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Venture Capital Networks:
An analysis using the exponential random graph model

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Abstract

Applying the exponential random graph model (Robins et al. 2007) to the investment data of Japanese venture capital (VC) firms, we document the relationship between VC performance and the dynamics of their co-investment networks. First, we find that VCs' co-investment network formation is not independent from VC characteristics. Second, VCs' past experiences of co-investments contribute to a higher likelihood of future co-investments among them, not only when VCs gain higher returns from their past co-investments but also when the jointly invested venture business companies (VBs) experience higher growth after an initial public offering (IPO). Third, such positive assortativity in terms of the returns obtained from their co-investment has become significantly weaker after the great financial crisis in 2007-2009. These results suggest that the poor financial market conditions make network structures less stiff. Fourth, somewhat puzzlingly, the positive assortativity in terms of jointly invested VBs' growth has become stronger after the great financial crisis.

Keywords: Venture capital firms, Network formation, Return, Firm growth, ERGM

JEL classification: G24; G31

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1. Introduction

Venture capital firms (VCs) are one class of financial intermediaries that invest their managed funds to venture business companies (VBs).[1] VCs attempt to find promising investment targets and support them to achieve VBs' business goals by providing not only the financial resources but also various kinds of expert advices, and eventually obtain return from their investments through initial public offering (IPO), trade sales, or management buyout. As invested firms can obtain access to those resources through VC investments, such a series of VC activities could contribute to the growth of invested companies.

Given such investment activities are highly knowledge-intensive, VCs are using a variety of resources accumulated inside their firms (e.g., human capital). While such resources accumulated inside VCs themselves are necessary for successful investments, better access to the resources accumulated outside of the VC firms could be also important for their investments. The resources accumulated outside of the VCs themselves are, for example, specific industry knowledge and pool of potential deals. It has been reported that VCs tend to specialize in specific industries so that they can efficiently accumulate industry-specific knowledge (e.g., Hochberg et al. 2007). The fact that VCs frequently co-invest implies such resources accumulated outside of their own firms are indispensable

[1] Following the tradition of the literature (Rin et al. 2013) we call VCs and VBs as firms and companies in this paper, respectively.

for successful investments.

These illustrations suggest that the pattern of co-investment network formation reflects how the resources held by VCs are employed, which is a great interest of both practitioner and academic researchers. Do VCs rely solely on their own resource or employ other VCs' resources to complement their own resources? If so, what kind of VC resources are exchanged among VCs? Does the past collaboration matter? Under what economic environment are such mechanisms more viable? In this paper, we tackle these questions by empirically documenting the pattern of co-investments among VCs and discuss its economic implication.

We are interested in how VCs with better track records in terms of their investment return and/or invested firms' growth after IPO co-invest in future. Following the literature in network science, we call the patterns of co-investment network formations associated with VC characteristics (e.g., better track records of co-investor VCs) as network/graph configurations, and study the emergence probability of network with specific network configurations given the VC characteristics.

Regarding such network configurations, we should note that there are many possible patterns associated with the network formation among VCs. As one plausible case, VCs with better resources might co-invest only with well-performed VCs. This could be the case, for example, that those "good" VCs can exchange their internal resources efficiently with each other so that they can obtain larger joint surplus. As a simple illustration, one

VC holding information about promising investment opportunity but lacking some resources on industry expertise might want to be matched up with other VCs with such resource. If this is the case, we would observe positive assortative matching among VCs in terms of their performance. As another case, consider the situation where well-performed VCs are holding small financing capacity. Such VC does not necessarily need to exchange, for example, deal flow or other expertise but only need to find someone satisfying financing needs. If this is the case, we might not observe any assortative matching among VCs in terms of their performance. Thus, it is an empirical question if there is any mapping pattern from VC's characteristics to the emergence probability of networks with specific configurations.

While the motivation of the study is straightforward, empirical examination encounters a number of challenges. First of all, it is not necessarily obvious how to measure VC characteristics meaningful for this co-investment pattern. Suppose a VC is exhibiting good performance in terms of the return obtained from the past investments. On the one hand, this could lead to a reasoning that this VC owns valuable resource attractive to other VCs. Thus, we might expect that such a VC would be involved in a large number of future co-investments. On the other hand, we should note that the abovementioned performance measure is constructed only from the VC's perspective but neither from other companion VCs nor from the target VB. Even if one specific VC enjoys high return from its investment, it could still be the case that other companion VCs did not do well because, for example, they needed to paid relatively high price for their investments. In the similar sense, the invested VBs might face business difficulty after accomplishing IPOs. As many extant studies have reported, VCs might induce VBs to go public even if it would not contribute to the VB's long-term growth (Hamao et al. 2000; Hellmann et al. 2008). Thus, from the viewpoint of empirical analysis, it is not entirely satisfactory to focus only on the return obtained by one VC as the characteristics meaningful for the co-investment pattern. Rather, we would need to employ multi-dimensional VC characteristics taking into account other co-investor VCs and invested VBs.

Second, we also have to take into account the investment history associated with each VC. Having a better characteristics would lead to higher likelihood of joint investments if such characteristics are well recognized by other VCs. This could be the case when, for example, the VC and the companion VC had an experience of joint investment in the past. This necessitates us to take into account not only each VC's characteristics but also their past investment history.

Third, we also need to take into account the economic environment surrounding VCs and VBs. To illustrate, under the difficult financing condition for VCs, each VC might be less picky about the quality of their investment partners as such collaboration could contribute to securing sufficient funds. Thus, it could be the case that the positive assortativity among VCs becomes weaker under such worse market condition. This discussion requires us to allow the time-variant feature of the mapping pattern from VC's characteristics to the emergence probability of graphs with specific graph configurations.[2]

Given these concerns, we need to choose the empirical methodology which can simultaneously account for the multi-dimensional performance measures, various matching configurations, and time-variant feature of the network formation. In this paper, we employ the exponential random graph model (ERGM) developed in network science literature (e.g., Snijders 2002; Robins et al. 2007).

A limited number of extant studies have been examining the economic implication of co-investment and the dynamics of VC networks. As a prominent study in this field, Hotchberg et al. (2010) found that VCs formulate networks as a barrier to entry. Also, Hotchberg et al. (2007) found that the VCs with higher centrality in the network perform well. These studies succeeds on illustrating the roles of VC co-investment networks. But it has not been clear how such networks are formulated. In this context, the most related study to ours is Hotchberg et al. (2015), which examine the determinants of network formation and confirm that the resource exchange motive is more important than the homophily motive. Against these backgrounds, applying the exponential random graph model to unique investment data of Japanese venture capital firms (VC) over the last two decades, we empirically examine the relationship between VC performance and the

[2] Regarding the investment cycle of VBs, Miyakawa and Takizawa (2015) examines how VCs with heterogeneous investment experiences provide funds to VBs under market upturn and downturn with controlling for VBs' fund demand by incorporating VB-time specific individual effects.

dynamics of their co-investment networks.

The findings we obtain in this paper are summarized as follows. First, we found that VCs' co-investment network formation is not independent from VC characteristics. Second, VCs' past experiences of co-investments contributed to higher likelihood of future co-investments among them not only when VCs had gained higher return from their past co-investments but also when jointly invested venture business companies (VBs) would experience higher growth after IPO. These results are stably observed over the data periods. Third, such positive assortativity in terms of the returns obtained from their co-investment became significantly weaker after the great financial crisis in 2007-2009, which is consistent with another result that VCs' co-investment network formation became less dependent on VC characteristics over the same periods. This suggests that the worse financial market condition made network structure less stiff. This could be partly motivated by VBs' need for finance. Fourth, somewhat puzzling, the positive assortativity in terms of jointly invested VBs' growth became stronger after the great financial crisis. This could be the case, for example, that there are elite networks of VCs holding resources contributing to VB companies' long-term growth and it became more difficult for VCs without resources to join such elite networks after the financial crisis.

The contributions of the present paper are at least three-fold. First, this is the first paper applying the ERGM to VC networks data and formally examine the dynamics of VC network formation. Second, the paper is also the first trial to study the time-variant feature of such network dynamics in the context of VC investments. Third, our empirical study is the first one to uncover the relationship between the network feature and invested VB companies' performance (i.e., growth after IPO).

The rest of the paper is organized as follows. In section 2 and 3, we briefly overviews the related literature and construct the hypotheses tested in the paper, respectively. In section 4, we detail the data used in our analysis. The empirical framework and the empirical results are presented in section 5. Section 6 concludes and provide potential avenues for future research.

2. Related Literature

The first group of literature related to the present study is the ones studying the role of VC networks. As a prominent study in this field, Hotchberg et al. (2010) found that VCs formulate networks as a barrier to entry. Also, Hotchberg et al. (2007) found that the VCs with higher centrality in the network perform well. These studies succeeds on illustrating the roles of VC co-investment networks. But it has not been clear how such networks are formulated. The second group of extant studies is the relationship between VC network formation and VCs' motivation. Hotchberg et al. (2015) examine the determinants of network formation and confirm that the resource exchange motive is more important than the homophily motive. Different from these extant studies, applying the methodology developed in network science literature to unique investment data of

Japanese venture capital firms (VC) over the last two decades, we empirically examine the relationship between VC performance and the dynamics of their co-investment networks.

3. Hypothesis formulation

In this subsection, we organize the hypotheses we test in the present paper. Motivated by the second group of the extant studies mentioned in the previous section, we examine how the characteristics of each VC contribute to the formation of networks with a specific configuration. First hypothesis is about the randomness of the network formation. We conjecture that well-performed VCs sharing the past co-investment experiences tend to be re-matched (i.e., another round of co-investment) again. This could be the case, for example, that such past co-investments served as an opportunity to confirm their ability/quality with each other. As the transaction cost with partners becomes smaller after co-working, it is natural to conjecture such persistency of co-investment relationships. Thus, the first hypothesis sets the null hypothesis on the randomness of VC network formulation.

Hypothesis 1: Each pair of two VCs co-investing in the same VB is randomly matched.

The second hypothesis augments this first hypothesis with taking into account both the past co-investment experiences and the characteristics of each VC. The first part of this second hypothesis focuses on VC's own investment net return, which is measured as subtracting one from the ratio of the initial price of an invested share as of IPO to the price the VC paid in its investment. The hypothesis is based on the conjecture that VCs having obtained higher return from their investments hold valuable resources, which are attractive to other potential co-investor VCs. Furthermore, we conjecture that the existence of such resources can be confirmed through the past co-investments.

Hypothesis 2-1: Two VCs having invested in the same VB and earned better investment return are more likely to co-invest again.

Obviously, this could not be the case when, for example, such a well-performed VC can invest solely, thus does not need to co-investment with other VCs. As majority of the investments are actually co-investments in our dataset, we do not think this becomes a serious concern. Nonetheless, higher past return might not attract other potential co-investor VCs when the well-performed VC does not have a good record from the perspective of the past co-investor VCs. This could be the case when the well-performed VC plays a role of general partners (GP) and gather funds from a number of limited partners, which are not necessarily well-equipped with resources.

The second part of the second hypothesis is focusing not on VC's investment return but the invested VB's growth after IPO as well as VCs' co-investment experiences. Instead of measuring VC performance from the VC's perspective, we are measuring the VC's performance based on the invested VB's long-term growth. If such a long-term growth represents the amount of resources held by VCs, we should observe the positive assortative matching based on the VC performance measured from VB's viewpoint.

Hypothesis 2-2: Two VCs investing in the same VB which exhibited better performance after IPO are more likely to be re-matched again

Note that these two sub-hypotheses are not mutually exclusive and could be supported simultaneously. As we will see later, the correlation between the two performance measures are not so high. Thus, we think it is possible to test the two sub-hypothesis simultaneously

While we estimate the possibility that well-performed VCs tend to be matched with well-performed VCs in the case of past co-investment, we also allow the mechanism to depend on external economic environments. The last hypothesis tested in this paper is about the time-variant property of the network formation.

Hypothesis 3: The pattern of network formation depends on the outside environment and time-variant

From the following section, we detail the dataset we use to test these hypotheses, empirical methodology we employ, and present the estimate results.

4. Data

4.1. Data overview

The data we used in the present paper is obtained from Japan Venture Research Inc., which is a Japanese data vendor specializing in VC industry. The dataset contains detailed investment information measured for each triplet consisting of VC, VB, and investment round. In the current version of our paper, we only use the data associated with the investments on VBs that eventually accomplished IPO.[3] Each data entry is identified by these triplets and associated with the date of investment, the share price of VB paid by VC at each investment, the date of IPO, the initial share price for the VB as of IPO, the initial market the VB is listed as of IPO, whether the VB changed the listed market after IPO or not, which market the VB moved to (if any), and whether the VB was delisted or not. The frequency of the data is monthly.

One unique feature of our data is that we can measure both the investment return that each VC obtained from their investments and the post-IPO dynamics (i.e., market

[3] We are also planning to use the additional three datasets corresponding to VBs that either (i) acquired by other companies, (ii) liquidated, or (iii) have not faced IPO, M&A, or liquidation. Note that these data are also recorded for the abovementioned triplet.

change) of each VB. These two information is not necessarily available in the extant studies. For example, Hochberg et al. (2007) employ the number of investment rounds for measuring VCs' performance. As clearly mentioned in their paper, the investment return measure we employ in the present paper is more suitable for characterizing VC performance, which presumably proxies for the resources held by VC. To measure the return, we use the bench-mark adjusted return from each investment by using the abovementioned data as well as the monthly-level time series data for TOPIX stock index. As we will detail later, employing not only such a measure corresponding to VCs' perspective but also another measure for VBs' growth can enrich the discussion.

Using the investment data of VCs to VBs over multiple investment rounds, we construct bipartite graph data which incorporate both VC and VB in the network data. As it is bipartite, each node of the network accounts for either VC or VB, and VC (VB) can be connected only to VB (VC) through edge. We transform this data so as to have unigraph data accounting only for the co-investments of VCs. In the next sub-section, we detail how to construct the data we use for our estimation.

4.2. Variable definition

First, we define the performance of VCs corresponding to the hypothesis 2-1 and 2-2. As a first performance measure of VCs in terms of their own investment return, we compute the annualized benchmark-adjusted return of the investment from VC i to VB j

implemented at t as $r_{ij}^{(t_{inv}, t_s(j))}$ as in the following equation (1):

$$r_{ij}^{(t_{inv}, t_s(j))} = \left(\frac{s_j}{w_{ij}^{(t)}}\right)^{\frac{t_S(j)-t+1}{365}} - \left(\frac{z(t_S(j))}{z(t)}\right)^{\frac{t_S(j)-t+1}{365}} \quad (1)$$

In this expression, $t_s(j)$ denotes the time when VB j accomplished IPO. $w_{ij}^{(t)}$ accounts for the price per share paid by VC i when it invested on VB j at time t. s_j accounts for the initial price of VB j's share as of IPO. Finally, $z(t)$ denotes the level of TOPIX as of time t. Figure 1 depicts the distribution of this return measure. Note that this return is measured for each investment from VC i to VB j. Reflecting the fact that the Japanese VC industry was in the development stage for most of our sample periods, large part of the histogram shows the negative benchmark-adjusted return. As detailed below, we will aggregate this information so as to obtain VC-level time-variant performance measure in terms of their investment return.

<Figure 1>

As a second performance measure of VC, we track the market movement of each VB j invested by VC i at t. Here, the market movement denotes the market upgrade such as JASDAQ to the TSE 1st section. Table 1 summarizes all the cases of the market upgrade we consider in the present study. We define a dummy variable taking value of one if the invested VB *j* experienced one of these market upgrades after its IPO. We presume that such market movements up to some extent account for firm growth represented by larger financing needs. We leave the employment of other growth measures such as sales growth for our future task. Again, this dummy variable is constructed for each investment from VC *i* to VB *j*, and we will aggregate this information so as to obtain VC-level time-variant performance measure in terms of the invested VBs' dynamics.

＜Table 1＞

5. Empirical analysis

5.1. Empirical framework

Using the dataset presented in the previous section, we define the investment graph $A^{[t-\Delta t,t]}$ over the local time interval $[t-\Delta t,t]$ as follows:

$$A^{[t-\Delta t,t]} = \left(A_{ij}^{[t-\Delta t,t]}\right)_{i,j} \tag{2}$$

where

$A_{ij}^{[t-\Delta t,t]} =$

$$\begin{cases} 1 \ \ if \ \ VC \ \ i \ \ invests \ \ VB \ \ j \ \ during \ \ [t-\Delta t, t] \\ 0 \ \ otherwise \end{cases}$$

Note that $A_{ij}^{[t-\Delta t,t]}$ accounts for the investment history of VC *i* over the local time interval $[t-\Delta t, t]$. In the similar fashion, co-investment graph $B^{[t-\Delta t,t]}$ over the local time interval $[t-\Delta t, t]$ an be defined as follows:

$$B^{[t-\Delta t,t]} = \left(B_{i_1 i_2}^{[t-\Delta t,t]}\right)_{i_1 i_2} \tag{3}$$

where

$$B_{i_1 i_2}^{[t-\Delta t,t]} =$$

$$\begin{cases} 1 \ \ if \ \ VC \ \ i_1 \ \ coinvests \ \ with \ \ VC \ \ i_2 \ \ during \ \ [t-\Delta t, t] \\ 0 \ \ otherwise \end{cases}$$

In our empirical analysis, we use the local time interval $[t-\Delta t, t]$ for measuring the VC co-investment network formation and study how the characteristics of each VC contribute to the emergence of VC networks with specific configurations. For measuring the VC characteristics, we use a preceding local time interval $[t-2\Delta t, t-\Delta]$ to $[t-\Delta t, t]$. Return associated with the investment of VC *i* on VB *j* over $[t-2\Delta t, t-\Delta t]$ is called as return-performance. To be more precise, for $t \in [t-2\Delta t, t-\Delta t]$, the average, median, and simple sum of $r_{ij}^{(t_{inv}, t_s(j))}$ for $t_s(j) \in [t-2\Delta t, t-\Delta t]$ and each VC *i* are computed. Then, we set a dummy variable taking value of one if such VC *i*-level average, median, and simple sum of $r_{ij}^{(t_{inv}, t_s(j))}$ for each

$t_s(j) \in [t - 2\Delta t, t - \Delta t]$ exceed their median level among all the measured $r_{ij}^{(t_{inv}, t_s(j))}$ for each $t_s(j) \in [t - 2\Delta t, t - \Delta t]$, and call it as "return-performance". We also set a dummy variable taking value of one if VB j invested by VC i accomplished market upgrade over $t \in [t - 2\Delta t, t - \Delta t]$, and call it as "growth-performance".

In order to document the emergence pattern of VCs' co-investment networks, we assume that observed co-investment graph B emerges from the following exponential random graph model (ERGM):

$$P(G;\theta) \equiv \left(\frac{1}{\kappa}\right) \exp\left(\theta \sum_{i_1,i_2} B_{i_1,i_2} \psi_{i_1,i_2}\right) \tag{4}$$

Here, θ is the model parameter and κ is the standardization term. ψ_{i_1,i_2} is a dummy variable taking value of one if the co-investing VB *i1* and VB *i2* satisfy a given configuration.

$$\psi_{i_1,i_2} = \begin{cases} 1 \ \ if \ \ VC \ \ i_1 \ \ and \ \ VC \ \ i_2 \ \ stisfy \ \ a \ \ given \ \ configuration \\ 0 \ \ otherwise \end{cases}$$

Suppose the emerged graph does not depend on VC characteristics (Hypothesis 1), then $\psi_{i_1,i_2} = 1 \ \ for \ \ \forall i, j$. Then, the estimated model is constructed as follows:

$$P(G;\theta) \equiv \left(\frac{1}{\kappa}\right)\exp\left(\theta \sum_{i_1,i_2} B_{i_1,i_2}\right) = \left(\frac{1}{\kappa}\right)\exp(\theta M) \quad where \ M \ is \ \#(edges)$$

(5)

Consider the possibility that some VC characteristics (e.g., return-performance) affect the probability of graph emergence, and define a dummy variable $\bar{u}_i$ taking value of one if VC *i* is categorized as successful in terms of return-performance. Then, the configuration accounting for "two VCs having invested in the same VB and earned better investment return are more likely to be re-matched again" can be written as follows:

$$P(G;\theta) \equiv \left(\frac{1}{\kappa}\right)\exp\left(\theta \sum_{i_1,i_2} B_{i_1,i_2}\bar{u}_{i_1}\bar{u}_{i_2}\right)$$

$$= \left(\frac{1}{\kappa}\right)\exp(\theta M_s) \quad where \ M_s \ is \ \#(edges \ between \ past \ success \ in \ return) \quad (6)$$

In order to incorporate multiple configuration to the model and test if those are rejected or not, we can generalize the model as follows:

$$P(G;\theta) \equiv \left(\frac{1}{\kappa}\right)\exp\left(\sum_k \theta^{(k)} \sum_{i_1,i_2} B_{i_1,i_2}\psi_{i_1,i_2}^{(k)}\right) \quad (7)$$

where

$\psi_{i_1,i_2}^{(k)} \ is \ kth \ configuration$

In our empirical analysis presented in the next section, we set up the configurations corresponding to the three hypotheses constructed in the previous section. Table 2 summarizes the 8 configurations we include in our ERGM estimation. To see the time-variant property, we estimate the model for each *t* belonging to each year with setting Δt as 36 months, and do the rolling regression.

5.2. Baseline results

In this subsection, we show the estimate results in the case of Δt=36 months and aggregating $r_{ij}^{(t_{inv}, t_s(j))}$ to VC-level using its average. Figure 2 depicts the estimated coefficients associated with 8 configurations summarized in Table 2. First, we find that the coefficient associated with the configuration 1 shows negative value and it is statistically away from zero (at 1% significant level). This implies that the matching between two VCs as a form of co-investment is not random.

Second, augmenting this result, the estimated coefficients associated with the configuration 4 and 5 show both positive coefficients, which are statistically away from zero (at 1% significant level). These results suggest that two VCs are more likely to be matched in their co-investment not only when those VCs had gained higher return from their past co-investments but also VBs jointly invested by those VCs would experience higher growth after IPO. As these results are stably observed over the data periods, we confirm that the positive assortative pattern in Japanese VC industry in terms of their performance.

We should note that the size of coefficient is much larger in the configuration 5 than that in the configuration 4. This means that the main driver of VC co-investments is the positive assortativity in terms of the growth performance. The fact that such a strong pattern is observed over all the sample periods suggests that VCs with better growth-performance are more likely to co-invest and the invested VBs tend to show better growth (i.e., market upgrade).

Third, from the dynamic pattern of the coefficients associated with the configuration 4, which is summarized in Figure 3 from 2006, we can confirm that the positive assortativity among VCs in terms of the returns became weaker after the great financial crisis in 2007-2009. This implies that the past return-performance mattered less under the weaker financial market environment. This is consistent with the fact the matching pattern between two VCs became less dependent on VC characteristics (configuration 1).

Somewhat puzzling, we can also confirm that the positive assortativity in terms of VCs growth-performance became larger after the great financial crisis in 2007-2009. This means the network among VCs were stiffer over the post-crisis periods. How can we interpret this result as a consistent way with the results associated with configuration 1 and 4? One conjecture is that there are elite networks of VCs holding resources contributing to VB companies' long-term growth and it became more difficult for VCs without resources to join such elite networks after the financial crisis.

5.3. Robustness

We repeat the same ERGM estimation by using Δt=12 month instead of 36 months. Such an estimation provides a qualitatively similar result to that presented in the previous section. We also measure the return-performance by using the median and total sum of $r_{ij}^{(t_{inv},t_s(j))}$ instead of the average of $r_{ij}^{(t_{inv},t_s(j))}$, and confirm that the results are robust.

6. Conclusion

In this paper, applying the exponential random graph model to unique VC investment data, we document the relationship between VC performance and the dynamics of their co-investment networks. The results imply the systematic pattern of network formation for VC co-investments. VCs' past experiences of co-investments contributed to higher likelihood of future co-investments among them not only when VCs had gained higher return from their past co-investments but also when jointly invested VBs would experience higher growth after IPO. Interestingly, such positive assortativity in terms of the returns obtained from their co-investment became significantly weaker after the great financial crisis in 2007-2009, which suggests that the worse financial market condition made network structure less stiff. As somewhat (at least seemingly) contradicting with this result, the positive assortativity in terms of jointly invested VBs' growth became stronger after the great financial crisis. This could be the case that there are elite networks of VCs holding resources contributing to VB companies' long-term growth and it became more difficult for VCs without resources to join such elite networks after the financial crisis.

Given the current study is still in its preliminary stage, we are planning to expand this research to a number of directions. First, we need to enrich the list of configuration so as to identify the central driver(s) of VC network formation. This is specifically important given a concern that the current results are driven by other attributes of VCs not taken into account in the present study. Among the potential set of configurations, it would be important to consider the homophily and heterogeneity in terms of VCs characteristics. Second, we need to examine if the observed positive assortativity among VCs in terms of their performance actually lead to better performance of VCs in future. If this is the case, we can confirm the "richer gets richer" pattern in VC industry. Third, we can use the exponential random graph model to study more complicated network configuration corresponding to more than two VCs. Given the importance of accommodating more and more start-up companies, which presumably contribute to vital economic condition, it is important to examine these research questions by using the analytical framework we use in the present study.

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Figures and Tables

Figure 1: Benchmark-adjusted return distribution

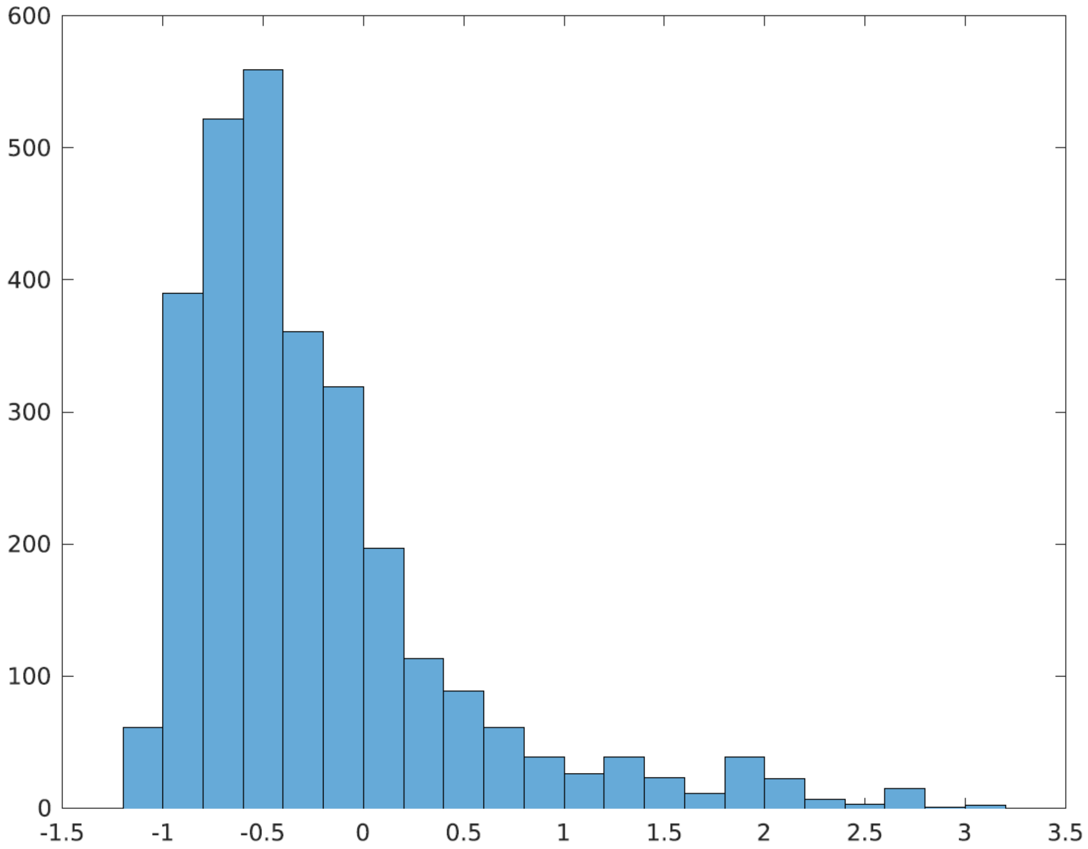

Figure 2: Estimate results for eight configurations

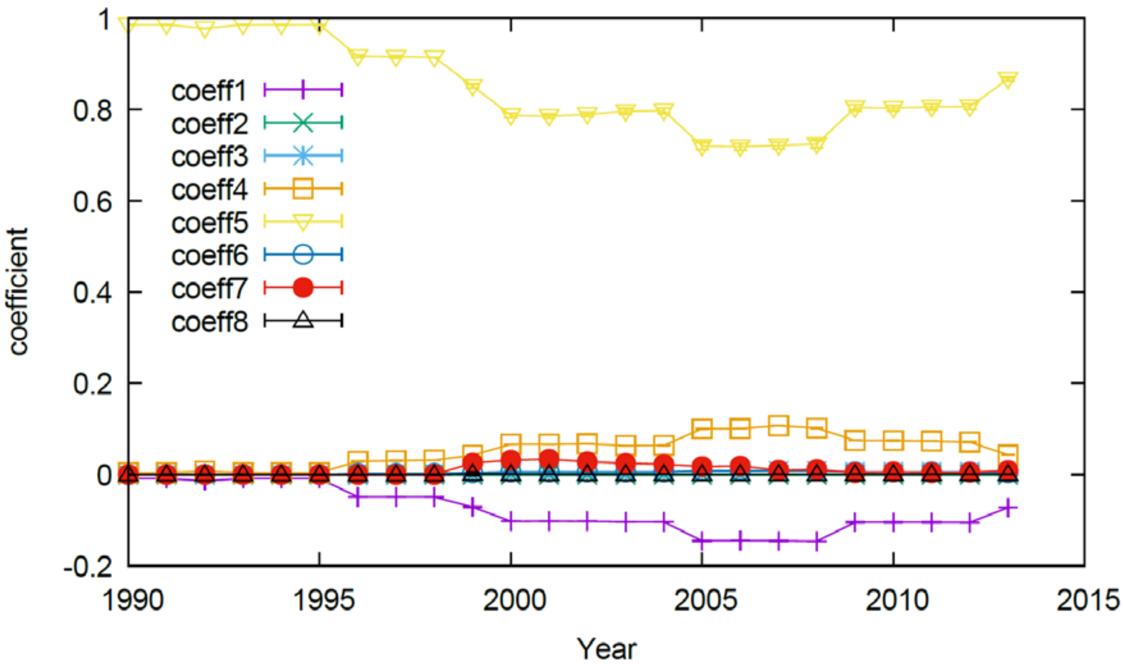

Figure 3: Estimate results for three configurations

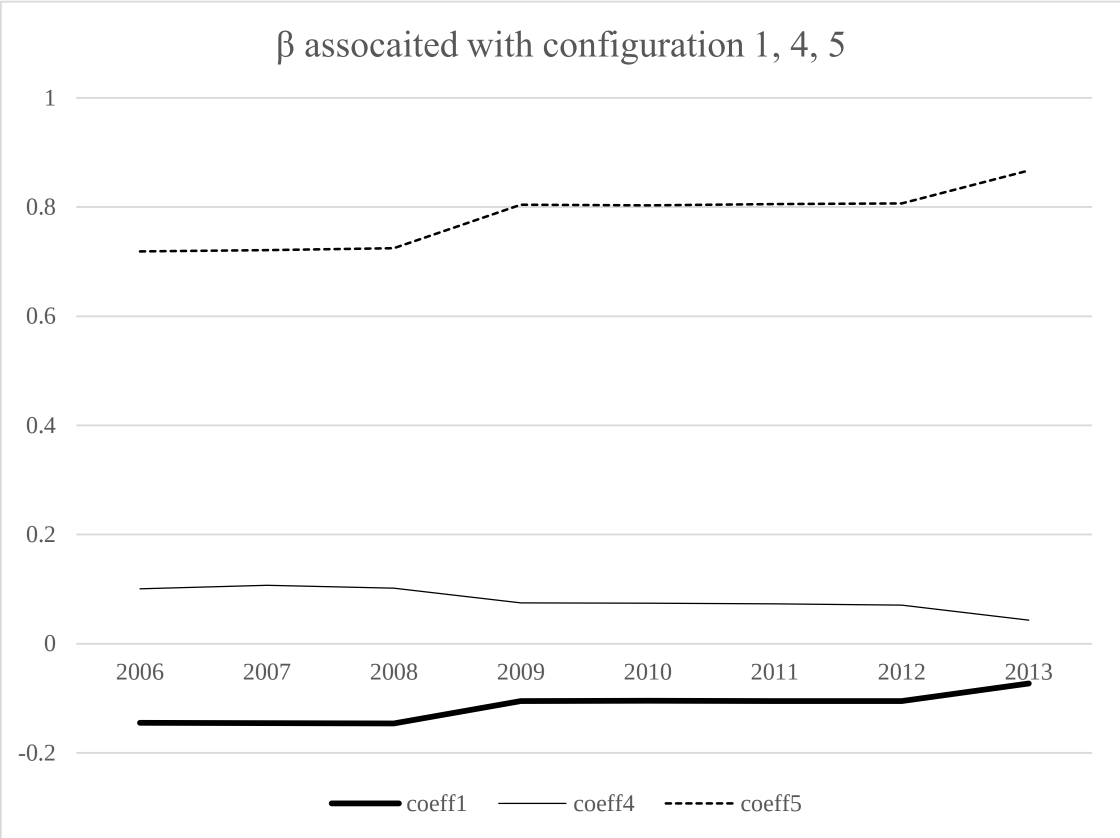

Table 1: List of market movements

Original market		New market
JASDAQ Standard	⇒	TSE 1st section
Old JASDAQ		TSE 2nd section
Mothers		
OLD Hercules		
Ambitious		
Centrex		

Table 2: Network configuration and tested hypotheses

#	Configuration	Hypothesis 1	Hypothesis 2-1	Hypothesis 2-2
1	VC *i1* is randomly matched with VC *i2*	×		
2	VC with return performance=1 tends to co-invest with VC with return performance=1			
3	VC with return performance=1 tends to co-invest with VC with return performance=0			
4	VC *i1* tends to co-invest with VC *i2* when they had past co-investment(s) and the return of the past co-investment exceeds the median level of return		○	
5	VC *i1* tends to co-invest with VC *i2* when they have past co-investment(s) and the VB invested in the co-investment accomplished market upgrade			○
6	#2 & #4			
7	#2 & #5			
8	#3 & #5			