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An empirical investigation on the relationship between co-patent network, structure embeddedness and innovation output

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Abstract: Based on social network theory, the article takes the co-patent network of China's mobile phone industry from 2003 to 2017 as the research object. Poisson regression model is used to investigate the impact of network structure embeddedness on innovation output. The empirical research results show that, (1) there exists optimal cooperation size for firms in the co-patent network, that is, moderate degree centrality may mean higher innovation output; (2) occupying more structural hole positions in the co-patent network may increase firms' innovation output; and (3) higher clustering coefficients significantly reduce firms' innovation output.

Keywords: co-patent network; structure embeddedness; innovation output

JEL Class：Z13

I. Introduction

In response to the rapid development of science and technology and intense competition for technology around the globe, more and more firms are establishing cooperative relationships and the co-patent network is playing an increasingly important role in technology innovation activities. Patent cooperation may not only be conducive to reducing R&D costs and controlling risks in innovation activities, but also be conducive to enhancing innovation output because interdisciplinary cooperation among partners may stimulate creativity. Co-patent network reflects the explicit partnerships among firms, R&D departments or individual inventors. The extant literature on the co-patent network can be roughly categorized into three research streams:

The first research stream focuses on the characteristics of co-patent networks and its evolution dynamics. Graf and Henning (2009) found that universities and research institutions occupy an important position in the regional co-patent networks. Lissoni (2010) showed that individual inventors in universities who co-operate with firms are more likely to occupy a core position in networks.

The second research stream focuses on the analysis of driving factors for the formation and evolution of co-patent networks. Merton (1968) found that the popularization of science, visibility and reputation are important factors driving the formation of cooperative networks. Good reputation may stimulate others to cooperate and is more likely to attract valuable partners. Balconi et al. (2004) argued that the degree of specialization and the quest for knowledge may affect the propensity to cooperate. The higher the degree of specialization with specific firms, the greater the demand for partners with different technical backgrounds, and the more likely they will seek to connect with their peers. Hussler and Rondé(2007) found that geographic proximity is an important driver in the evolution of co-patent networks. When researchers work in the same lab or in the same geographic area, they naturally have a higher tendency to cooperate. Knowledge exchange becomes easier once the individual inventors are free of space constraint. Therefore, it is very important for firms to locate in areas where similar or complementary technologies are available. Inventors and research departments should also work together on a regular basis, rather than maintain a very long geographical distance.

The second research stream focuses on the relationship between co-patent networks and innovation outputs. Lecocq and Looy (2009) analyzed patent data in biotechnology in European countries and creatively introduce life cycle theory into the co-patent network. They found that patent cooperation can effectively promote scientific and technological progress and innovation performance in certain countries or regions. However, as the life cycle progresses backward, this positive push is gradually weakened. Schilling and Phelps (2007) used patent data of 1106 organizations to build a large-scale co-patent network, and examined the impact of network structure on organizational creativity. The results showed that the network structure has an important impact on innovation performance. Network structures with higher clustering coefficients higher reach ability (the average path between nodes is shorter) may stimulate innovation performance.

In summary, the extant literature mainly uses social network analysis to describe the patterns and structure of co-patent networks, and the evolution characteristics in the context of specific industries. Only a few literatures explored the relationships between co-patent network and innovation output. Such literature mainly focused on the co-patent networks in the context of developed countries, while largely overlooked the co-patent networks in the context of developing countries or transition economies. This paper attempts to investigate the impact of firms' network structure embeddedness on innovation output in the context of the co-patent networks of China's mobile phone industry from 2003 to 2017.

II. Theory and Hypotheses

Network centrality is one of the important measures of structural embeddedness. Network centrality is an indicator which describes the positions of an actor in social networks. Network centrality includes four indicators: degree centrality, betweenness centrality, close centrality and eigenvector centrality, of which degree centrality is one of the most widely used indicators in social network analysis.

Dougherty and Hardy (1996) argued that firms with higher degree centrality may be able to combine various forms information to form unique and novel knowledge because they have more sources of information. On the perspective of organizational learning theory, Brown and Duguid (1991) found that firms with access to more information may enhance their ability to identify the value of new information. By acquiring, combing, internalizing and absorbing the ed external information with existing knowledge, firms may create new knowledge and thus improve firms' innovation performance. However, as the degree centrality increases, firms may be exposed to more network actors, increasing the possibility of redundant information, which may increase the difficulty of firms' processing and combing the acquired information. In addition, maintaining more ties with network actors may incur increasing cost, which will inevitably crowd out the R &D expenses. Therefore, when the degree centrality is too high, the innovation output of firms will be impaired. Therefore, this paper proposes the following hypothesis:

Hypothesis 1: There is an inverted U-shaped relationship between degree centrality and innovation output.

Structural holes imply non-redundant ties between actors, which are sources of profit or value-added for actors. Burt (1992) argued that structural holes facilitate the acquisition of heterogeneous information, and actors occupying the "bridge" position may obtain competitive advantage than other actors. Soda (2004) found that firms occupying structural holes are serving as the role of boundary-spanners in the network. Such actors are responsible for linking firms which may not be connected otherwise, and are in a strategic position where multi-group information is gathered. Actors occupying the structural holes position has the control benefit Hence, the paper proposes the following hypothesis:

Hypothesis 2: Structural holes positively affect the firms' innovation output.

The clustering coefficient is a measure of the degree to which nodes in a graph tend to cluster together. Katz and Martin (1997) argued that firms can obtain a range of resources and skills to solve practical problems through collaboration between scientists from different disciplines. Adams et al. (2005) believed that collaboration across discipline may lead to increased output, which may be due to the division of labor and the need for interdisciplinary collaboration. Open network may be conducive to reducing the redundancy of network resources, and therefore has a significant advantage in cooperation with researchers from different knowledge fields. Hence, this paper proposes the following hypothesis:

Hypothesis 3: The clustering coefficient negatively affects the firms' innovation output

III. Data, Variables and Research Methods

3.1 Data

This paper takes the co-patent network in the mobile phone industry in China as the research context, and uses the Chinese Patent Full-text Database (CNKI)as the data source. Since this paper focuses on the patent cooperation on the firm level, the patent search is based on the applicant name. Specifically, we first click the patent option button on the China Knowledge Network homepage and select the advanced search option. Second, we click the Chinese patent button and enter the following search statement: applicant = (company) or (group) and the main classification number = H04M.Third, we include the invention patent only and eliminate the utility model patent and the design patent. Considering the small number of patent cooperation between firms before 2003, only the data from 2003 to 2017 will be analyzed in the search results. In this paper, a total of 34,107 patent data were obtained, and the patent data was screened manually one by one. Since we are interested in the co-patent network, the patent which indicate that firms are independent right holders was deleted, which resulted 2288 patents. After calculation, we obtain 570firms which are involved in the 2288 patents.

3.2 Variables

3.2.1 Dependent Variable

Innovative output: The number of patent outputs is generally regarded as an important indicator for measuring innovation output. Therefore, this paper takes the firm's number of co-patents (NOPC) as the dependent variable.

3.2.2 Independent Variables

Degree centrality (DEGREE). The degree centrality measures the number of all direct ties by a node. In this paper, the degree centrality of firm *i* (DEGREE) is measured by the frequency of cooperation with other firms in the co-patent network that have a direct relationship with firm *i*. It is equal to the size of an actor's ego-network, and the formula is as follows:

$$DEGREE(N_i) = D_i$$

where D_i represents the number of firms with direct ties with firm *i*.

Structural holes (STRHOL). A structural hole is a non-redundant connection between two actors in a social network. Burt (1992) believed that structural holes provide opportunities for actors to gain "information benefits" and "control benefits" which may lead to competitive advantage. Constraint is generally used to measure structural holes. It refers to the ability of actors to use structural holes in networks. The higher the constraint coefficient, the fewer structural holes and the higher degree of network closure would be. The calculation formula of the structural hole:

$$C_{ij} = (P_{ij} + \sum_q P_{iq} m_{qj})^2$$

where,P_{ij} represents the ratio of the relationship of input q to the total relationship in all relationships of company *i*. p_{iq} is proportion of *i*'s energy invested in relationship with *q*, and m_{jq} is calculated as *j*'s interaction with *q* divided by *j*'s strongest relationship with anyone.

Clustering coefficient (CLUCOE). The clustering coefficient is a measure of the degree to which nodes in a graph tend to cluster together. In the network, if node *k, i*, and *j* has direct ties with each other, then a closed network is formed between the three nodes. The higher the probability that node *k* and any two other neighboring nodes can form a closed network, the higher the clustering coefficient of node *k* would be. On the contrary, the network where node *k* is located is more open. The formula for calculating the clustering coefficient is:

$$\mathrm{CLUCOE}(P_i) = 2\mathrm{E}(P_i)\ /\ C_D(P_i)[C_D(P_i) - 1]$$

where $E(P_i)$ represents the number of direct ties between neighbors of node *i*, and $C_D(P_i)$ represents the total number of companies adjacent to node *i*.

3.2.3 Control Variable

In order to eliminate the impact of other factors on dependent variable, the firm's size (SCALE) is used as a control variable.

3.3 Research Methods

In this paper, the social network analysis and the Poisson regression method are used. For the network embeddedness variables, the co-occurrence matrix for the co-patent network is obtained by the SATI software, and the matrix is analyzed with UCINET. Degree centrality, constraint coefficient, and clustering coefficient are all derived from UCINET. The information on the patent cooperation is obtained from the Chinese Patent Full-text Database.

Since the number of patent cooperation is taken as the dependent variable and the value of the dependent variable is a non-negative integer, such data are no longer subject to the normal distribution, and may be subject to the Poisson distribution or the negative binomial distribution. The count model is more suitable than a linear model. In the empirical research, the Poisson regression model and the negative binomial regression model are compared. The fitting index of the Poisson regression model is better than the negative binomial regression model. Therefore, the Poisson regression model is finally selected. The regression model is as follows:

$$\mathrm{E(NOPC)} = \exp(\alpha + \beta_1 DEGREE + \beta_2 DEGREE \times DEGREE + \beta_3 STRHOL + \beta_4 CLUCOE + \beta_5 SCALE)$$

Its log-linear regression model is as follows:

$$\ln[E(NOPC)] = \alpha + \beta_1 DEGREE + \beta_2 DEGREE \times DEGREE + \beta_3 STRHOL + \beta_4 CLUCOE + \beta_5 SCALE + \varepsilon$$

IV. Empirical Research

3.1 Mapping the co-patent network

In this article, the co-patent network in the mobile phone industry is obtained by mapping the co-occurrence matrix of the co-patent network, as shown in Figure 1.

As shown in Figure 1, the largest component is the co-patent network connected with the State Grid Corporation. There are 87 firms which has direct ties with the State Grid Corporation. During the research period, the State Grid Corporation and its partners shared the same in the mobile phone industry, with 94 co-patents. The Second largest component is the co-patent network connected with China Mobile Communications Group. There are 14 companies with direct ties and 26 co-patents. In addition to these two largest components, the co-patent network with Hon Hai Precision Industry Co. Ltd. includes 14 firms, and the co-patents in the mobile phone industry has the largest number of 441.

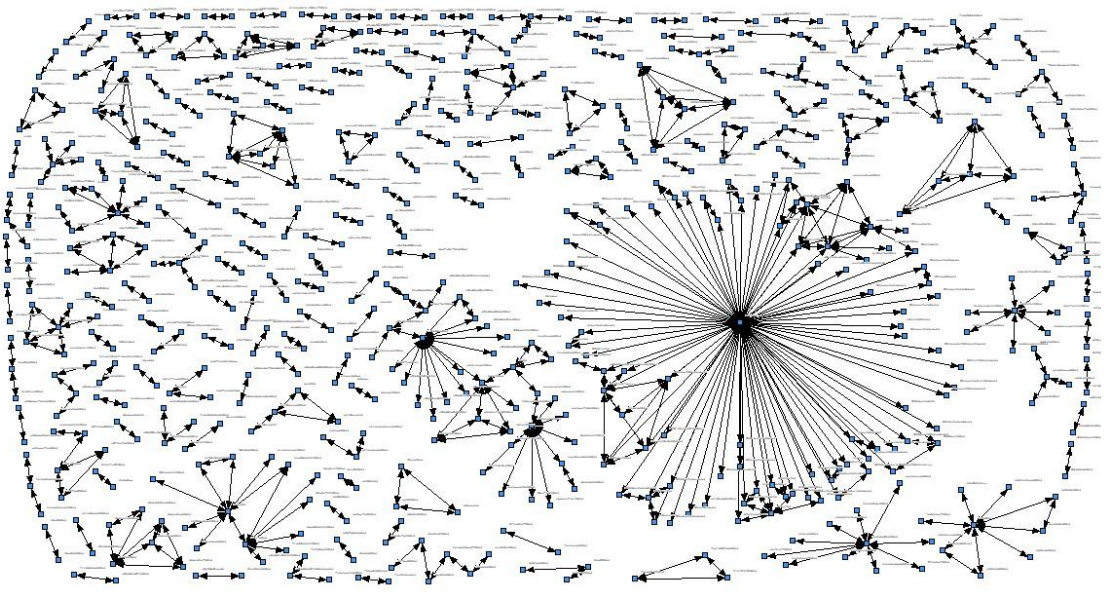

Figure 1*The co-patent network of the mobile phone industryinChina*

3.2 Empirical Results and Discussions

In this paper, the number of firms involved in the co-patent network in the mobile phone industry is 570. First, descriptive statistical analysis and collinearity analysis were performed on all variables by statistical software SPSS. As can be seen from Table 1, the average number of patent cooperation is 7.56; the average value of the degree centrality is 1.75, indicating that each firm has nearly 2 collaborators. In addition, the value of the variance inflation factor is less than 10, indicating that the problem of multicollinearity is not serious.

TABLE 1 *Descriptive statistics of variables*

	Minimum	maximum	Mean	Standard deviation	VIF
DEGREE	1	87	1.75	3.686	1.231
STRHOL	0.035	1.784	0.938271	0.1922127	1.486
CLUCOE	0	104	1.226838	8.4990358	1.205
SCALE1	0	1	0.31	0.462	1.552
SCALE2	0	1	0.42	0.493	1.467
NOPC	1	441	7.56	33.720	

TABLE 2 *Correlation matrix*

	DEGREE	STRHOL	CLUCOE	SCALE1	SCALE2	NOPC
DEGREE	1					
STRHOL	-0.400**	1				
CLUCOE	0.020	0.335**	1			
SCALE1	0.153**	-0.246**	0.092*	1		
SCALE2	-0.090*	0.162**	-0.069	-0.563**	1	
NOPC	0.199**	-0.137**	-0.012	0.271**	-0.152**	1

** Significant at the 0.01 level (two-tailed test)，* Significant at the 0.05 level two-tailed test).

It can be seen from the correlation matrix in Table 2 that the degree centrality and the number of co-patents is significantly positively correlated, indicating that the larger the size of the firm's ego-network, the more co-patents will be obtained. The number of co-patents is significantly positively correlated with the firm size, indicating that larger firms will have more patent output than smaller firms. The clustering coefficient and the number of co-patents is related, but this relationship is not significant.

3.3 Poisson Regression Results

In order to more accurately discuss the relationship between the structure embeddedness and innovation output, the Poisson regression model was established with the co-patents as the dependent variable. The analysis results are shown in Table 3. As can be seen from Table 3, the model has a fitting coefficient of0.236923 and LR statistic of 8837.202, and a probability value of LR statistic of zero, indicating that the fit between the model and the data is good.

TABLE 3 *Poisson regression results*

	β coefficient	Z Statistics	Sig.
DEGREE	0.494638	47.72868	0.0000
DEGREE*DEGREE	-0.004984	-47.19535	0.0000
STRHOL	3.233303	27.50807	0.0000
CLUCOE	-0.070989	-9.391925	0.0000
SCALE1	2.543984	37.70938	0.0000
SCALE2	-0.012778	-0.154228	0.8774

R^2(Adjusted R^2)	0.236923(0.229356)
LR statistic(8df)	8837.202
Probability (LR stat)	0.000000

The degree centrality has a significantly positive impact on the number of co-patents (β_1=0.494638, p=0.0000), while the square of degree centrality has a significantly negative impact on the number of co-patents (β_2=-0.004984, p=0.0000), that is, the degree centrality has an inverted U-shaped impact on the number of co-patents. This result supports hypothesis 1, indicating the firm may increase innovation output by maintaining a moderate level of cooperation.

The number of structural holes has a significantly positive impact on the number of co-patents (β_3=3.233303, p=0.0000). This result supports Hypothesis 2, indicating that more network structural holes locations may contribute to the innovation output.

The clustering coefficient has a significantly negative impact on the number of co-patents (β_4=-0.070989, p=0.0000), which supports hypothesis 3, indicating that the smaller the clustering coefficient, the more innovation output will be.

For control variables, the size of the firm has a significantly positive impact on the number of co-patent (β=2.543984, p=0.0000, β=-0.012778, p=0.8774), indicating that larger firms may be in a better position to increase in the innovation output.

3.4. Discussions

There is a significant inverted U-shaped relationship between degree centrality and innovation output, which means that there is optimal cooperation size in patent cooperation. The results are different from that of Chi (2015), who argues that network centrality has a positive effect on innovation output. This paper believes that knowledge creation requires information exchange between firms, and the exchange and combination of diverse and heterogeneous knowledge promotes the generation of new knowledge. This means that the firms can further expand the breadth and depth of the relationship through the cooperation network, thereby improving innovation output. The higher the degree centrality is, the more direct ties the firms have in the co-patent network, the greater access to knowledge and resources, which has a positive impact on innovation output. However, it cannot be simply assumed that the higher the degree centrality is, the more innovation output would be. Although the increase in the number of relationships will improve the potential for firms to create new knowledge, more ties may also lead to cooperation costs that outweigh the benefits and negatively affect the innovation output.

The structural hole index has a significantly positive impact on the innovation output, which means that the larger the structural hole index is, the more closed the co-patent network will be, and the more favorable it is to improve the innovation output. This confirms the importance of network closure for knowledge acquisition and innovation, consistent with most previous research findings. For example, Hansen (1999) argues that dense, interconnected networks enhance the actual transfer of rich non-coded information. This paper argues that the cohesiveness of closed networks may not only increase the scope and speed of information transfer between firms, but also provides them with additional assurance on how to use this information. Closed networks reduce the uncertainty of resource exchanges and can also inhibit opportunistic behavior of partners, thereby increasing innovation output.

The clustering coefficient has a significantly negative impact on innovation output. This means that the smaller the clustering coefficient is, the more diverse the cooperative network will be. In a diversified cooperation network, the direct links between firms are reduced, and the information and knowledge that are owned by each other are more likely to be non-redundant. Actors with such non-redundant ties can access partners who understand different information and knowledge, and the non-redundancy of information makes partnerships more valuable. Oliver (2004) argued that the information superiority of diversified networks derives from the diversity of actors, while the control advantage stems from the relative lack of information. The lack of linkages between actors' means that the information obtained from any one ties may be scarce and therefore more valuable to others. This paper argues that firms can effectively enhance innovation output by acquiring non-redundant resources and controlling information in open networks.

V. Conclusion

Based on social network theory, the article takes the co-patent network of China's mobile phone industry from 2003 to 2017 as the research object. Poisson regression model is used to investigate the impact of network structure embeddedness on innovation output. The empirical research results show that, (1) there exists optimal cooperation size for firms in the co-patent network, that is, moderate degree centrality may mean higher innovation output; (2) occupying more structural hole positions in the co-patent network may increase firms' innovation output; and (3) higher clustering coefficients significantly reduce firms' innovation output.

This study also suffers some limitations. First, we use co-patent to measure the cooperation between firms. Future studies may collect cooperation data through other channels, such as sampling and questionnaires. Secondly, the empirical results by taking the mobile phone industry as an example may not be generalizable to other industry, and more cases and empirical analysis are needed to verify the conclusions of this paper.

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