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The dynamics of network communities and venture capital performance: Evidence from China

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ABSTRACT

This paper examines the impact of the dynamics of network communities on venture capital (VC) investment performance in China. We use Chinese VC market data for the period 2000 to 2015 and find that VCs' cross-community movements have significant positive impacts on their subsequent performances, such as exit probability via initial public offerings (IPOs) and internal rate of return (IRR).

1. Introduction

Venture capital investment is risky and resource intensive. For the purpose of risk and resource sharing, VCs frequently jointly invest with others in syndicated investments that result in VC networks. According to Sytch and Tatarynowicz (2014), the existing research looks at networks from three perspectives: the ego network (micro-level), the global network (macro-level), and the network community (meso-level). The ego network perspective mainly looks at the actors' ties to their partners and the partners' ties among themselves (Ahuja, 2000; Zaheer and Bell, 2005). For example, the work of Hochberg et al. (2007) takes the ego network perspective and looks at the VC's centrality and closeness to and betweenness with other VCs. The global network perspective emphasizes the overall structure of firms and their ties within their industry (Abrahamson and Rosenkopf, 1997; Schilling and Phelps, 2007). For instance, Hochberg et al. (2010) investigate the density of the entire network from the perspective of the global network. Network communities are located between the structure of a firm's ego network and their industry's network structure (global network). They are "dense, non-overlapping structural groups within a global network" (Sytch and Tatarynowicz, 2014). In each network community, actors are connected more closely to each other than they are to the actors outside their community (Knoke, 2009: 1697). In other words, the connections within network communities (internal connections) are dense; the connections between communities (external connections) are sparse (Girvan and Newman, 2002; Newman; 2004). As a result, knowledge is relatively more homogeneous within a community and relatively more heterogeneous between communities.

Network research has been attracting wide interest from both scholars and practitioners for a long time (Abrahamson and Rosenkopf, 1997; Ahuja, 2000; Schilling and Phelps, 2007; Zaheer and Bell, 2005). Although the earlier literature on statistical physics states that "many networks display community structure" (Girvan and Newman, 2002; Newman; 2004), most of the current network research is from the perspective of either the ego network or the global network. In the management and finance literature, investigations on network communities are limited and still in their early stages. In early social-network studies, network

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communities are called “cliques”. Rowley et al. (2004, 2005) examine how the heterogeneity of firms in a community can affect their decisions to leave the community and also the community's market performance. Recently, Sytch et al. (2012) investigated the determinants of bridge ties between network communities. Sytch and Tatarynowicz (2014) show that firms’ moderate cross-community movements can enhance their innovation output. In the VC literature, only one paper addresses the network community: Bubna et al. (2016) use computational techniques to identify VC communities; they find that community VC-funded firms display more innovation, especially for funded earlier-stage firms that have limited innovation histories. This paper attempts to fill in the gap in the literature by investigating how a VC's move from one network community to another affects its performance.

It is well known that sharing resources and information is important for VC investment performance. Within a network community, the internal connections are close and the network distances are short (Rowley et al., 2005). This can reduce transaction costs and facilitate the exchange of resources among community members (Ahuja, 2000). Thus, VCs within network communities can easily absorb and acquire and utilize a series of locally available resources from a shared pool. Moreover, VCs can have access to more potential actors with which to make deals. As a result, a VC's investment performance may improve due to the improved quality and flow of deals (Hochberg et al., 2007). However, the frequent exchange of resources may lead to resource homogeneity within communities (Gulati et al., 2012; Lazer and Friedman, 2007), which limits the possibility of VCs acquiring heterogeneous resources and all of the inherent advantages thereof. In addition, different network communities are structurally independent (Sytch and Tatarynowicz, 2014). The inter-community connections are sparse and transaction costs are high (Girvan and Newman, 2002; Newman; 2004). Consequently, resource exchange among different network communities will become more difficult (Gulati, 1995) and lead to the heterogeneity of resources among communities (Rowley et al., 2005; Sytch et al., 2012). Thus, VCs in one network community may find it difficult to obtain heterogeneous resources from different network communities, thereby limiting their resource-and-information set, which leads to lower investment performance. Therefore, the overall effect on VC performance of joining a network community is not obvious.

This paper addresses this dilemma by focusing on the dynamics of VC network communities, that is, a VC's movement from one network community to another and how this movement affects its investment performance. Joining different network communities means that a VC is moving across the boundaries of a number of network communities. On the one hand, this movement enables the VC to gain access to the resource pools of different network communities, thus, facilitating the diffusion of information, contacts and resources among VCs (Bygrave, 1988). A more heterogeneous resource implies that a VC can gain more information on more promising companies, thereby improving its selection ability in terms of investments. On the other hand, moving across network communities also helps the VC provide more value-added services to their portfolio of firms, including expanding the potential range of their strategic alliance partners, suppliers and customers; they can also gain better access to other VCs’ service providers, such as investment banks, also for their portfolio of companies (Hochberg et al., 2007). Therefore, moving across network communities will improve VC performance by affecting the two main drivers of a VC's investment performance: the ability to select promising companies, and the ability to add value to their portfolio of companies. However, it is worth noting that a VC's movement across communities may potentially result in losing access to the resources of the former community, which thereby reduces the VC's investment performance. Thus, how VC cross-community movements affect VC performance remains an empirical question.

This paper uses data for the period 2000 to 2015, for China's VC market, to examine the impact of cross-community VC movements on their subsequent investment performance. It finds that cross-community movements have significant positive impacts on subsequent VC performance, such as in the probability of exit via IPOs and internal rate of return. This implies that the benefits of obtaining new heterogeneous resources from VC cross-community movements are important to VC investment performance and outweigh the costs of losing access to the resources of their former communities.

This research contributes to the literature in the following ways. First, while there is a vast literature on the network, most look at the topic from the perspective of either the ego network or the global network (Sytch and Tatarynowicz, 2014). Limited attention is paid to network communities. This paper contributes to the social-networks literature by focusing on network communities. By taking this perspective, we are able to identify new ways to examine VCs’ access to diverse knowledge and information inputs and their impacts on VC performance. Second, among the limited literature on network communities (Greve, 2009; Rowley et al., 2004, 2005; Sytch et al., 2012; Sytch and Tatarynowicz, 2014 etc), little work has been done on the dynamics of network communities; the exception is Rowley et al. (2005) and Sytch and Tatarynowicz (2014). However, research on dynamics of network communities of VCs is still rare. This paper's unique focus on the movement of VCs across different network communities provides a new way of investigating how access to heterogeneous resources and information is diffused throughout an inter-organizational system over time.

The remainder of this paper is organized as follows: Section 2 describes the sample selection and empirical strategy; Section 3 presents our empirical results; and the final section provides a conclusion.

2. Research design

Our sample includes all VC investments and performances, in China, for the period 2000 to 2015.[1] All of the data used in this paper are obtained from Zero2IPO, China's largest VC data vendor. To examine investment performance, we require data on investments that are five years old or more. Thus, we include only VC investments made before 2010. Following the previous literature (Cumming et al., 2009; Nanda and Rhodes-Kropf, 2013), we only use first-round investments. This helps avoid funds’ strategic round-to-round investment considerations (Cumming et al., 2009); this also allows us to focus on VCs’ initial investment decisions and to

[1] Data prior to 2000 are excluded as VC was less developed in earlier years and data availability is not as good as recent years.

follow these investments to see their eventual outcome (Nanda and Rhodes-Kropf, 2013). We also drop non-community VCs and their investment observations. This is because if we include the non-community VC investment events, then we can only compare community and non-community VCs and assesses how joining a community affects VCs' investment performance. However, the focus of the paper is on how a VC's movements from one community to another affects its performance. This requires that the VCs in the selected sample belong to a certain community. As a result, our final sample includes 3702 rounds of investments made by 381 VCs in 2511 firms.

Eq. (1) is a baseline regression model that shows how VC movements across network communities affect VC investment performance for any year *t*.

$$\mathrm{VC_i\ performance} = a + \beta^{*}\mathrm{VC_i\ movements_t} + \gamma^{*}\mathrm{controls} + \delta^{*}\mathrm{year_t} + \varepsilon \tag{1}$$

Where ***VC_i performance*** is defined as VC_i investment performance five years after year *t*. We measure VC performance, using both a dummy variable that is equal to 1 if the VC exits via an IPO, and the IRR of the investment (measured as 1 plus IRR, then taking the natural logarithm).

VC_i movements are defined as cross-community movements, which are measured by the number of movements across network communities before year *t*. To do this, first we need to identify the network communities. A network community is defined using a three-year moving time window. For example, suppose year *t* is year 2005; in this case, we define the network community that a VC belongs to during each year of the three-year time windows 2000–2002, 2001–2003 and 2002–2004. Two main methods are used in the current research: a splitting algorithm and an aggregation algorithm. This paper employs a Girvan-Newman algorithm, which is the most widely used splitting algorithm, to identify the communities. We eliminate communities with less than three VCs, following Wasserman and Faust (1994).[2] To observe the VC's cross-community movements, we then make a pair-wise matching of all the communities in two consecutive time windows to determine whether the communities in these windows are the same communities as at the outset, following Sytch and Tatarynowicz (2014). If the overlap ratio of the group members of two communities is more than 30% in two consecutive time windows, then the two communities are considered the same community. Otherwise, they are viewed as different communities. Then the number of movements across the network communities is defined as ***VC_i movements***.

For example, suppose VC_i made an investment in year 2005 and we want to see whether the performance of VC_i in the following five years is related to its movement across communities prior to 2005. Using the method in the first step, it is found that VC_i belonged to community C during the time window 2002–2004, it belonged to community D during 2001–2003, and it belonged to community B during 2000–2002. This means that before 2005 VC_i moved across three different network communities: B → D → C. In this case, we assign the value of 3 to VC*i's cross*-community movements.

Meanwhile, in the regressions, we control for ***VC_i's historical performance*** (number of IPO exit events, divided by the total investment made by the VC_i during the three years prior to year *t*), ***VC_i reputation*** (the number of IPO exits made by the VC_i prior to year *t*), ***VC_i network centrality*** (the number of nodes connected to a specific VC_i within a VC network), ***VC_i age*** (the total number of years from the VC's establishment to its investment, in the natural logarithm) and ***VC_i size*** (the total funds raised by VC_i during the three years prior to year *t*). The industry fixed effects are also controlled.[3] Our regression method is either a logit regression (when the dependent variable is the dummy for exit via IPO) or a GLS regression (when the dependent variable is the IRR). We use Huber–White robust standard errors to control for heterogeneity and we cluster the standard errors at invested firm level.

3. Empirical results

Table 1 shows the summary statistics of our key variables. The mean of the IPO exit is 0.157, indicating that 15.7% of the investment rounds are exit by IPO. The average IRR is 99.5% and the standard deviation is as large as 122.8%, showing that VCs in China enjoy high financial returns on investments, and that the variation among these returns is large. The average number of cross-community movements is slightly greater than one and the maximum number of movements is four, implying that VC movements among network communities do exist, although these movements are not quite frequent.

Table 2 shows the regression results of Eq. (1). The first two models report the logit regression results for IPO exit and the last two models report the GLS regression results for the IRR. It is shown that VC movements are positively related with the possibility of an exit via an IPO and obtaining a higher IRR. Thus, our findings suggest that VC movements across network communities are positively related with good future investment outcomes for VCs.

In the above analysis, we assume that cross-community movements can benefit VC performance by providing more resources. However, there may be a "reverse causality" problem. That is, a joint investment in a new community also needs approvals from other VCs; however, these other VCs may only allow VCs that have better historical performances to join their community. To address this concern, first, we orthogonalize VC movements by VC historical performance and then use the residual as a proxy of VC movements. This residual can be considered as the VC movements that are not driven by VC historical performance. Table 3 shows the new results and our main results remain the same.

[2] We thank the referee to point out this.

[3] According to the 2001 industry classification guidelines of the China Securities Regulatory Commission, the comparable regulatory authority to the SEC in the United States, listed firms are classified under 13 industries. In our empirical analysis, we added 12 industry dummies to control for the industry fixed effects.

Table 1
Summary statistics and correlation matrix.

This table presents the summary statistics of our key variables and the correlation coefficients among them. IPO exit is a dummy variable that is equal to 1 if the VC exits via an IPO. IRR is the internal rate of return of the VC investment. VC movements at year *t* are defined as cross-community movements, which are measured by the number of movements across network communities before year *t*. VC historical performance at year *t* is the number of IPO exit events, divided by the total investment made by the VC during the three years prior to year *t*. VC reputation at year *t* is the number of IPO exits made by the VC prior to year *t*. VC network centrality is the number of nodes connected to a specific VC within a VC network. VC age is the total number of years from the VC's establishment to its investment. VC size is the total funds raised by VC during the three years prior to year *t*. Coefficients in bold indicate statistical significance at $p < 0.10$.

No.	Variables	N	Mean	S.D.	1	2	3	4	5	6	7
1	IPO exit	3702	0.157	0.364	1						
2	IRR	564	0.995	1.228	**0.444**	1					
3	VC movements	3702	1.261	0.596	**0.055**	**0.133**	1				
4	VC historical performances	3702	0.065	0.085	**0.059**	−0.003	**0.236**	1			
5	VC reputation	3702	2.951	4.902	−0.001	0.026	**0.602**	**0.350**	1		
6	VC network centrality	3702	2.696	2.629	**−0.030**	0.003	**0.173**	**0.122**	**0.572**	1	
7	VC age	3702	8.132	6.159	−0.017	0.026	**0.193**	**0.237**	**0.353**	**0.348**	1
8	VC size ($Million)	3702	407.100	781.900	**−0.042**	**0.071**	**0.201**	**0.133**	**0.376**	**0.338**	**0.238**

Table 2
VC cross community movements and VC performance.

This table presents the regression results based on Eq. (1). The dependent variables are VC performance measured by IPO exit and IRR. IPO exit is a dummy variable that is equal to 1 if the VC exits via an IPO. IRR is the internal rate of return of the VC investment, measured as 1 plus IRR, then taking the natural logarithm. The first two columns report the logit regression results for IPO exit and the last two columns report the GLS regression results for IRR. VC movements at year *t* are defined as cross-community movements, which are measured by the number of movements across network communities before year *t*. VC historical performance at year *t* is the number of IPO exit events, divided by the total investment made by the VC during the three years prior to year *t*. VC reputation at year *t* is the number of IPO exits made by the VC prior to year *t*. VC network centrality is the number of nodes connected to a specific VC within a VC network. VC age is the total number of years from the VC's establishment to its investment in the natural logarithm. VC size is the total funds raised by VC during the three years prior to year *t* in the natural logarithm. Robust standard errors are reported in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.

Variable	IPO exit		IRR	
	(1)	(2)	(3)	(4)
VC movements		0.334***		0.104***
		(0.099)		(0.036)
VC historical performances	1.835***	1.880***	−0.234	−0.255
	(0.494)	(0.506)	(0.229)	(0.229)
VC reputation	−0.001	−0.033*	0.003	−0.006
	(0.015)	(0.019)	(0.006)	(0.006)
VC network centrality	−0.008	0.012	−0.014	−0.005
	(0.029)	(0.030)	(0.011)	(0.011)
VC age	−0.069	−0.082	0.015	0.010
	(0.072)	(0.072)	(0.033)	(0.033)
VC size	−0.066*	−0.072*	0.028*	0.023
	(0.040)	(0.041)	(0.015)	(0.016)
Constant	−0.779*	−1.116**	0.599***	0.504***
	(0.430)	(0.449)	(0.124)	(0.123)
Industry fixed effect	Yes	Yes	Yes	Yes
N	3702	3702	564	564

4. Conclusion and discussion

This paper provides the first evidence that VC movements across network communities have significant positive impacts on subsequent VC performance as measured by IPO exit probability and IRR. It is found that the benefits of cross-community movements in the acquiring of new heterogeneous resources outweigh the potential loss of access to the resources of the VCs' previous communities. Our findings enrich the related research in the fields of both VC and network communities.

Nevertheless, satisfying the 5-year performance observation window requirement means that only VC investments before 2010 are included. This limits our sample selection and representativeness. Future research could provide more robust findings if it uses a longer window and conducts its analysis on larger samples. In addition, research on the dynamics of network communities as they pertain to the VC is still at the early stage. Many questions remain unanswered, such as: What determines the optimal number of VC cross-community movements? Do independent VCs behave differently from captive VCs? Does the VC's ownership background matter? Future research on these questions will provide more insight to the literature.

Table 3
Endogeneity test.
This table presents the endogeneity test results using orthogonalized VC movements as a key independent variable. The dependent variables are VC performance measured by IPO exit and IRR. IPO exit is a dummy variable that is equal to 1 if the VC exits via an IPO. IRR is the internal rate of return of the VC investment, measured as 1 plus IRR, then taking the natural logarithm. We orthogonalize VC movements by VC historical performance and then use the residual as a proxy of VC movements. VC historical performance at year *t* is the number of IPO exit events, divided by the total investment made by the VC during the three years prior to year *t*. VC reputation at year *t* is the number of IPO exits made by the VC prior to year *t*. VC network centrality is the number of nodes connected to a specific VC within a VC network. VC age is the total number of years from the VC's establishment to its investment in the natural logarithm. VC size is the total funds raised by VC during the three years prior to year *t* in the natural logarithm. Robust standard errors are reported in parentheses; ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.

Variable	IPO exit (1)	IRR (2)
VC movements (orthogonalized)	0.334***	0.104***
	(0.099)	(0.036)
VC historical performances	1.882***	−0.254
	(0.506)	(0.229)
VC reputation	−0.003	0.003
	(0.015)	(0.006)
VC network centrality	−0.006	−0.011
	(0.029)	(0.010)
VC age	−0.077	0.012
	(0.072)	(0.033)
VC size	−0.070*	0.023
	(0.041)	(0.016)
Constant	0.334***	0.104***
	(0.099)	(0.036)
Industry fixed effect	Yes	Yes
N	3702	564

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2018.03.009.

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