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Network Structure and Innovation Performance in University-Enterprise Cooperation

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Abstract

Under the background of University-Enterprise Cooperation innovation (UEC), this paper explores the relationship between the network structure of UEC and its cooperative innovation performance. In the negative binomial model, the explained variable is the number of UEC patent applications, and explanatory variables are clustering coefficient, structural holes and centralities. The result shows that eigenvector centrality has an inverted U-shaped relationship with UEC performance especially.

Keywords

University-Enterprise Cooperation, Network Structure, Innovation Performance

1. Introduction

In the face of increasingly fierce competition, enterprises not only need to save costs from the operational level, but also need to effectively carry out technological innovation activities. In order to effectively use resources and reasonably disperse risks, enterprises are actively seeking cooperative R&D partners, in which the scientific research power of universities cannot be underestimated. Universities with scientific research as their basic task are also facing the challenge of the market; how to apply research results and how to solve practical problems are important issues that they need to face in scientific research. At present, there are more and more cooperative innovation activities between enterprises and universities, which has attracted wide attention from the industry and academia. The knowledge innovation ability of enterprises is mainly embodied in the form of patents, through the network crawler to collect the patent data applied by Hon Hai Precision Industry Co Ltd. in the United States Patent and Trademark Office (USPTO). It is found that Hon Hai Precision Industry Co Ltd. in the decade 2005-2014, cooperated with other institutions to apply for patents, and the group's molecular companies accounted for 84.4% of the total number of patents. Cooperation with other external enterprises accounted for 0.6%. And cooperation with universities accounts for 15%, and proportion is increasing every year.

For the research on the performance of University-Enterprise Cooperation innovation, scholars put forward the impact on its performance from the perspective of network structure. Enterprises in different network positions have different information, through the empirical analysis of biopharmaceutical industry cooperation network. Mazzola & Kamuriwo. (2015) pointed out that the concentration of the network is beneficial to product innovation. Enterprises in the network structure are more central and dominant position, and it can accept and obtain a lot of information and resources. Guan et al. (2016) studied the impact of the structural characteristics of the cooperation network on the innovation performance from the national level. The results showed that the centrality index and structural holes of the network had a positive effect on the innovation performance. Based on this, under the background of University-Enterprise Cooperation innovation, this paper regards the number of cooperative patent applications as performance output, and uses appropriate econometric model to empirically explore the relationship between the network structure of University-Enterprise Cooperation and its cooperative innovation performance.

2. Theory and Hypothesis

The structure of University-Enterprise Cooperation innovation network is constantly changing, and the network indicators are different in different periods, mainly including the Clustering Coefficient, Structural Holes, Centralities indicators of the network, so as to analyze how the various network indicators of University-Enterprise Cooperation innovation affect its innovation performance.

2.1. Clustering Coefficient

The Clustering Coefficient measures the degree to which the points in the graph tend to cluster together, and it is a reflection of the degree of network clustering. Some studies support that Clustering Coefficient has a positive effect on R&D capability. High clustering can promote the partnership between partners, share knowledge and other resources, and jointly undertake the risks of cooperation. Using the cooperation data of American high-tech manufacturing industry, Schilling & Phelps (2007) empirically tested that high clustering network can increase the innovation output of enterprises, and concluded that higher Clustering Coefficient will make the flow of information more smooth, and the transfer and diffusion of knowledge more convenient. And the overall knowledge capacity of the cooperative object can be expanded. However, Guan et al. (2015) pointed out that clustering is not always beneficial, high Clustering Coefficient may lead to repeated information and more confused views among cooperative objects, higher clustering degree will lead to parochialism and rigidity and lack of different new views. It may have low cooperation output rate, and ultimately reduce the performance of cooperative innovation to a certain extent. Because this paper discusses the cooperative relationship between universities and enterprises, those two have great differences in various aspects. Universities have complex discipline research background and more diversified knowledge reserves, so the cooperation between universities and enterprises may eliminate the rigid situation caused by high clustering, and the participation of universities will introduce more fresh and effective views. Based on this, the first hypothesis is put forward:

Hypothesis 1: Clustering Coefficient has a positive impact on the performance of University-Enterprise Cooperation innovation.

2.2. Structural Holes

Structural Holes refer to the gaps in social networks, that is, one or some individuals in a network have direct contact with some individuals, but have no direct contact with other individuals, and only through a third person can network contact be formed. Gözübüyük & Kock (2011) found that the third party occupies a "hole" in the cooperative network, which can provide more services and returns for itself. Therefore, if university-enterprise organizations want to maintain competitive advantage, they should establish more links with other nodes in the network, so as to occupy more Structural Holes and obtain diversified information and resources. Peng & Wang (2013) studied the citation network of journals and the University-Enterprise Cooperation innovation network of equipment manufacturing industry, and found that if the organization is in the "bridge" position of the whole network structure, it has a positive impact on innovation performance. However, Obstfeld (2005) found that Structural Holes have a negative impact on innovation performance. If the network is relatively sparse, then the scattered nodes may be difficult to mobilize and coordinate. Fleming & Chen (2007) showed that Structural Holes may lack the necessary of density and trust, and may reduce the willingness of cooperative innovation between objects, which may have a negative impact on innovation performance. The research like this is mainly to discuss the influence of Structural Holes on the whole or local network, not for a single node. The node in this position is still beneficial to itself, easier to obtain and control different social resources and capital. It can cooperate with different objects, so as to improve its own and other nodes cooperative R&D capabilities. Based on this, the second hypothesis is put forward:

Hypothesis 2: Located in the Structural Holes has a positive impact on the performance of University-Enterprise Cooperation innovation.

2.3. Centrality

Centrality is a kind of important network structure index, which represents the position of a node in the network and reflects the importance of the node. Centrality is the focus of social network research, which reflects the degree of node power in social network, which has a great impact on the mode that effect information and knowledge dissemination in the whole network. Everett & Borgatti (2010) and Li et al. (2013) found this kind of knowledge flow also has a certain impact on the innovation performance and value of University-Enterprise Cooperation network. It plays an important role in the network. Breschi & Catalini (2010) showed that a given node has higher centrality, can connect with other organizations and exchange more knowledge among other organizations. It also can provide opportunities to establish tripartite or multi-party relationships, which are conducive to the performance of cooperative innovation. Ahuja et al. (2012) found that nodes with higher centrality have higher status and prestige in the network, so they have the ability to take greater risks. In this paper, Degree Centrality, Closeness Centrality, Betweenness Centrality and Eigenvector Centrality are used to measure Centrality.

Degree Centrality is a measure of the degree to which a node is related to all other nodes in a network. It has high degree centrality, the node is connected with other more nodes. Closeness Centrality reflects the closeness between a node and other nodes in the network, that is, the shortest distance between a given node and other nodes. Betweenness Centrality is the number of the shortest path through a node to reflect the importance of the node, reflecting the importance of the node as a "bridge". Eigenvector Centrality takes into account the centrality of other nodes connected to a given node, and then measures the centrality index of the node. A node with a small number of influential contacts may be more central than a node with a large number of mediocre contacts.

Based on the above, the following hypotheses are put forward:

Hypothesis 3: Degree Centrality has a positive impact on the performance of University-Enterprise Cooperation innovation.

Hypothesis 4: Closeness Centrality has a positive impact on the performance of University-Enterprise Cooperation innovation.

Hypothesis 5: Betweenness Centrality has a positive impact on the performance of University-Enterprise Cooperation innovation.

Hypothesis 6: Eigenvector Centrality has a positive impact on the performance of University-Enterprise Cooperation innovation.

3. Data and Model

3.1. Data

Based on the database of patents granted from USPTO website, this paper collected the University-Enterprise Cooperation patents from 2002 to 2011, and searched the Assignee Name (AN) owned jointly by the university and the enterprise, like AN ((University OR Institution OR Institute OR College OR

School) AND (Corporation OR Company OR Co OR Inc OR Ltd OR Enterprise)). The information conclude the patent number, inventor, grant time, patent category, application number, patentee country, etc.

Cleaning the data to obtain the required data sets.

First, the case where only one organization applies for a patent is deleted. Since the search is based on the relevant English terms of the words "university" and "enterprise", there is a situation where an organization name contains two English words at the same time, for example "University of Georgia Research Foundation, Inc. (Athens, GA)".

Second, eliminating the duplication and incomplete data, as well as individual invalid patents, and finally get the data of University-Enterprise Cooperation patents.

Third, the data may also include other scientific research institutions, in order to make the data of University-Enterprise Cooperation more accurate, we need to further subdivide and narrow the scope of the data, according to the United States News and World Report (US News) World University Ranking 500. These cooperation data of the top 500 universities and enterprises in the world are selected for main analysis.

Fourth, we need to unify organization names, because there is a situation where different names of the same organization exist in USPTO, such as "US Biomaterials Corp. (Baltimore, MD)" and "US Biomaterials Corporation (Baltimore, MD)". After data cleaning, there are 2345 University-Enterprise Cooperation patents in this study finally.

3.2. Model

The explained variable in this study is the number of University-Enterprise Cooperation patents by each node (*Patent Num*). *Patent Num* refers to the output of University-Enterprise Cooperation innovation, which can reflect the innovation performance. It means the more the number of patents applied for by a node, the stronger its cooperation innovation performance. Clustering Coefficient (*CC*), Structural Holes (*SH*), Degree Centrality (*DC*), Closeness Centrality (*CNC*), Betweenness Centrality (*BC*) and Eigenvector Centrality (*EC*) are used as explanatory variables.

The explained variable is a discrete positive integer greater than zero and a count-type variable. Therefore, compared with the general linear regression model, this study is more suitable to use the count model for analysis and will have a better effect. Poisson model requires that the dependent variable follow Poisson distribution, the mean is equal to the variance, but the mean value in this study is 1.9258, variance $2.4186^2 = 5.8496$, the mean and variance have obvious difference, which cannot meet the requirement of Poisson model in counting model. Therefore, the negative binomial model is used to verify the hypotheses. First, a single explanatory variable is added to the model, and then a combination of other variables is used to verify. Finally, all explanatory variables are introduced into a model at the same time, so as to establish a complete model.

4. Result Analysis

The statistical characteristics of the explained variable and explanatory variables are described in Table 1, and Table 2 is the correlation coefficient matrix. Except for the correlation coefficient between *DC* and *SH*, the correlation coefficients between other explanatory variables are less than the threshold value of 0.7, indicating the good discrimination validity. The correlation coefficient between *DC* and *SH* is 0.7447, so delete the index of *DC* in order to make good distinction among all the explanatory variables. Therefore, the remaining explanatory variables are *CC*, *SH*, *CNC*, *BC* and *EC*.

Table 3 shows the results of the negative binomial model. It can be seen from the table that the fitting effect of this model is good, and the mean significance level is less than 0.01. The results of other models maintain a high degree of consistency and stability except for the unstable performance of *CNC*. Model 1 to model 6 are to add an explanatory variable, model 7 to model 31 are to verify the combination of each variable, and finally model 32 includes all explanatory variables, the following analysis is based on model 32.

Table 1. Statistics characteristic of explained and explanatory variables.

Variable	N	Mean	Std.dev	Min	Max
Patent Num	2345	1.9258	2.4186	1	28
CC	2345	0.2251	0.4006	0	1
SH	2345	1.1487	0.2645	0.3190	2
DC	2345	0.0086	0.0092	0.0029	0.1067
CNC	2345	0.5586	0.3340	0.1045	1
BC	2345	0.0025	0.0119	0	0.1845
EC	2345	0.0746	0.1662	0.0014	1

Table 2. Correlation coefficient matrix of explained and explanatory variables.

	Patent num	*CC*	*SH*	*DC*	*CNC*	*BC*	*EC*
Patentnum	1						
CC	−0.1213	1					
SH	0.5970	0.0320	1				
DC	0.6792	0.2201	0.7447	1			
CNC	−0.0813	0.0083	−0.1557	−0.0212	1		
BC	0.6161	−0.0797	0.4760	0.4852	−0.1943	1	
EC	0.2254	0.2815	0.4510	0.6531	−0.1186	0.2272	1

Table 3. Negative binomial model.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
CC	−0.4456***						−0.4498***
	(0.0520)						(0.0470)
SH		2.0395***					2.0376***
		(0.0487)					(0.0474)
CNC			−0.3127***				
			(0.0572)				
BC				27.4526***			
				(1.1826)			
EC					1.2696***	4.4051***	
					(0.0972)	(0.2973)	
EC^2						−3.6837***	
						(0.3305)	
	Model 8	**Model 9**	**Model 10**	**Model 11**	**Model 12**	**Model 13**	**Model 14**
CC	−0.4407***	−0.3009***	−0.6289***				
	(0.0519)	(0.0488)	(0.0522)				
SH				2.0445***	1.7352***	2.0656***	
				(0.0494)	(0.0543)	(0.0554)	
CNC	−0.3033***			0.0304			0.0789
	(0.0568)			(0.0507)			(0.0554)
BC		26.4764***			9.4510***		27.9456***
		(1.1594)			(0.7455)		(1.2448)
EC			4.6646***			0.8742***	
			(0.2891)			(0.0290)	
EC^2			−3.6683***			−1.2886***	
			(0.3207)			(0.2832)	
	Model 15	**Model 16**	**Model 17**	**Model 18**	**Model 19**	**Model 20**	**Model 21**
CC			−0.4498***	−0.3954***	−0.4480***	−0.3002***	−0.6332***
			(0.0470)	(0.0464)	(0.0501)	(0.0488)	(0.0523)
SH			2.0414***	1.7639***	1.9730***		
			(0.0481)	(0.0533)	(0.0548)		
CNC	0.0330		0.0235			0.0736	0.0780
	(0.0614)		(0.0494)			(0.0551)	(0.0603)
BC		23.2304***		8.4091***		26.9289***	
		(1.1634)		(0.7080)		(1.2194)	
EC	4.4782***	2.5056***			1.1820***		4.8440***
	(0.3269)	(0.2962)			(0.2629)		(0.3193)
EC^2	−3.7602***	−2.2897***			−1.3026***		−3.8540***
	(0.3599)	(0.3258)			(0.2755)		(0.3500)
	Model 22	**Model 23**	**Model 24**	**Model 25**	**Model 26**	**Model 27**	**Model 28**
CC	−0.4211***					−0.3929***	−0.4477***
	(0.0506)					(0.0464)	(0.0502)
SH		1.7474***	2.0748***	1.8040***		1.7751***	1.9796***
		(0.0544)	(0.0556)	(0.0589)		(0.0534)	(0.0551)
CNC		0.1627***	0.1358**		0.2680***	0.1503***	0.1293**
		(0.0507)	(0.0544)		(0.0593)	(0.0498)	(0.0535)
BC	20.9001***	10.0154***		9.4815***	24.1369***	8.9167***	
	(1.1284)	(0.7703)		(0.7598)	(1.1984)	(0.7293)	
EC	2.8394***		1.1387***	0.3660	3.0465***		1.4349***
	(0.2934)		(0.2890)	(0.2663)	(0.3193)		(0.2830)
EC^2	−2.3859***		−1.5792***	−0.8213***	−2.8834***		−1.5790***
	(0.3210)		(0.3063)	(0.2786)	(0.3512)		(0.2986)

Continued

	Model 29	Model 30	Model 31	Model 32
CC	-0.3674^{***} (0.0495)	-0.4274^{***} (0.0506)		-0.3613^{***} (0.0496)
SH	1.7601^{***} (0.0580)		1.8088^{***} (0.0589)	1.7614^{***} (0.0581)
CNC		0.2785^{***} (0.0587)	0.2560^{***} (0.0542)	0.2405^{***} (0.0536)
BC	8.3171^{***} (0.7356)	21.7473^{***} (1.1592)	10.1415^{***} (0.7747)	8.9556^{***} (0.7509)
EC	0.6544^{**} (0.2627)	3.4073^{***} (0.3166)	0.8152^{***} (0.2825)	1.0721^{***} (0.2788)
EC^2	-0.8739^{***} (0.2728)	-3.0042^{***} (0.3462)	-1.3210^{***} (0.2980)	-1.3405^{***} (0.2924)

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

Firstly, the *CC* has a negative impact on the performance of University-Enterprise Cooperation innovation, which is contrary to the hypothesis one put forward before, but similar to some research results mentioned before, the local *CC* of a node is too large, which means that the adjacent nodes will form a close group, but this high clustering may lead to the rigidity of thinking, repetition, confusion, invalid information, thus affecting the output and performance of cooperative innovation. For enterprises, they should look for universities with low *CC* in the network. This kind of universities does not stick to a class of research fields and partners, which has more sorts of resources and information, and will promote the cooperative innovation performance. Similarly, for universities, they should cooperate with enterprises with lower *CC* which is good for cooperative innovation performance.

Secondly, *SH* have a positive impact on the performance of University-Enterprise Cooperation innovation, which supports hypothesis two. The more *SH* occupied, the more objects they can cooperate with, which represents easy access and control different social resources. Also it can improve own and other nodes' cooperative R&D capabilities. For enterprises, cooperation with universities occupying *SH* will share different types of resources, and the same is true for universities.

Thirdly, the results of each model about *CNC* in this study are inconsistent, and the positive and negative effects are unstable and not significant, so it is impossible to judge the impact of *CNC* on the performance of University-Enterprise Cooperation innovation. The *BC* has a positive impact, which supports the hypothesis five. It acts as a role similar to the broker, which has the ability to control the interaction of others. The node has a higher *BC* that will have a positive impact on its performance of University-Enterprise Cooperation. For enterprises, choosing to cooperate with universities with higher *BC* is beneficial to recognize and make friends with new partners. Of course, the innovation performance will also be improved.

In particular, the relationship between the *EC* and the performance of University-Enterprise Cooperation innovation presents an inverted U-shaped relationship, showing a positive influence first and then a negative influence. And the results of many models are relatively stable. The *EC* considers the centrality of other points connected, and the nodes connected to important nodes are more important. The results show that *EC* of nodes is within a certain range, which will have a positive impact on performance, but once it exceeds a certain range, too many important nodes will be connected with it, which may be due to the limited energy, ability, resources and manpower of its own organization. The cooperation with many important core nodes may have no time to take into account, which will have a negative impact on the performance of University-Enterprise Cooperation. For enterprises, it will have a positive role in promoting cooperative innovation performance to find universities within the appropriate scope of *EC* to cooperate with them, and so will universities.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

Ahuja, G., Soda, G., & Zaheer, A. (2012). The Genesis and Dynamics of Organizational Networks. *Organization Science, 23,* 434-448. https://doi.org/10.1287/orsc.1110.0695

Breschi, S., & Catalini, C. (2010). Tracing the Links between Science and Technology: An Exploratory Analysis of Scientists' and Inventors' Networks. *Research Policy, 39,* 1426. https://doi.org/10.1016/j.respol.2009.11.004

Everett, M. G., & Borgatti, S. P. (2010). Induced, Endogenous and Exogenous Centrality. *Social Networks, 32,* 339-344. https://doi.org/10.1016/j.socnet.2010.06.004

Fleming, L., & Chen, M. D. (2007). Collaborative Brokerage, Generative Creativity, and Creative Success. *Administrative Science Quarterly, 52,* 443-475. https://doi.org/10.2189/asqu.52.3.443

Gözübüyük, R., & Kock, C. J. (2011). *Triafd Dynamics: Structural Holes, Cliques and the Tragedy of Brokers* (pp. 510-519). Rochester, NY: Social Science Electronic Publishing. https://doi.org/10.2139/ssrn.1798638

Guan, J. C., Zuo, K. R., Chen, K. H., & Yam, R. C. M. (2016). Does Country-Level R&D Efficiency Benefit from the Collaboration Network Structure? *Research Policy, 45,* 770-784. https://doi.org/10.1016/j.respol.2016.01.003

Guan, J., Zhang, J., & Yan, Y. (2015). The Impact of Multilevel Networks on Innovation. *Research Policy, 44,* 545-559. https://doi.org/10.1016/j.respol.2014.12.007

Li, E. Y., Liao, C. H., & Yen, H. R. (2013). Co-Authorship Networks and Research Impact: A Social Capital Perspective. *Research Policy, 42,* 1515-1530. https://doi.org/10.1016/j.respol.2013.06.012

Mazzola, E. P. G., & Kamuriwo, D. S. (2015). Network Embeddedness and New Product Development in the Biopharmaceutical Industry: The Moderating Role of Open Innovation Flow. *International Journal of Production Economics, 160,* 106-119. https://doi.org/10.1016/j.ijpe.2014.10.002

Obstfeld, D. (2005). Social Networks, the Tertius Iungens and Orientation Involvement in Innovation. *Administrative Science Quarterly, 50,* 100-130. https://doi.org/10.2189/asqu.2005.50.1.100

Peng, T. Q., & Wang, Z. Z. (2013). Network Closure, Brokerage, and Structural Influence of Journals: A Longitudinal Study of Journal Citation Network in Internet Research (2000-2010). *Scientometrics, 97,* 675-693. https://doi.org/10.1007/s11192-013-1012-x

Schilling, M. A., & Phelps, C. C. (2007). Interfirm Collaboration Networks: The Impact of Large-Scale Network Structure on Firm Innovation. *Management Science, 53,* 1113-1126. https://doi.org/10.1287/mnsc.1060.0624