

Impact of Network Centrality Positions on Innovation Performance of the Firm: Evidence from China Automobile Industry

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Abstract

Innovation has attracted attention of researches in last 20 years, while networks and clusters are relatively new research subjects. In our paper we made an attempt to find the relationship between network centrality indexes and innovation performance. Each index represents different features of being in the network. To find the network indexes we have constructed adjacency matrixes based on alliance data. For our research we have chosen China's automobile industry network as an example, for the reason that Chinese automobile industry showed tremendous growth in recent decade and is fit to research scope which we are conducting. We have collected the data on innovation performance for 59 firms in China's automobile industry. We used UCINET software program to get the data regarding network properties. After we ran the negative binomial regression model on Gretl software program and constructed 5 models, with total of 7 variables. We have analyzed the relationship between innovation performance and three network centrality measures. According to our new findings firms in the network with more total number of connections and firms with more connections with well-connected firms have better innovation performance. We found

that there is no effect on innovation performance when firms have capability to pass information fast.

Keywords: Innovation, Networks, Eigenvector centrality, Closeness centrality, Degree centrality

1. Introduction

Economic theories of firms mostly were focused on external environment of organizations in context of competition and resource availability and networks were considered as beneficial sources for partnership until the researches proved that it is broader than that. According to Laumann et al. (1978) a social network can be defined as a set of nodes (e.g., persons, organizations) linked by a set of social relationships of a specified type. The original focus of network research was on understanding how the embeddedness of individuals influences their behavior, later the same approach has been extended to organizations (Burt, 1982; Walker, 1988; Mizruchi, 1992; Gulati, 1998). Firms can be interconnected with other firms through a wide array of social and economic relationships, each of which can constitute a social network. These include supplier relationships, resource flows, trade association memberships, interlocking directorates, relationships among individual employees, and prior strategic alliances. Network perspectives are based on common understanding that economic actions occur not in vapid social context, but integrated into social network relationships. Networks can benefit in a lot of aspects such as expanding the customer base of a firm, sharing costs and risks, learning new technologies through knowledge exchange and trainings, conducting common R&D projects (NESC, 1996), increasing the speed of reacting to market and technological changes.

O'Doherty (1998) summarized the benefits of networking as follows:

- material benefits: firms can increase sales and lower production costs by working together;
- psychological benefits: as firms eliminate their isolation they learn that their problems are shared by others;
- developmental benefits: by promoting interaction with other firms, networking increases learning and the ability to adapt to the changing economic environment.

We can see that firms which are in networks have higher survival chances and that with support of alliance partners firms can increase their innovativeness, enhance economic performance and even their goodwill. It seems that to be in networks is beneficial for firms, but do all network members get same advantages? Question on studying advantageous positions in the network becomes significant, along with the need to know what kind of partners should be chosen for getting into alliance partnership, because there is a high chance that each new partner can be the source of new opportunities for the firm. In the end each new partner itself is a member of some network, so partnership with one new firm, can possibly bring access to knowledge of other firms. These all lead us to have this research and study the effect of positions in the network on innovativeness of the firm.

2. Literature Review

According to the literature reviewed, actors join networks in order to: (1) share the costs and risks of innovation (Penrose, 2008); (2) take advantage of the superiority of networks in

terms of transaction costs (Kogut, 1988; Coase, 1988; Williamson, 1991; 1975), thus reducing risks of opportunism and economic friction between partners along with misunderstandings and conflicts that may lead to delays, breakdowns, and other malfunctions (Williamson, 1994); (3) take advantage of strategic and resource-based fit (Kogut, 2000); (4) benefit from social and cultural fit among actors (Eisenhardt & Shoonhoven, 1996); and (5) benefit from trust in network dynamics (Ring & Van de Ven, 1994). On the other hand, Sociology is based on exchange theories (Emerson, 1962; see also Molm, 2003) in which the main assumptions are that network formation is the result of: (1) an actor's behavior motivated by the desire to increase gain and avoid loss; (2) exchange relations developing into structures of mutual dependency and power dynamics; (3) actors engaging in recurrent, mutually contingent exchanges with specific resources and partners over time; or (4) valued outcomes obeying the economic law of diminishing marginal utility (Molm et al., 2000; Molm, 2003) which leads to the principle of equilibrium that is presented later.

On this basis, Exchange theories predict that the behavior of individual and autonomous actors depends on exchange dynamics and its effects as outcomes in the structure itself (Emerson, 1962; 1987; see also Molm, 2003). This requires a closer look at structural dynamics and the notion of power and governance.

3. Network Estimation and Construction

In this research in order to construct and estimate China's automobile industry we will have to use strategic alliances in this industry and build up innovation networks. For this we will use strategic alliance as the relationship between enterprises to build innovation networks, and construct China's automobile industry unbalanced panel data for definite period, this period is from 2002 to 2009 due to data eligibility. Obtaining the data included the following five procedures: first we established the strategic alliances database of China's automobile industry, then we formed the alliance network, third step included independent variables' acquisition and Network indexes calculation, fourth step was the work on Control Variables, and last we worked on dependent variable—acquisition and statistics of enterprises' patent data.

4. Strategic Alliances Database and Network in Chinese Automobile Industry

We used eligible data sources from Thomson Corp.'s SDC Platinum database to obtain China's Automobile industry data. Periods we collected the data on alliances announced is in range during the year of 2000 to 2009.

As an emerging industry in recent years of China, automobile industry has been chosen as objective for our samples due to its representativeness. Each enterprise's own industry it belongs to is dependent on the primary four-digit SIC (automobile 3711, 3713, 3714), and the sample will include listed companies and non-listed companies.

We used two steps to construct the database of China's automobile strategic alliances. First,

alliance information extracted according to rules, which we establish as followed: there should exist at least two Chinese enterprises in each alliance; each alliance should include at least one firm that was a member of the target industry or operated in the target industry. Second, due to some non-standard data which is common for SDC Platinum database, such as names' incorrectness of alliances partners, missing of corporate names, the enterprise's industry classification errors, thus as for the alliance information selected, we should make the efforts of proofreading, information errata, modification, complement, perfecting and then translate them into Chinese for final check of data. Eventually we form a "strategic alliance database of China's automobile industry".

Tortoriello & Krackhardt (2011) argued that, in strategic alliance network, the strength and direction of ties have no influence on the information communication and innovation. Hence, we construct inter-enterprise innovation network as maps without direction and weight. The participants in the network are enterprises forging the strategic alliance which is the event formed the relationships within different roles.

Alliance data are naturally equivalent to Bipartite networks. Adjacency matrixes are corresponded to networks and can be transformed into each other. Adjacency matrixes can be generated directly by alliance data or bipartite graph. By using graph theory, bipartite graph are converted into several fully linked cliques, which depend on the ties to the same player who has participated in several alliances.

Alliances typically last for more than one year, but alliance termination dates are rarely reported. Many researches have used windows ranging from one to five years (Gulati and Gargiulo 1999; Stuart 2000), while our research assumed that alliance relationships last for three years. So we have used three-year windows based alliance network. Then we used UCINET computer program to build those networks. In the end we had the graph with formed network of China's automobile industry for specific period. (2000-2009).

5. Hypotheses

5.1 Innovation Performance and Eigenvector Centrality

Eigenvector, power, information, influence are similar centrality measures and count the number of walks. In a walk you can repeat edges and nodes but it weights each walks inversely by its length. Short link is weighted more heavily than long walks. They basically measure influence. (Diederik van Liere, 2004). Eigenvector is higher if it is connected to other well-connected nodes, so it measures popularity and power. We can assume that more popularity and power of influence on others can increase the innovativeness of the firm and we propose the hypothesis.

Hypothesis 1. A firm's high level of influence and popularity in the network is positively related to the firm's innovation performance.

5.2 Innovation Performance and Closeness Centrality

The measure pertains to the closeness of an actor in relation to all the other actors in the network. Firms are considered to have high level of closeness when they can quickly react with others. In the closeness concept, a central ego actor has minimum path distances from the $g-1$ alters. An actor that is close to many others can quickly interact and communicate with them without going through many intermediaries. Thus, if two actors are not directly tied, requiring only a small number of steps to reach one another is important to attain higher closeness centrality. It is an index which shows the expected time until arrival for given node of any flow in the network, in other words it is a “gossip network” measure, where “central player” hears first the information. It is known that information is crucial for innovation performance of the company, but beside of information quality, it is important to have the speed of necessary information in order to have on-time competitive information. So we can assume the following hypothesis:

Hypothesis 2. The high speed of information flow in the network to the actor has a positive effect on innovation performance of the firm.

5.3 Innovation Performance and Degree Centrality

Network position describes the pattern of interaction between firms in a cluster. The degree of which an individual actor is connected to others in a network is called centrality (Borgatti et al., 2002). Centrality is used to obtain the positional features of an individual firm within networks. An individual firm's centrality captures the extent of its access to knowledge. A firm's network position reveals its ability to access external information and knowledge. By occupying a central position in the network, a firm is likely to access desired strategic resources, such as knowledge and skills. Such resources will fuel the firm's innovative activities by providing the external information necessary to generate new ideas. Equally, the innovative work of firms will benefit from access to the new knowledge necessary to resolve the designing and manufacturing problems. However, such complementary knowledge is not distributed unevenly between firms in a cluster. For these reason, it is important for firms to locate themselves in a central position in order to gain access to knowledge benefits from their network linkages, which in the end can help to innovate more. Hence, the following hypothesis is proposed:

Hypothesis 3. A firm's centrality of network position in a cluster is positively related to the firm's innovation performance.

6. Variables Measurement

As we mentioned we will use negative binomial regression model due to our count data. We will make our regression on Gretl software and will present results in results section. We should make in total 5 models. For this we have in total 7 parameters.

Dependent Variable.

Innovation performance. In general most studies categorize innovation performance in to two dimensions: innovation quantity and innovation quality. Innovation quantity is measured as the number of patents granted to a firm in a given year. Due to more objectivity of this way of measurement of innovation performance we will use number of patents as our dependent variable in the model. We will measures the number of successful patent applications for firm i in year t . We will use the State Patent Bureau to collect yearly patent counts for each of the firms. One patent could be invented by several companies, and it will be aggregated into each company's patent counts, respectively. In our research overall number of patents is the sum of the number of radically new "clear" patents, which represent pure technological innovation, number of Utility models and the number of Designs for the firm i year t .

Independent variables

Eigenvector centrality. Eigenvector centrality refers to the extent to which an actor is central due to the centrality of the actor to which it has ties (Borgatti et al., 2002). Therefore, a firm can be central through interaction because it is connected to another firm who is highly central. Relating this to access to innovative information, a firm who is high on eigenvector centrality is connected to many firms who are themselves connected to many firms, thus multiplying interconnection of important information.

Closeness centrality. Closeness centrality is the reciprocal of farness, while the farness of a node is the sum of the lengths of the geodesics to every other node. It is in formula:

$$C_c(n_i) = \left[\sum_{j=1}^n d(n_i, n_j) \right]^{-1} \quad [5], \text{ where } d(n_i, n_j) \text{ denotes the distance between } n_i \text{ and } n_j$$

(Borgatti et al., 2002).

Closeness can be calculated only for a connected graph, because distance is "infinite" (undefined) if members of a nodal pair are not mutually reachable (no paths exist between i and j). However, UCINET will compute separate "in" and "out" closeness scores for a nonsymmetric matrix.

Degree centrality. Degree centrality refers to a count of the number of ties an actor has, meaning the number of organizations the actor is in contact with. It can be defined as follows: $CD(n_i) = d(n_i)$ [4], where $d(n_i)$ is the sum of the nodes adjacent to i node (Borgatti et al., 2002). Degree centrality illuminates the most visible actors in the network.

Control Variables

Firm age. The number of years since a company was found. This variable has been used in some researches as a control variable (Sorensen and Stuart, 2000) and can have control function, because of its availability of data for all companies. Firm age is related, to a certain extent, to the level of experience and managerial competences of the firm in carrying out innovations (Huergo and Jaumandreu, 2004). We calculate a firm's age from its starting year

of operations to 2009.

Firm size. The link between innovation and firm size has long been a debated issue in the innovation literature (Freeman and Soete, 1997). Most empirical studies regarding innovation performance include firm size as a control variable. We use the logarithm of sales as a control variable for the firm size effect (Lu and Beamish, 2004).

R&D centers. As we mentioned in literature review part of our paper in all innovation related researches R&D factor has been taken as crucial and the one with highest probability to influence on innovation capability. Here we use presence of own R&D centers in firms. We do not include research centers which are in balance of other branches or institutions, also we do not include R&D centers hold by maternal company and owed by universities. We use dummy variable, where, if 0 firm does not have any R&D center for its own, and 1 if there is any R&D center owed by the firm.

Table 1. Summary statistics and correlations matrix*

	Min	Max	Mean	Std. Dev.	1	2	3	4	5	6
1 Innovation performance	1	1139	35.707	114.251	1					
2 Eigenvector	-0.447	0.545	0.013	0.125	0.11	1				
3 Closeness	1.099	2.937	1.705	0.456	-0.02	0.10	1			
4 Degree	0	9	2.477	1.481	0.05	0.19	0.25	1		
5 Firm age	0	162	26.972	29.498	-0.005	-0.008	0.02	0.05	1	
6 R&D centers	0	1	0.663	0.473	0.20	-0.16	-0.12	0.03	0.23	1
7 Firm size	15.42	25.66	21.188	2.290	0.12	0.02	0.15	0.15	0.56	0.43

*Correlation coefficients calculated by using the observations 1:1 - 59:8, (missing values were skipped), 5% critical value (two-tailed) = 0.0903 for n = 472

7. Data Processing and Statistical Analysis of Results

According to our research method first we have made adjacency matrixes for each year of alliance data. Each year matrix includes only alliances for three years prior to year of observation. For example, if the observation year is going to be 2002, so it includes alliance data for 2000, 2001 and 2002. For 2003 adjacency matrix it will still include the data for

2003, 2002 and 2001 but will not take into consideration the data of 2000, because we consider that alliances have the power only for three years. When we calculate network related data we include all the companies in the alliance, if there is at least one Chinese automobile industry representative company, but when we make our regressions we took off from our sample companies which do not have enough number of patents, in order to avoid excess zeroes in our initial data. The total number of companies in alliance data is equal to 161. We include all companies in network analysis, but only 59 companies had enough innovativeness level and we included only them into our sample, when we used our regression analysis.

To get the data for variables degree centrality, eigenvector centrality, closeness centrality we used the prepared adjacency matrixes to run the Ucinet 6 software program and got the data for all firms for the years from 2002 to 2009.

The data is suitable for using panel form. We collected number of patents, utility models and designs for 59 firms from the web-site of State Intellectual Property Office of People's Republic of China www.sipo.gov.cn for each year from 2002 to 2009. The initial data has been translated and checked several times in order to avoid mistakes and double counting.

The highest amount for number of overall patents was 1139 for one observed year and minimum was 1 patent which has been registered for one year of observation. We present summary statistics and correlation matrix in table 1. None of our variables have a multicollinearity problems regarding to each other.

Table 2. Negative binomial regression: Innovation performance (n=59)

	Model 1: Control only		Model 2: Eigenvector		Model 3: Closeness		Model 4: Degree		All predictor variables	
			Hypothesis 1.		Hypothesis 2.		Hypothesis 3.			
	C.	S. e. (sig)	C.	S.e. (sig)	C.	S.e. (sig)	C.	S. e. (sig)	C.	S. e. (sig)
Eigenvector			2.06766	1.01**					1.37	0.87*
Closeness					-0.35	0.30			-0.41	0.23
Degree							0.055	0.09*	0.36	0.11***
Firm age	-0.01	0.00***	-0.01	0.00***	-0.01	0.00***	-0.01	0.00***	-0.01	0.00***
RnD centers	2.51	0.19***	2.59	0.29***	2.51	0.33***	2.54	0.29***	1.21	0.27***
Firm size	0.14	0.04***	0.11	0.06*	0.16	0.07**	0.13	0.06**	0.23	0.06***
Constant	-1.43	0.83*	-0.82	1.23	-1.12	1.29	-1.38	1.20	-1.03	1.30

Log likelihood		-1751.14		-833.59		-822.38		-835.91		-575.88
Alpha	2.34	0.13***	2.31	0.19***	2.34	0.19	2.35	0.19	1.20	0.13***

***P<.01, **P<.05, *P<.10

Control variables had negative signs in some of results and they were minor and low level of correlation with other parameters, if not to take into consideration the relationship between control variables itself. In order to check our hypotheses we have used Negative binomial regression model on software Gretl. We did not use Poisson regression because of possible overdispersion in data. In our regression analysis data has been interpreted in time-stacked panel form. We use Negative binomial regression also because our data regarding dependent variable is count data.

8. Discussion of Results

In model 1 we use only control variables to check their significance and they show the high level of significance and it has been proved by other researchers. Model 2 is designed to test innovation performance with eigenvector centrality, which represents popularity and power in the network. Regression results show that there is a positive and significant relationship between innovation performance and eigenvector centrality. We can conclude that hypothesis 1 has been accepted and confirmed, which states that a firm's high level of influence and popularity in the network is positively related to the firm's innovation performance. This means that firms which are connected to well-connected firms, and particularly when there are more such connections for firm in the network, this firm can have better innovation performance, due to better information access and due to higher number of possible channels for information to come. In the end it can have its influence on knowledge absorption, because of its quantity. In other words, there is a higher chance for innovative idea, when there are more valuable information channels, which in the end gives the power and as a result popularity. This kind of position can also give the power of controlling the information, which can give more attractiveness to other firms to cooperate, or to have an interest in exchanging of existing knowledge of their own. Model 2 shows, that for each additional coefficient of eigenvector centrality, there is a possibility to have 2 more patents for the firm. So we can conclude that increasing of power and popularity in the network can result to more innovation and for this, firms should first of all have cooperation and alliance agreements with the firms who already have a reasonable number of alliances and network links with other firms.

Relationship between innovation performance and closeness centrality has been performed in Model 3, where according to hypothesis the high speed of information flow in the network has a positive effect on innovation performance of the firm. Regression results for this model showed the opposite results with negative effect and statistical insignificance. The idea here

was that the speed and possibility to reach other actors in network as fast as possible can positively influence on innovation performance, through the fast knowledge access, when it is necessary in new technology construction. In our sample China automobile industry network is structured on the basis of alliances, which are strong official relationships but usually they have the limited number of links in overall network. We can assume this is the reason why the closeness centrality is not sufficiently significant for innovativeness of firms. Firms simply don't have the enough number of close relationships with each other, it seems that firms splitted to small groups and there united in some small clusters. As soon as there are gaps in some links, the closeness can't be that important in the process of creating the new patents as could seem. In next model we check the hypothesis 3, which proposes that a firm's centrality of network position in a cluster is positively related to the firm's innovation performance. The results show that indeed they are positively and significantly influence on innovation performance, although we had to accept it with 10% error probability. In the model, where all variables are included eigenvector centrality showed even higher significance. Closeness centrality was negatively related and still was insignificant, so in any way we have to reject the hypothesis 2. Degree centrality was positively and significantly related to innovation performance. So here are summary results concerning hypothesis and significance level of each variable on table 3.

In summary, we have made analyses on relationship between innovation performance and different parameters of network location. We tested three centrality measures.

Table 3. Summary results for all variables where innovation performance is dependent variable

Variable	Significance	Hypothesis	Results on relationship with innovation performance
Degree centrality	Significant	Supported	Positive
Eigenvector centrality	Significant	Supported	Positive
Closeness centrality	Insignificant	Rejected	Unclear
Firm age	Significant	Control	Negative
R&D centers	Significant	Control	Positive
Firm size	Significant	Control	Positive

Two centrality measures, such as eigenvector centrality and degree centrality were confirmed to be positively and significantly related to innovation performance, which actually was proposed in hypothesis. Closeness centrality is measured in order to find the speed of information flow, and as we see in our network it does not make an essential effect on innovation performance, beside of it, it had a negative relationship; it is actually different vector than what we were expecting. It means that more future research should be done

concerning relationship between speed of information flow in the network and innovation performance. When the coefficient is insignificant and also has different vectors in models, it is very hard even to assume the possible relationship between variables, if there are any.

Also we should discuss control variables, as they also effect on innovativeness of the firm. We used firm age, R&D centers availability and firm size as control variables. These variables were used by many researchers as an important factor which can impact on innovation performance. In our results we got same conclusions as other researchers. They all were significantly related to innovation performance of the firm. But we had one exception were firm age was negatively related to innovation. And we can explain it with conjuncture in the automobile market and also with overall world's technological progress. Firms are making more innovation in recent years, despite of fact that they are still young companies, because there is strong and consecutive overall technological progress. Beside of it, most of companies in China start their business with a sufficient investment amounts, due to their state support with financial privileges. This puts old companies and young companies to the same financial position, where young unexperienced firm can allow itself the access to the same technology and equipment as the old ones do. As the result we have a relationship, which says where the younger the firm is, more it can be innovative, where is important to mention that the reason is not on the age of the firm, but in world's overall technological progress, financial support by government in China, and Chinese market conjuncture.

9. Conclusions

In this research we have provided sufficient arguments that connections with more number of alliances in the network and connections with well-connected partners is positively and significantly effects on overall innovation performance. Finally, below we will summarize our new findings and contribution to the field in this research:

1. We found that the speed of knowledge and information arrival is not crucial in firm's innovativeness. It can help CEOs not to be distracted with the claim of partner to be the one who is well located and has a central player role. This benefit in fact does not essentially help to increase the innovation.
2. We found that simple well connection and direct influence has a significant and positive effect on innovation. It supports the idea that the quantity of connections is essential and that firm's should try to increase the number of new contacts, and it is not necessarily has to be an alliance-partner-firm. The suppliers, branches, buyer companies are also can be a good source of knowledge and this kind of direct influence can help increase the overall innovativeness.
3. We found that to be connected to well-connected firms can improve the innovation performance of the firm. It can help CEOs to choose partners for cooperation, when they do their researches. So they should stop their choice, if factors are equal, on the ones who are well-connected to other companies.
4. We found that in China automobile industry young companies are more successful in

registering new patents, utility models and designs, than the ones who are operating for a very long time. This fact can help to other researchers, when they want to include firm age as a factor influencing to innovation performance that they should be cautious with this variable and should take into account that it can be different to different industries and markets.

5. We confirmed that availability of own research and development centers and bigger firm size is a significant factor which effects on innovation performance. This information is useful for future academic purposes.

Executives in developing new strategies with focus on increase of innovativeness also may take into consideration those factors which were analyzed in our research, particularly in choosing new partners.

We derive our empirical results from a sample of China's automobile industry, thus raising the concern about the external generalizability to other sectors and industries, so recommendations still should be used with caution. Future research is therefore suggested to empirically test the validity of the framework and hypotheses in other high-tech industries. Secondly, we use only patent counts and they are proxy measures of innovation performance. We suggest for further studies use also other measures such as patent citations or number of new products.

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