=1} p_{iq}p_{qj}\right)^2$ is the constraint index of firm i. The higher values, the more structural holes a firm has.

4.4.3. Moderate variables

Firm size (FS): To test the moderating effects of firm size on the relationship between within-community characteristics and innovation performance, we used the natural log of the number of employees as a measure of *firm size*.

4.4.4. Control variables

To ensure robust results, we controlled for a range of other possible firm-level and cluster-level determinants of a firm's innovation performance.

As for the firm level, first, we controlled *ROA* (measured as return on assets), *RDE* (measured as expenses on research and development), and *Sales* using data from Osiris (Grigoriou and Rothaermel, 2017; Sytch and Tatarynowicz, 2014). These variables were logged to correct for their distributional skewness. Second, to control for the effects of a firm's ego network position on its innovation performance, we specified a static measure: *Ego-network degree centrality*, measured as the total number of ties between the firms and its partners divided by the number of all maximum possible connections (Ahuja, 2000). Finally, we also controlled the *Global-network density* measured as the total number of existing ties among all firms in the network divided by the number of all possible ties among these firms (Freeman, 1991; Gilsing et al., 2008).

As for the cluster level, we controlled for a range of features of virtual clusters (Clement et al., 2018; Sytch and Tatarynowicz, 2014). We specified *Cluster size* as the total number of firms that were members of the firm's virtual cluster in year t, including the focal firm. And *Cluster density* reflected the total number of existing ties among firms that were members of the focal firm's virtual cluster in year t divided by the number of all possible ties among these firms.

4.5. Estimate model

Given that our dependent variable is a non-negative count with overdispersion, we utilized a negative binomial regression model with both firm fixed-effects and year fixed-effects to test the hypotheses (Hausman et al., 1984). We also lagged all independent variables by one year to enable causal interpretation. *Firm size*, $DCentrality_{WVC}$, and $Structural\ hole_{WVC}$ are all mean-centered to eliminate nonessential multicollinearity. The econometric model of this study is shown below.

$$\begin{aligned} IP_{i,t+1} = \exp\Big(&\beta_0 + \beta_1 DCentrality_{WVC\,i,t} + \beta_2 Structural\ Hole_{WVC\,i,t} + \beta_3 FS_{i,t} \\ &+ \beta_4 DCentrality_{WVC_{i,t}} \times FS_{i,t} + \beta_5 Structural\ Hole_{WVC_{i,t}} \times FS_{i,t} \\ &+ \sum \beta_k Controls_{i,t} + \gamma_{i,t} + \tau_{i,t} + \varepsilon_{i,t}\Big) \end{aligned} \tag{4}$$

5. Results

5.1. Features of global networks and virtual clusters

Fig. 4 shows the network features of the hydropower industry innovation ecosystem. We noticed that the degree centralization (ranging from 0.007426 to 0.030407) and betweenness centralization (ranging from 0.000040 to 0.009158) were mostly at medium and low levels respectively. And the closeness centralization was at a relatively high level (ranging from 0.014842 to 0.117376). The number of organizations in the innovation ecosystem is also growing. The downward trend in the last stage may be caused by the limitations of patent data. Referring to existing studies, we constructed the inter-organizational networks in the innovation ecosystem based on patent data (Xu et al., 2020). This may ignore some organizations that focus on business activities in the innovation ecosystem. Different stages of industrial development may also lead to fluctuations in the number of innovation organizations. In general, the growing trend of three types of centralization indicates that the inter-organizational network in the hydropower industry is denser and more concentrated over time.

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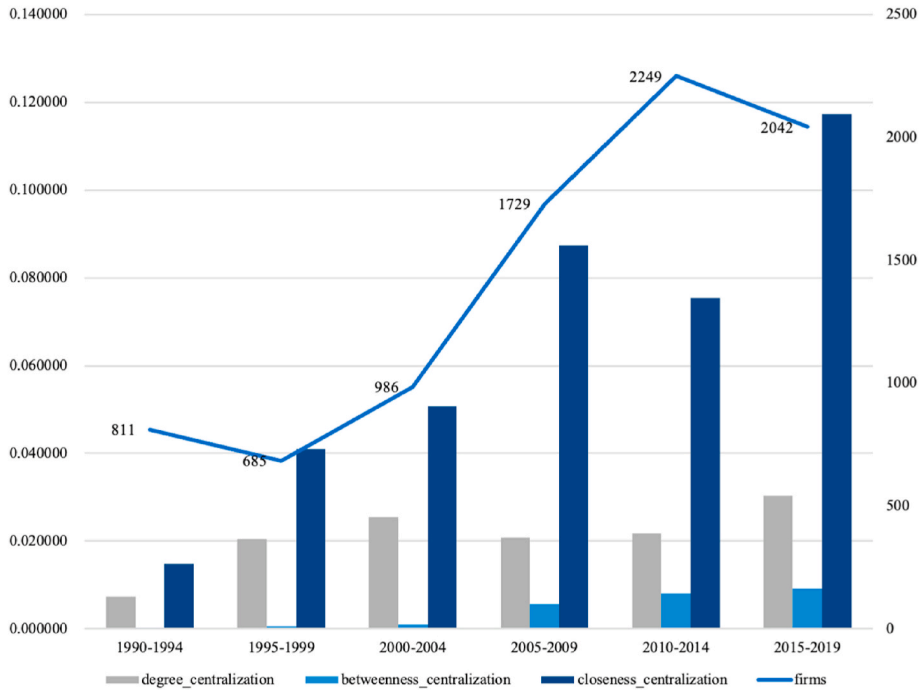

Fig. 4. The network features of the hydropower industry innovation ecosystem.

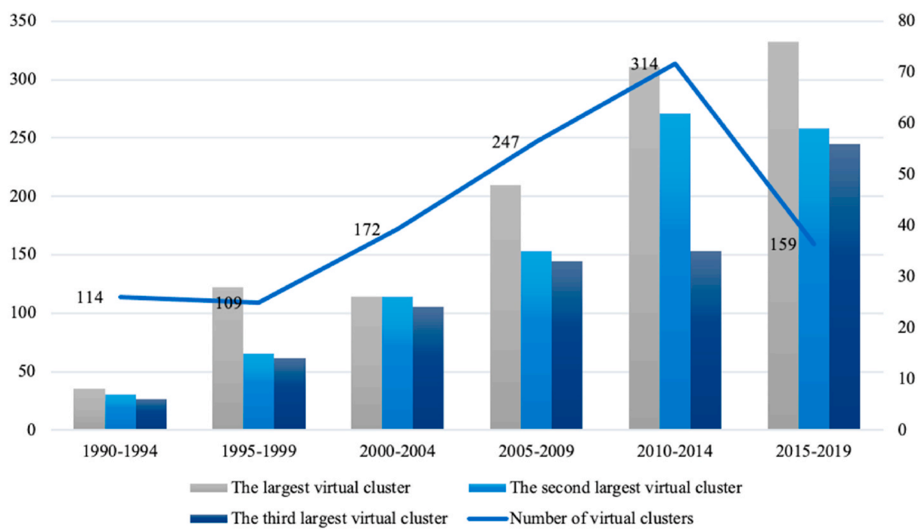

Fig. 5. The network features of virtual clusters.

Fig. 5 shows the features of virtual clusters. As for the size of virtual clusters, the clusters were both small in the first two stages. More and more isolated organizations formed into clusters over time. The size of the top three clusters in the final stage was 76, 59, and 56 firms, respectively. As for the number of virtual clusters, there were 114 and 109 virtual clusters in the two stages of 1990–1994 and 1995–1999 respectively. After that, the number of clusters in the network continued to increase from 109 to 314 in the stage of 2010–2014 but declined in 2015–2019, with 159 clusters in total. The reason behind this phenomenon may be that, compared with the previous stages, more closely-connected organizations form into larger-scale virtual clusters in the last stage. Especially in recent years, large and extensity projects in the global hydropower industry increased rapidly (Li et al., 2018), which also promotes the agglomeration of more organizations. These findings can also be verified in Fig. 6.

5.2. Descriptive results

Table 2 presents descriptive statistics and correlations between the variables. As noted in Table 2, a significant positive correlation between degree centrality within the virtual cluster and innovation performance is found ($\beta = 0.060, p < 0.1$). There is also a significant positive correlation between structural hole within the virtual cluster and innovation performance ($\beta = 0.430$, $p < 0.1$). These provide initial evidence in support of hypotheses 1 and 2.

5.3. Regression results

Table 3 presents the results of the negative binomial models with firm-level and year-level fixed effects. In Table 3, Model 1 is the baseline model, including only the control variables. Model 2 includes the control variables and moderating variable. In line with prior studies (Ruiqian

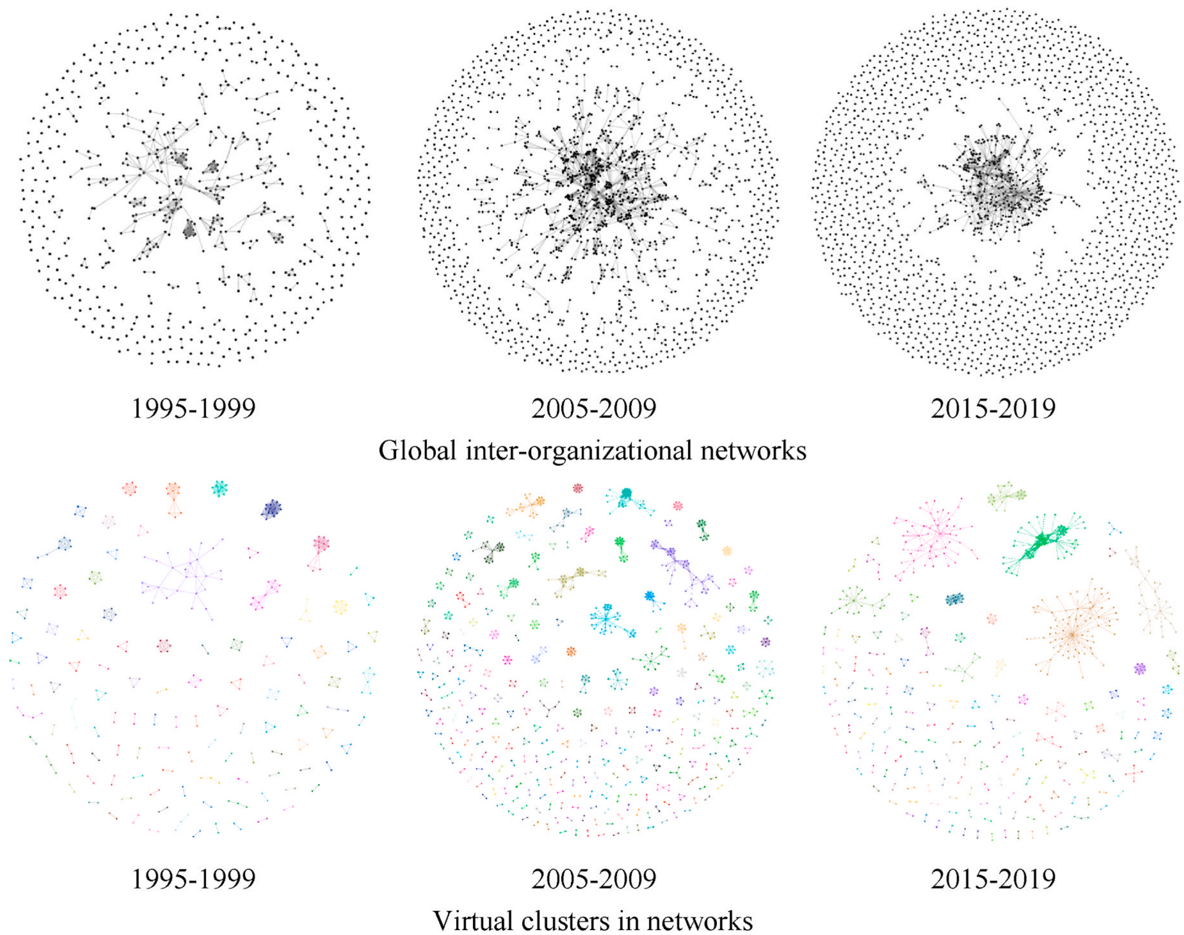

Fig. 6. Illustrations of the global inter-organizational networks and virtual clusters.

Table 1
Measurements of variables.

	Variables	Measurement	References	Data Source
Dependent variable	Innovation performance	Number of patents	Ahuja (2000); Lahiri and Narayanan (2013)	DWPI
Independent variables	Degree centrality within virtual cluster	$\frac{n_i}{Cluster\ Size_i - 1}$	Freeman (1991)	DWPI
	Structural holes within virtual cluster	$1 - \sum_{j=1}\left(p_{ij} + \sum_{q=1} p_{iq}p_{qj}\right)^2$	Burt (1992)	DWPI
Moderating variable	Firm size	Number of employees	Ahuja (2000)	Osiris
Control variables – Firm-level	ROA	Return on assets	Grigoriou and Rothaermel (2017);	Osiris
	RDE	Expenses on research and development	Sytch and Tatarynowicz (2014)	Osiris
	Sales	Sales		Osiris
	Ego network degree centrality	Total number of ties between the firms and their partners divided by the number of all maximum possible connections.	Ahuja (2000)	DWPI
	Global network density	Total number of existing ties among all firms in the network divided by the number of all possible ties among these firms	Freeman (1991); Gilsing et al., (2008)	DWPI
Cluster-level	Cluster size	Total number of firms that were members of the firm's cluster	Clement et al., (2018); Sytch and	DWPI
	Cluster density	Total number of existing ties among firms that were members of the firm's network cluster in year *t* divided by the number of all possible ties among these firms	Tatarynowicz (2014)	DWPI

et al., 2021), we find that virtual *Cluster size* has positive and significant impacts on innovation performance.

Models 3–5 represent the predicted main effects. In model 3, we tested hypothesis 1. $DCentrality_{WVC}$ has positive effects on firms' innovation performance ($\beta = 0.606, p < 0.01$). The coefficients of $DCentrality_{WVC}$ in models 5, 6, 7, and 8 are also positive and significant ($p < 0.01$), providing support for Hypothesis 1. Building connections can bring more resources and information to a firm, which may enhance firms' innovation (Ahuja, 2000).

In model 4, we tested hypothesis 2. Innovation performance increases with higher $Structural\ hole_{WVC}$ ($\beta = 0.696, p < 0.01$). The results are also robust in models 5, 6, 7, and 8. Structural holes can bring heterogeneous resources and information, and thus help improve firms' innovation performance (Burt, 1992). Thus, Hypothesis 2 is supported.

Table 2
Descriptive statistics and Pearson correlations.

Variables		1	2	3	4	5	6	7	8	9	10	11
1	Innovation performance	1										
2	ROA [a]	−0.056*	1									
3	RDE [a]	0.054*	0.422*	1								
4	Sales [a]	0.061*	0.394*	0.747*	1							
5	Ego network degree centrality	0.409*	0.008	0.072*	0.059*	1						
6	Cluster size	0.475*	−0.028	0.081*	0.071*	0.533*	1					
7	Cluster density	0.042*	0.018	0.025	0.002	0.347*	0.120*	1				
8	Global network density	0.109*	0.004	0.145*	0.131*	0.383*	0.248*	0.403*	1			
9	Firm size [a]	0.075*	0.331*	0.641*	0.711*	0.059*	0.069*	−0.004	0.106*	1		
10	$DCentrality_{WVC}$	0.060*	0.007	0.077*	0.100*	0.206*	0.017	0.475*	0.685*	0.043*	1	
11	Structural $hole_{WVC}$	0.430*	−0.016	0.074*	0.057*	0.811*	0.630*	0.194*	0.297*	0.060*	0.115*	1
Mean		0.5369	0.9779	9.6433	13.7891	0.0008	2.9307	0.1760	0.0007	7.6241	0.4472	0.0577
Median		0.0000	1.0526	12.3063	16.2136	0.0000	1.0000	0.0000	0.0006	9.9967	0.0548	0.0000
SD		2.2810	1.0379	5.9223	6.2196	0.0023	9.0357	0.3508	0.0010	4.9024	0.4817	0.1837
Skewness		11.3091	−0.1872	−0.8909	−1.6596	5.3497	5.7372	1.6690	1.1483	−0.8085	0.2086	2.9623

[a] Logarithm.

Table 3
Results of negative binomial regression models with firm-level and year-level fixed effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	model 1	model 2	model 3	model 4	model 5	model 6	model 7	model 8
ROA	−0.015	−0.015	−0.023	−0.008	−0.017	−0.032	−0.017	−0.032
	(-0.272)	(-0.265)	(-0.399)	(-0.141)	(-0.293)	(-0.561)	(-0.304)	(-0.566)
RDE	0.005	0.005	0.008	0.007	0.010	0.011	0.008	0.009
	(0.454)	(0.459)	(0.681)	(0.561)	(0.811)	(0.917)	(0.695)	(0.791)
Sales	0.033***	0.033***	0.032***	0.030**	0.029**	0.022*	0.030**	0.023*
	(2.941)	(2.754)	(2.629)	(2.502)	(2.365)	(1.827)	(2.428)	(1.900)
Ego network degree centrality	13.991	13.988	5.958	−11.356	−22.002	−9.756	−23.717	−11.887
	(1.186)	(1.185)	(0.505)	(-0.729)	(-1.428)	(-0.629)	(-1.524)	(-0.758)
Cluster size	0.025***	0.025***	0.032***	0.022***	0.029***	0.026***	0.029***	0.026***
	(7.990)	(7.976)	(9.033)	(6.561)	(7.924)	(6.855)	(7.943)	(6.849)
Cluster density	0.153	0.152	0.056	0.163	0.058	0.039	0.061	0.044
	(1.294)	(1.291)	(0.476)	(1.359)	(0.479)	(0.325)	(0.509)	(0.362)
Global network density	272.222***	272.426***	20.571	258.798***	−6.612	0.463	−9.017	−5.149
	(3.957)	(3.957)	(0.226)	(3.743)	(-0.073)	(0.005)	(-0.099)	(-0.057)
Firm size		−0.001	0.001	0.002	0.005	0.067***	0.001	0.063***
		(-0.080)	(0.060)	(0.168)	(0.350)	(3.330)	(0.048)	(2.977)
$DCentrality_{WVC}$ (a)			0.606***		0.642***	1.353***	0.649***	1.361***
			(3.961)		(4.190)	(6.020)	(4.229)	(6.062)
Structural $hole_{WVC}$ (b)				0.696***	0.773***	0.716***	0.646**	0.575*
				(2.842)	(3.180)	(2.969)	(2.070)	(1.874)
Firm size * a						−0.091***		−0.091***
						(-4.498)		(-4.513)
Firm size * b							0.018	0.020
							(0.653)	(0.746)
_cons	−0.810***	−0.811***	−1.065***	−0.857***	−1.143***	−1.553***	−1.117***	−1.521***
	(-3.817)	(-3.818)	(-4.771)	(-4.030)	(-5.071)	(-6.135)	(-4.893)	(-5.941)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3276	3276	3276	3276	3276	3276	3276	3276
chi2	220.86	220.81	245.31	226.45	251.90	258.23	254.77	262.17

Different from existing studies (Gilsing et al., 2008; Gonzalez-Brambila et al., 2013), we find that ego network degree centrality and global network density don't always have significant effects on innovation performance in these three models.

Model 6–7 represent the predicted moderating effects of firm size. Model 8 represents the fully specific regressions containing all predicted effects. In model 6, we tested hypothesis 3a. The coefficient of interaction between $DCentrality_{WVC}$ and *firm size* is negative and significant ($\beta = -0.091,\ p < 0.01$). Model 8 also shows the robust result ($\beta = -0.091,\ p < 0.01$). This indicates that *firm size* plays a negative role in the relationship between $DCentrality_{WVC}$ and innovation performance. We plotted this interaction in Fig. 7 to gain further insights. The graph shows the positive effects of $DCentrality_{WVC}$ on innovation performance are greater to small firms than big firms. The results largely support Hypothesis 3a. In line with existing studies, the relationships between network characteristics and innovation performance are mediated by firms' characteristics (Rogers, 2004; Shipilov, 2006).

In model 7, we tested hypothesis 3b. It depicts a positive but insignificant interaction effect of *firm size* and *Structural* $hole_{WVC}$ ($\beta = 0.018$, $p > 0.1$). This result is also in line with the coefficient in model 8. Hypothesis 3b is not supported. It seems that the benefits of big firms obtained by structural holes may not always outweigh small firms. The reasons may be that the innovation transformation not only depends on the firms' resources and reputation but also on its strategic orientation (Adams et al., 2019; Zhou et al., 2021). Although big firms have abundant financial resources and specialized researchers to innovate, their strategic orientation to innovation is not sure.

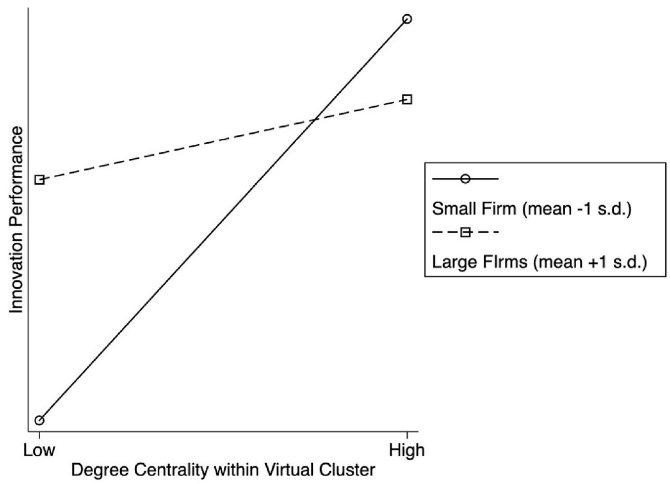

Fig. 7. Interaction between degree centrality within the virtual cluster and firm size.

5.4. Robustness checks

We also conducted a series of additional analyses to check the robustness of the findings (see Appendix A). These tests included changes in the measurement of the dependent variable, the window of network construction, and the estimation method.

First, referring to Vasudeva et al., (2013), we explored the sensitivity of our results to alternative ways of constructing the inter-organizational network. While in the main analysis we modeled inter-organizational ties as lasting for five years, in additional analyses we set the duration of ties to three years. Our results remained substantively unchanged in these tests (see Appendix A Table A1).

Second, referring to Sytch and Tatarynowicz (2014), we created an alternate measurement of the dependent variable by counting the patents filed within three or five years from *t* respectively (see Appendix A Table A2 and Table A3), rather than capturing the patents filed in year *t+1*. Our statistical results remained robust to these modifications.

Our final series of robustness checks focused on alternate estimation methods. While the negative binomial regression model used in our main analysis can effectively deal with the issue of overdispersion in the dependent variable, it can also lead to biased estimates should data suffer from autocorrelation or distributional misspecification. Thus, referring to Sytch and Tatarynowicz (2014), we re-estimated our models using firm-level and year-level fixed-effects Poisson estimates. In addition, referring to Grigoriou and Rothaermel (2017), we also used the negative binomial regression model with the random-effects specification. The results of these additional tests were similar (see Appendix A Table A.4 and Table A.5).

6. Conclusions and implications

6.1. Conclusions

This study examines how the firms' characteristics within the virtual cluster affect their innovation performance. With consideration of the moderating effects of firm size, we conduct an empirical study in the global hydropower industry. Toward this end, the study has the following key findings:

First, empirical results show that when firms deploy higher degree centrality and more structural holes within the virtual cluster, they are more likely to have better innovation performance. Because they can exchange knowledge and other critical resources with other members easily, which provides critical materials for innovation. Firms with more structural holes in the virtual cluster can gain information and control benefits to improve their innovation performance.

Second, empirical results also show that firm size plays a negative role in the relationship between degree centrality within the virtual cluster and innovation performance. It may generate higher innovation performance if small firms can utilize their network connections within the cluster. However, the moderating effects of firm size on the relationship between structural hole within the virtual cluster and innovation performance are not significant, which requires further analysis.

6.2. Theoretical contributions

First of all, this paper takes a meso-level perspective to make up for the lack of existing research on virtual clusters. Existing literature applies two complementary perspectives to explore the impacts of innovation ecosystem on innovation performance (Ahuja, 2000; Panetti et al., 2019; Schilling and Phelps, 2007; Zhou et al., 2020b). But the above two perspectives risk providing a complete picture of the innovation ecosystem. They cannot explain how virtual clusters affect innovation. Thus, by emphasizing the role of virtual clusters in promoting innovation, this study enriches the innovation ecosystem from the meso-level.

Second, this research also opens the black box behind the virtual cluster by investigating how innovation is affected by firms' characteristics within the virtual cluster. Existing studies mainly discuss the concept and causes of virtual clusters using qualitative methods (Chen et al., 2021; Passiante and Secundo, 2002). Only a few scholars explore how virtual clusters' characteristics affect innovation empirically (Ruiqian et al., 2021). But existing studies ignore the heterogenous of firms' network relationships within virtual clusters, which may have different impacts on firms' behaviors and performance. By exploring the impacts of degree centrality and structural hole within the virtual cluster on innovation performance, this study enriches the studies on the influence mechanism of virtual clusters.

Third, this study contributes to the methodology in terms of virtual clusters in the ecosystem. Based on large-scale patent data, this study utilizes topological clustering algorithms (Newman, 2004) to effectively identify virtual clusters in the hydropower industry according to the actual closeness of inter-organizational relationships. This provides a valuable method for further research on the meso-level of the innovation ecosystem.

6.3. Implications

The presented results provide valuable practical implications for managers and policymakers in the hydropower industry. It enhances the understanding of virtual clusters and the specific mechanisms that may drive successful innovative performance.

As for managers, both establishing more connections or occupying the bridge position are valid collaboration options for strategic consideration when promoting innovation by virtual clusters. Firm size is also an important strategic consideration for network resource allocation. Small firms are more beneficial when they establish more cooperative relationships across geographic boundaries.

As for policymakers, although different firms' characteristics within the virtual cluster have heterogeneous mechanisms, they are both good for innovation. In this case, in the hydropower industry, the government should guide firms to cooperate with innovation organizations actively, and promote the free flow of innovation resources all over the world. Meanwhile, the policymakers should encourage the development of platform firms, which can provide an environment for virtual agglomeration.

6.4. Limitations and directions for future research

The limitations of this research provide potential opportunities for future research.

First, our empirical context is the global hydropower industry, while we think that our results are likely to hold in other industries with similar features, especially in emerging industries. We may apply the virtual cluster perspective to open up new avenues for analyzing a wider spectrum of industrial contexts. Second, patent data represent only one type of innovation output, and innovation may be measured by other indicators. Therefore, we encourage future research to go beyond patents when assessing firm-level innovation performance. Thirdly, due to the data availability, this paper constructs inter-organizational networks and identifies virtual clusters based on patent data. Future research can use other data, such as alliance data and product transaction data to establish networks and identify the virtual clusters.

CRediT authorship contribution statement

Ning Kang: are the co-first authors of the paper, They contributed equally to the paper, Conceptualization, Writing – original draft, Methodology. **Guannan Xu:** are the co-first authors of the paper, They contributed equally to the paper, performed, Writing – review & editing, Supervision, Data curation, Funding acquisition. **Xianzhong Mu:** Visualization. **Hongrui Yang:** performed, Software, and, Methodology. **Yuanyuan Qiao:** Software.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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