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A Model Study Based on Social Network Relational Dimensions and Structural Dimensions

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Abstract

This paper uses the data of China's venture capital industry in the CVSource and Zero2IPO databases from 1999 to 2018 as a research sample. By using UCINET software to build the entire network of venture capital industry for social network analysis, I calculate the group tie density based on network interaction, status heterogeneity and faults based on network centrality, to analyse whether those group network characteristics affect the complementarity effect. Based on this, I use probit model regression test to carry on an examination.

Keywords: complementarity, network status heterogeneity, network status-based faults, group tie density.
AMS 2010 codes: 03C30.

1 Introduction

In recent years, an increasing number of interorganisational networks have developed, from a simple bilateral relationship to multilateral consociations that involve many parties [1]. Since a multilateral alliance involves multiple organisations, it shows more complexity and differences in its dynamics than bilateral alliances [2], such as group differences and cooperation complexity [1, 3–5].

A multiparty alliance has a unique nature. First, a multilateral alliance includes other members outside the bilateral relationship, and the organisation considers cooperation with several partners at the same time and adjusts its behaviour accordingly. Second, unlike the bilateral perspective, the multilateral perspective includes group-level constructs, such as the overall density of the network tie among members and the structural differences among groups [5,6]. The industry network between members affects each other's interactions, so that the complementarity effect between members is affected by the group-level network feature. Although different researchers have different perspectives on the division of social network dimensions, their division criteria are mainly based on the two aspects of structural and relational dimensions, according to Tichy et al. [7] Therefore,

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this paper attempts to consider how the group tie density (calculated by network interaction) and the network status-based difference (based on the structural centrality) enhance or weaken the impact of complementarity. Group tie density refers to the degree of repeated linkages among members of a multilateral alliance. Network tie leads to social capital, such as trust, reciprocity and social identity, affecting communication between members [8–10]. In addition, this paper examines the role of network structural difference for the complementarity effect based on network centrality. The status-based difference of members refers to whether there is a difference between members' positions in the industry network, which is divided into status heterogeneity and status-based faults.

This paper uses China's venture capital industry as a data sample to analyse the complementarity effect, as well as to calculate and analyse the boundary conditions of group tie density, network status heterogeneity and status-based faults. Improving on the shortcomings of previous studies, this paper attempts to solve two key research questions: first, how complementarity between members affects the performance of multilateral cooperation; second, on the group level, whether members' tie density and network status-based difference enhance or undermine the positive impact of the complementarity effect.

2 Materials and Methods

2.1 Materials

I argue that greater complementarity increases the breadth of the knowledge and information pool of the entire group, which facilitates correct decision-making and improves the effectiveness of alliance management [11–13].

H1: Complementarity will increase the performance of multiparty investment alliance.

Group tie density refers to the number of duplicate connections in a group divided by all possible binary connections in the group [14]. The junction density aggregates the degree of association duplication in all bilateral relationships. Therefore, the group tie density improves the communication and coordination among members, which facilitates the flow and utilisation of complementary resources, as well as reduces the opportunistic behaviour.

H2: The group tie density will increase the positive impact of complementarity.

Status represents an organisation's position relative to other organisations throughout the industry network [15, 16]. In a multiparty alliance, there are two different types of status-based differences, which are status heterogeneity and status-based fault. Status heterogeneity refers to the different levels of network centrality among multiple members. Status-based fault refers to the degree of subgroups formed by multiple members based on their network centrality.

Network status heterogeneity leads to decreases in motivation and ability to share complementary resources among members, thereby reducing the advantages of the complementarity effect. Therefore, when there is network status heterogeneity, it weakens the advantage of complementarity.

H3a: Network status heterogeneity will reduce the positive impact of complementarity on multiple-unit joint investment performance.

The concept of faults is mostly seen in studies of the individual team level, which focus on the similarity within the team and the differences between groups. Network status-based faults lead to a lack of trust between subgroups and can weaken the interactions among subgroup members [6]. Therefore, due to the positional fault, the degree of sharing and utilisation of complementary resources between subgroups is reduced.

H3b: Network status-based faults will reduce the positive impact of complementarity.

2.2 Data Sources

This paper uses China's venture capital industry as an empirical scenario, using data from two major venture capital data providers, CVSource and Zero2IPO [17, 18]. Both CVSource and Zero2IPO are China's leading research institutions, which contain the entire range of data from China's venture capital industry. This paper combines the information from the two databases to obtain the most comprehensive data coverage and industry data for the period 1999–2018. Although the first international venture capital firm entered China in the early 1980s, China's venture capital field did not develop until the late 1990s. Therefore, this paper uses 1 January 1999 as the starting point of the sample and 31 December 2014 as the end point, so that I can leave the 4-year window period up to 31 December 2018, to better evaluate performance. Since most Chinese venture capital firms were set up after 2000, left censoring is not a serious problem.

2.3 Measurement

Performance. The investment performance is a binary variable. If the investment is finally exited by initial public offerings, it takes the value "1"; otherwise, it takes "0".

Complementarity. Venture capital institutions invest in different stages, and different levels of expertise are required at the different stages to complement each other. Therefore, complementarity is an average of two–two correlations between the investments of the alliance partners at different stages of investment in the industry: Complementarity $= 1 - \frac{\sum_K cor(S_x;S_y)}{N_k}$, where S_x and S_y are, respectively, the investment phase vectors of a pair of institutions x and y 5 years before the alliance; N_k is the number of all possible bilateral associations. Complementarity is a continuous variable between the values "0" and "1"; higher values indicate greater complementarity [19].

Group tie density. Group tie density is the ratio of all pre-existing bilateral connections in the multiparty alliance to all the possible bilateral connections between members. In the 5 years prior to the cooperation, when two organisations jointly invested in the same venture at least once in the same round, those two organisations had a tie. For example, suppose a group contains three parties A, B and C, where A and B have a network tie in the first 5 years. Then, the group tie density is 1/3, i.e., one of the three pairs of bilateral relations has a network interaction foundation over the period of 5 years [5].

Network status heterogeneity. This calculation is based on a joint investment event in the whole industry, which better reflects the position of venture capital institutions in the venture capital industry. Since the enterprise's network location is relatively stable, I use a 5-year window (t – 5) to build the current t-year network matrix. This paper uses Bonacich's (1987) [20] centrality to measure the member's network location: $C_{i,t} = \sum_j(\alpha + \beta C_{ij})R_{ijt} - 1$, where $C_{i,t}$ is the centrality of member i in t years, $R_{ijt} - 1$ refers to the common investment matrix, α is a proprietary coefficient and β represents a weight parameter that indicates the degree to which the centrality of the member i is a function of others' centrality in the matrix $R_{ijt} - 1$ [16,20]. Referring to Zhang et al. (2017) [5], I first calculate the similarity of each pair of bilateral positions, i.e., I divide the smaller party by the larger one and then calculate the group level by subtracting the mean of all bilateral similarities.

Network status-based fault. I calculate the degree of status-based faults at the group level using the standard deviation of all possible bilateral similarities in the group [21].

I control the group-level variables that affect group performance. First, I control the variables associated with the group's activity; as the study sample is from the venture capital industry, the variables include factors such as investment activity uncertainty and whether there are multiple rounds of investment. Among them, the factor ***Stage*** refers to investment uncertainty, which is measured by the degree of development of an investment deal [22, 23]. Early investments have high uncertainty, while late investments have relatively low risk. These take values 1–4; so, a high value represents high activity uncertainty. ***Unsingle*** measures whether the investment is a multistage one; if the investment has had two or more rounds, its value is "1"; otherwise, it takes value "0". Second, I control the overall resources and capabilities of the group. I use the total initial public offerings record, which is the number of successful investments in the group level, to represent the ***Group Ability***. I also control the ***Group Resources*** in each group, i.e., the total number of previous investment deals. Third, I control the composition of the group, such as size, geography and age. The ***Size*** refers to the number of members in the group. I control the average ***Age*** of each group. I also control the ***Proportion of Foreign Members*** and ***Average Geographical Proximity*** in a joint investment group. At the same time, some industries (such as high-tech industries) are fertile grounds for the successful exit form of initial public offerings. To address this heterogeneity and other factors related to industry that affect the investment performance, I added a fixed effect of industry segmentation.

2.4 Model Selection

Given the binary classification characteristics of the dependent variable, in this paper, I use the probit model to estimate the investment exit tendency, which refers to multilateral interorganisational performance: $Pr(I = 1|X) = F(X,\beta)$, where F is the standard normal cumulative distribution function. Based on variable selection and the factors affecting performance in this paper, a probit regression model was constructed [24].‘ Model 1 is a model that only adds control variables; Model 2 is the main effect model of complementarity to performance; Models 3, 4 and 5 are models with moderator variables; and Model 6 is a full model with all variables. Among them, X_i includes all control variables I mentioned above.

$$Performance\ i = \beta_0 + \beta_1 \sum X_i + \sum Industry + \varepsilon_i \tag{1}$$

$$Performance\ i = \beta_0 + \beta_1 Complementarity + \beta_2 \sum X_i + \sum Industry + \varepsilon_i \tag{2}$$

$$Performance\ i = \beta_0 + \beta_1 Compementarity + \beta_2 Complementarity \times Group\ tie\ density + \beta_3 \sum X_i + \sum Industry + \varepsilon_i \tag{3}$$

$$\begin{aligned} Performance\ i =& \beta_0 + \beta_1 Compementarity + \beta_2 Complementarity \times Network\ status\ heterogeneity \\ &+ \beta_3 \sum X_i + \sum Industry + \varepsilon_i \end{aligned} \tag{4}$$

$$\begin{aligned} Performance\ i =& \beta_0 + \beta_1 Compementarity + \beta_2 Complementarity \times Network\ status - based\ fault \\ &+ \beta_3 \sum X_i + \sum Industry + \varepsilon_i \end{aligned} \tag{5}$$

$$\begin{aligned} Performance\ i =& \beta_0 + \beta_1 Compementarity + \beta_2 Complementarity \times Group\ tie\ density \\ &+ \beta_3 Complementarity \times Network\ status\ heterogenity \\ &+ \beta_4 Complementarity \times Network\ status\ heterogenity \\ &+ \beta_4 Complementarity \times Network\ status - based\ fault + \beta_5 \sum X_i + \sum Industry + \varepsilon_i \end{aligned} \tag{6}$$

3 Results

Table 1 is the descriptive statistics table, and Table 2 contains the correlation analysis of key variables in this paper. The sample of this paper is a multiparty investment alliance in the venture capital industry from 1999 to 2018. Since the network centrality needs to be calculated in the backward 5-year window, the performance of this paper needs to move forward 4 years. The number of observations is 651 multiparty groups from 2004 to 2014. Overall, the average performance of this group is 0.276, which means that about 27% of the investment has successfully exited through initial public offerings in 4 years [25]. The correlation coefficient between each variable is <0.65, which indicates that the multi-collinearity problem is not large, and the reliability of subsequent regression results can be basically guaranteed. In addition, the correlation coefficient between each control variable and Performance also shows that the control variables are effective.

In order to ensure the consistency and validity of the model estimation, the data is processed as follows. First, to avoid the influence of outliers, the main continuous variables are subjected to tailing processing at the 1% level. Second, I standardise the main variables. Third, to overcome the effect of multi-collinearity, I centralise

Table 1 Descriptive statistics

	Variable	Mean	SD	Min	Max
1	Performance	0.276	0.448	0	1
2	Complementarity	0.729	0.094	0.667	0.978
3	Group tie density	0.092	0.191	0	1
4	Network status heterogeneity	0.576	0.170	0	0.914
5	Network status-based fault	0.240	0.101	0	0.563
6	Stage	3.095	0.686	1	4
7	Size	3.641	1.109	3	10
8	Unsingle	0.656	0.475	0	1
9	Resource	10.40	11.34	0	70
10	Age	5.779	8.120	0	53
11	Proportion of foreign members	0.246	0.300	0	1
12	Average geographical proximity	0.279	0.300	0	1

the interaction term variables. The variance inflation factor (VIF) diagnosis for all explanatory variables and control variables is <3, so I can eliminate the multi-collinearity problem.

Model 2 in Table 3 reports the results of testing for complementarity and joint investment performance. The coefficient of complementarity (β = 0.552, $p<0.01$) and its significance support Hypothesis 1, viz., an increase in complementarity between members increases the performance of the multiparty investment alliance. Model 3 in Table 3 reports the testing results of the moderating effect of group tie density. The results show that the coefficient of the interaction term of the group tie density and complementarity is significantly positive (β=0. 476, $p<0.01$), i.e., complementarity is an advantage for the group with increased previous network connection among the members. Model 4 in Table 2 also shows that the coefficient of the interaction heterogeneity and complementarity is significantly negative (β=–0.278, $p<0.01$), indicating that the heterogeneity due to network centrality weakens the impact of complementarity. In addition, the results of Model 5 show that the network status-based fault does not significantly moderate the relationship between complementarity and group performance; H3b has not been verified.

4 Discussion

This paper constructs a theoretical analysis model of complementarity and performance of a multilateral alliance, and then puts forward a few research hypotheses. Based on the investment data of China's venture capital institutions from 1999 to 2018, I analyse the complementarity effect between members in multilateral alliances. Based on the social network theory, I calculate the network ties and network centrality at the industry network level and then explore (a) the group tie density based on relational embedding and (b) the status-based difference based on structural embedding.

5 Conclusion

The main conclusions are as follows. First, in a multiparty cooperation, the complementarity of members is conducive to group-level performance. Second, the density of network tie between group members strengthens the positive impact of complementarity. Third, network status heterogeneity between partners can undermine the positive impact of complementarity. The heterogeneity of network status increases the preferences and cognitive conflicts of the different investment institutions in the alliance, in addition to weakening the positive effects brought about by complementarity, which is not conducive to the improvement of multiparty cooperation performance. Network status-based fault is not a significant boundary condition for the resource's complementarity effect.

Table 2 Correlation analysis

	Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	Performance	1											
2	Complementarity	0.132*	1										
3	Group tie density	0.03	0.012	1									
4	Network status heterogeneity	-0.010*	0.043	0.037	1								
5	Network status-based fault	-0.186*	-0.002	0.004	0.134*	1							
6	Stage	-0.011	0.091*	-0.182*	0.028	-0.054	1						
7	Size	0.085*	0.524*	-0.008	0.025	-0.016	0.105*	1					
8	Unsingle	-0.037	0.035	0.154*	-0.033	0.076*	-0.111*	0.074	1				
9	Resource	-0.069	0.196*	0.115*	0.096*	0.019	-0.03	0.190*	-0.017	1			
11	Age	-0.092*	-0.051	0.168*	0.089*	-0.014	-0.221*	-0.089*	0.087*	0.538*	1		
12	Proportion of foreign members	-0.019	-0.003	0.250*	0.025	-0.03	-0.268*	-0.06	0.057	-0.009	0.190*	1	
13	Average geographical proximity	0.023	-0.083*	-0.073	-0.057	0.007	0.009	-0.124*	-0.009	-0.062	-0.046	-0.232*	1

*Indicates significant levels at 10%.

Table 3 Probit regression results

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Complementarity		0.552*** (3.322)	0.555*** (3.192)	0.568*** (3.309)	0.551*** (3.310)	0.578*** (3.223)
Complementarity Group tie density			0.476*** (4.215)			0.513*** (4.496)
Complementarity Network status heterogeneity				–0.278*** (–2.824)		–0.331*** (–3.176)
Complementarity Network status-based heterogeneity					–0.007 (–0.065)	–0.029 (–0.233)
Group tie density	0.784 (1.501)	0.753 (1.426)	0.853 (1.372)	0.707 (1.330)	0.754 (1.427)	0.880 (1.409)
Network status heterogeneity	–0.756 (–1.417)	–0.835 (–1.537)	–0.806 (–1.466)	–0.871 (–1.567)	–0.836 (–1.538)	–0.936 (–1.637)
Network status-based heterogeneity	–4.925*** (–4.623)	–5.215*** (–4.775)	–5.534*** (–4.966)	–5.394*** (–4.875)	–5.216*** (–4.777)	–5.820*** (–5.099)
Stage	0.482*** (4.053)	0.722*** (4.025)	0.801*** (4.021)	0.792*** (4.019)	0.759*** (4.006)	0.901*** (4.009)
Size	0.210** (2.371)	–0.187 (–1.221)	–0.209 (–1.261)	–0.207 (–1.284)	–0.188 (–1.222)	–0.239 (–1.409)
Unsingle	–0.250 (–1.208)	–0.217 (–1.030)	–0.274 (–1.288)	–0.175 (–0.826)	–0.216 (–1.026)	–0.227 (–1.061)
Resource	0.000 (0.011)	–0.002 (–0.074)	–0.001 (–0.047)	–0.004 (–0.181)	–0.002 (–0.075)	–0.004 (–0.194)
Age	–0.003 (–1.351)	–0.003 (–1.537)	–0.004* (–1.669)	–0.003 (–1.595)	–0.003 (–1.537)	–0.004* (–1.787)
Proportion of foreign members	–0.572 (–1.449)	–0.720* (–1.792)	–0.875** (–2.102)	–0.727* (–1.803)	–0.719* (–1.790)	–0.883** (–2.109)
Average geographical proximity	0.114 (0.345)	0.034 (0.103)	0.058 (0.171)	0.029 (0.086)	0.033 (0.099)	0.057 (0.166)
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	1.970** (2.335)	3.753*** (3.667)	3.971*** (3.756)	3.942*** (3.729)	3.755*** (3.665)	4.291*** (3.926)
N	651	651	651	651	651	651

, ** and * indicate significant levels at 10%, 5% and 1%, respectively.*

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