The Analysis of Cross-border Venture Capital Networks and Investment Performances Using a Logit Model

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Abstract

This paper explores if venture companies are more successful if they receive venture capital support from institutional venture capital (VC) investors that have a greater number and quality of network ties to other VC investors. In particular, this paper looks at 285 U.S.-based companies that received syndicated investments from both U.S. and Asian VC funds between 1995 and 2016. There are precedent studies represented that VC funds with a wider range of partners will outperform to help companies achieve successful market exits, with better information diffusion. This paper suggests that those same reasons should be amplified if there are cross-national partnerships among U.S. and Asian VC funds in the U.S. market, too. This paper structured the unweighted and undirected adjacency matrix using graph theory to compute the quality and quantity of inter-fund network ties and enhanced effectiveness of analysis by using the logit model. Ultimately this paper finds a positive impact of larger VC syndicate networks on successful portfolio company exits in sampled cross-border VC syndication set. Previous research identified comparative benefits of VC investors with wide-ranging connections are also applicable to the narrower set of companies that are funded through both U.S. and Asian VC funds.

Keywords: Social Networks, Strategic Alliances, Graph Theory, Logit Model, Venture Capital

1 Introduction

Venture capital (VC) investment is a core funding source for startups and growing private companies, which have limited access to other types of financing due to uncertainty in their businesses. While many VC funds speculate on their invested portfolio companies for high returns, they frequently structure a VC syndicate, a single investment made by multiple co-investor funds, to mitigate high investment risk [1].

VC investments have contributed to the rapid economic growth with occasional lucrative exits of invested portfolio companies, represented by IPO and M&A [2]. This VC investments are traditionally made by local VC funds to the local companies within similar geographic location, due to better information accessibility about companies. Often times, local VC funds syndicated with other local VC funds to collect more information and disperse the risk [3].

Due to this traditional local VC investment and syndication pattern, precedent studies examined VC syndicate networks mostly focused on local VC inter-organizational networks in the Western capital markets.

However, international VC investment, particularly Asian VC investment, has risen as new funding sources in the Western markets, after Asia VC markets have risen as emerging markets with rapidly increasing Asia VC funds since 2000. Especially China VC institutional investors has shown surged VC international investments, with advantage of government incentives and imperatives given under the Chinese economy rebalancing plan made by China since 2008 [4].

With globalization in VC investment, U.S. VC market expects increasing capital inflows from foreign institutional investors [5]. Lately, cross-border VC syndicates including both U.S. and Asian VC funds are rising as VC co-investment structure satisfying this global trend [6].

As existing cross-border VC syndication studies mainly focused on the U.S. and European VC syndication in the Western market or U.S. and Asia VC syndication in Asia markets that not many studies researched on the U.S. and Asia cross-border syndicate networks and performances in the U.S. market.

This paper explores at 285 U.S.-based companies that received syndicated investments from both U.S. and Asian VC funds between 1995 and 2016 to shed the light upon U.S. and Asia cross-border VC syndicate networks and performances in the U.S. market.

2 Literature Review & Theoretical Framework

There are many precedent studies examined the purpose of VC syndicate and effects of VC syndication's co-investing network ties on investment performances. VC syndication is popular co-investment structure used in the U.S. market to mitigate high risk derived from uncertainty with limited information on VC investment opportunities, even in first rounds of investments.

Lerner studied the syndicated domestic VC investments on 271 U.S.-based private biotechnology companies and found neutralization of risk by comparison of investment rationales with other co-investors, capital constraints overcome, and window dressing available from syndicated networks as three rationales of VC syndication [7].

Trapido also reviewed comparative advantages of VC networks structured by syndication and represented trust generation, prevention of information asymmetries, sharing of management experience, and sharing of risk evaluation expertise as main functions of VC syndication networks [1].

Sorenson and Stuart examined the geographically localized VC investments in the U.S. and found potential portfolio company's information diffusion across geographic boundaries as the main driver of the VC investment clustering around local spatial boundary near investment companies. Sorenson et al found Venture capitalists with axial positions may take risk of joining co-investment network to fund spatially distant companies [8].

Hochberg et al conducted social network analysis on domestic VC syndicate networks and investment performances in the U.S. market. Using graph theory, Hochberg et al considered existence of network ties among VC funds if they invested in same company and represented positive correlation between VC funds' network ties and performances, measured by the survival to subsequent financing of participant funds and the proportion of investments' eventual IPO or acquisitions [9].

While many VC syndication studies focused on syndicated VC deals in the Western markets, several studies illustrated the cross-border VC syndicates and partner choice selection in Asia markets. Dai et al observed Western-based dominant VC firms' foreign market experiences are somewhat offset by major disadvantages in information collection and monitoring due to both geographic and cultural distances and syndication with local VCs alleviate information asymmetry and monitoring problem for foreign VCs, when they invest in Asia market [10].

Kenney et al, narrower the cross-border VC syndicate research to foreign-China cross-border VC syndication and partner selection in China market. Kenny et al found foreign VC investors' partner selection preference of Chinese VC investors over foreign VC investors in later investment rounds and financing of more mature portfolio firms. Also, they found foreign VC firms with more China market experiences are more likely to partner with Chinese VC firms, while this tendency gets weaker among the older foreign VC firms [11].

Precedent management scholars pointed out broader information diffusion and capital and strategy sharing available within VC syndication networks and identified the positive effects of rich VC inter-fund networks on performances.

This study focuses on cross-border VC syndicates including both U.S. and Asian VC funds in the U.S. market and examines the effects of quantity and quality of VC inter-fund networks within syndicates on investment performances of invested companies, measured in their successful market exits.

3 Hypothetical Development

Hypothesis 1: In the U.S. market, cross-border VC syndicates including U.S. and Asian VC funds with higher number of inter-fund network ties would lead more successful market exits of their invested companies.

Hypothesis 2: In the U.S. market, cross-border VC syndicates including U.S. and Asian VC funds with higher quality of inter-fund network ties would lead more successful market exits of their invested companies.

4 Methodology

4.1 Network Analysis

This study conducts a network analysis to examine the multiple VC funds as economic actors embedded in cross-border VC syndicates, including both U.S. and Asia VC funds, in the U.S. market, and identifies influential economic actors on portfolio company exits.

For network analysis model, graph theory is used to make the concept of network centrality more precise [12]. A graph theory describes network as a square adjacency matrix, the cells of which reflect the co-investment ties among the VC fund economic actors in the network [9].

Influence within VC inter-fund co-investment network is measured in quantity of network ties and quality of network ties. Quantity of VC network ties are measured by assessing a degree centrality of an actor's network position in cross-border VC syndicates, based on the count of the actor's unique co-investment experience with other VC funds participated in VC syndicates. For example, if VC fund *i* and VC fund *j* invested in the same portfolio company *X* at least once, even if they did not participate in the same investment round, both VC fund *i* and VC fund *j* has a unique tie to each other.

In my setting, I neither discern the possible network direction from lead VC fund to invited VC fund in VC syndication nor weighted the multiple co-investment experiences among venture capital inter-funds, once they built co-investment network ties for calculating degree centrality of VC inter-fund network.

I created undirected and unweighted adjacency socio-matrix to record the co-investment network ties in cross-national VC syndicates, including at least one or more U.S. and Asia VC funds, invested in U.S. VC companies between 1995 and 2016.

Each VC fund as an economic actor is represented as node and each line connecting VC funds represents the co-investment ties among them.

As undirected degree centrality simply represents the existence of co-investment experience between VC funds, degree centrality score for each VC fund represents the number of co-investment experience with other VC funds. VC fund with higher degree centrality score is considered as the fund with more abundant VC inter-fund networks in the VC syndicates.

Degree Centrality of VC inter-fund Network (Undirected Method)

p_{ij} = 1, if at least one VC syndication relationship exists between VC funds, i and j;
p_{ij} = 0, otherwise;
VC fund i's degree of centrality= $\sum_j p_{ij}$
Undirected network degree, $\sum_j p_{ij} = \sum_i p_{ji}$

Then, eigenvector centrality is used to measure the influence of a node in a VC inter-fund network, as graph theory uses eigenvector centrality to assess the quality of network ties.

As eigenvector centrality assigns relative scores to all nodes in the network, VC fund with higher eigenvector centrality score's connection is considered more powerful than connections of VC funds with lower eigenvector centrality scores.

Both unweighted and weighted adjacency socio-matrix is used to calculate unweighted eigenvector centrality score and weighted eigenvector centrality scores.

Eigen-vector Centrality of VC inter-fund Network (Undirected Method)

Adjacency matrix A = (p_{ij})
$x_i = \frac{1}{\lambda}\sum_{j\in M(i)}$,
$(M(i) is\ a\ set\ of\ neighbors\ of\ VC\ fund\ i, \lambda\ is\ constant)$;
$x_j = \frac{1}{\lambda}\sum_{j\in G} p_{ij}\ x_j$, (G is given graph);
Eigenvector equation: $\mathrm{Ax} = \lambda\mathrm{x}$

4.2 Descriptive Statistics & Correlation

Descriptive statistics illustrates the structure and components of data, by providing mean, standard deviation, minimum and maximum values in Figure 3.

To check robustness of variables and correlativity of each predictor variable in my setting, correlation matrix and plot are presented.

4.3 Regression Models

Logit regression model is used to explore the effects of syndicated VC fund networks on invested portfolio companies' market exits after all investment rounds.

The Logit is the inverse of Logistic regression, widely used for binary data, which is shown below:

Equation (1) for Logistic Regression:

$$\pi(\mathrm{x}) = \frac{e^{\beta_0+\beta_1 x+\beta_2 x+\cdots+\beta_n x}}{1+e^{\beta_0+\beta_1 x+\beta_2 x+\cdots+\beta_n x}} = \frac{e^{g(x)}}{1+e^{g(x)}} \quad (1)$$

While the left-hand side represents the probability $\pi(\mathrm{x})$ that has to be between zero and one, the right-hand side, which represents linear predictor, can take any real value. This can cause the predicted values not in the correct range, without complex restrictions on coefficients. To solve this problem, I take transformation of the probability at Equation (1) to remove the range restrictions and model the transformation as a linear function of the covariates. This can be illustrated as the ratio of the probability to its complement (Rodriguez) as shown at Equation (2):

$$\text{Odds (x)} = \frac{\pi(x)}{1-\pi(x)} \quad (2)$$

I log-transformed the odds ratio at Equation (2) and drive the Logit function in Equation (3) used for regression models.

$$g(x) = \ln\left[\frac{\pi(x)}{1-\pi(x)}\right] = \beta_0 + \beta_1 x + \beta_2 x + \cdots + \beta_n x \quad (3)$$

4.4 Goodness of Model Fit Test

McFadden Pseudo R-squared values are used to test and compare goodness of model fits. The higher McFadden Pseudo R-squared values, the better the model fit:

$$R^2_{MCF} = 1 - \ln(L_M)/\ln(L_0) \quad (4)$$

5 Data

All U.S.-based venture capital deals, except money tree and buy-out deals, invested by VC syndicates contain both U.S. and Asian VC funds between 1995 and 2016 are collected from VentureXpert.

In U.S. VC capital markets, institutional investor makes an equity investment on a private company is defined as Private Equity (PE) fund, rather than a VC fund, but in foreign VC markets, the terms VC and PE are often used interchangeably [10]. So, U.S. funds are limited to the institutional venture capitalist, but Asian and other continental VC funds are broadly defined as all types of institutional investors make equity investment in ventures including private firms for data extraction.

11 years of sampled time range represents typical VC fund's life cycle of 10 years along with addition of 1 year, offsetting possible lagging in capital influx or investment performance driven by a selected fund's vintage year [9]. Also, this time frame includes the time period of emerged Asia VC funds' capital inflows into the U.S. market.

285 venture companies, funded by VC syndicates, including both U.S. and Asia VC funds, across all investment rounds between 1995 and 2016 and headquartered in the United States are sampled. Total 2,626 Venture Capital funds are detected in this sample.

6 Measures

VC syndicate is defined as the VC funds invested in same portfolio company in this study and this measurement is applied to 285 venture companies and 285 VC syndicates.

6.1 Dependent Variable

As VentureXpress data does not include investment rate of return of VC syndicate's invested portfolio company, the company's successful market exit after receiving all rounds of investments is used to measure the investment performance of the company and VC syndicates funded the company. If a portfolio company's current status after the last round of investment is either "IPO", "Acquisition", "LBO", "Merging", "Pending Acquisition" or "Went Public", then a binary variable represents 1, indicating successful market exit; otherwise, represent 0.

6.2 Independent Variables

Independent variables represent quantity and quality of VC inter-fund network ties embedded in VC syndicate. The quantity of VC inter-fund network is measured by log-transformed sum of unweighted and undirected network degree centrality and the quality of VC inter-fund network is measured by eigenvector network centrality.

As some VC funds undisclosed their names and some fund properties, their actual network properties are not precisely illustrated. Due to this limitation, I excluded such undisclosed VC fund when summing total degree centrality and eigenvector centrality inter-fund network ties of each VC syndicate invested in a portfolio company.

6.3 Control Variables

Control variables are portfolio company characteristics, VC fund characteristics, VC syndicate size, and proportion of disclosed VC funds, Asian VC funds, China VC funds, North America-based VC funds, U.S. VC funds and other continental VC funds of each VC syndicate.

Portfolio Company Characteristics represent portfolio company's industry in three categorical variables, "1: Information Technology", "2: Medical/Health/Life Science" and 3: Non-High Technology", industry class details in six categorical variables, portfolio company age, and location of portfolio company in binary variable, measures if a portfolio company is headquartered in either of VC hotbed states: California or Massachusetts, where show VC geographic business clusters. If yes, represents 1, otherwise, 0.

VC fund characteristics in each VC syndicate represent total number of VC funds, average age of VC funds, average investment experience of VC funds, measured in average investment frequency of VC funds, and average VC fund size, a log-transformed average of total known invested asset amount under management of VC funds participate in same VC syndicate.

VC syndicate size is a sum of log-transformed total amount invested to portfolio company by all participant VC funds in VC syndicate.

Proportion of disclosed VC funds within the VC syndicate is marked as a rate of disclosed VC funds in the VC syndicate.

Proportion of Asia VC funds within the VC syndicate is represented as a rate of Asian VC funds in the VC syndicate.

Proportion of China VC funds within the VC syndicate is a rate of China-based VC funds in the VC syndicate. China-based VC funds are headquartered in either mainland China, Hong Kong or Taiwan and a subset of a rate of Asian VC funds in the VC syndicate.

Proportion of North America-based VC funds within the VC syndicate is a rate of North America VC funds in the VC syndicate; most of the funds are concentrated in the U.S.

Proportion of U.S.-based VC funds within VC syndicate is a rate of U.S.-based VC fund in the VC syndicate and a subset of a rate of North America VC funds in the VC syndicate.

Proportion of Other Continent VC funds within the VC syndicate is represented as a rate of Other Continent VC funds in the VC syndicate. Other Continent VC funds are located in Europe, Middle East and Africa; most of the funds are concentrated in Europe.

7 Data Analysis Results

7.1 Descriptive Statistics

Out of 285 cross-national VC syndicates funded the 285 U.S. companies, majority of the syndicate participant are North America-based VC funds, with average participant rate of 74.9%; U.S.'s is 72.9%. Asia VC fund's average participant rate in VC syndicate is 11.6%, and China's is 3.5% in Figure 1.

Although the investment report highlighted the rapidly increasing Asian VC funds' investments in the U.S. markets [6], North America-based VC funds are the dominant economic actors, followed by Other Continent funds and Asia VC funds when they foster the cross-national VC syndicate.

Out of 285 companies funded by the VC syndicates, 195(68.4%) portfolio companies successfully exited through IPO or M&A; 90 (31.6%) companies are either liquidated or remained its private ownership status after a all rounds of investments.

In Figure 2, among 90 portfolio companies failed to exit, 66 (73.3% out of portfolio companies failed to exit; 23% out of total companies) are located at the VC hotbed states, Massachusetts or California, and among 195 portfolio companies successfully exited, 144(73.8% out of portfolio companies successfully exited; 51% out of total companies) are located at the VC hotbed states. Out of 210 companies headquartered in the VC hotbed states, 66 (31%) companies failed to exit; out of 75 companies not headquartered in the VC hotbed states, 24 (32%) failed to exit. This showed the cross-border VC syndicate's geographic investment preference in the VC hotbed states, while the portfolio company's location in the VC hotbed states does not better off its chance to successfully exit.

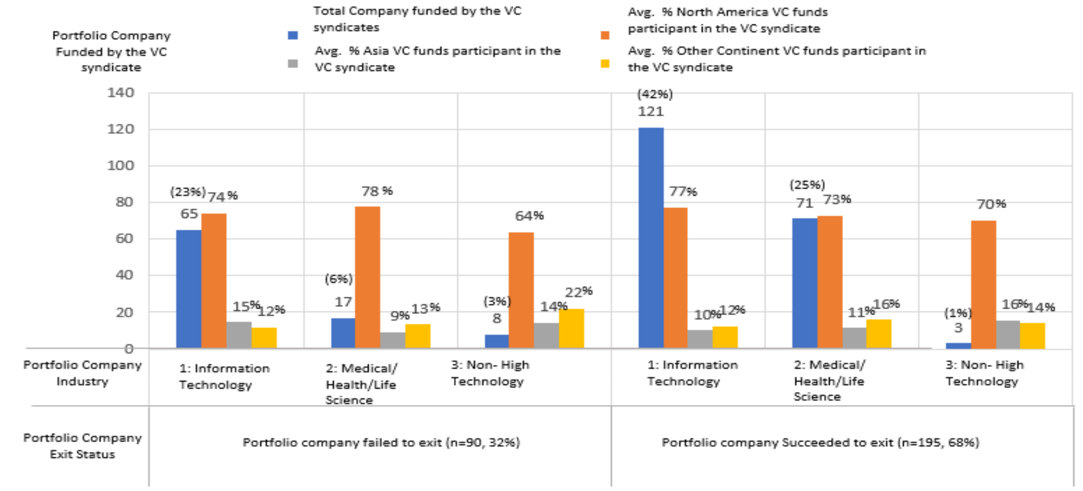

Figure 1. VC Syndicate participant VC Fund's Average Portfolio Company Industry Preferince and Performance

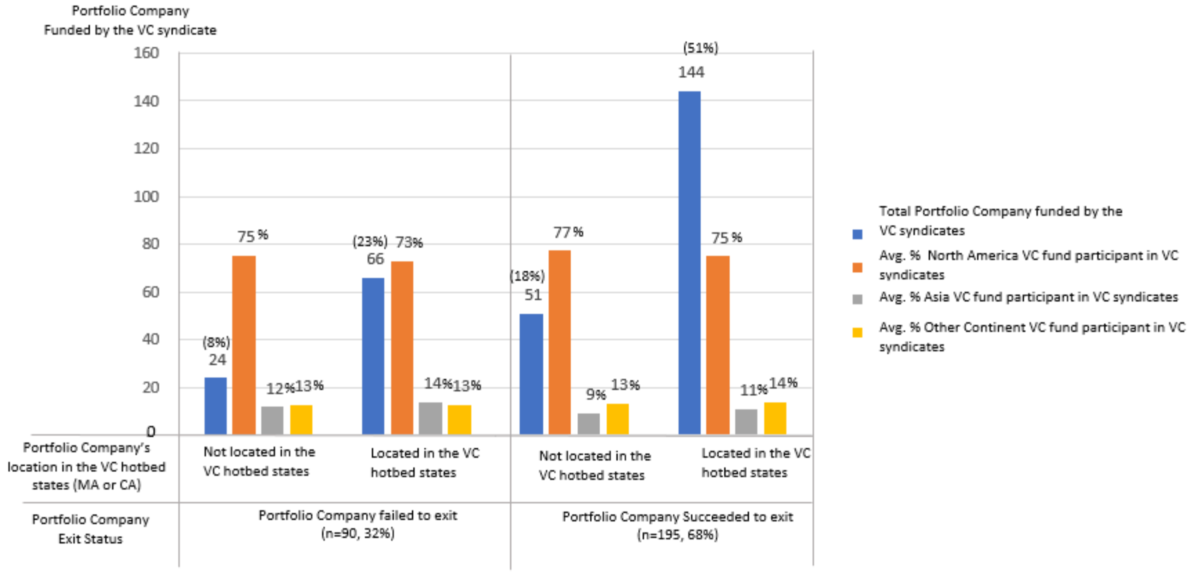

Figure 2. Portfolio Company Location in the VC hotbed states and Market Exit

Table 1. Market Exit of Portfolio Company by Industry

Market Exit (N =285)	Information Technology	Medical/Health/Life Science	Non-High Technology	Total
Liquidated	65 (22.8%)	17 (6%)	8(2.8%)	90 (32%)
Exited	121 (42.5%)	71 (24.9%)	3(1.1%)	195 (68%)

Table 2: Market Exit of Portfolio Company by Industry Detail

	N=285	Portfolio Company Industry Details								
		1	2	3	4	5	6	7	8	9
Portfolio Company Market Exit	Liquidated	13 (4.6%)	16 (5.6%)	14 (4.9%)	18 (6.3%)	4 (1.4%)	8 (2.8%)	9 (3.2%)	5 (1.8%)	3 (1.1%)
	Exited	27 (9.5%)	29 (10.2%)	26 (9.1%)	30 (10.5%)	9 (3.2%)	46 (16.1%)	25 (8.8%)	3 (1.1%)	0 (0%)

Note: 1: Computer Software and Services,2: Communications and Media,3: Semiconductors/Other Elect.,4: Internet Specific,5: Computer Hardware,6: Biotechnology,7:Medical/Health,8:Industrial/Energy, and 9:Other Products

Table 1 and 2 represent the VC syndicate investment preference in the high-tech industry, such as Information Technology, Biotechnology, Internet and Media, and suggest a partial effect led by a company industry on a company exit.

In Figure 3, overall maximum, minimum, mean and standard deviation values of each variable for 285 selected VC syndicates is represented; VC fund characteristics varied widely with a wide range of spread between minimum and maximum values.

7.2 Correlations

Quality and Quantity of VC inter-fund networks are negatively correlated to the rate of Asia VC fund and positively correlated to the rate of North America VC fund in the VC syndicate, due to a dominant participant number of North America VC funds in the VC syndicate, and statistically insignificant correlations are crossed in Figure 4.

Average VC fund characteristics are negatively correlated to the VC inter-fund network measures. This result could be affected by disclosed proportion of VC funds per the VC syndicate, as undisclosed VC funds' characteristics are imputed as missing variables.

After the review of Figure 4, I dropped variables with collinearity to other variables, portfolio company industry details and proportion of North America-based VC funds in the VC syndicate and run regression analysis on remained variables.

7.3 Regression Analysis

The results of logit regression analysis on the effects of 13 predictors comprise of portfolio company characteristics, fund characteristics and VC syndicate network variables of VC syndicate networks on portfolio company's market exits in Table 3. The regression analysis represents positive and statistically significant impact of quantity of VC inter fund-ties in the syndicate on the portfolio company investment performance, measured in its market exit. Hence, null hypothesis for Hypothesis 1 can be rejected. However, quality of the VC inter-fund networks on the investment performance is statistically insignificant, with p-value over 0.05 and the null hypothesis of Hypotheses 2 cannot be rejected.

Along with the quantity of VC syndicate's inter-fund networks, funded company's industry is statistically significantly impacting on the company market exits. Non-High technology industry of portfolio company gave negative impacts on their exits with coefficient of -.15 and selected companies are skewed to high technology industry that company industry variable is replaced to company industry variable for additional regression analysis on company industry effects.

Variables (N = 285)	Mean	St. Dev.	Min	Max
Portfolio Company Age	17.081	2.966	6	21
Quantity of VC syndicate network	6.567	0.930	2.197	8.397
Quality of VC syndicate network	0.448	0.312	0.016	1.712
% Disclosed VC funds in the VC Syndicate	0.804	0.122	0.429	1.000
% Asian VC funds in the VC Syndicate	0.116	0.101	0.025	0.750
% China VC funds in the VC Syndicate	0.035	0.070	0.000	0.500
% North America-based VC funds in the VC Syndicate	0.749	0.156	0.091	0.963
% U.S. VC funds in the VC Syndicate	0.729	0.164	0.091	0.963
% Other Continental-based VC funds in the VC Syndicate	0.135	0.120	0.000	0.818
VC Syndicate Size	11.412	0.798	6.685	14.499
Average participant VC Fund Age	27.098	4.546	16.571	45.000
Average participant VC Fund Investment Experience	1,738.553	920.240	21.529	4,823.900
Average participant VC Fund Capital under Management ($m)	12.784	0.755	10.770	15.512
Average participant VC Fund Investment Experience	7.234	0.863	3.069	8.481

Figure 3. Descriptive Statistics

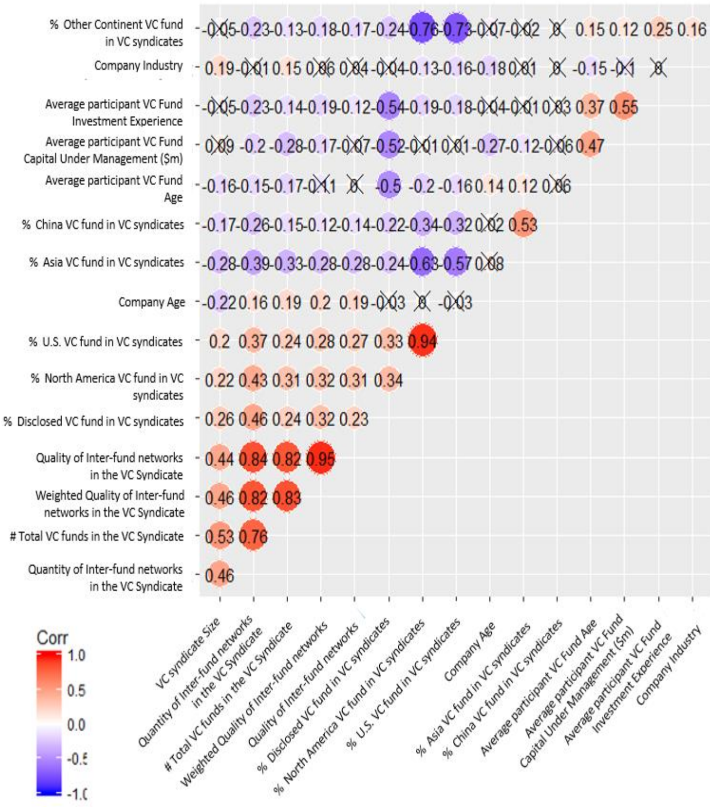

Figure 4. Correlations

Table 3. The Effect of VC syndicates' Inter-Fund Network on Portfolio Company Exit

Variables	Estimate	Std. Error	Z-Value	Pr(>|z|)	*Variables*	Estimate	Std. Error	Z-Value	Pr(>|z|)
(Intercept)	-8.24	5.51	-1.50	0.14	% Asia VC funds in the VC syndicate	2.77	2.73	1.02	0.31
Company Industry 2: Medical/ Health/Life Science	0.83	0.36	2.31	0.02**	% U.S. VC funds in the VC syndicate	3.34	2.35	1.42	0.15
Company Industry 3: Non- High Technology	-1.49	0.74	-2.01	0.04**	% Other Continent VC funds in the VC syndicate	4.58	2.75	1.70	0.09*
Company Age	-0.06	0.06	-1.00	0.32	VC Syndicate Size	-0.14	0.21	-0.66	0.51
Company Location in the VC hotbed states (MA or CA)	-0.08	0.33	-0.23	0.82	Average participant VC Fund Age	-0.01	0.04	-0.18	0.86
Quantity of Inter-fund networks	0.92	0.37	2.51	0.01**	Average participant VC Fund Capital under Management ($m)	0.04	0.27	0.14	0.89
Quality of Inter-fund networks	-1.59	0.92	-1.73	0.08*	Average participant VC Fund Investment Experience	0.23	0.2	1.13	0.26
% Disclosed VC fund in the syndicate	110	1.72	0.64	0.52					

*** Note 1 :** n= 285 for number of portfolio companies and invested VC syndicates; n = 2,626 for number of total VC funds participated in the VC syndicates. Standardized coefficients are reported.

*** Note 2:** *p<0.1; **p<0.05; ***p<0.01

None of VC fund's characteristics were statistically significant, but syndication participant VC fund's age was negatively impacting on the VC syndicate funded companies' successful market exit, while VC funds' capital under management and investment experience are positively impacting on the company exit.

Proportion of Asia, U.S. and other continental-based VC funds in the VC syndicate variables all showed positive relationship to the company market exits, while involvement of other-continent-based VC funds had highest coefficients to the investment performance, followed by the involvement U.S. funds and Asian funds. However, none of these variables were statistically significant to the company exits and U.S.-based VC funds' involvement is dominant in the sampled set, as shown in Figure 1.

Though Sorenson et al proved the positive effects of participant VC funds' age, investment experience and capital under management on the VC syndicate performance, and stressed the comparative advantages of geographic- and industry-localization of VC investments [8], these effects are insignificantly shown in the cross-border VC syndicates' investment performances.

Logit regression results in Table 3 represented the positive effects of quantity of VC syndicate networks, but effect of quality of VC syndicate networks is not shown, due to multicollinearity against quantity of VC syndicate networks used in the model.

Hence, I selected seven most important features for exploring the effects of VC syndicate networks on the portfolio company market exits and run the logit regression analysis again in Table 4.

Model 1 and Model 3 explore the effects of quantity of VC syndicate networks on portfolio company exits.

Model 2 and Model 4 explore the effects of quality of VC syndicate networks on portfolio company exits.

For Model 1 and 2, quantity of VC syndicate networks for Model 1, quality of VC syndicate networks for Model 1, portfolio company industry details, portfolio company age, proportion of Asia VC participant funds in the VC syndicate, proportion of other continental-based VC participant funds in the VC syndicate, VC syndicate size, average participant VC fund age in the syndicate are selected as predictors on portfolio company exits.

For Model 3 and 4, quantity of VC syndicate networks for Model 3, quality of VC syndicate networks for Model 4, portfolio company industry details, portfolio company location in the VC hot bed states, portfolio company age, proportion of Asia VC participant funds in the VC syndicate, proportion of other continental-based VC participant funds in the VC syndicate, proportion of U.S. VC participant funds in the VC syndicate, proportion of disclosed VC participant funds in the VC syndicate, VC syndicate size, average participant VC fund age in the syndicate are selected as predictors on portfolio company exits.

After figuring the significant and positive impact of portfolio company industry as high technology on its market exit in Table 3 and observing the high-technology industry skewed sampled 258 companies in Table 1 and 2, I used industry class details for the regression analysis in Table 4 to determine which specific sector in high technology industry of the portfolio company is likely to drive successful market exits.

Table 4. Effect of VC syndicates inter-fund network on portfolio company exit, with selected features

	Company Market Exit			
Variables	(1)	(2)	(3)	(4)
Network Measures:				
Quantity of Inter-fund networks in the VC Syndicate	0.476**		0.473**	
	(0.196)		(0.218)	
Quality of Inter-fund networks In the VC Syndicate		0.424		0.320
		(0.551)		(0.562)
Company Characteristics:				
Company Industry Class Details:				
Communications and Media	-0.253	-0.236	-0.186	-0.170
	(0.483)	(0.476)	(0.486)	(0.480)
Semiconductors/ Other Elect	-0.112	-0.108	-0.020	-0.037
	(0.490)	(0.485)	(0.506)	(0.502)
Internet Specific	-0.182	-0.177	-0.159	-0.164
	(0.468)	(0.463)	(0.471)	(0.467)
Computer Hardware	0.006	-0.019	0.036	-0.107
	(0.711)	(0.706)	(0.738)	(0.731)
Biotechnology	0.882	0.821	1.030*	1.007*
	(0.539)	(0.530)	(0.558)	(0.552)
Medical/Health	0.012	0.119	0.160	0.294
	(0.547)	(0.540)	(0.566)	(0.555)
Industrial/Energy	-1.205	-1.363	-1.126	-1.292
	(0.844)	(0.833)	(0.863)	(0.852)
Other Products	-15.993	-16.247	-15.910	-16.125
	(821.541)	(830.150)	(805.667)	(819.15)
Company Location in VC hot beds			-0.052	0.066
			(0.335)	(0.327)
Company Age	-0.079	-0.052	-0.074	-0.052
	(0.053)	(0.053)	(0.057)	(0.058)
VC Syndicate Characteristics				
% Asian VC funds in the VC Syndicate	-0.604	-1.570	2.932	1.383
	(1.420)	(1.350)	(2.827)	(2.650)
% US VC funds in the VC Syndicate			3.409	2.712
			(2.456)	(2.342)
% Other Continental-based VC funds in the VC Syndicate	1.538	1.075	4.895*	3.835
	(1.296)	(1.268)	(2.870)	(2.739)
% Disclosed VC funds in the VC Syndicate			1.402	2.499
			(1.803)	(1.755)
VC syndicate size	-0.148	0.019	-0.189	-0.034
	(0.208)	(0.206)	(0.214)	(0.213)
Participant VC Fund Characteristics				
Average participant VC Fund Capital under Management ($m)			0.011	-0.027
			(0.274)	(0.273)
Average participant VC Fund Age	-0.008	-0.014	-0.006	0.005
	(0.032)	(0.032)	(0.040)	(0.040)
Average participant VC Fund Investment Experience			0.188	0.203
			(0.202)	(0.202)
Constant	0.826	1.723	-4.827	-4.077
	(2.607)	(2.833)	(5.115)	(5.197)
Observations	285	285	285	285
Pseudo-R^2 $(McFadden)$	0.087	0.071	0.096	0.084
Log Likelihood	-162.334	-165.076	-160.598	-162.841
Akaike Inf. Crit.	354.669	360.152	361.196	365.683
Note:	*p<0.1; **p<0.05; ***p<0.01			

As described by descriptive statistics in Table 2 and Figure 3, portfolio companies in biotechnology are highly likely to successful exit, according to the regression results with statistically significant and positive estimated coefficients.

Models' goodness of fits is tested by McFadden Pseudo R-squared comparison in Table 4 and the Model 3 had the best fit, followed by Model 1, Model 4 and Model 2 in order. Though McFadden R-squared values are near 0.1 and not extremely fit well, models describe the effects of VC syndicate networks on the performances with moderate fits.

Based on regression analysis results in Table 4, quantity of VC syndicate inter-fund network is statistically significant and positively impacting on the VC syndicate's investment performance, measured in portfolio company's exits in all four models. Though quality of VC syndicate inter-fund networks is not statistically significant, it also showed positive impacts on the portfolio company exits.

8 Discussion

Both quality and quantity of VC syndicate inter-fund networks are positively impacting on the invested portfolio company's performance, and this effect enhances when the invested company is in the high technology industry, more specifically in the biotechnology and average participant VC funds' investment experience is richer and capital under management is larger. However, only the high technology industry of portfolio company and the quantity of VC syndicate network show statistical significance in the selected VC syndicates. Increase of the number of VC syndicates and classification of VC syndicates by each investment round may give depth to the analysis and may show better results.

Also, inclusion of event study, such as China government's mitigated regulation and economics reform in the model may illustrate the properties of the cross-border VC syndicate better and perhaps answer the syndicate's highly skewed investment preference in the biotechnology industry.

Another suggestion for future research would be testing of portfolio company fixed effects and VC fund fixed effects. Also, elaboration of this study's simple unweighted and undirected adjacency socio-matrix to weighted and directed socio-matrix should be considered as a next step of the VC syndicate network research.

9 Conclusion

This study demonstrates that the cross-national VC syndicate involving more VC funds with higher inter-fund ties outperform by leading more invested portfolio company's successful market exits.

Also, the cross-national VC syndicate prefer to invest in the portfolio company in the biotechnology industry and headquartered in the geographic VC hotbeds.

Although Asia VC investment inflows are gradually increasing in the U.S. market, North America VC funds, mostly comprised of the U.S. VC funds, are still the dominant economic actor leading the cross-border VC syndicate networks in the U.S. VC market.

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