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How strong clustering and centrality position in the alliance network impacts on innovation performance?

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***Abstract**: Innovation in networks and in clusters recently attracted attention of scholars from management science and engineering. In our paper we made an attempt to find the relationship between centrality position with short path length between nodes and innovation performance. Also we examined another relationship between clustering coefficient and innovation performance. In order to find the network indexes we have constructed adjacency matrixes based on alliance data. As a sample we have used China's automobile industry network. 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 4 models, with total of 6 variables. According to our new findings there is no effect on innovation performance when firms have a short path length between nodes in the network and found that strong local clustering has a negative effect on innovation performance.*
Keywords: *innovation, networks, clustering coefficient, betweenness centrality*

I. Introduction

Innovation as a key factor influencing on overall economic performance attracted the interest of most researchers in field of management science. There are a lot of factors which can impact on innovativeness of the firm, where knowledge flow is considered one of the most significant ones. Innovation is a complex process with interaction of different factors. As alliance networks are the outer environment which can support knowledge flow, we believe that such networks, interactions and positions of the firm in it should be studied deeply. The cluster concept focuses on the linkages and interdependencies among actors in value chains. It goes beyond the traditional ideas on clusters, which involved horizontal networks of firms operating on the same end-product market in a same industry group [1]. In our paper we study local clustering within the alliance network based on Chinese automobile industry. In our opinion links in alliance networks are stronger and carry some obligations for sides, hence this kind of relations can positively impact on innovation processes. Also we study the location of nodes in the alliance network and we are interested in questions on effects of positions in the network on overall innovativeness of the firm.

II. Literature Review

Network is defined as a set of actors who are interconnected by a series of relationships [2]. Among the many types and existing definitions of Networks and Business Networks [3], Networks of Innovation highlight the fact that firms can not innovate alone, requiring searching for and engaging in productive relationships [4, 5, 6].

According to the literature reviewed, studies on Networks of innovation can focus on the types of innovation involved, on network functions, clusters, and structural attributes such as "innovativeness" and structural change. Scholars conducting researches on innovation related networks first examine the type of innovation, to define if these networks stimulate radical or continuous innovations [7] or unique or systemic changes [8]. Here, innovation studies emphasize the level of connectivity between complementary components [8,9]. Studies on network functions encompass diffusion [10] or – in very few analyses - on innovation generation [11,12], temporary entrepreneurial structures [13], or even transitional organizations placed at the meso-level of analysis, between industry structures, markets and business organizations [14]. Other studies focus on networks as "innovation clusters" or "hot spots", revealing the dependencies of contemporary firms upon their network relationships. Clusters enable and support business by raising productivity, the speed of innovation, and the faster formation of new companies [15, 16]

Finally, structural studies examine focal firms, relational dynamics, network density, positions and the network capacity of "innovativeness" [17,18,19]. They focus on processes of innovation and dynamics [20, 21] that are normally expressed as the generation of paths or trajectories [22, 23]

III. Data Sampling, Network Estimation And Construction

In order to construct and estimate Chinese automobile industry we have used strategic alliance as the relationship between firms to build innovation networks, and constructed Chinese automobile industry unbalanced panel data period from 2002 to 2009 due to data eligibility. To obtain the data we established the strategic alliances database of China's automobile industry, then we formed the alliance network, after that we collected data for independent variables and calculated network indexes, also collected data for control variables, and last worked on dependent variable acquisition which was based on collecting patent data for all firms for the period of observation.

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.

China's automobile industry has been chosen as object for our research because of impressive statistic results in terms of emerging in the industry in recent years. 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.

Tortoriello & Krackhardt [23] 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 [24,25] 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 and NETDRAW software to show those networks. In the end we had the graph with formed network of China's automobile industry for specific period. (2000-2009).

IV. Hypotheses

4.1. Innovation performance and betweenness centrality.

Short path lengths ensure that diverse sources of information can be tapped. [26] Therefore, we argue that networks with short path lengths will significantly enhance innovation performance of member firms [27,28,29].

On the organizational level, Ahuja [30] provided evidence against structural holes, in a study on collaboration networks in the chemical industry. Walker et al. [31] provided evidence in support of cohesion, in a study in the biotechnology sector. On the interpersonal level, McEvily and Zaheer [32] provided evidence against redundancy in an advice network, for the acquisition of capabilities. Burt [33] found similar evidence in favor of structural holes, for managers to come up with valuable ideas. On the other hand, Reagans and McEvily [34] found support for cohesion in a study on knowledge transfer, but combined cohesion with range. This last study is part of a stream of literature on interpersonal networks that, as a result of the discrepancy of the empirical results listed above, has considered that an 'optimal' network may need to contain both structural holes as well as social closure.

Podolny and Baron [35] were amongst the first to acknowledge that "where structural holes can provide managers with opportunities, social closure can provide the cooperative behaviour needed to explore those opportunities". Others have made similar claims [34,36,37]. Small world literature stipulates that high levels of clustering enhance trust, which promotes cooperation and resource or risk sharing between firms [28]. We will propose the hypothesis that clustering is positively effects on innovation of the firm.

Shorter path lengths, on the other hand, give firms faster and easier access to new information, even if firms are geographically far apart. Short path lengths, together with frequent and in-depth exchange of information e.g. through long-term strategic alliances makes these firms, be it geographically far, very proximate in social space [38]. Based on this discussion, we find that short path length increases the innovation performance of firms. Nodes with high betweenness centrality have a high load placed on them, lending them importance in the network. They are responsible for effective flows through the network, placing them in the role of gatekeepers, able to impede flows. Hence, we propose the following hypotheses:

Hypothesis 1. A short average path length between nodes in the innovation network has a positive effect on a firm's innovation performance.

4.2. Innovation performance and clustering coefficient.

Schilling and Phelps [29] also studied the impact of overall network structure on firm's innovation performance. In particular, they examined the effect of two large-scale network properties, clustering and reach, on the innovative performance of members of the network. The dense connectivity of clusters creates enables large amounts of information to rapidly diffuse Therefore, we argue that networks with high clustering will significantly enhance innovation performance of member firms [27; 28; 29]. Clustered relations facilitate trust and close collaboration [26,39,40]. As a consequence of this discussion, we formulated the following hypothesis:

Hypothesis 2. The high local clustering has a strong positive effect on innovation performance.

V. Model

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.

5.1. 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 used number of patents as our dependent variable in the model. We measured the number of successful patent applications for firm i in year t. We used the official web-site of State Intellectual Property Office of the People's Republic of China to collect yearly patent counts for each of the firms. If one patent invented by several companies it has been aggregated into each company's patent counts, respectively.

5.2. Independent variables.

Betweenness centrality. The variable related to a firm's alliance network is its betweenness centrality. Betweenness centrality measures the centrality of a focal firm in a network, and is calculated as the fraction of shortest paths between other companies that pass through the focal firm. Betweenness is, in some sense, a measure of the influence a focal firm has over the information through the alliance network. In other words, it also forms a network wide (global) measure and takes direct and indirect ties into account. This is important as this indicates how far a firm can reach potentially all (including distant) parts of the network. This provides us with an indication of the potential for novel combinations that a firm may have. So, the variable indicates the percentage of the shortest path node i involved in above all the shortest path in the network [41] It captures the extent to which a firm is located on the shortest path between any two actors in its alliance network.

$$BC_{it} = \frac{\sum_{j<k} g_{jk}(n_i)}{g_{jk}} \quad (1)$$

Where g_jk refers to the number of shortest paths between firms j and k, and gjk (ni) captures the number of shortest paths linking j and k that contain focal i.

Betweenness centrality index measures the degree of interconnectedness of a firm on the basis of its propensity to be in-between of other firms' knowledge linkages. Betweenness does not 'care' about the direction of the ties and does not symmetrize the data, other centrality measures do. There is no inBetweenness or outBetweenness. Betweenness has typical a high level of variance.

Clustering coefficient. Many network indexes usually can be directly obtained through the UCINET software such as Betweenness Centrality or Network Density, the indexes such as Clustering coefficient can be obtained indirectly by UCINET software program and it shows the level of clustering in the network.

5.3. 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 [42]. Firm age is related, to a certain extent, to the level of experience and managerial competences of the firm in carrying out innovations [43]. 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 [41]. 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 [44].

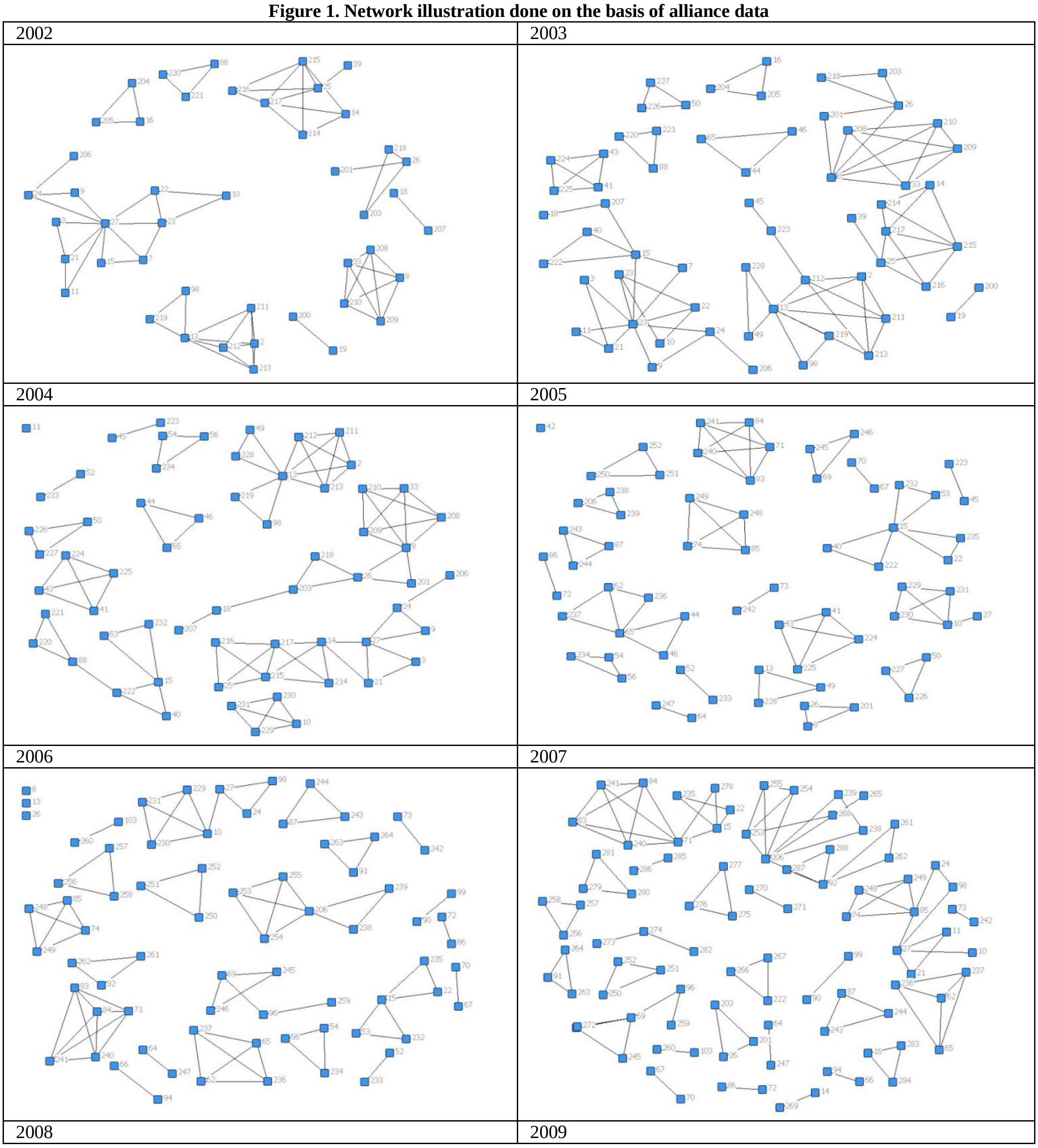
R&D centers. All innovation related researches emphasize the R&D factor as crucial and with highest probability to influence on innovation capability. Here we use presence of own R&D centers in firms. We do not include research centers which are in balance of other branches or institutions, also we do not include R&D

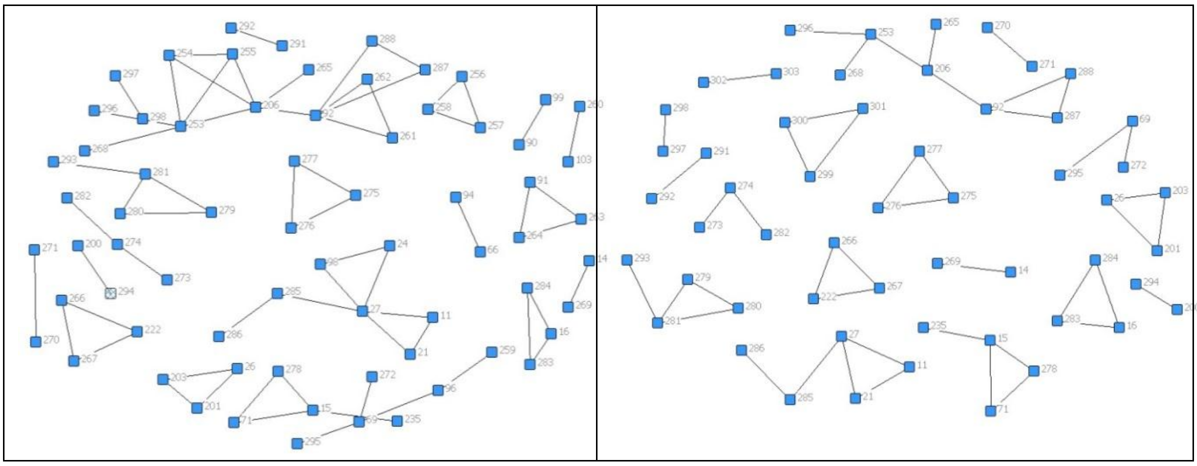
centers hold by maternal company and owed by universities. We use dummy variable, where, if 0 firm does not have any R&D center for its own, and 1 if there is any R&D center owed by the firm.

VI. 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, because we consider that alliances have the power only for three years. 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. The rest 102 companies do not participate in analysis of regression models, but they do their contribution on network related data results. We marked with personal numbers all the companies in the list. Companies which have enough innovativeness level were marked with order numbers with 2 or 3 digits, and which are in range from 1 to 103. All the rest companies are marked only with 3 digits and for all of them the first digit starts with 2 (example, 212, 213 and so on). (Fig 1.)

Figure 1. Network illustration done on the basis of alliance data





To get the data for variables such as betweenness centrality, and clustering coefficient, we used the prepared adjacency matrixes to ran the Ucinet 6 software program and got the data for all 161 firms for the years from 2002 to 2009.

The network related data is presented in overall data set and network illustrations are presented in our figures below for each year of observation. It has been done in Netdraw software.

The data is suitable for using panel form. We collected all kinds of patents for our sample firms including number of patents, utility models and designs. 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. Network properties such as betweenness centrality had 81.5 of maximum index and 0 as minimum; Standard deviations for control variables such as firm age, R&D centers availability and log of firm size are 29.49, 0.47, and 2.29 correspondingly. We present summary statistics and correlation matrix in Table 1.

Table 1. Summary statistics and correlations*

		Min	Max	Mean	Std. Dev.	1	2	3	4	5
1	Innovation performance	1	1139	35.70	114.25	1				
2	Betweenness centrality	0	81.5	3.03	8.95	0.08	1			
3	Clustering coefficient		5	0.81	0.45	-0.27	-0.10	1		
4	Firm age	0	162	26.97	29.49	-0.00	0.13	-0.05	1	
5	R&D centers availibility	0	1	0.66	0.47	0.20	0.12	-0.08	0.23	1
6	Firm size	15.42	25.66	21.18	2.29	0.12	0.19	-0.05	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

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. Coefficients for control variables show that firm age has a negative relation with innovation performance, which means that younger the company is better its innovation activity, which does not coincide with previous researches. It can be the result of own specifics which China automobile industries have, where old companies registered most of their novelties as patents and new designs much before the time of our observation, and by the time of observation they were already strong, financially stable and with comparatively less need for innovations. On the other hand young companies make stronger and more active efforts towards innovation to present a new product in market, due to their still relatively week positions. Another assumption is related with the market conjuncture. Our observation period is from 2002 to 2009 when there was a tremendous growth in China automobile market and when China became main consumer of automobiles, which is naturally pushed market players to hold more active innovation related measures. Firm age showed negative relationship with innovation performance in all our models.

Control variable R&D centers availability was in form of dummy variable and has shown high significance level. In Model 1, the relationship with innovation performance shows that if there are research and development centers owed by firms the innovation activity can grow to 2.5 patents for a firm, which is very close to other researches' results. These results can be explained with that when firms use their own R&D centers they have more freedom in conducting researches and technically it becomes easier to organize and pass all formal procedures. With Universities or Independent Research Centers or with R&D centers of other firms the communication problems occur and it can also be more expensive in long term.

Firm size in our analysis has been measured by the revenue of the firm for observation period and in the end we used logarithm of this parameter. It showed very strong significance as it has been predicted based on previous researches. It shows that there is a positive relationship and the growth of revenue can increase the number of patents, which is also similar to most studies done before.

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

	Model 1: Control only		Model 2:		Model 3: Clustering		Model 4: All predictor	
			Hypothesis 1.		Hypothesis 2.			
	C.	S. e. (sig)	C.	S. e. (sig)	C.	S. e. (sig)	C.	S. e. (sig)
Betweenness centrality			0.02	0.01			0.02	0.01
Clustering coefficient					-1.69	0.29***	-0.89	0.29***
Firm age	-0.01	0.00***	-0.01	0.00***	-0.01	0.00	-0.01	0.00***
RnD centers	2.51	0.19***	2.52	0.29***	2.08	0.34	1.21	0.27***
Firm size	0.14	0.04***	0.13	0.06**	0.21	0.08	0.23	0.06***
Constant	-1.43	0.83*	-1.14	1.23	-1.31	1.49	-1.03	1.30
Log likelihood		-1751.142		-835.353		-625.739		-575.882
Alpha	2.34	0.13***	2.34	0.19***	1.93	0.18	1.20853	0.13***

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

In the second model we have tested the relationship between innovation performance and betweenness centrality. The results have shown positive relationship, which was proposed in hypothesis 1, but with weak significance of its influence on innovation. This partially confirms our hypothesis, but the theory does not show enough confidence and needs more in depth analysis on other industries. These results do not coincide with the results done by other researchers [27, 28, 29]. So we looked at this relationship's significance level on the model where all predictor variables were included, we were assuming if still the significance level is low, we would conclude that a short average path length between nodes in the innovation network do not have a significant effect on a firm's innovation performance in case of China automobile industry example. And as a result, betweenness centrality again was positive but still insignificant in our model with all predictor variables. So we can confirm that hypothesis 1 has not been supported.

In hypothesis 2 we assumed that the high local clustering has a strong positive effect on innovation performance. Results of Model 3 show that the relationship has a negative sign, which is the opposite of what has been proposed in hypothesis. This variable regarding dependent variable showed a high statistical significance and we can accept the model, but the hypothesis needs to be corrected and now we can say that increase of clustering coefficient to one point will decrease the number of all kind of patents to 1.6. The main explanation for this is that strong local clustering forms several groups which do exchange actively knowledge and information between themselves, but it cuts them out from other sources and other players of the network. In our view, as stronger and especially as longer the local clustering is, as less chances for firms to register new patents, because clustering is effective in the beginning of its formation and can bring valuable results regarding innovation, but can't be productive in long term, as it reduces the number of channels for new knowledge flow.

Clustering coefficient is significant in both models and in both models show negative relationship, which can assure us that this relationship is true.

VII. Discussion Of Results

We tested betweenness centrality measure and clustering coefficient regarding to innovativeness of the firm. Betweenness centrality was simply insignificant in both models and the hypothesis has been rejected, question here was: whether firms have more innovation if they have a short path length location in the network, where we found out that this relationship is not strong and that this network index does not impact on innovativeness of the firm. This has been confirmed in both models, in individual and in the one where all predictor variables are included. We think the reason for such results is in the data for China automobile industry network. These network relations are based on alliance data, which are strong and official relations. It is not easy to construct one proper alliance-based relationship, because of this reason there are not that many alliances for one firm, although there are many for overall network. It means that the path length in such network does not become crucial and does not effect on innovation performance.

The interesting results we got also for clustering coefficient and innovation performance relationship, here this coefficient represents the high local clustering in the network. We assumed that high clustering has a strong influence on increase of innovation in the firms, but as results show it is the opposite of it. In both models the coefficient was significant, so we can say that we made a new finding in our research, which says that high local clustering make the patents registration to decrease. The only reason for that can be that high level of local clustering is prominently increases the local exchange of information, knowledge and new ideas, while put firms in that position when they are local focused but do not have the sufficient knowledge exchange with other players in the network. Actually this is the same reason which has rejected the importance of short path lengths. Both factors where influenced by one reason - the strong local clustering in our sample. We know that trust and confidence in partners is crucial for business, knowing the fact that Chinese people are more tend to be careful in choosing partners for business, we can assume that China's automobile industry network formed a bunch of strong local clusters, probably it can bring a lot of benefits for sides in terms of new investments, financial stability and confident relations, but in terms of technological exchange and knowledge flow this kind of strong grouping in local clusters can decrease number of new patents comparing with the ones which are less locally clustered and have more various partners, which are on their own also have more partners. Results with local clustering become logical and natural when we think of recommendations to be given to CEOs. We suggest to have more possible connections and spread the own net as far as possible and avoid too much local clustering, for that it is advised to check the recent five year agreements done by the partner with other players. According to that the firm can choose its future partner and get more benefit if chooses the partner which has more alliance agreements with others. We say five years, while in our research we used three year effect of alliance, because it is not definite that its effect cannot last longer. So partners with more agreements and particularly with diverse partners can bring more new knowledge flow, which in the end can be in the benefit of the firm.

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 explained 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.

VIII. Conclusion

We proved that short path length between nodes in the network do not necessarily effect on innovation and it does not play a crucial role in the increasing of firm's innovativeness. It can help firm CEOs in choosing partners for cooperation, that potential partner's brokerage, gatekeeping role and ability to control information does not necessarily mean that this potential partner is well-enough to be the one who passes the necessary knowledge which might be crucial for innovation benefits. We found that there is a negative relationship between strong local clustering and innovation performance. It means that firms should try to avoid strong local clustering and go beyond it, in order to have more sources for new knowledge. We found that in China automobile industry young companies are more successful in registering new patents, utility modes 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. 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.

Beside of it managers can use our findings in choosing partners or in the process of convincing partners for cooperation relying on our findings, they can assure that their positions might be beneficial for partners. Executives in developing new strategies with focus on increase of innovativeness also may take into consideration those factors. Still our recommendations are based on empirical analyzes and are based on one particular industry, of one particular country, they should be used with caution.

We used only one source for measuring innovation, which are patents, future research can include other sources, such as data based on surveys to supplement the objective measures. Also this study is based on alliance data, which is strong official relations, however there is still concern about other non-formal relations, effects of social capital, new forms of cooperation agreements, which should be taken into consideration in future researches. We have not examined the moderate effect of various factors, future research can explore how these or other factors contingently contribute to improve or deprave the network position on innovation outcome.

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