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Time to IPO: Role of heterogeneous venture capital

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Abstract

Venture Capital (VC) is often syndicated to invest. The characteristics of each syndicate can vary not only in the number of VC but also in the heterogeneity of VC types included in a syndicate (e.g., bank-dependent, independent, and public etc.). This paper empirically studies how these two characteristics are related to the dynamics of client firms' Initial Public Offerings (IPOs). We test whether the IPOs of VC-backed entrepreneurial firms tend to be achieved in shorter periods when financed by many and/or heterogeneous VC. The results of our hazard estimation show that the hazard ratio of IPOs increases not only when the number of VC sources in a syndicate increases but also when the VC become more heterogeneous. The latter result implies the existence of the complementarity among heterogeneous VC in the process of screening and managerial value added. We also confirm that such positive impact of heterogeneous VC becomes more sizable in the absence of bank-dependent VC. This implies that complementarity among VC arises when the uncertainty about venture firms, which could diminish, for example, due to the existence of informed VC, remains high.

Keywords: IPO; VC syndication; Complementarity; Hazard estimation; Panel estimation

JEL classification: G24, G32, C41, C23, C26

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1. Introduction

Venture capital (VC) is a class of financial intermediaries that finances venture firms mainly through equity investment (Gompers and Lerner 2001). It provides funds, screens investment targets, and gives various advices aiming at adding value to the firms. The object of VC is successful exits from investments with higher return through, for example, Initial Public Offering (IPO) or acquisition (trade sales).[1] VCs employ their strategic, management, marketing, and administrative expertise to achieve the successful exits (Cumming et al. 2005).

As one important feature of VC investments, it is observed that VCs are often syndicated to invest (Lerner 1994; Brander et al. 2002; Hopp 2010).[2] Theoretical mechanisms justifying such syndication consist of the following three channels: (i) Better screening and advising activities achieved by the complementarity among VCs, (ii) portfolio diversification, and (iii) exposure to larger number of potential deal-flow coming from other VCs (Lockett and Wright 2001; Cumming 2006). This paper intends to empirically study how and to what extent syndicated venture capitals can contribute to successful VC investments. In particular, we are interested in how the complementarity among VCs (i.e., the first channel) could expedite the IPO of their client entrepreneurial firms.

The accumulated empirical understandings suggest that larger number of VCs involved in investment could contribute to more successful IPOs through, for example, more precise screening activities (e.g., Giot and Schwienbacher 2006; Cumming 2006). In this paper, we extend this discussion about the impact of complementarity among VCs. For this purpose, we measure the source of complementarity not only through the number of VCs involved in a syndicate but also the heterogeneity of VCs in terms of their type (e.g., bank-dependent, corporate, independent etc.). Note that extant literature has already pointed out that different types of VCs could separately contribute to the performance of investments. For example, Tykvová and Walz (2007) find that the involvement of independent and/or foreign-owned VCs contributes to better performance of investments. As far as we know, however, there has been no empirical study about how syndicates involving heterogeneous VCs could contribute to the performance of investments, which is the central theme of this paper.

We employ a unique sample of more than 6,800 investment rounds for 615 Japanese VC-backed firms accomplishing IPO over the last decade.[3] The data allows us to categorize each

[1] Although it has not been a major exit route in Japan, Leveraged Buyout (LBO) is another important option in the U.S. and Europe.
[2] Brander et al. (2002) reports that 60% of VC investments in Canada were syndicated in 1993. According to Wright and Lockett (2003), the shares of syndicated VCs are 30% in Europe and 60% in the U.S. (in 2000s). In our data, 89% of Japanese venture firms accomplishing IPO were financed by syndicated VCs in the last decade.
[3] As we discuss later, one caveat of our sample is that it consists of venture firms eventually accomplish IPO as of the timing we correct data.

VC based on its origin, which we call as “type”. To illustrate, many VCs are funded by financial institutions such as bank, security firm, and insurance company. Non-financial entity such as a corporation is another origin as well as university and government. Such information enables us to measure the heterogeneity of VCs involved in a syndicate as an independent characteristic from the number of VCs in a syndicate.

In order to evaluate the performance of VC investments, we focus on how quickly IPO is achieved. As pointed out in literature (e.g., Giot and Schwienbacher 2006), another exit route such as trade sales is major in the U.S. and Europe. We feature IPO as a major exit route in this paper since it still has a dominant presence in Japan. Figure-1 depicts the distribution of the time from the first-round investment from VC to IPO in our data. We can immediately notice the large variation of the time to IPO. The target of this paper is to examine the correlation between such a distribution and the heterogeneity VCs involved in each syndicate.

[Figure-1 is inserted around here]

Understanding such a microeconomic mechanism behind the IPO dynamics is important particularly when we consider the recent Japanese economy. Facing the episode of the "Lost two decades" in Japan, academic researchers have been studying the causes of such long and sustained recession. One of the key consensuses obtained so far is that the observed low growth rate in Japan is not only due to the declined labor and capital inputs but also the low productivity growth (Fukao 2012). This result naturally stipulates the researches on the sources of productivity improvement, most of which have suggested that innovative entrant firms could be a vital source of productivity improvement (e.g., Kawakami and Miyagawa 2008).[4] Many studies also claim that debt finance, which has been a major financing channel in Japan, might not be the best scheme for funding the intangible investment of start-up firms including R&D. For example, Hosono et al. (2004) finds that the firms with higher R&D investment in machinery industry tends to depend less on bank finance partly because of the difficulty to use such intangible assets as collateral.

Reflecting this concern, Japanese VC industry has been advancing a certain development as an additional financing channel over the last two decades. Many governmental supports including the introduction of emerging markets (e.g., Tokyo Stock Exchange-Mothers) have also encouraged such development. Figure-2 shows the number of IPOs in Japanese stock market over the last two decades, which includes a large number of IPOs in 2000s. The lower prospect of VC investments represented by sharp decline of IPOs since the late 2000s, however, has been making it difficult for

[4] Kawakami and Miyagawa (2008) find firms in 8 years old exhibit the highest productivity in their samples consisting of Japanese firms.

potential entrepreneurial firms to raise enough funds from VCs in Japanese market. While macroeconomic factors including stock market environment are the obvious candidates causing this phenomenon, it should be still informative to study the microeconomic mechanism behind IPO. We think examining the dynamics could be useful to provide a guide for more active VC investments.

[Figure-2 is inserted around here]

This paper is structured as follows. Section 2 briefly surveys the related literature, which provides the theoretical underpinnings of our empirical study. Section 3 explains the data and the empirical framework we use in this paper. Section 4 empirically studies the shape and determinants of the hazard function for IPO. Section 5 concludes and presents future research questions.

2. Related Literature

2.1. Role of syndication

The major motivations of VC syndication are three-fold: Better screening and advising (Sahlman 1990), portfolio diversification (Wilson 1968), and deal-flow (Manigart et al. 2002). Extant discussion about the first motivation is based on a premise that syndication enhances the quality of screening and advising. They conjecture, for example, the complementarity among VCs that are tied with different information sources could lead to better screening activities through the way modeled in Sah and Stiglitz (1986). This conjecture leads to the selection hypothesis proposed in Lerner (1994) that the inclusion of multiple VCs in investments could provide an informative "second-opinion" as well as the value-added hypothesis proposed in Gompers and Lerner (2001) that additional VCs contribute to some value-enhancing works (e.g., advising).[5] In this strand, Casamatta and Haritchabalet (2007) provide a unified framework incorporating these two functions and theoretically show under what conditions syndication leads to higher investment performance.

Extant researches have also studied the role of VCs in terms of the speed toward IPO. They establish a dynamic pattern of IPO after the intervention of VCs. Giot and Schwienbacher (2006) establish the hump-shaped hazard of IPO by applying the survival analysis to the spell data measured from the initial (or second and/or third) investment round to the timing of IPO. Dynamics of IPO is also affected by various characteristics of syndicated VCs. It includes, for example, the size

[5] One subtle issue is the return implication of these two hypotheses. While the value-added hypothesis predicts higher return from syndicated investment, the selection hypothesis predict opposite. Brander et al. (2002) makes a horse-race between the selection hypothesis proposed in Lerner (1994) with the value-added hypothesis proposed in Gompers and Lerner (2001). They empirically show that the project with multiple VCs tend to exhibit higher rates of return, which implies that additional VCs contribute to some kind of value-added activities rather than just double-check of the project quality. The theoretical controversy is overcome in the model by Casamatta and Haritchabalet (2007) showing that syndication may or may not lead to higher investment performance according to the experience of lead VCs.

of VC syndication (Megginson and Weiss 1991; Lerner 1994; Brander et al. 2002), the experience of VCs in a syndication (Giot and Schwienbacher 2006), and/or the geographical location of VCs (Hochberg et al. 2007). These studies imply that VCs not merely provide funds but also contribute to the successful exit of the investment in various ways.

2.2. Contribution of ex-ante heterogeneous members

One caveat of the studies mentioned above is that they focus on the number of VCs as a sole proxy for the source of complementarity. The number of VCs, however, could represent other factors. For example, when VCs face investment capacities, the number of VCs could simply reflect the portfolio diversification motive of each VC. Based on this thought, we use the heterogeneity of the VC composition with controlling the number of VCs in a syndicate for measuring the source of complementarity among VCs. To illustrate, suppose there are two entrepreneurial firms ($FIRM_i$, i=1,2) invested by the same lead VC_L categorized as bank-dependent VC as well as another secondary VC_{Sj} (j=1: bank-dependent VC,2: independent VC). We are interested in whether the likelihood of establishing IPO differs between the teams of ($FIRM_1$, VC_L, VC_{S1}) and ($FIRM_2$, VC_L, VC_{S2}) with controlling the other characteristics of firms and banks potentially affecting the time to IPO.

Contribution of heterogeneous members has been examined in broader discipline. For example, Hamilton et al. (2003), Jones et al. (2009), Bercovitz and Feldman (2011), find a team including researchers with more heterogeneous backgrounds is more likely to succeed. Our main interest is in whether such a mechanism could be identified in the context of VC investments. Note that there is also a discussion about the cost of heterogeneous members. For example, Steffens et al. (2011) tests how the composition of new venture team is related to the performance of it and find the negative impact of member heterogeneity especially in shorter periods. We take into account these potential pros and cons of heterogeneity in our empirical analysis.

Traditional empirical studies on financial intermediation have been paying limited attention to such a complementarity among credit suppliers. The multiple loan syndication has been discussed mainly in the context of either discipline device for borrowers, borrowers' liquidity insurance motive, or the strategic interaction among lenders. These discussions heavily rely on the perspective that the creation of soft-information about borrower firms is costly and taking time to establish (e.g., Rajan 1992; Boot 2000). One important premise here is that banks are initially homogeneous and can become heterogeneous only through the long and sustained loan relations. Potential clients for financial intermediaries, however, have been drastically changed to more opaque and riskier firms, which require more specialized skills to screen and monitor. Also, syndicated loans and non-recourse project finance have been more and more popular in banking industry. This inevitably requires expert knowledge in each stage of financing. In this sense, the discussion about the VC syndication explicitly featuring the ex-ante heterogeneity and the complementarity among them could be informative for the discussion about the role of concurrent financial intermediaries.

3. Data and Methodology

3.1. Data Overview

The data used for this study are the firm-level unbalanced panel data provided by Japan Venture Research (JVR). The data covers all the IPOs dated from 2001 to 2011.[6,7] The data consist of, for example, firm identification, IPO date, and the market where the firms are initially listed. An important feature of this data is that it stores the list of all VCs investing to each firm and the investment amount from each VC to the firm in each investment round. The data also store a part of the characteristics of each VC and entrepreneurial firms such as industry classification and location.[8,9] Figure-3 depicts the distribution of the number of months between the first-round investment by VCs and the actual timing of IPO over some selected industries.[10] The total number of round-VC observations for 615 VC-backed firms is more than 6,800, and the total number of VC is 686.

[Figure-3 is inserted around here]

Since we hypothesize that the heterogeneity of VCs in a syndicate affects the time to IPO, we need to characterize each syndicate. For this purpose, we use the number of VCs in the syndicate as of each investment round as well as the number of the VC types included in the syndicate. The type of VC consists of bank-dependent, security firm-dependent, insurance company-dependent, trade company-dependent ("Shosha" in Japanese), corporate (i.e., non-financial firm-dependent), mixed origination, foreign-owned, foreign-located, independent, university, government, and others.[11] Most of VCs could be also characterized by the age, the size of capital, the number of

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6 The first investment rounds for each investment are from December 1983 to October 2011.

7 It has been said the IPO cycle is 5-year frequency. In this sense, our data covers possibly two cycles.

8 We are planning to augment this data with firms' post-IPO financial information stored in Development Bank of Japan Corporate Financial Databank System as well as the pre-IPO financial information obtained from JVR and DBJ. The former information could be used to study the relationship between the post-IPO performance of firms and the composition of syndicated VCs.

9 The data also contains the ex-post movement of each firm. It consists of, for example, the movement to the larger stock market, delisted with bankruptcy, delisted by being merger, and delisted by MBO etc. We are planning to use this information to study the correlation between the composition of syndicated VCs and the ex-post performance of entrepreneurial firms.

10 We will test if the time to IPO systematically depends on the industry characteristics by including the industry dummy in our empirical analysis.

11 The numbers of VCs in each type are as follows: 82 bank-dependent, 35 security firm-dependent, 12 insurance company-dependent, 18 trade company-dependent 98 corporate, 19 mixed origination, 19 foreign owned, 151 foreign located, 196 independent, 5 university-based, 16 government-based, and 35 others (restructuring, buy-out, other

employees, location, and brief historical back grounds.[12] From these multiple sources of data, we construct a firm-level spell data (i.e., censored panel data) with time-varying covariates including the number of VCs and the number of VC types. As another time-varying covariate, the aggregate-level stock price data (e.g., (i) the monthly growth rate of the indexed stock prices and (ii) the monthly average of the indexed stock price) is merged to our spell data.[13] This intends to consider the claim in the literature that the condition of stock market matters for the timing of IPO (Ritter 1984, 1991; Baker and Wurgler 2000).

Our current sample is limited to the VC-backed firms eventually accomplishing IPO. In this sense, the empirical results obtained in this paper are limited to "high" quality firms from ex-post perspective. To generalize the results, it is beneficial to add sample firms which are targets of VC investments but have not accomplished IPO so far. For this purpose, we could employ the large set of unlisted firms from, for example, the Basic Survey on Business Structure and Activities (BSBSA). This is a firm-level data set collected annually by the Ministry of Economy, Trade and Industry for the period 1997-2008. The survey covers all firms with at least 50 employees or 30 million yen of paid-in capital in the Japanese manufacturing, mining, and commerce sectors and several other service sectors. The survey contains detailed information on firm-level business activities such as the 3-digit industry classification, the number of employees, sales, and purchases. Since some of them have accomplished IPO without the investment by VCs, it would be possible to implement the propensity-score matching type analysis to more explicitly see the impact of VC investments (i.e., by treating the non-VC-backed-firms as control samples), which we leave as our future research object.

3.2. Empirical Framework

Using the firm-level spell data, we examine how the heterogeneity of VCs in a syndicate, which could vary over investment rounds, affects the likelihoods of IPO by employing the hazard estimation with time-varying covariates.[14] One important premise in our analysis is that the team of a venture firm and a VC syndicate aims at accomplish IPO as early as possible.[15] This premise could be justified by the limited length of VC's investment horizon (i.e., 10 years in general). Such a motivation also reflects the limited amount of financial and managerial resources VCs hold. To

financial). Note that our dataset could not further categorize the foreign owned and foreign located VCs into other classifications (e.g., bank-dependent) due to the data limitation.

[12] In this version of paper, we have not included the detailed information about VCs to characterize VC syndication but only the type and ages of VCs.

[13] It might be more appropriate to include the stock-index explicitly representing the emerging market (e.g., TSE Mothers index). Due to the data availability, unfortunately, we use this widely used stock index.

[14] The spell data used in the current analysis is measured from the first investment round. We are planning to repeat the same exercise by defining the spells from the second and third round investments as in Giot and Schwienbacher (2006).

[15] As one example, Tykvová (2003) theoretically models the timing of IPO as a problem solved by VC.

efficiently use the resources, the shorter investment duration up to exit is preferable for most of VCs. Given this premise, we examine under what characteristics IPO can be effectively expedited.

One of the key explanatory variables is the number of VC types included in the syndicate. While this number has a positive correlation with the total number of VCs in the syndication (i.e., the correlation coefficient = 0.79), the number of types also shows a different variation from the VC number. Figure-4 shows the distribution of the number of types in a syndication depicted over the VC number in the syndication.[16] We could see a certain variation of the number of types given a VC number. We use this variation to study the impact of the heterogeneity of VC.

[Figure-4 is inserted around here]

The basic structure of the duration model is as follows.[17] The spell T is defined as the duration of time passing before the occurrence of a certain random event. In our case, the random event is IPO and the beginning of the spell is determined as the first-round investment. The distribution of the spell can be summarized by a survivor function $\mathrm{S(t)}$, which denotes a probability that the event has not happened yet as of t.

$$\mathrm{S(t)} \equiv \mathrm{Pr(T \geq t)} \tag{1}$$

The survivor function can be used to further define the hazard function $\lambda(\mathrm{t})$. This represents a probability that the event occurs in the next instantaneous moment, conditional on the nonoccurrence of the event as of t.

$$\lambda(\mathrm{t}) \equiv \lim_{\tau \to \infty} \frac{\mathrm{Pr}(\mathrm{t}+\tau > T \geq t | T \geq t)}{\tau} = -\frac{\mathrm{d} \ln \mathrm{S(t)}}{\mathrm{dt}} = \frac{\mathrm{f(t)}}{\mathrm{S(t)}} \tag{2}$$

where $\mathrm{f(t)}$: Density associated with the distribution of spells

The goal of the duration model is to estimate the hazard function and the survivor function while considering the effects of potentially time-varying covariates.[18] Suppose $\mathrm{x(t)}$ and $\theta \equiv \{\alpha, \beta\}$ denote the time-varying covariates at time t and the time-invariant model parameters, respectively. Then, the survivor function takes the following structure.

16 For demonstration purpose, the figure only contains the VC number up to 30.
17 For more detailed discussion about the duration model, see Kiefer (1988).
18 By construction, a hazard function has information equivalent to the corresponding survivor function.

$$S(t, x(t); \theta) \equiv \Pr(T \geq t, x(t); \theta) \tag{3}$$

The proportional hazard model, which is the most widely used specification, assumes the hazard function $\lambda(t, x, \theta)$ takes a multiplicative form consisting of one component (baseline hazard) depending only on the duration $\lambda_0(t, \alpha)$ and another component exclusively capturing the effects of the covariates $\phi(x(t), \beta)$.[19]

$$\lambda(t, x(t), \theta) \equiv \lim_{\tau \to 0} \frac{\Pr(t + \tau > T \geq t | T \geq t, x(t); \theta)}{\tau} = \lambda_0(t; \alpha)\phi(x(t), \beta) \tag{4}$$

If there is no censoring problem discussed below, and we can specify the functional forms for $\lambda_0(t; \alpha)$ and $\phi(x(t), \beta)$, it is possible to estimate $\theta \equiv \{\alpha, \beta\}$ by maximizing the likelihood function with the data $\{t_i, x(t_i)\}_{i=1}^{n}$ where t_i and $x(t_i)$ denote the length of completed spell for i th observation out of n samples and the set of time-varying explanatory variables of the i th observation, respectively.

One typical problem associated with the duration data is censoring. If all of our observations are uncensored, we can simply apply the maximum likelihood estimation (MLE) to the data. However, the existence of censoring requires us to make adjustments. For right-censoring, the adjustment is well established and straightforward (Kiefer, 1988). Note that our data consists of the firms eventually establishing IPO. This means that there is supposed to be no right-censored samples. Since we limit the time-horizon of the spell data up to 20 years, there are still a few samples censored from right.[20] The idea is to treat the right-censored observations as survivors at the end of the observation period. In order to use the information that the right-censored observations have survived at this timing, we can simply use a Tobit-type adjustment to the likelihood function. We use this adjustment for our data. Note that if we are only considering right-censoring, then nonparametric estimation for the survivor function (e.g., Kaplan and Meier, 1958) can be done. Thanks to our way to define the start point of the duration, we are not suffering from the left-censoring problem.

As the components of $x(t)$, which is the covariates of the estimated hazard function, we use the growth rate of the monthly-average aggregate stock price from the previous month $t-1$ to the current month t (*NKY_RETURN*), the monthly-average aggregate stock price at the current month t (*NKY_AVERAGE*), the number of VCs involved in the investments (*VCNUM_TOTAL*) at t, and the number of the involved VC types (*VCNUM_TYPE*) at t, the square terms of the last two variables (*VCNUM_TOTAL_SQ* and *VCNUM_TYPE_SQ*) as well as the accumulated total investment

[19] For the discrete time expression for the time-varying covariate model, see D'Addio and Honoré (2011).
[20] The share of the right-censored group (i.e., firm) is less than 0.3% (i.e., 2 groups) out of 615 groups.

amounts from VCs (*AMOUNT_INVEST_ACC*) at t. The inclusion of two square terms reflects the discussion in Steffens et al. (2011) that heterogeneous members could be associated with some costs. Considering the industry specificity on the speed toward IPO discussed, for example, in Giot and Schwienbacher (2006), we also control the 3-digit level industry fixed-effect. The summary statistics and the correlation coefficients of each variable including the VC number of each type in a syndicate, the ages of venture firms and venture capitals are summarized in Table-1 and Table-2.[21] In order to see the firm distribution over industries, Table-3 summarizes the number of firms categorized in each industry.

[Table-1 is inserted around here]

[Table-2 is inserted around here]

[Table-3 is inserted around here]

4. Empirical Analysis

4.1. Nonparametric estimation results

Before examining the semi-parametric and parametric analyses, first, we show the results based on a nonparametric estimation. The benefit of this method is that we do not need to assume any specific functional form for the hazard function. We use Nelson-Aalen's estimator for a cumulative hazard function in (5).

$$\widehat{H}(t) = \sum_{j|t_j \le t} \left(\frac{d_j}{n_j}\right) : \text{Nelson Aalen's estimator for cumulative hazard function} \quad (5)$$

where

n_j: Number of firms having not established IPO until t_j

d_j: Number of firms having established IPO at t_j

Then, we can approximate the hazard function by using a Gaussian kernel with a specific bandwidth. Figure-5 depicts the estimated hazard function with the approximated hazard function smoothed by a Gaussian kernel with a bandwidth of 10. We limit the sample duration to 240 months which covers more than 99% of the IPO events in our data as mentioned above.

21 We will use the ages of venture firms and venture capitals to instrument the number of VC types and the number of VCs in a later section to take into account for the endogeneity issue.

[Figure-5 is inserted around here]

We can observe the hump-shaped hazard function with a bumpy feature in the tail. The peak of the hazard ratio is located around 60 months (i.e., 5 years), which is comparable to the ones in the extant literature (e.g., 1000 to 1500 days in Giot and Schwienbacher 2006). The seemingly increasing hazard on the tail of the function is possibly generated by a small number of IPO out of a few "survivor" (i.e., the firms having not established IPO for more than 10 years).

4.2. Semiparametric and parametric estimation

In this section, we estimate semiparametric and parametric models. First, we apply Cox's partial likelihood model (Cox 1972). The benefit of this model is that we do not need to put any restrictions on the functional form for the baseline hazard function $\lambda_0(t;\alpha)$. By using the estimators, we can also depict the hazard function graphically. This gives us appropriate ideas for the model selection in parametric duration models, the results of which we discuss in the following section. It also provides the baseline estimates for the coefficients associated with each covariate. By checking the consistency between the coefficients on the semiparametric and parametric estimations, we can confirm the appropriateness of the specification for the baseline hazard function in the parametric estimation.

[Figure-6 is inserted around here]

[Table-4 is inserted around here]

Figure-6 depicts the estimated baseline hazard function $\lambda_0(t;\alpha)$, and Table-4 (1) and (2) summarize the estimation results associated with the covariates in the case of Cox proportional hazard estimation.[22] First, Figure-6 shows the similar hump-shaped feature to Figure-3. This provides a criterion for our choice of parametric specification. Second, the “hot” market environment expedites IPO (i.e., the positive impact of *NKY_RETURN* on the estimation of hazard; the coefficient is greater than 1), which is consistent with the view that entrepreneurs and VCs are timing market (Ritter 1984, 1991; Baker and Wurgler 2000) as in Table-4 (1). Note that the level of indexed stock price *LN_NKY_AVR* does not show such a systematic impact on the hazard of IPO as in Table-4 (2). This could reflect VCs’ way to time market. Namely, VCs want to buy low and sell high, which means that high stock prices are not sufficient to determine the timing of IPO but the

[22] Figure-6 is based on the estimation summarized in Table-4 (1).

high growth of stock price is.[23] Third, the first columns in Table-4 (1) and (2), which correspond to the model without *AMOUNT_INVEST_ACC*, show that both the number of VCs and the number of the types of VCs involved in the investment contribute to the shorter time to IPO. This implies that not only the size of syndication but also the heterogeneity of the member VCs matters for the successful exit of venture investments. We repeat the same estimation by including *AMOUNT_INVEST_ACC* (the second columns of Table-4 (1) and (2)). In this estimation, the higher hazard generated by the larger number of the types of VCs is kept although the impact of VC number disappears. Considering the fact that the hazard increases as *AMOUNT_INVEST_ACC* becomes larger, we can conjecture the accumulated amount of investment plays a similar role to the number of VCs involved in the investment for our estimation. This casts a clear doubt on using the number of VCs as a proxy for the source of complementarity as mentioned above. Fourth, the third columns in Table-4 (1) and (2), which correspond to the model with selected industries where a relatively large number of samples are observed, show the firms in pharmaceutical and realty tend to take longer and shorter times to IPO compared to the firms in other industries, respectively. Unlike our presumption and the results in Giot and Schwienbacher (2007), we could not find any special features associated with information and telecommunication industry. This could be partly because the level of the industry classification we use for the current estimation is inappropriate. We are planning to re-categorize the firms into several interested industries (e.g., internet, biotech, computer, semiconductor, medical, and communication & media) and repeat the estimation. Fifth, the squared term of the number of the types of VCs has a negative impact on the hazard of IPO. This means that it tends to take longer times to IPO when too many types of VCs are involved in the investment. This is consistent with the discussion about the cost of heterogeneity in Steffens et al. (2011).

Based on the results of the semiparametric estimation, we further estimate the parametric models with the log-logistic distribution, which allows the hump-shaped baseline hazard function. The first two columns in Table-5 summarize the estimation results with full industry dummy variables and selected industry dummy variables, respectively. Figure-7 also depicts the estimated baseline hazard function in the case of the log-logistic distribution.

[Table-5 is inserted around here]

[Figure-7 is inserted around here]

[23] Precisely speaking, what is supposed to matter is the growth of stock prices from the timing of purchasing the stock. We think the relatively short term change in stock prices represented by NKY_RETURN partly reflects this phenomenon.

First, from the estimated shape parameter for the log-logistic case, we can statistically infer that hump-shape has better fit than monotonically decreasing baseline hazard.[24] Second, all the case supports the results associated with *VCNUM_TYPE*. This reconfirms the robustness of our results. Third, in particular, the model including the characteristics of VC syndication at the first-investment round (i.e., the third column) shows that the results associated with *VCNUM_TYPE* are maintained even if we control for such first-round information. One interesting feature is that the investment amounts at the first-round (*AMOUNT_INVESTMENT_ACC (1st round)*) substitute the impact of the time-varying investment amounts at each round (*AMOUNT_INVESTMENT_ACC*), which has statistically significant and positive impact on the time to IPO. This implies that the initial investment size is more informative than the round investment from the perspective of IPO dynamics.

4.3. Frailty model

One caveat of our analysis is the lack of the detailed time-varying firm characteristics such as profitability and/or leverage, which are used in most of standard empirical studies about firm dynamics. This is due to the lack of valid historical data on firm characteristics prior to IPO.[25] As one remedy, we employ a frailty model used in the literature of survival analysis. The idea is to measure the unexplained variation in the duration (i.e., the difference between the model predicted duration and the observed duration to IPO) as over-dispersion, and model it as a latent multiplicative effect on the hazard function. In short, the frailty model takes into account for the individual-effect and estimates the hazard ratio of the interested covariates through the model with the individual-effect. Following Gutierrez (2002), we consider the model as in (6) where α_i denotes the individual-effect (random-effect) specific to firm i.[26]

$$\lambda_i(t, x(t), \theta) = \alpha_i \lambda_0(t; \alpha) \phi(x(t), \beta) \tag{6}$$

The numbers summarized in the last column of Table-5 show the reasonably identical results to the ones without considering the individual effect (and with considering the industry-level fixed-effect). The likelihood-ratio test for the existence of individual-effect could not reject the null hypothesis that the individual effect does not exist. These confirm the robustness of our results in Table-4.

[24] There are several ways to test whether the baseline hazard takes hump-shape of monotonically increasing shape. See Miyakawa (2011) as one example.

[25] We attempt to augment the current dataset with other data sources, for example, DBJ corporate databank system. One crucial problem is that most of the database could not cover the enough number of periods prior to IPO. Unless we have such information, we could not use the variation of the number of VC types in time-series direction.

[26] We assume gamma distribution for the random effect since it has a large flexibility on its shape. We estimate this model without the industry dummy.

4.4. Sample split based on the length of spell

Among the empirical evidences related to VC finance, it is claimed that the room for collaboration among multiple VCs is limited to the early stage of investment (Sapienza 1992). This is mainly because the uncertainty of the projects, which is supposed to be resolved more effectively by collaborative screening, is higher in the early stage. Another presumption leading to this feature is that the expert advises aiming at adding value to venture firms are especially valuable when there is a larger room for the firms in early stage to incorporate the strategic, management, marketing, and administrative advices. In order to check this presumption, Table-6 estimates the model with the samples in shorter and longer spells separately by assuming Gompertz distribution for the baseline hazard function, which identifies monotonically increasing and decreasing hazard functions.[27]

[Table-6 is inserted around here]

First, the shape parameter (i.e., gamma) allows us to statistically infer the shape of the baseline hazard function. As we establish in the previous estimations, the hazard function takes positive (second column) and negative (third column) slopes for the shorter and longer spell samples, respectively. Second, we could find the significant response associated with the number of VC types only in the case of shorter spell samples. This implies that the benefit of collaboration among heterogeneous VCs could be sounding when the uncertainty about the project is still high and/or the room for firms to incorporate VC's advices is still large. Once the duration becomes long enough, the room of collaboration disappears.[28] Third, the impact of the total VC number is detected as statistically significant only in the longer spell samples. This illustrates that the involvement of more VCs could be beneficial in the latter stage, which tends to be associated with larger required capital (Casamatta and Haritchabalet 2007). It reconfirms that the number of VCs in a syndicate, which is used to represent the source of complementarity among VCs in the extant studies, might not be an appropriate proxy. The number of VCs would rather account for the portfolio diversification motive of syndication than the screening and advising motives feature.

4.5. Contribution of separate VC types

Among the types of VC, bank-dependent VC could be unique. First, a segment of firms

[27] In the analysis associated with shorter spell samples, we treat the samples with longer spell as right-censored. In this sense, the analysis with shorter spells is not necessarily a sub-sample analysis since we use all the samples in our estimation.

[28] We also estimate the model with the sample having less or more than 10 VCs, separately. Only the former sample exhibits the similar feature we establish in the previous estimation. This implies that the collaboration among VCs can arise up to some moderate number of VCs.

keeping a relation with a bank for long periods might spin off having financed from VCs funded by the incumbent bank. Under this circumstance, bank-dependent VC may be able to access the information accumulated in the bank. One conjecture is that the heterogeneity of VCs in a syndication does not matter when such bank-dependent VC is involved in a syndicate while the number of VCs could still matter. Second, another conjecture related to the bank-dependent VC is their motivation of investments. Hellmann et al. (2008), for example, illustrates that bank-dependent VCs invest smaller amounts of money to broader venture firms than other VCs in order to construct relation, which lead to future lending business for the banks financing the bank-dependent VCs. Such a motivation blurs the contribution of the complementarity among heterogeneous VCs.[29] Third, bank-dependent VC is also related to the conjecture about market timing. Bank-based VC tends to have more stable financing structure compared to, for example, independent VCs. Thanks to this stable capital structure, it might be possible for bank-based VCs to time market. In either case, it is informative to treat bank-dependent VCs separately.

[Table-7 is inserted around here]

In order to take into account for these conjectures, we split the sample into two groups based on whether the firm has had a relation with bank-based VC at $t-1$ or not. This latter sub-sample analysis also intends to check whether the results obtained so far is robust or not when we exclude the bank-dependent VCs, which are characterized somewhat differently in literature (Hellmann and Puri 2000). The first two columns in Table-7 summarize the results and confirm our first prediction. Namely, the number of VC type matters only for the sample without bank-based VCs, which is consistent with the first and second conjectures. The last conjecture is also confirmed in the estimation (i.e., stock return matters only for the firms with bank-based VC). This implies that the venture firms with bank-based VC are more likely to time market. The third column shows the result based on the sample with bank-based VC but without security firm-based VC. The result shows the stock return governs most of the variation in the timing of IPO. This could reflect the relatively weak financial structure of security firm-based VC. In other words, when the major investor is bank-dependent VC, the market timing could be an important issue determining the IPO timing. It is an interesting research question whether this is a robust result, and how this finding is theoretically justified.

Extant studies have also documented the contribution of other types of VCs. For example, Tykvová (2004) point out the inclusion of independent VC tends to lead to better performance.

[29] Hamao et al. (2000) discusses a similar issue by using Japanese VC data.

Tykvová and Walz (2007) further establish that international VC works better while public VC tends to exhibit low performance. Corporate VCs have been also discussed as a special entity in the literature (Hellmann and Puri 2000; Park and Steensma 2011). In order to explicitly take into account these discussions, Table-7 summarizes the parametric estimation based on Gompertz distribution including the type dummy variable for each VC type except for "Others". The result shows that the inclusion of independent and corporate VCs expedite IPO while the VCs backed by university slow down the speed toward IPO. Note as the most important feature, the impact of *VCNUM_TYPE* for the shorter duration samples is completely kept in a consistent way with the previous estimations even if we control these VC characteristics separately.

[Table-8 is inserted around here]

4.6. Causality

So far, we have largely ignored the endogeneity of *VCNUM_TYPE* at $t-1$, which could be determined by the reverse causality from the hazard of IPO at t. Presumably, it is admissible to treat the number of VC types in a syndicate as exogenous if we consider a certain length of the interval between the investment and IPO. Moreover, it is not clear how the reverse causality occurs under the current context. Nonetheless, it is still beneficial to control the endogeneity issue and establish the causality.

For this purpose, we estimate a fixed-effect panel linear probability model of IPO with instrument variables. The dependent variable is a dummy variable taking the value of one if the sample firm accomplishes IPO. We instrument the endogeneous variables, which are either (*VCNUM_TYPE*, *VCNUM_TYPE_SQ*) or (*VCNUM_TOTAL*, *VCNUM_TYPE*) by using the ages of venture firms and venture capitals at each investment round. The choice of these two instruments is based on the extant studies finding that the opacity of venture firms and the experience of lead venture capitals are the important determinants of employing syndication (e.g., Hopp 2010; Casamatta and Haritchabalet 2007). In this estimation, we also include VC type dummy employed in the previous section and the selected industry dummy for venture firms.

[Table-9 is inserted around here]

Table-9 summarizes the estimation results. The first column corresponds to the case where we instrument *VCNUM_TYPE* and *VCNUM_TYPE_SQ*. As the coefficients associated with *VCNUM_TYPE* and *VCNUM_TYPE_SQ* show, it is more likely for venture firms to IPO when it is financed by larger number of VC type although the impact diminishes as the number increases. This is consistent with what we have observed in the hazard estimation. The second column repeats the same exercise by instrumenting *VCNUM_TOTAL* and *VCNUM_TYPE* with dropping the two squared terms, which delivers the same implication as above.[30,31] These results confirm that the results obtained in this paper is valid even after controlling the endogeneity of the characteristics of VC syndication.

5. Conclusion

In this paper, we empirically study the contribution of syndicated VCs to their client firms' IPO. We examine whether the IPOs of VC-backed entrepreneurial firms are expedited by more heterogeneous VCs in a syndicate. The results of hazard estimation and panel IV estimation show that not only the size of VC syndication but also the heterogeneity of VCs in a syndicate positively contribute to the speed of IPO. This implies the existence of complementarity among various types of VCs. We also confirm that this result is sounding in the case of shorter investment duration, and mainly driven by the syndication not including bank-dependent VCs, which could easily access to the soft-information and/or be driven by different motivations, hence does not need the collaboration with other types of VCs.

This paper also provides an important policy implication. As clearly shown by our empirical findings, larger availability of heterogeneous VCs' collaboration seems to be beneficial for young and productive start-up firms. Given such importance of collaboration, it could be one fruitful important policy challenge to foster VC industry consisting of various types of VCs. More precisely, it would be beneficial to set up round tables for various VCs and encourage new VCs which have additional expertise and information to the incumbents. Reducing matching friction through these trials would be one important policy target. It is also important for effective policy intervention to take into account the information about the structure of each VC syndicate, which certainly contain valid information potentially used in the process of policy implementation

To conclude, we list several future research questions. First, the correlation between the heterogeneity of VCs in a syndicate and the ex-post performance of each firm (e.g., Tian 2012) should be studied by using our dataset. While IPO could be recognized as one important milestone for entrepreneurial firms, the performance after IPO tends to vary among venture firms. Studying the impacts of syndicated VCs onto IPO decision as well as the ex-post performance would be an interesting research topic. This also intends to examine whether unsuccessful IPO is induced by VCs or not (see, for example, Miyakawa and Takizawa 2013). Second, the heterogeneity of VCs studied

[30] Since we employ only two instrument variables in this estimation, we can choose only two endogeneous variables. This is the reason we drop the two squared terms in this estimation.
[31] It is one promising way to use the geographical proximity of each VC and entrepreneurial firms as well as the industry expertise of VC as alternative instruments.

in this paper could be re-examined in finer ways. For example, it would be interesting to see what combinations among various types of VCs (e.g., university and independent etc.) tend to generate better performance. Third, the way through the heterogeneity of VCs works needs to be examined in more detailed way. In particular, separately identifying the contribution of screening and advising activities to the speed toward IPO is one interesting research issue. Furthermore, it is beneficial to classify the advices provided by VCs in more detailed way. For example, Cumming et al. (2005) finds that the advice based on the financial, strategic, and management expertise is central in the process of advising compared to the ones based on marketing and administrative expertise. Fourth, the dynamics of the composition of VCs in a syndicate is another interesting topic. By examining the pattern of including additional VCs in a syndicate, we could reconfirm the results established in this paper. We believe all of these issues provide further guides for better understanding of IPO dynamics, which contributes to the vital financial system supporting the entry of productive entrepreneurial firms.

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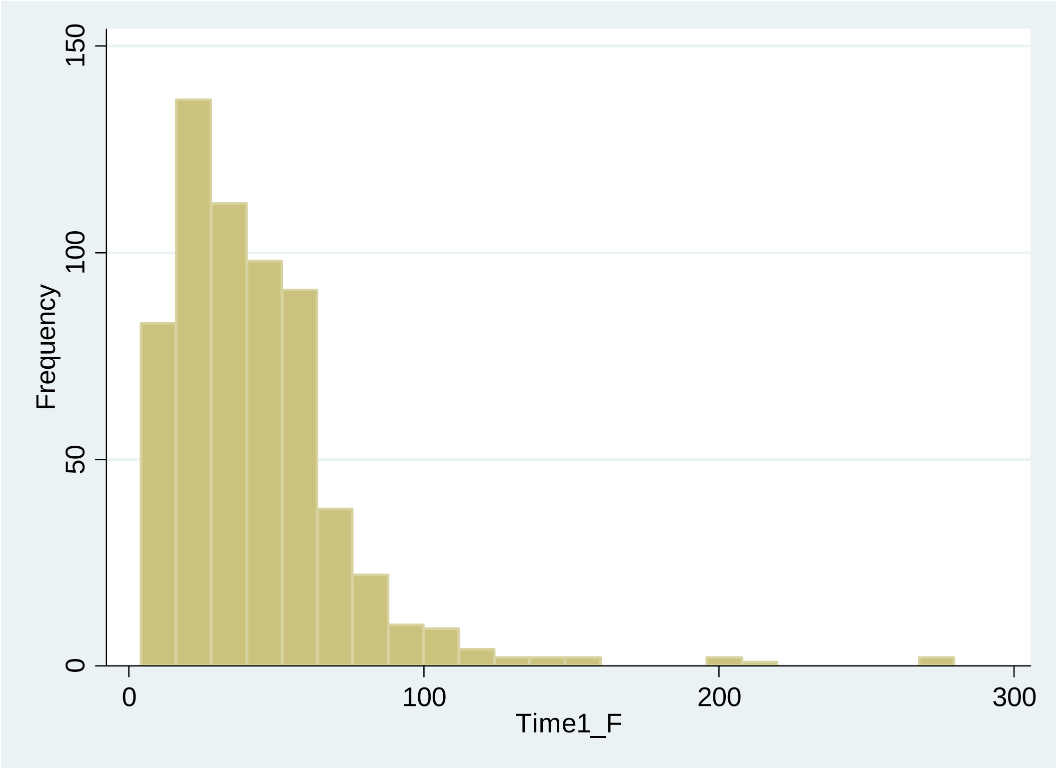
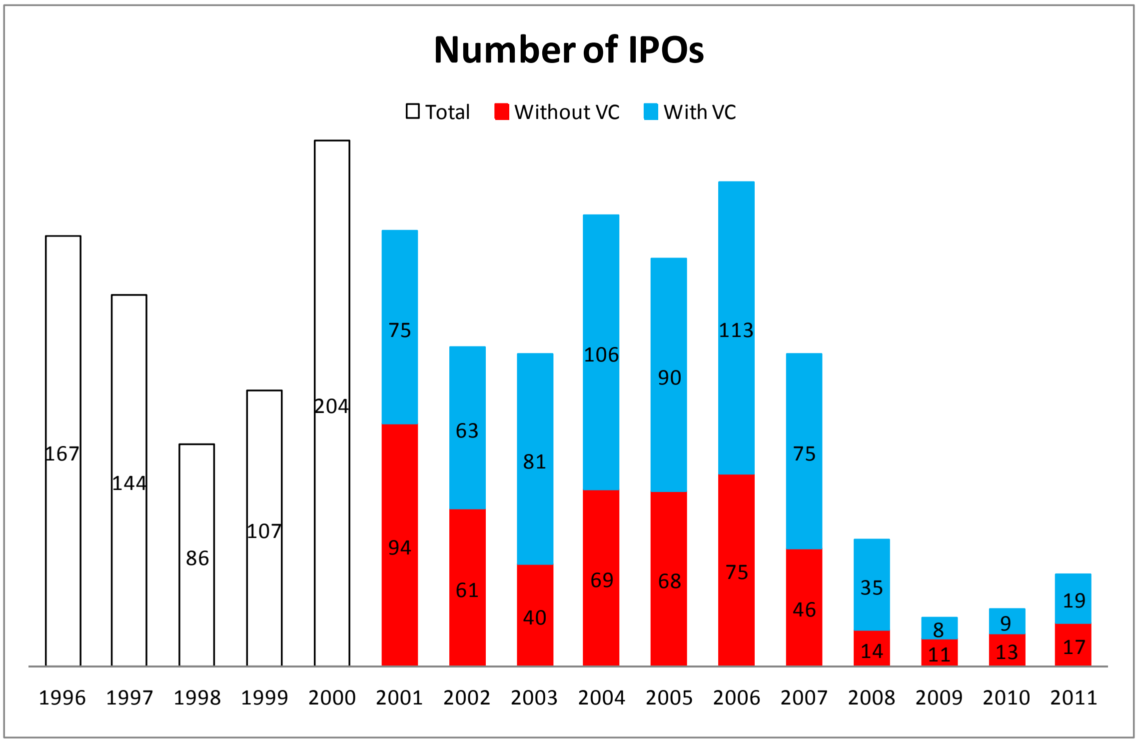
Tables and Figure

Figure-1: Distribution of the time to IPO



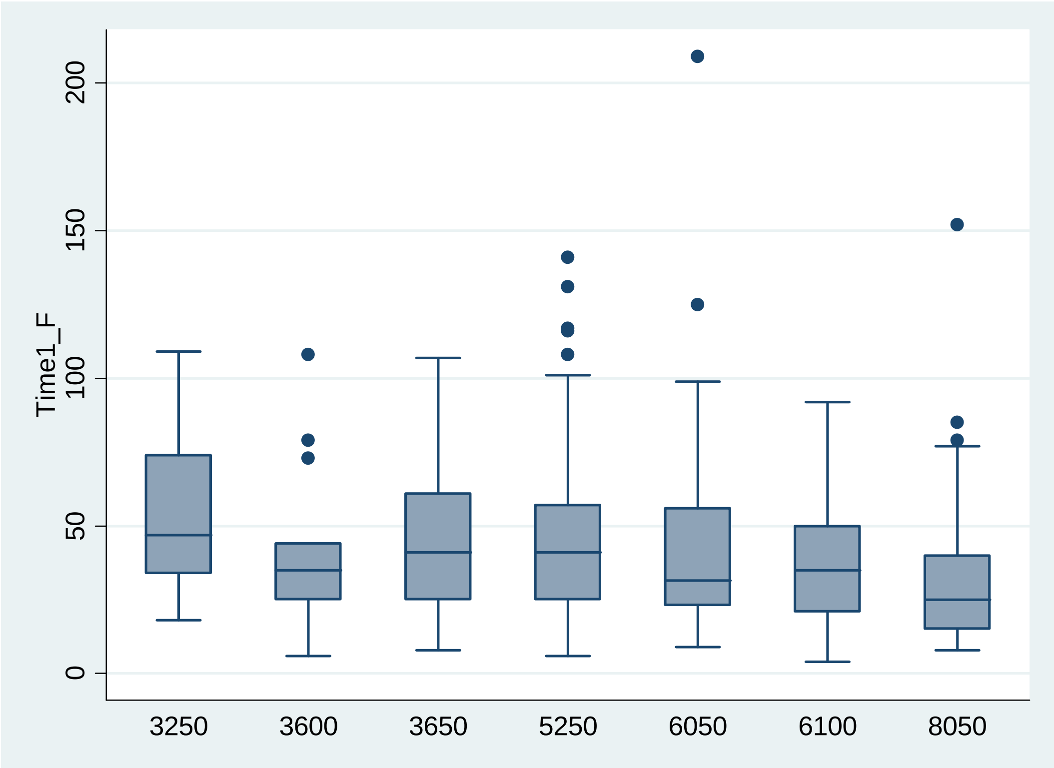
Note: The horizontal axis accounts for the number of months between the first-round investments by VCs and IPO. The vertical axis represents the number of observations which establish IPO between the each bin. In the estimation, we mainly use the samples doing IPO until 240 months from the first investment round (i.e., 613 firms out of 615 total sample firms).

Figure-2: Number of IPO



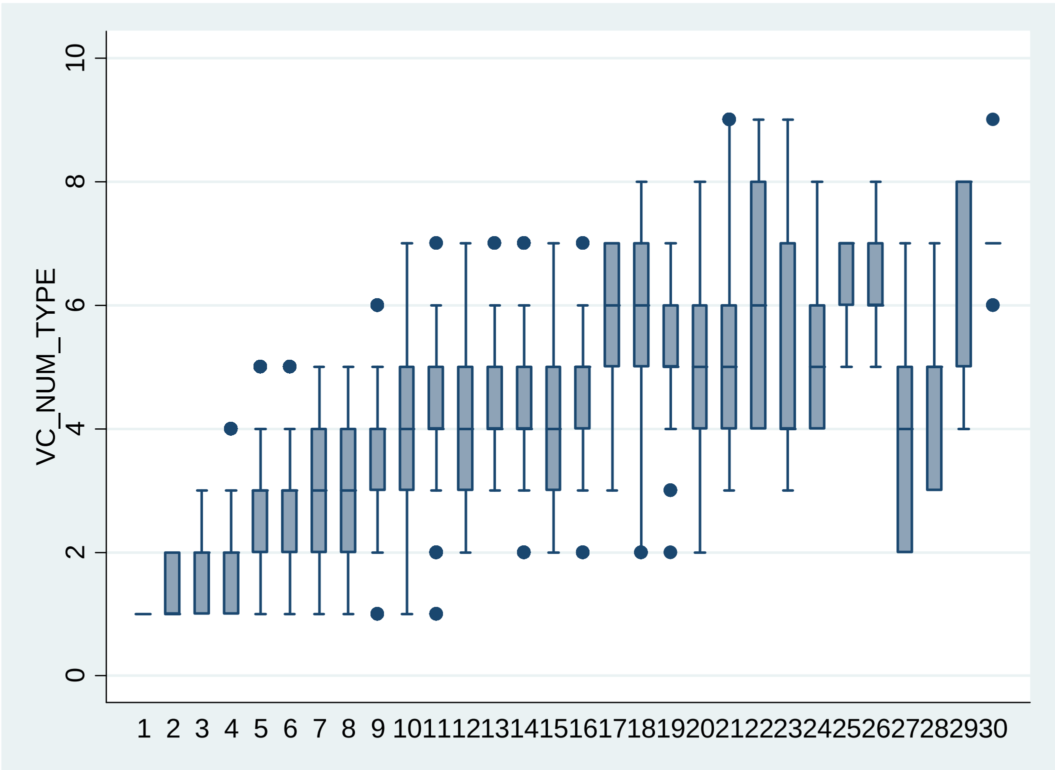
Note: The above figure shows the number of IPO in each year in Japan. From 2001, the number of firms establishing IPO and having relation with venture capital(s) prior to IPO and without having the relation.

Figure-3: Distribution of the time to IPO



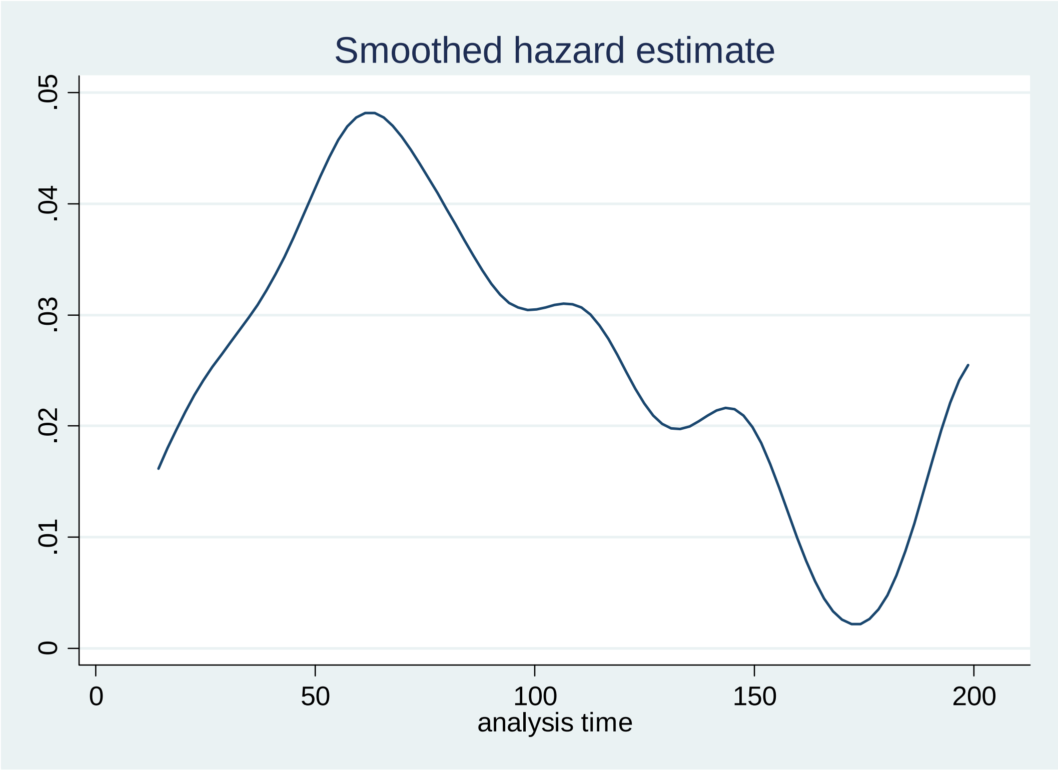
Note: Each box-plot depicts the distribution of the number of months between the first-round investments by VCs and IPO for some selected industries. Each industry code corresponds to as follows: 3250 (Medicine), 3600 (Machinery), 3650 (Electricity), 5250 (Information and telecommunication), 6050 (Wholesale), 6100 (Retail), and 8050 (Realty).

Figure-4: Number of VC types and Number of VCs in a Syndication



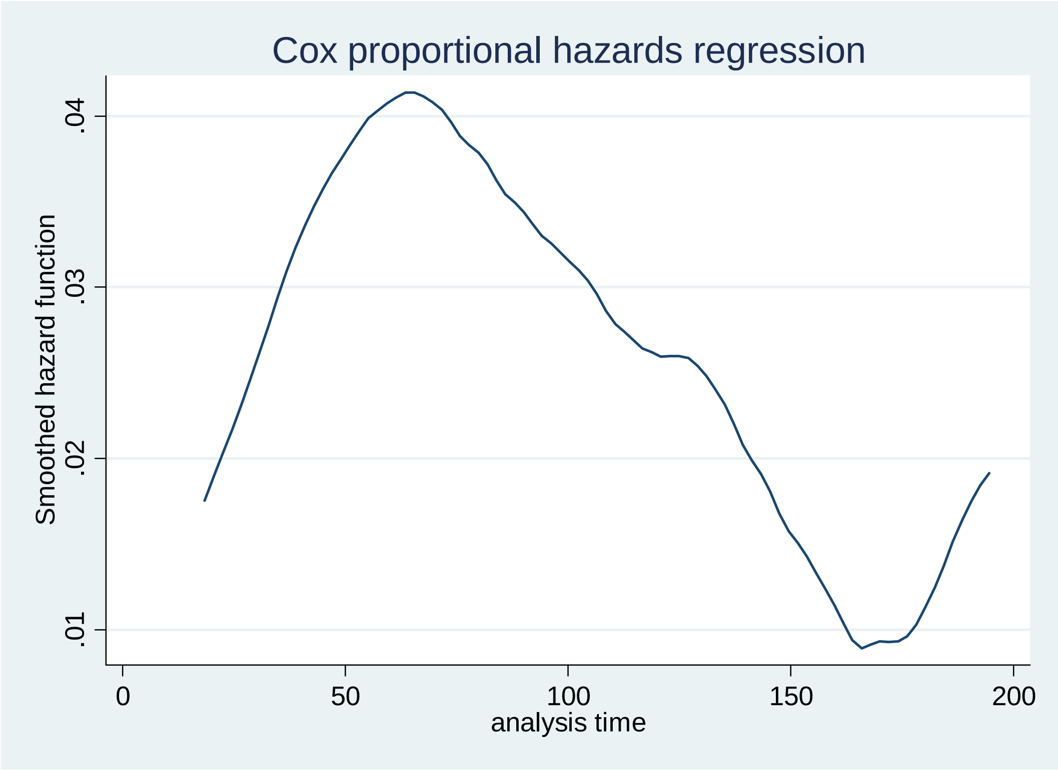
Note: The horizontal axis accounts for the number of VCs in a VC syndication. The vertical axis represents the number of VC types in the VC syndication. For the demonstration purpose, the figure is based only the samples with at most 30 VCs in the syndication.

Figure-5: Non-parametrically estimated hazard function



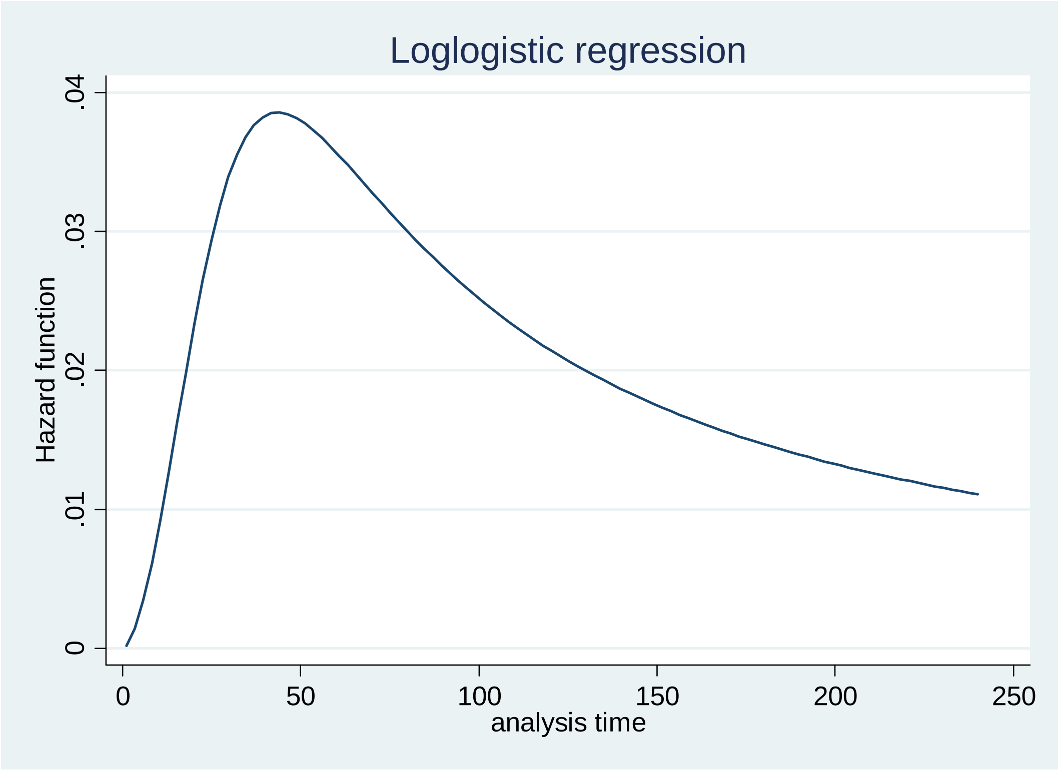
Note: The horizontal axis accounts for the number of months measured from the first-round investments by VCs (i.e., analysis time). The vertical axis represents the hazard ratio of IPO corresponding to each analysis time.

Figure-6: Semi-parametrically estimated hazard function



Note: The horizontal axis accounts for the number of months measured from the first-round investments by VCs (i.e., analysis time). The vertical axis represents the base-line hazard function of IPO corresponding to each analysis time. The model is estimated with full (i.e., 15) industry dummy variables.

Figure-7: Parametrically estimated hazard function (Log-logistic distribution)



Note: The horizontal axis accounts for the number of months measured from the first-round investments by VCs (i.e., analysis time). The vertical axis represents the base-line hazard function ratio of IPO corresponding to each analysis time. The model is estimated with full (i.e., 15) industry dummy variables.

Table-1: Summary statistics

Variable	Definition	Obs.	Mean	Std. Dev.	Min.	Max.
LN_NKY_AVR	Log of the monthly average of Nikkey Stock Price Average Index at t	25674	9.44	0.25	8.95	10.55
NKY_RETURN	The growth rate of Nikkey Stock Price Average Index from t-1 to t	25674	0.00	0.05	-0.25	0.25
VCNUM_TOTAL	Total number of VCs in the syndication	25674	7.33	9.08	1	116
VCNUM_TYPE	Total number of VC types in the syndication	25674	2.68	1.87	1	11
AMOUNT_INVEST_ACC	Accumulated investment amount for each firm at each time (unit: billion yen)	25674	0.43	1.67	0	43
VCNUM_BANK	Total number of bank-dependent VCs	25674	1.96	2.59	0	24
VCNUM_SEC	Total number of security firm-dependent VCs	25674	1.61	3.25	0	28
VCNUM_INSURANCE	Total number of unsurance company-dependent VCs	25674	0.51	1.16	0	9
VCNUM_TRADE	Total number of VCs backed by trade company ("Shosha")	25674	0.10	0.51	0	8
VCNUM_MIXED	Total number of VCs backed by multiple origins	25674	0.52	1.20	0	16
VCNUM_INDEP	Total number of independent VCs	25674	1.00	2.13	0	26
VCNUM_CORP	Total number of corporate VCs	25674	0.35	1.00	0	10
VCNUM_GOV	Total number of VCs backed by government	25674	0.28	0.84	0	12
VCNUM_UNIV	Total number of VCs backed by university	25674	0.06	0.43	0	8
VCNUM_OVERSEAS	Total number of VCs located in foreign countries	25674	0.27	1.26	0	23
VCNUM_FOREIGN	Total number of VCs owned by foreing investors	25674	0.08	0.56	0	9
VFAGE_FIRST	Age of venture firm at the first round	21734	12.04	13.11	0	71
VCAGE_FIRST	Age of venture capital at the first round	21734	25.18	11.91	1	59

Note: The numbers are computed from all the round-VC samples with at least one VC.

Table-2: Correlation table

(Obs.= 21734)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) LN_NKY_AVR	1.00																	
(2) NKY_RETURN	-0.01	1.00																
(3) VCNUM_TOTAL	-0.08	0.00	1.00															
(4) VCNUM_TYPE	-0.10	0.00	0.79	1.00														
(5) AMOUNT_INVEST_ACC	-0.03	0.01	0.38	0.24	1.00													
(6) VCNUM_BANK	-0.12	-0.01	0.71	0.55	0.14	1.00												
(7) VCNUM_SEC	0.01	-0.01	0.74	0.51	0.28	0.36	1.00											
(8) VCNUM_INSURANCE	-0.01	-0.01	0.58	0.58	0.14	0.45	0.29	1.00										
(9) VCNUM_TRADE	-0.02	0.01	0.44	0.34	0.16	0.30	0.17	0.28	1.00									
(10) VCNUM_MIXED	-0.06	0.00	0.63	0.57	0.19	0.44	0.31	0.39	0.35	1.00								
(11) VCNUM_INDEP	-0.07	0.00	0.62	0.45	0.32	0.25	0.33	0.21	0.24	0.33	1.00							
(12) VCNUM_CORP	-0.04	0.00	0.38	0.32	0.16	0.17	0.28	0.19	0.09	0.16	0.19	1.00						
(13) VCNUM_GOV	-0.01	0.00	0.22	0.25	0.06	0.04	0.08	0.18	0.03	0.10	0.11	-0.03	1.00					
(14) VCNUM_UNIV	-0.04	0.00	0.30	0.26	0.25	0.11	0.19	0.08	0.02	0.08	0.37	0.05	0.15	1.00				
(15) VCNUM_OVERSEAS	-0.02	0.01	0.44	0.30	0.26	0.21	0.17	0.16	0.49	0.32	0.37	0.00	0.03	0.22	1.00			
(16) VCNUM_FOREIGN	0.01	0.01	0.19	0.14	0.04	0.05	0.09	0.09	0.11	0.11	0.08	0.04	0.04	-0.02	0.22	1.00		
(17) VFAGE_FIRST	0.03	0.00	-0.26	-0.27	0.06	-0.13	-0.17	-0.14	-0.10	-0.14	-0.21	-0.19	-0.03	-0.10	-0.05	-0.10	1.00	
(18) VCAGE_FIRST	0.03	0.02	-0.03	-0.06	-0.05	-0.06	0.12	-0.11	-0.05	-0.05	-0.10	-0.22	0.28	0.03	0.02	-0.15	0.17	1.00

Note: The numbers are computed from all the round-VC samples with at least one VC.

Table-3: Sample distribution over industry

	Fishery & Agg	Mine	Construction	Food	Fiber	Paper	Chemical
Industry Code	50	1050	2050	3050	3100	3150	3200
#(Firms)	2	0	9	7	0	2	8

	Phamaceutical	Oil & Coal	Rubber	Ceramic	Iron	Nonferrous metal	Metal goods
Industry Code	**3250**	3300	3350	3400	3450	3500	3550
#(Firms)	**13**	1	0	1	1	1	1

	Machinery	**Elec**	Transport machinery	Fine machinery	Other manufact	Elec & Gas	Transportation
Industry Code	**3600**	**3650**	3700	3750	3800	4050	5050
#(Firms)	**15**	**27**	3	9	9	1	2

	Marine transport	Air transport	Wherehouse	**Inforamtion & Telecom**	**Wholesale**	**Retail**	Bank
Industry Code	5100	5150	5200	**5250**	**6050**	**6100**	7050
#(Firms)	0	0	2	**160**	**47**	**71**	1

	Security	Insurance	Other financial	**Realty**	Service
Industry Code	7100	7150	7200	**8050**	9050
#(Firms)	9	3	7	**59**	145

Note: Industry classification is based on Nikkei mid-level industry classification. The numbers in each second row represent the number of sample firms belonging to each industry. The shaded industries the ones we include in the "Full" industry dummy case. The industries with bold characters are the ones we include in the "Selected" industry dummy case.

Table-4(1): Semi-parametric estimation

	Metric = Proportional Hazard Cox								
Hazard Estimates (First-Round to IPO)	Hazard Ratio	Robust Std.	Effect on Duration	Hazard Ratio	Robust Std.	Effect on Duration	Hazard Ratio	Robust Std.	Effect on Duration
NKY_RETURN	4.1039	2.995	− *	4.1043	2.998	− *	4.1668	3.033	−− **
VCNUM_TOTAL	1.0229	0.011	−− **	1.0179	0.011		1.0160	0.011	
VCNUM_TYPE	1.1823	0.111	− *	1.1954	0.110	− *	1.1916	0.109	− *
VCNUM_TOTAL_SQ	0.9999	0.000		1.0000	0.000		1.0000	0.000	
VCNUM_TYPE_SQ	0.9760	0.011	++ **	0.9758	0.011	++ **	0.9764	0.011	++ **
AMOUNT_INVEST_ACC				1.0454	0.018	−−− ***	1.0428	0.019	−− **
Industry Dummy	Full			Full			Selected (below)		
Pharmaceutical							0.5281	0.148	++ **
Machinery							1.0699	0.294	
Electricity							0.7985	0.166	
Info & Telecom							0.8965	0.085	
Wholesale							0.9058	0.159	
Retail							1.1871	0.151	
Realty							1.4914	0.258	−− **
# Obs	24997								
# Subjects	615								
# Failures	613								
Time at risk	24997								
Wald chi2	375.74			378.84			44.56		
Prob > chi2	0.0000			0.0000			0.0000		
Log Pseudo-Likelihood	-3320.58			-3318.26			-3321.48		

Notes: ***:1%, **:5%, *:10%. The dependent variable is the hazard of IPO. NKY_RETURN is the growth rate of Nikkei Average Stock Index from t-2 to t-1, VCNUM_TOTAL is the number of the VCs involved in the investment, VCNUM_TYPE is the number of the types of VCs involved in the investment, the variables with _SQ stand for the squared terms. AMOUNT_INVEST_ACC stands for the accumulated amount of investment by VC syndication to each firm. All the explanatory variables are one-month lagged variables. The group for this hazard analysis is firm. All the standard errors are adjusted for clusters (firm-level). The column named "Effect on Duration" shows the sign of the response of estimated duration with respect to each covaraite (+/- implies that the duration becomes longer/shorter as the covariate becomes larger). +++/---, ++/--, and +/- denote the significance levels of 1%, 5%, and 10%, respectively. In the row of "Industry Dummy", "Full" case includes the dummy variables corresponding to 15 industries shaded in Table-2 while "Selected" covers 7 selected industries, for which the estimated coefficients are shown.

Table-4(2): Semi-parametric estimation

	Metric = Proportional Hazard Cox								
Hazard Estimates (First-Round to IPO)	Hazard Ratio	Robust Std.	Effect on Duration	Hazard Ratio	Robust Std.	Effect on Duration	Hazard Ratio	Robust Std.	Effect on Duration
LN_NKY_AVR	0.9567	0.176		0.9618	0.177		0.9551	0.175	
VCNUM_TOTAL	1.0222	0.011	−− **	1.0172	0.011		1.0153	0.011	
VCNUM_TYPE	1.1805	0.111	− *	1.1938	0.110	− *	1.1896	0.109	− *
VCNUM_TOTAL_SQ	0.9999	0.000		1.0000	0.000		1.0000	0.000	
VCNUM_TYPE_SQ	0.9764	0.011	++ **	0.9761	0.011	++ **	0.9767	0.011	++ **
AMOUNT_INVEST_ACC				1.0453	0.018	−−− ***	1.0426	0.019	−− **
Industry Dummy	Full			Full			Selected (below)		
Pharmaceutical							0.5289	0.148	++ **
Machinery							1.0641	0.293	
Electricity							0.7983	0.163	
Info & Telecom							0.8962	0.085	
Wholesale							0.9086	0.158	
Retail							1.1874	0.151	
Realty							1.4851	0.258	−− **
# Obs	24997								
# Subjects	615								
# Failures	613								
Time at risk	24997								
Wald chi2	371.76			374.65			39.87		
Prob > chi2	0.0000			0.0000			0.0001		
Log Pseudo-Likelihood	-3322.18			-3319.87			-3323.11		

Notes: ***:1%, **:5%, *:10%. The dependent variable is the hazard of IPO. LN_NKY_AVR is the log of the average of Nikkei Average Stock Index, VCNUM_TOTAL is the number of the VCs involved in the investment, VCNUM_TYPE is the number of the types of VCs involved in the investment, the variables with _SQ stand for the squared terms. AMOUNT_INVEST_ACC stands for the accumulated amount of investment by VC syndication to each firm. All the explanatory variables are one-month lagged variables. The group for this hazard analysis is firm. All the standard errors are adjusted for clusters (firm-level). The column named "Effect on Duration" shows the sign of the response of estimated duration with respect to each covaraite (+/- implies that the duration becomes longer/shorter as the covariate becomes larger). +++/---, ++/--, and +/- denote the significance levels of 1%, 5%, and 10%, respectively. In the row of "Industry Dummy", "Full" case includes the dummy variables corresponding to 15 industries shaded in Table-2 while "Selected" covers 7 selected industries, for which the estimated coefficients are shown.

Table-5: Parametric estimation

	Metric = Accelerated Failure Time															
	Loglogistic															
Hazard Estimates (First-Round to IPO)	Failure Time	Robust Std.	Effect on Duration		Failure Time	Robust Std.	Effect on Duration		Failure Time	Robust Std.	Effect on Duration		Failure Time	Robust Std.	Effect on Duration	
NKY_RETURN	-0.6554	0.553			-0.6101	0.558			-0.6730	0.544			-0.7311	0.528		
VCNUM_TOTAL	0.0037	0.014			0.0043	0.014			0.0096	0.013			0.0021	0.013		
VCNUM_TYPE	-0.1183	0.067	−	*	-0.1125	0.067	−	*	-0.1108	0.067	−	*	-0.1136	0.065	−	*
VCNUM_TOTAL_SQ	-0.0002	0.000			-0.0002	0.000			-0.0004	0.000			-0.0001	0.000		
VCNUM_TYPE_SQ	0.0159	0.007	++	**	0.0150	0.007	++	**	0.0147	0.007	++	**	0.0161	0.008	++	**
AMOUNT_INVEST_ACC	-0.0299	0.017	−	*	-0.0314	0.016	−−	**	0.0154	0.011			-0.0322	0.013	−−	**
VCNUM_TOTAL (1st round)									-0.0228	0.027						
VCNUM_TYPE (1st round)									-0.0358	0.097						
VCNUM_TOTAL_SQ (1st round)									0.0010	0.001						
VCNUM_TYPE_SQ (1st round)									0.0065	0.015						
AMOUNT_INVEST_ACC (1st round)									-5.5900E-08	0.000	−−−	***				
cons	3.7616	0.126	+++	***	3.7290	0.090	+++	***	3.8127	0.135	+++	***	3.7016	0.082	+++	***
<Shape Parameter>																
/ln_gamma	-0.9856	0.034	Hump	***	-0.9782	0.033	Hump	***	-0.9963	0.034	Hump	***	-0.9627	0.035	Hump	***
/ln_p																
Industry Dummy	Full				Selected (below)				Full				No			
Pharmaceutical					0.3720	0.196	+	*								
Machinery					-0.0684	0.168										
Electricity					0.1060	0.135										
Info & Telecom					0.0491	0.070										
Wholesale					-0.0050	0.115										
Retail					-0.1041	0.097										
Realty					-0.3378	0.097	−−−	***								
Frailty	No								No				Yes Likelihood-ratio test of theta=0 chibar2(01) = 1.5e-05 Prob>=chibar2 = 0.498			
# Obs	25614															
# Subjects	615															
# Failures	613															
Time at risk	25614															
Log Pseudo-Likelihood	-604.43				-608.62				-601.65				-618.62			

Notes: ***:1%, **:5%, *:10%. The dependent variable is the hazard of IPO. NKY_RETURN is the growth rate of Nikkei Average Stock Index from t-2 to t-1, VCNUM_TOTAL is the number of the VCs involved in the investment, VCNUM_TYPE is the number of the types of VCs involved in the investment, the variables with _SQ stand for the squared terms. AMOUNT_INVEST_ACC stands for the accumulated amount of investment by VC syndication to each firm. The variables with (1st round) stands for the time-invariant variable measured at the first investment round. All the explanatory variables other that that with (1st round) are one-month lagged variables. The group for this hazard analysis is firm. All the standard errors are adjusted for clusters (firm-level). The column named "Effect on Duration" shows the sign of the response of estimated duration with respect to each covaraite (+/- implies that the duration becomes longer/shorter as the covariate becomes larger). +++/---, ++/--, and +/- denote the significance levels of 1%, 5%, and 10%, respectively. In the row of "Industry Dummy", "Full" case includes the dummy variables corresponding to 15 industries shaded in Table-2 while "Selected" covers 7 selected industries, for which the estimated coefficients are shown. In the row "Shape Parameter", Hump means the hump-shaped hazard function (i.e., initially increasing, then decreasing). The row "Frailty"indicates whether the estimated model contains the shared frailty in firm-level.

Table-6: Short and long spell samples

	Metric = Proportional Hazard Gompertz											
	All sample				Spell < 4 years				Spell > 4 years			
Hazard Estimates (First-Round to IPO)	Hazard Ratio	Robust Std.	Effect on Duration		Hazard Ratio	Robust Std.	Effect on Duration		Hazard Ratio	Std.	Effect on Duration	
NKY_RETURN	6.2565	4.420	−−−	***	3.3404	3.065			6.2124	7.425		
VCNUM_TOTAL	1.0448	0.011	−−−	***	0.9841	0.020			1.0431	0.019	−−	**
VCNUM_TYPE	1.2899	0.118	−−−	***	1.4154	0.163	−−−	***	1.1956	0.201		
VCNUM_TOTAL_SQ	0.9997	0.000	+++	***	1.0006	0.000			0.9997	0.000	+	*
VCNUM_TYPE_SQ	0.9647	0.011	+++	***	0.9568	0.015	+++	***	0.9746	0.019		
AMOUNT_INVEST_ACC	1.0344	0.014	−−−	***	1.0540	0.017	−−−	***	1.0106	0.018		
cons	0.0093	0.002	+++	***	0.0045	0.001	+++	***	0.0359	0.015	+++	***
<Shape Parameter> /gamma	0.0084	0.002	Positive	***	0.0399	0.004	Positive	***	-0.0042	0.002	Negative	**
Industry Dummy	Full				Full				Full			
# Obs	25614				20575				5039			
# Subjects	615				613				209			
# Failures	613				406				207			
Time at risk	25614				20575				5039			
Log Pseudo-Likelihood	-666.83				-624.89				28.08			

Notes: ***:1%, **:5%, *:10%. The dependent variable is the hazard of IPO. NKY_RETURN is the growth rate of Nikkei Average Stock Index from t-2 to t-1, VCNUM_TOTAL is the number of the VCs involved in the investment, VCNUM_TYPE is the number of the types of VCs involved in the investment, the variables with _SQ stand for the squared terms. All the explanatory variables are one-month lagged variables. The group for this hazard analysis is firm. All the standard errors are adjusted for clusters (firm-level). The column named "Effect on Duration" shows the sign of the response of estimated duration with respect to each covaraite (+/- implies that the duration becomes longer/shorter as the covariate becomes larger). +++/---, ++/--, and +/- denote the significance levels of 1%, 5%, and 10%, respectively. In the row "Shape Parameter", Positive and Negative mean the positive and negative duration dependence. The second and third column show the results based on the two sub-samples based on the length of spell. In the case of "Spell<4 years", the spells more than 4 years are treated as the left-censored samples.

Table-7: Type of VC in a syndicate

	Metric = Proportional Hazard: Cox								
	With Bank VC at t-1			Without Bank VC at t-1			With Bank VC but Without Sec Firm VC at t-1		
Hazard Estimates (First-Round to IPO)	Hazard Ratio	Robust Std.	Effect on Duration	Hazard Ratio	Robust Std.	Effect on Duration	Hazard Ratio	Robust Std.	Effect on Duration
NKY_RETURN	4.4456	3.779	– *	4.1279	6.091		10.0719	11.158	– – **
VCNUM_TOTAL	1.0293	0.014	– – **	1.0616	0.058		0.9800	0.028	
VCNUM_TYPE	1.0041	0.110		1.8326	0.557	– – **	1.2644	0.250	
VCNUM_TOTAL_SQ	0.9998	0.000	+ *	0.9978	0.002		1.0007	0.001	
VCNUM_TYPE_SQ	0.9910	0.012		0.9166	0.047	+ *	0.9619	0.027	
AMOUNT_INVEST_ACC	1.0479	0.016	– – – ***	1.0526	0.029	– *	1.0338	0.025	
Industry Dummy	Full								
# Obs	15726			9271			8987		
# Subjects	428			331			284		
# Failures	427			186			237		
Time at risk	15726			9271			8987		
Wald chi2	44.96			161.21			133.16		
Prob > chi2	0.0018			0.0000			0.0000		
Log Pseudo-Likelihood	-2115.05			-819.13			-1052.19		

Notes: ***:1%, **:5%, *:10%. The dependent variable is the hazard of IPO. NKY_RETURN is the growth rate of Nikkei Average Stock Index from t-2 to t-1, VCNUM_TOTAL is the number of the VCs involved in the investment, VCNUM_TYPE is the number of the types of VCs involved in the investment, the variables with _SQ stand for the squared terms. AMOUNT_INVEST_ACC stands for the accumulated amount of investment by VC syndication to each firm. All the explanatory variables are one-month lagged variables. The group for this hazard analysis is firm. All the standard errors are adjusted for clusters (firm-level). The column named "Effect on Duration" shows the sign of the response of estimated duration with respect to each covaraite (+/- implies that the duration becomes longer/shorter as the covariate becomes larger). +++/---, ++/--, and +/- denote the significance levels of 1%, 5%, and 10%, respectively. In the row of "Industry Dummy", "Full" case includes the dummy variables corresponding to 15 industries shaded in Table-2.

Table-8: Impact of each VC type

	Metric = Proportional Hazard Gompertz								
	All sample			Spell < 4 years			Spell > 4 years		
Hazard Estimates (First-Round to IPO)	Hazard Ratio	Robust Std.	Effect on Duration	Hazard Ratio	Robust Std.	Effect on Duration	Hazard Ratio	Std.	Effect on Duration
NKY_RETURN	6.2728	4.442	−−− ***	3.4964	3.203		6.9599	8.247	
VCNUM_TOTAL	1.0383	0.012	−−− ***	0.9724	0.022		1.0360	0.016	−− **
VCNUM_TYPE	1.0802	0.126		1.4033	0.228	−− **	0.8571	0.183	
VCNUM_TOTAL_SQ	0.9998	0.000	+++ **	1.0009	0.001	− *	0.9998	0.000	
VCNUM_TYPE_SQ	0.9717	0.012	+++ **	0.9607	0.016	++ **	0.9758	0.018	
AMOUNT_INVEST_ACC	1.0385	0.013	−−− ***	1.0565	0.018	−−− ***	1.0144	0.021	
cons	0.0089	0.001	+++ ***	0.0045	0.001	+++ ***	0.0285	0.010	+++ ***
VC Type Dummy									
Bank	1.3802	0.180	−− **	0.9942	0.172		1.8624	0.502	−− **
Security	1.1366	0.137		1.1429	0.186		1.4661	0.333	− *
Insurance	0.9672	0.129		0.8343	0.158		1.1940	0.261	
Trade	1.1652	0.197		0.8203	0.220		1.3490	0.411	
Mixed	1.0591	0.137		0.9940	0.175		1.0964	0.247	
Independent	1.3807	0.164	−−− ***	1.0144	0.166		2.0744	0.457	−−− ***
Corporate	1.6365	0.211	−−− ***	1.5146	0.265	−− **	1.6154	0.328	−− **
Government	0.9528	0.142		0.8219	0.160		1.3189	0.293	
University	0.7834	0.147		0.1519	0.096	+++ ***	1.8543	0.624	− *
Overseas	1.0686	0.170		0.9057	0.187		1.3524	0.308	
Foreign	1.1984	0.313		1.0441	0.389		1.2336	0.476	
<Shape Parameter> /gamma	0.0094	0.002	Positive ***	0.0400	0.004	Positive ***	-0.0025	0.002	Negative
Industry Dummy	Selected			Selected			Selected		
# Obs	25614			20575			5039		
# Subjects	615			613			209		
# Failures	613			406			207		
Time at risk	25614			20575			5039		
Log Pseudo-Likelihood	-654.99			-619.16			32.71		

Notes: ***:1%, **:5%, *:10%. The dependent variable is the hazard of IPO. NKY_RETURN is the growth rate of Nikkei Average Stock Index from t-2 to t-1, VCNUM_TOTAL is the number of the VCs involved in the investment, VCNUM_TYPE is the number of the types of VCs involved in the investment, the variables with _SQ stand for the squared terms. All the explanatory variables are one-month lagged variables. VC Type Dummy shows the coefficient of each VC type dummy. The group for this hazard analysis is firm. All the standard errors are adjusted for clusters (firm-level). The column named "Effect on Duration" shows the sign of the response of estimated duration with respect to each covaraite (+/- implies that the duration becomes longer/shorter as the covariate becomes larger). +++/---, ++/--, and +/- denote the significance levels of 1%, 5%, and 10%, respectively. In the row "Shape Parameter", Positive and Negative mean the positive and negative duration dependence. The second and third column show the results based on the two sub-samples based on the length of spell. In the case of "Spell<4 years", the spells more than 4 years are treated as the left-censored samples.

Table-9: Endogeneity of VC number and type

	Dependent Variable = Dummy for IPO Insturment: (Age of venture firm), (Age of lead venture capital)					
	Insturmented: (VCNUM_TYPE) (VCNUM_TYPE_SQ)			Instrumented: (VCNUM_TOTAL) (VCNUM_TYPE)		
Linear Probability Model by IV Estimation (Fixed-effect)	Coef.	Robust Std.	Effect on Duration	Coef.	Robust Std.	Effect on Duration
NKY_RETURN	-0.0056	0.030		0.0386	0.021	− *
VCNUM_TOTAL	0.0183	0.003	−−− ***	0.0214	0.002	−−− ***
VCNUM_TYPE	0.3844	0.041	−−− ***	0.2089	0.032	−−− ***
VCNUM_TOTAL_SQ	0.0000	0.000	−− **			
VCNUM_TYPE_SQ	-0.0862	0.012	+++ ***			
AMOUNT_INVEST_ACC	0.0045	0.003	−−− *	-0.0302	0.004	+++ ***
cons	-0.7172	0.102	+++ ***	0.0457	0.007	−−− ***
VC Type Dummy	Full			Full		
Industry Dummy	Selected			Selected		
# Obs	24449			24449		
# Groups	615			615		
Obs per group						
min	2			2		
avg	39.8			39.8		
max	238			238		
Wald chi2	521			970		
Prob > chi2	0			0		
Corr(u_i, xb)	-0.86			-0.88		

Notes: ***:1%, **:5%, *:10%. The dependent variable is the dummy variable taking the value of one when the sample firm accomplishes IPO. Bothe models are estimated by fixed-effect panel instrument variable estimation. The variables instrumented are VCNUM_TYPE and VCNUM_TYPE_SQ (left column) or VCNUM_TOTAL and VCNUM_TYPE. The instrument variables are the age of each venture firms at each data point and the age of each lead venture capital at each investment round. NKY_RETURN is the growth rate of Nikkei Average Stock Index from t-2 to t-1, VCNUM_TOTAL is the number of the VCs involved in the investment, VCNUM_TYPE is the number of the types of VCs involved in the investment, the variables with _SQ stand for the squared terms. All the explanatory variables are one-month lagged variables. The group for this hazard analysis is firm. The column named "Effect on Duration" shows the sign of the response of estimated duration with respect to each covaraite (+/- implies that the duration becomes longer/shorter as the covariate becomes larger). +++/---, ++/--, and +/- denote the significance levels of 1%, 5%, and 10%, respectively.