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Venture Capital Firm's Reputation Effect on its Start-up Company's Long Term Operating Performance and Survivorship

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Abstract

In this paper, I tested the effects of three proxies for venture capitalist (VC) reputation on its invested company's long term industry-adjusted operating performances (ROA , ROE), market-to-book ratio and survival time (time to delisting) in the aftermarket. VC's market share and VC's IPO share have strong and positive association with the post-IPO long-term performance metrics, and the effects are statistically significant even after accounting for self-selection bias. For long term survivorship of start-up companies, I applied hazard analysis to the IPO company's time to delisting with accelerated failure time (AFT) model as the baseline hazard function, and found that start up companies with backing from higher VC's market share and VC's IPO share VC firms tend to have lower hazard rate of de-listing. The expected time to delisting is also found to be much shorter in the pre-technology bubble period (1985-1996) compared to during and post-technology bubble period (1997-2007) for higher than median value reputable VCs. As the findings are robust even after controlling for business expansion and contraction cycles, this lend credence to the idea that during the technology bubble period, over optimism in VCs and too much uncommitted capital chasing after too few quality deals have resulted in reputable VC investing in mediocre quality companies. By cross-testing the effects of different quartiles of VC reputation proxy rankings on the long-run survivorship of the companies, VC market share is found to be the most consistent and effective amongst the proposed VC reputation proxies in explaining its effect on the IPO companies' long-run survival.

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Chapter 1: Introduction

1.1 Background

The subject of post-IPO performance and survivorship of new issuers in the capital markets has been a topic of great interest since Ritter's (Ritter, 1984) exposition on the potential wealth hazards of a buy-and-hold strategy in IPO investment. These hazards served to highlight the asymmetric information present in the capital markets and provide opportunities for reputable financial intermediaries to leverage their reputation and obtain competitive advantages (Kreps & Wilson, 1982; Shapiro, 1983). This reputation effect has been theoretically modeled to be important (Holmstrom & Tirole, 1997) and empirically researched to be critical in areas such as underwriter's reputation in IPO issues (R. B. Carter, Dark, & Singh, 1998).

Venture capital is defined as self-determining, professionally managed, committed pools of capital that center on equity or equity-linked investments in privately held, high and internally growth companies (P. Gompers & Lerner, 2001). Compared to more traditional modes of capital financing such as debt financing by banks, VC financing is still considered a relatively nascent mode financial intermediation, but its vital role in creation of public companies has been a topic of interest within academic circles (Barry, Muscarella, Peavy, & Vetsuypens, 1990; Lerner, 1994b). Through intimate participation and leveraging their knowledge in screening, monitoring, decision-making and support functions in the pre-initial public offering (IPO) stages, VCs investing in their specialized industries can utilize their knowledge, networks and management know-how to effectively assist the entrepreneurs in strategic, financial and operational planning (Gorman & Sahlman, 1989; Macmillan, Kulow, & Khoylian, 1989).

Given the critical nature of venture capital (VC) advisory services and the risk they undertake by supplying capital to privately-held and usually young high technology companies [In UK market, 34% of informal venture capital investments exits at a loss and 12% exits at a partial loss or break even (Mason & Harrison, 2002)], the VC reputation effect should be an important factor in influencing its investment opportunity set and its selection. Yet, extant literature has shown that scant research has been done in the area of VC reputation and its effect on the performance metric of its vested investments in their portfolio companies.

1.2 The Relevance of VC Reputation and Proposed Study

This study proposes to investigate in depth VC's reputation effect on its invested companies long term performance and survival being the early stages in public markets. Most of the current literature in VC research emphasizes the value-add proposition of VCs beyond traditional financial intermediation and the hypothesis of VC certification value suggests that when the difficulty of observing directly the quality of a early stage entrepreneurial company arises, the performance and quality of the company's affiliates as a signal of the quality of the start-up company itself (Megginson & Weiss, 1991), which in this case are the VC firms that provides private financing. Apart from providing certification value, the network or keiretsu effect that a VC firms possesses due to its unique position of being common investors to a portfolio of firms, allows it to be able to spot joint ventures or strategic alliances opportunities between its financially supported start-up companies (Lindsey, 2002). By estimate the effect that reputable VCs have on its invested companies' long-run performance, the value-add in a reputable VC's advisory services and network can be quantified in the company's superior performance over one that is not backed by reputable VC.

As explained, the benefits for a prospective start-up company to associate with a reputable VC are apparent, i.e. the VC certification value, Keiretsu or networking and VC's value added advisory services. Most of the existing literature, however, assumes homogeneity within the VC sample set and ignores the potential heterogeneity in the quality of VCs. An exception is an empirical research piece conducted by Gompers (Paul A. Gompers, 1996) that conducted studies into the relationship between the reputation magnitude of VCs and the under-pricing in the IPO of its portfolio companies. It is found that young VC firms, presumably with less than an established reputation, have a tendency to grandstand, i.e. young firms would be willing to the incur the cost of not maximizing value of the issuing company by bringing the company public earlier, such as to signal the VC's ability and append its reputation base. This provides belief in the potential heterogeneity in the quality of the venture capital firms distinguishable from one another.

Owing to the lack of commonly accepted reputation proxy measures for VC firms, most of the existing research studies have focused on the VC's role and value-add on its start-up firms without any distinction on the VC's relative standing in its industry in terms of experience, visibility and depth of funding strength. A prominent VC firm such as Kleiner Perkins Caufield & Byers may be indistinguishable from a newly formed VC firm in terms of its advisory value it can provide to its portfolio of start-up companies. In comparison to the research that has been conducted on equity issuing and underwriting studies, where large amount of research work has been conducted on the influence of underwriters reputation effect on the issuing firms[2] and valuable findings concluded, this actually imply the latent value and benefits that can be gleaned from a reliable VC reputation proxy with consistent and significant effects on the long-run operating performance and survivorship of the venture backed company in the post-IPO.

Hence, in order to take the research in venture capital studies one step further, one major goal of this paper is to incorporate VC reputation proxies in the empirical study to measure the strength in the association between these proposed VC reputation metrics and its invested companies' performance and survivorship. I am able to find consistent and strong association between higher VC reputation proxies' value and better long-run performance metrics and survivorship of the VC invested companies. This indicates the effect of venture capital reputation is not trivial in explaining its portfolio company's performance and survivorship in the post-IPO when the VC has long exited from its vested capital. As such, the advisory, certification and network value that a reputable VC is able to render to its portfolio company can be seen as critical providing it with a decisive advantage in terms of performing better and surviving longer in the post-IPO.

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[2] Notable research studies in underwriter reputation effect on IPO company performance include "Initial Public Offerings and Underwriter Reputation" by Carter and Manaster (1990), "Underwriter Reputation, Initial Returns, and the Long-Run Performance of IPO Stocks" by Carter, Dark and Singh (1998) and "Why Has IPO Underpricing Changed Over Time?" by Loughran and Ritter (2004).

In terms of measuring and quantifying a VC's achievements and reputation for comparison, an attractive approach to measure VC performance will be to focus on ability to help achieves IPO success in its vested set of companies, measured by future, post-IPO long term operating performance and the company's long-run survivorship. The use of the company's post-IPO success is appropriate as it has been readily used in other research studies due to the ease of measurement and readily available data over public financial databases[3]. It is also reasonable that, VC firms with prior strong records of bringing their portfolio companies to a profitable exit via IPOs will likely to attract stronger investors' interests in their future IPOs, due to their repeated successes. This allows the VC firm easier access to better future investment opportunities and at more advantageous terms due to higher demand for their advisory services (Hsu, 2004), and increases the likelihood of a successful IPO exit with lower risk to its vested capital (due to lower price paid), enabling the VC firm to earn better returns and eventually achieving a better reputation.

With the reasons stated above, three promising VC reputation proxy measures are selected for analysis. Similar to underwriter reputation proxy used in Megginson and Weiss exposition (Megginson & Weiss, 1991), I used VC market share of bringing the private start-up company public as one of the reputation measure proxies for capturing a

[3] Jain and Kini (1995) find that venture capitalist-backed IPO firms exhibit relatively superior post-issue operating performance compared to non-venture capital-backed IPO firms and that the market appears to recognize the value of monitoring by venture capitalists as reflected in the higher valuations at the time of the IPO. This lends weight to using after market success of the venture backed IPO company to measure the VCs skill and ability to provide value-add to the company in the pre-IPO.

VC's relative ability and standing amongst its peers in its success to bring its portfolio firms to public markets. A variation of VC's market share using VC's IPO investments as a proportion of its total investments over a period time is used as the second measure of the VC's deal making capability and stature as IPO exits are usually the most profitable for the VCs and their limited partners. For the third proxy for VC reputation, I utilized Gompers (Paul A. Gompers, 1996) and Lee & Wahal (Lee & Wahal, 2004) reputation proxy in their VC grandstanding studies that suggested VC firm age as an appropriate measure for VC reputation. I note that these reputation proxy measures are also employed as alternative reputation measures in a current working paper by Ivanov, Krishnan, Masulis & Singh (Ivanov, Krishnan, Masulis, & Singh, 2008).

With the identification of appropriate VC reputation proxy measures, the next step in my research study was to associate the VC reputation proxy measures with long-term IPO issuer performance and long-run listing survivorship. Post-IPO performances is measured by industry-adjusted operating performances (ROA and ROE), market-to-book ratio, and long term survivorship is measured by the period of time from IPO issuer first listed on the exchange till the time it de-lists. There is, by common VC industry practice, a lock-up period of half a year (for partial exit and usually full year of lock up for full exit) which acts as a commitment device to minimize the tendency for general partners in VC firms from grandstanding (P. Gompers & Lerner, 1998) and to alleviate information asymmetry between the principal and agent which is usually greatest during IPO exits (Cumming & MacIntosh, 2003). So, the criticality of long term post-IPO performance and the survivorship of the IPO issuer backed by VC cannot be understated as they are relevant to all the stakeholders of the venture capital investment. For the shareholder-entrepreneurs, it can be deciding factor in whether the cost of association with reputable VCs is justified to allow it in gaining access to VC expertise in building the organization and professionalize its start-up company (Hsu, 2004; Thomas & Manju, 2002) beyond traditional financial intermediation of gaining access to funds. For the limited partners of the business venture, the long term performance and survivorship of the venture backed company further provides information to alleviate the information asymmetry inherent in the certification value of reputable VCs (Cumming & MacIntosh, 2003) as this study directly associates the long-run success of the VC invested company in the after market with its reputation level. This can be valuable in allowing the limited partners to increase their chances in selecting the appropriate VC fund to participate and optimize their returns on investment. For the general partners of the venture firm, by being able to quantify the VC firm's reputation level and its effect on its portfolio company's long-run performance and survival, they will be able to make informed decisions on whether the efforts and costs to obtain better reputation will be correlated to better performances of its portfolio of start-up companies and consequently more successful and cheaper fund raising, better rate of future successful IPO exits and increases in its returns on investments.

1.3 Thesis Outline

In the following chapters, the broad research objectives and its summary of contents are as follows:

In chapter 2, the data sample set and primary test methodologies utilized in this research study are explained. This includes discussion in detail on the data sources and filters in obtaining the IPO sample data set for the testing period from1985 to 2007. The VC reputation proxy measures, post-IPO operating performances and survivorship variables and the selection of control variables are also explained in depth. A detailed treatment on the survival analysis methodology with AFT as baseline hazard function is also discussed to facilitate basic understanding for the IPO issuer long-run survivorship testing done later in the chapter 5.

In chapter 3, the descriptive test statistics and empirical test results of our IPO sample set are presented. To verify that the sample set of VC backed IPO investments from our study is correlated to literature findings of the positive influence of VC's networking and value-add have on its IPO issuing companies over non VC backed IPO issuing companies (Bharat A. Jain & Kini, 1995; Lindsey, 2002; Thomas & Manju, 2002), I first tested that our sample set of VC backed IPO investment does in fact perform better than non VC backed samples from the same period, by regressing the long-run operating performance measures against VC and Non VC backed characteristics of the IPO issuing companies. This indicates that our VC backed IPO investment sample set is viable for further testing as the preliminary testing results do correlate with the current extant literature findings.

To learn more about the characteristics of IPO firms backed by VCs of different reputation levels, a cross sectional regression for the VC reputation proxy measures against the chosen control variables are conducted. This is important to validate that the IPO issuer characteristics controlled are critical to the post-IPO performance analyses. By establishing this groundwork, it then allowed us to conduct the test to assess the explanatory power of the selected VC reputation proxy measures by checking if the prediction of better post-IPO operating performance and market-to-book ratios are significantly associated with higher values in the proxy measures of the respective proposed VC reputations. From these series of tests, I am able to also assess the relative strengths and explanatory powers of the different VC reputation proxies in its association to better long term operating performances of the VC supported IPO issuing companies.

In chapter 4, the results of the robustness test is presented by applying the two stage Heckman's correction method (Heckman, 1979) to account for the potential self selection bias of more reputable VCs, which can argued to have access to better investment opportunity set and more promising private start-up companies (Lee & Wahal, 2004; Sorenson, 2006). I am able to find that, even after accounting the potential self selection bias, the proposed VC reputation measurement proxies are still statistically significant in its explanatory power to show that the more reputable VC's non traditional financial intermediation role provides valuable advisory and professionalization services to its portfolio of start-up companies.

In chapter 5, survival analysis is conducted on the IPO issuing companies using survival analysis through hazard rate modeling that have been widely used in bio-medical sciences, and have in recent times found applications in finance research studies. Through survival analysis with AFT as the baseline hazard model function and additionally controlling for business contraction and expansion cycles as determined by National Bureau of Economic Research (NBER), I am able to compare between IPO issuers backed by VCs of differing reputation measurements listed at different time frames and operated in the public space for different length of time. We further segregated the survival analysis into time period splits to test for the VC reputation effect and IPO issuer survivorship during the pre-technology bubble period and during and post-technology bubble period. This is to account for the alleged effect of overvaluation and over optimism in investment sentiment towards high technology equity offerings during the latter period. We also conducted tests with quartile splits on VC reputation proxy measurements to check for differences in the sensitivity of the different VC reputation proxies by cross comparing the top versus bottom quartiles and 3rd versus 2nd quartiles VC reputation effects on the IPO issuers' long term listing survivorship.

The final chapter summarizes and concludes the findings in our study.

Chapter 2: Data Description and Methodology

2.1 IPO Sample Set

Our IPO sample set comprises U.S IPOs offered for the 1985 – 2007 period. The IPO issuing details are extracted via Thomson Financial's Security Data Corporation's (SDC) Global New Issue database. Pertinent information extracted from the database include filing , offer and issue dates, company incorporation date, original filing high and low offer prices, IPO principal amount offered, lead and co-underwriter details, VC investors details in the IPO issuer and total amount invested by VC firms in the IPO issuer.

The individual IPO issuer is then tracked until the end of 2007 on the Centre for Research in Security Prices (CRSP) database to determine if it continues to trade or fails. IPO issuer-related data including issuer net operating income, total assets, book value of equity, outstanding number equity shares and equity prices are also obtained from the Compustat database. We excluded from our dataset:

1) IPO offer price less than 5 dollars or small offerings that raised less than 5 million dollars at the IPO,

2) Stocks not listed on major exchanges or reported in the CRSP database,

3) Unit offerings, Reverse leveraged buy-outs (LBO), spinoffs and carve-outs.

Non-operating companies such as REITs and closed-end funds, offers priced below 5 dollars are usually subject to anti-fraud provisions and small issues less than 5 million dollars usually require less stringent disclosure rules and also because less information are available for them (Ivanov et al., 2008), they are hence excluded. Omitting IPO offerings with less than complete information set, we are able identify 1876 venture backed IPO issuers for the 1985-2007 period for testing.

On survivorship of the IPO issuers in the post-IPO, the research focus on survivorship is consistent with the notion of the firms that continue to operate independently as public corporations. Firms that are delisted from the trading exchange due to negative reasons or are acquired are categorized as non-survivors. This is consistent with previous studies that have been conducted on firm survivorship (Hensler, Rutherford, & Springer, 1997; B. A. Jain & Kini, 2000) which used companies delisted for negative reasons as proxy for failures. Hence, companies with CRSP delisting codes for negative reasons that include bankruptcy, insufficient capital, insufficient float liquidation, failure to meet financial guidelines to list, insufficient number of market makers, nonpayment of fees or delinquent in filings, price falling below acceptable levels, insufficient number of shareholders are considered to be non survivors.

The decision to treat acquired firms as non survivors is based on research studies that suggest such firms are typically distressed and suffer from declining stock price performance prior to the acquisition (Welbourne & Andrews, 1996). The exclusion of acquired firms also allows us to focus the research on firms that continue to operate as independent public entities.

2.2 Assessment of VC Reputation Proxy Measures

This paper, as been briefly mentioned in the introduction chapter, proposes three proxy measurements for VC reputation, namely:

1) VC Market Share

2) VC IPO Share

3) VC firm age

As the research objective is to examine the strength of association between these VC reputation proxies and the venture backed IPO issuers' long term performances and survivorship, the VC reputation proxies need to be treated in a careful manner.

One complexity to VC reputation proxy measurements is that the VC funding of start-up companies usually occurs in syndicates. VC syndication helps to disseminate information across industry sector borders and expands the locus of exchange which improves the diversification value of their investments[4] (Olav & Toby, 2001). Similar to what has been employed in a working paper by Ivanov, Krishnan, Masulis & Singh (Ivanov et al., 2008), we aggregated the VC syndicate reputation as the average reputation across all the VCs investing in start-up company. This approach takes in account the past performance (since we are to take a three year average value of past

[4] In other notable studies on VC syndication, Lerner (Lerner, 1994a) finds that apart from diversifying the risks of funding the staged capital infusion all by themselves, VCs, especially in the early stages of funding, prefers a partner VC who is on similar level or higher level of experience as a legitimate "second opinion" on their target entrepreneurial company due to the risks entailed. Metrick (Metrick, 2007) also notes that commonness of syndication varies over time, depending also on external conditions such as relative supply of capital. Syndication is more prevalent in pre-boom period than in boom periods as it is more profitable to go alone when the flow of capital into the VC industry is high.

performance) of all the VCs that are vested in the portfolio company. We omitted the usage of the lead VC as the key barometer to the VC reputation of the syndicate due to the limitation that the lead VC can change across different funding rounds which might potentially confound and reduce our viable sample set of IPO issuing companies.

To make sure that we do not over appraise the explanatory powers of VC reputation proxy measurements due to the influence of underwriter reputation effect, we also take pains to make sure the underwriter reputation (Carter-Manaster scale) is included in our regression model to avoid any false attribution to the VC reputation effect. The long term post-IPO performance measures in this study are estimated over the first 3 year period after the IPO issuer offering. But to minimize the survivorship bias in this study, we also included firm performance for IPO issuers with less than 3 years of listing period.

The proposed VC reputation proxies are formally defined as follows:

VC Market Share: This is calculated by taking the VC's dollar market share of its venture backed IPOs weighted to the total dollar size of all venture backed IPOs for the immediate preceding 3 calendar years. For example, to analyze the long-run performance of an IPO issue in 2000, the VC market share is the aggregation of the dollar value of all IPOs backed by the VC funding the IPO issue in question during 1997,1998 and 1999 as proportion of the total dollar size of all venture backed IPOs for 3 year period. The dollar size of an IPO is obtained as the gross proceeds from the offering.

VC IPO Share: As earlier stated that IPO exits are usually the most profitable option for VCs to divest from their vested capital in their portfolio of start-up companies, the VC IPO share is calculated to measure proportion of successful VC exits using the IPO route. It is calculated as proportion of VC's investments in IPO issuers in the 3 calendar years prior to the IPO in question, to the VC's total investments over the same period.

VC Firm Age: This third VC reputation proxy measurement assumes that the longer the VC firm has operated the more experience and expertise it has gathered, and has access to better investment opportunity set and makes superior selection decisions. The VC firm age, hence, will be calculated from the date of incorporation for the VC to the date of IPO offering for IPO in question. This follows the VC reputation proxy measurement suggested in VC grandstanding studies by Gompers (1996) and Lee & Wahal (2004)[5]

2.3 Post-IPO Long-run Performance Measures

In this research study, the three measures of post-IPO long-run performance metrics used are: industry-adjusted operating return on assets (ROA), industry-adjusted operating return on outstanding equity (ROE) and market-to-book ratio. The ROA and market-to-book ratio are standard measures widely used in existing literature (Paul A.

[5] Gompers (1996) finds that young venture capital firms take companies pubic earlier than older venture capital firms in order to establish a reputation and successfully raise capital for new funds and companies backed by young venture capital firms tend to be are younger and more underpriced at their IPO than those of established venture capital firms. Moreover, young venture capital firms have been on the board of directors a shorter period of time at the IPO, hold smaller equity stakes, and time the IPO to precede or coincide with raising money for follow-on funds. Lee and Wahal (2004) also finds consistent underpricing by younger VC firms and venture capital backed IPOs experience larger first-day returns than comparable non-venture backed IPOs.

Gompers, Ishii, & Metrick, 2003; Bharat A. Jain & Kini, 1995), with ROA focusing on the profitability per dollar of assets while market-to-book can be seen as the growth projection of the company, not unlike a real option value of the company. ROE is used as a variation to ROA to gauge the VC reputation effect on the rate of return on the ownership interest of the common stock owners in terms of profitability per outstanding common share.

The first measure, ROA, is the industry-adjusted rate of return on assets, defined as Net Income (NIQ) divided by Total Assets (ATQ) minus industry median ROA, and taking average for first three years following the IPO. Each IPO issuer is matched to their respective sample of companies based on the 4 digit SIC code, by deducting the sample companies' median ROA off IPO issuing company's ROA to account for the industry effects. If the IPO issuing company do not survive beyond 3 years, the maximum number of quarters data available in is taken and matched against the industry median ROA for the same number of quarters to account in the attempt to minimize survivorship bias. The data, NIQ and ATQ, are taken off the Compustat Quarterly Database.

The second measure, ROE, likewise similar to the ROA, is the industry-adjusted rate of return on outstanding equity, defined as Net Income (NIQ) divided by the Total Common Shares Outstanding (CSHOQ) minus the industry median ROE, and taking average for the first three years following the IPO. The adjustment for industry effects and survivorship bias is similar to the ROA as above and data NIQ and CSHOQ are also taken off Compustat Quarterly Database.

The third measure, market-to-book value is calculated as the ratio of the market value of equity to book value of equity. The market value of equity is defined as number of shares outstanding (CSHOQ) multiplied by its closing stock price for prior quarter (PRCCQ). The book value of equity is defined as total common/ordinary equity (CEQQ) plus net deferred balance sheet income taxes (TXDBQ), minus carrying value of preferred stock (Data 55). Again, this is adjusted for survivorship bias similar to ROA and ROA for issuing companies that survived less than 3 years. Data CSHOQ, PRCCQ, CEQQ, TXDBQ and carrying value of preferred stock (Data 55) [in database of the old data format] are also taken off Compustat Quarterly Database.

2.4 Methodology for Survivorship Study – Accelerated Failure Time Modeling

In the study of venture backed company survivorship in the post-IPO, I adopted survival analysis by using hazard rate modeling on the time to IPO issuer failure (de-listing due to negative reasons or being acquired) for the VC invested companies that have gone public. As this methodology is my primary tool to analyze the VC reputation effect associated to its venture backed companies long-run survivorship, the hazard rate modeling utilizing accelerated failure time (AFT) baseline model bears some closer scrutiny.

Survival analysis involves the modeling of time to event data; where in our context of finance studies, bankruptcy or firm delisting can be considered an "event" in the survival analysis. Survival analysis has its roots in bio-medical sciences, and has in recent times been argued in literature to be useful in modeling corporate failure (Keasey, McGuinness, & Short, 1990) and have since found broad applications in finance research studies to predict events such as bank and company failures[6] (Hensler et al., 1997; Lane, Looney, & Wansley, 1986).

Jain and Kini (2000) note the main benefit of using survival analysis is that it avoids some problems arising from the cross sectional models such as multiple discriminant analysis and logistic regression to predict failure. Cross sectional regression models assume a steady state for failure process which is usually not supported in finance studies and the logit and discriminant models are hence only able to predict whether an event will occur but not when it will occur. Using survival analysis hazard models such as Cox hazard model or AFT model over the conventional logit/probit or discriminant analysis, however, produce estimates of probable time to failure, rather than just providing probability estimates of failure over the specified period of event study.

An additional advantage of survival analysis is that it allows assessment of the conditional probability of failure given that the firm has survived up till the present time, as the models are able to deal with censored data which represents scenarios where the failure event has yet to occur and when each data set has different starting and ending time horizons. This is especially critical for a study such as the survivorship of publicly listed firms in the post-IPO period; our data sets are right censored since at any point in

[6] In their seminal paper, Lane, Looney & Wansley (1986) first applied survival analysis using Cox Proportional Hazard Model to bank failures and find the results comparable to discriminant analysis. Hensler et al. (1997) used accelerated failure time (AFT) model to investigate the effects of several characteristics suggested as indicators of firm survival for initial public offerings (IPOs) and find that the survival time for IPOs increases with size, age of the firm at the offering, the initial return, IPO activity level in the market, and the percentage of insider ownership.

time a large proportion of firms that have gone public are still in business and through survival analysis, we are able to compare between firms that are listed at different time frames and operated in the public space for different length of time.

Hensler (1997) and Jain and Kini (2000) paper outlined the intuition behind hazard methodology in performing tests of the hypothesized determinants of IPO survivability, in which the basic Cox hazard methodology is used to determine the time-dependent behavior of IPO survival, proxied by the length of time in which a firm remained listed in the post-IPO. The hazard function, H(t), in the context of post-IPO survival of firms is the conditional de-listing rate defined as the probability of de-listing during a very small time interval (after IPO) assuming that the firm has survived to the beginning of this time interval. In terms of probability density function and cumulative distribution function, the hazard function can be written as:

$$H(t;X) = \frac{f(t;X)}{1 - F(t;X)} \qquad \textbf{(2.1)}$$

Where H(t;X) is hazard function; f(t;X) is the probability density function on T (time in months that the IPO company has survived); F(t;X) is probability that an IPO with characteristics X has been de-listed before time t.

The general form of the hazard model is

$$T(t;X) = T_0(t)e^{X\beta} \qquad \textbf{(2.2)}$$

Where T = the length of trading period in months; T_0(t) = Baseline hazard function describing the expected pattern of trading-period durations for a pool of IPOs that have been publicly listed; X = vector of independent variables (covariates) hypothesized to affect length of the IPO firms' trading period; β = Vector model parameters

The baseline hazard function describes the hazard probability distributions for IPOs de-listing for negative reasons under homogeneous conditions. If this is true, the Cox proportional hazard model can be employed, which is a fairly "simple" linear model that can be readily estimated by taking log on both sides in equation (2.2):

$$\ln\left(T(t;X) \middle/ T_0(t) \right) = X\beta \tag{2.3}$$

This model is not based on any assumptions concerning the nature or shape of the underlying survival distribution and assumes that the underlying hazard rate is a function of the covariates. While no assumptions are made about the shape of the underlying hazard function, the model equation shown above does imply two assumptions. First, it specifies a multiplicative relationship between the underlying hazard function and the log-linear function of the covariates. This assumption is also called the proportionality assumption. In practical terms, it is assumed that, given two observations with different values for the independent variables, the ratio of the hazard functions for those two observations does not depend on time. The second assumption is that there is a log-linear relationship between the independent variables and the underlying hazard function (Kalbfleisch, 2002).

These two assumptions might not be tenable in events such as delisting on IPOs as it might vary greatly between different public firms. For example, in both Hensler

(1997) and Jain and Kini's (2000) papers, the failure distribution of IPO firms is shown to be non-monotonic and hence another baseline hazard model is needed to be employed.

A variety of other hazard models are available and they differ mainly by the assumption regarding the shape of the hazard function. In both Hensler's and Jain and Kini's papers, the accelerated failure time (AFT) model was used. This is a parametric model which restricts the baseline function to follow an assumed density function based on deductive expectations. The AFT model is useful in situations when the covariates are assumed not to have a proportional effect on probability of the hazard event (in this case the delisting of an IPO firm) or when the hazard is restricted to follow a specific functional form (Smith, 2002). In other words, the usage of the AFT model allows the effect of the covariates to have non proportional effect on the time to failure, but rather it is able to accelerate or decelerate based on weighted importance of the covariates and its effect with length of trading time. In its functional form, The AFT Model can be written as:

$$T(t;X) = T_0(t)^{\sigma} e^{X\beta} \qquad \textbf{(2.4)}$$

Or $$\ln T(t;X) = \sigma \ln T_0(t) + X\beta \qquad \textbf{(2.5)}$$

With $$\ln T_0(t) = \ln e^{\omega} = \omega \qquad \textbf{(2.6)}$$

Where T, $T_{0,}$ X, β are previously defined in equation (2.2), e^{ω} is the baseline hazard function with a specified continuous density and σ is an ancilliary scale parameter which shapes the function.

Figure 2.1 illustrates the delisting frequency for our sample set of ventured back IPOs of the research study for the full period of 1985 -2007, sliced in quarter of a year. The peak period for de-listings is around the second year and shows declining trend there after. This suggests that the de-listing frequencies exhibit non-monotonic characteristics.

Several density functions are usable as a functional form for the time period to IPO delisting, but both theoretical and empirical considerations justify a non monotonic function, as already shown in figure 2.1 where the peak period of delisting is in the second year. Theoretically, controlling for company age at IPO should lead to increase rate of de-listing as firms strive to succeed. And as firms take root in the industries, the delisting should decrease as time passes. This suggests the non-monotonic assumption is appropriate and is consistent with Hensley's (1997) suggestion that the AFT model is appropriate for analysis of IPO delisting.

It is suggested that the log-logistic density function is a plausible functional form to model the baseline hazard function for non monotonic data distributions (Kalbfleisch, 2002). The log-logistic baseline hazard model is shown to be:

$$T_0(t) = \lambda\rho(\lambda t)^{\rho-1} \Big/ (1+(\lambda t)^{\rho}) \qquad \textbf{(2.7)}$$

Where λ, ρ are density parameters and t is the individual company failure time. It can be seen that if ρ >1, the log-logistic function is non-monotonic and the conditional probability that an IPO firm will be de-listed increases with time to a maximum and decreases after that, with the most probable delisting period to be:

$$t = (\rho - 1)^{1/\rho} / \lambda \qquad \textbf{(2.8)}$$

These model parameters can be estimated using maximum likelihood method and the maximum likelihood estimates with $\lambda = e^{X\beta}$, $\rho = 1/\sigma$ (as denoted in equation 2.7); the model appropriateness is tested using likelihood ratio test statistic computed as $-2(\ln L_0 - \ln L_n)$, where $\ln L_0$ is the maximum log likelihood of restricted model and $\ln L_n$ the maximum log likelihood of the estimated model (Hensler et al., 1997). The likelihood ratio statistic is asymptotically χ^2 distributed.

As there is the possibility that the duration data is right- censored, which means that the venture backed IPO companies in study continues trading through the entire study period without being de-listed. The estimation of such a model with censored data requires additional binary variable that denotes whether the observation is censored. By defining the censoring indicator as δ, the general form of the likelihood function is:

$$L = c\prod_{i=1}^{n} f_i(t_i; X_i)^{\delta_i} (1 - F_i(t_i; X_i))^{1-\delta_i} \qquad \textbf{(2.9)}$$

Where $f_i(t_i; X_i)$ and 1-$F_i(t_i; X_i)$ are already defined in equation (2.1) and c is a constant term that does not affect the maximum likelihood function.

A positive outcome from this hazard modeling study is that the AFT model allowed the analysis of the effect of more reputable VC (based on higher reputation proxy measurements selected in section 2.2) and its association with higher survival rates of its ventured back IPO companies, which implies that value-add of the advisory services in strategic, financial and operational areas provided by better VCs to their portfolio of start-up companies are able make them more competitive and fitter to survive the long-run once they have gone public.

2.5 Selection of Control Variables

As we need to measure the marginal effect in unit change of the VC reputation proxy value on the long-run issuer operating performances, selected issuer characteristics that might also influence the companies' long-run performances and confound the VC reputation effect needs to be controlled for to segregate the VC reputation effect for analysis.

A common issuer characteristic used in previous IPO research studies is the natural logarithm of the gross proceeds from the IPO (IPO size). IPO size have been considered to proxy for the extent of information asymmetry regarding the prospects of the IPO issuer as higher proceeds raised at the offering signal lesser uncertainty regarding the future expected performance of the issuing firm(B. A. Jain & Kini, 2000). Hence, its inclusion is intended to control for any systematic influence due to offering size of the issue. As larger offerings are often made by more established and geographically well dispersed firms, the risks and uncertainty in the prospect of the company should be lower and investor would expect lower initial returns (R. B. Carter et al., 1998). This data set is obtained from SDC New Issues database.

In the seminal paper by Carter, Dark and Singh (1998), it is implied that the age of the issuing company (Age) can be used as a control variable for company age factor and was suggested to proxy for the risks of the IPO firm (Ritter, 1984). Older firms which have survived for a longer period of time remaining listed are deemed to have made fewer critical mistakes over the passage of time, have more tangible assets, have developed a competent management team and established strong customer connections which allowed it to weather adverse economic condition, and hence judge to be less risky. It is also documented that higher initial returns and more pronounced long-run underperformance are common for younger IPOs (Ritter, 1991). These findings highlight the potential importance of the Age factor in affecting the issuing companies operating performances and Age is incorporated in the regression model as one of the control variables. This data is obtained from SDC New Issues databases and when not available, collated from the company's official website and taken as its natural logarithm.

The technology intensive firms, commonly backed by VC firms, have to be flagged because of the possibility of higher technological risks in terms of abandoned adoption for the said technology industry-wide and also of its higher level of expected potential growth (Loughran, 2004). A binary indicator (Tech) to indicate that the issuing company is from a technology intensive industry is marked as 1 for technology based companies and 0 otherwise. Tech is useful as a control variable to capture the technology intensive industry characteristics. Sorting whether a company is technology based is straightforward—we simply classify an IPO company as Tech = 1 if SDC assigns that IPO a high tech industry classification flag and as Tech = 0 for the IPO company if SDC does not. This high tech/non high tech industry demarcation is sorted according to the primary line of businesses based on North American Industry Classification System (NAICS). A list of this primary business classified as technology intensive in SDC is provided in the Appendix B.

As the post-IPO performance of the issuers is likely to be influenced by the investment banking advisory activities before and after the IPO, a direct measurement of the underwriters' effectiveness is not easy to identify (B. A. Jain & Kini, 2000). Similar to past studies, lead underwriter reputation have been used as a catch-all proxy to the investment banking value-add provided and many studies have found to have significant explanatory powers in explaining the initial and long-term IPO returns (R. Carter & Manaster, 1990; R. B. Carter et al., 1998). Adopting the same approach, we will proxy the lead underwriter's reputation (Underwriter) by the Carter-Manaster 9 point scale, obtained from Professor Ritter's web site at: http://bear.cba.ufl.edu/ritter/ipodata.htm. This is used to control for the underwriter's value-add effect on the going public process such as not to mix up the VC reputation effect which is our main focus in this study. To further capture and segregate the influence of important external activities of the going public process on the issuing firms long term performance, we also included a proxy to control for the success level of the pre-IPO road show (Roadshow) which takes on the value of 1, 2 or 3 depending on whether the offer price is below, within or above the initial filing range respectively.

In our survivorship testing, in order to control for the business contraction and expansion cycles, I also included one more independent variable (Bcycle) for testing, a binary indicator with 1 for an IPO issued during business cycle expansion and 0 during business cycle contraction. This is taken off NBER's online database which defines economic expansion and contraction dates for the US economy[7].

[7] The business cycle dates are extracted from: http://wwwdev.nber.org/cycles/cyclesmain.html. NBER define a recession as a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales. Hence, these contractions (recessions) period are measured from the start at the peak of a business cycle to end at the trough of a business cycle. Our research study period have two business contraction cycles, from July 1990 to March 1991 and from March 2001 to November 2001, lasting 8 months on both occasion.

Chapter 3: Empirical Results

Following the discussion in the previous chapter on the data and the methodology to be used for our testing of the VC reputation proxy effect on the venture backed IPO company's long-run performance, this chapter documents the empirical results from the our testing. First, a discussion on the summary statistics of our sample IPO dataset and its control variables is warranted.

3.1 Summary Statistics

Table 1 provides the industrial composition of venture-backed IPOs with High Tech and Non High Tech Splits for our IPO sample set from 1985 to 2007. Based on the viable set of 1876 IPOs brought to public over this period, the ventured back IPOs are mostly in high technology industries (as defined by SDC using the NAICS classification), comprising 80.9% of the total sample set of the test period. Conventionally, VCs invest more prominently in high technology industries where information asymmetry is most significant and potential for maximum returns in investment to the VCs are the highest to justify the resource intensive cost of monitoring the companies, for example, via costly staged capital infusion (P. Gompers & Lerner, 2001; Paul A. Gompers, 1995). Based on Table 1, it is also note worthy that the highest proportion (38.9%) of venture backed high technology IPOs falls into business services category, which mainly comprises businesses that are involved in the internet services & software development industry, and majority of the sample IPOs are listed between 1995 – 2000 period, during the peak of the infamous "technology bubble" period. The next two most popular venture backed sectors are in Chemicals & Allied Products (16.7%) and Electronic, Electrical Equipment & Components (11.7%), and are mainly industries that support gestation of early stage companies that are involved in high technology, research and development (R&D) intensive type of business. These companies are also deemed to be highly risky due to the low cash-flows and uncertain future prospects in the early stages. Tying in to literature findings, VC investments in these high risk ventures are consistent with the finding that VCs invest in industries in which their expertise and ability to monitor and guide are most in demand (Barry et al., 1990), and to monitor these technology specific companies require niche and specialized skills only VCs with the requisite knowledge in the industry are able to provide (P. Gompers, Kovner, Lerner, & Scharfstein, 2006). This also provides an explanation on the industry composition distribution of investments made by VCs into high tech and non high tech companies shown in Figure 1, that the IPOs issued by VC backed high technology companies are much more focused on the industries as previously mentioned from spikes in the figure, while VCs investments in non high tech companies are more well spread out and leveled from the comparison in the same figure.

Table 2 illustrates the distribution of the delisted venture backed IPOs for high tech and non high tech firms in a cross sectional view for the IPO issue year versus period (number of years, Y) after the IPO is launched. Overall, 768 out of the 1876 (40.4%) of the venture backed IPO issues in the sample set delisted on negative reasons over the period of our study (1985 to 2007). Anecdotally, from the start of the sample study in 1985 of 13 failed venture backed IPO issues (6 high technology and 7 non high technology issues), the total number of failed venture backed IPOs rises steadily and peaks at 1995 with 94 failed IPO issues (79 high technology and 15 non high technology issues), and continued to maintain elevated throughout the late 1990s and again increases to 70 (60 high technology and 10 non high technology issues) in 1999, 67 (62 high technology and 5 non high technology issues) in 2000, at the height of the technology bubble. It is documented that the level of fund-raising was rising steeply in the late 1990s and the amount paid by VCs for the investments into new companies became unsustainably high which resulted in "money chasing deals" phenomenon (P.A Gompers & Lerner, 2004).

The proverbial bubble deflated on the much diminished profitable investment opportunity set in 2001, and the number of failed venture backed issues dropped to 6 (4 high technology and 2 non high technology) in 2001 and have remained low thereafter till the end of the study period in 2007, indicating increased caution and selectivity in the VC investments. This is further augmented by the data that 71.4%, 61.7% and 66.1% of the venture backed high technology IPO issues in 1998, 1999 and 2000 respectively delisted (for negative reasons) within three years of the IPO. The earlier IPO issues before 1998 mostly have less than 20% de-listing rate for the same period of time. It is also notable that the peak de-listing rate occurs at the third year after the IPO listing (13.2%) and gradually drops after the third year. This same trend is re-affirmed from the Figure 2 using a more granular quarterly slicing on the IPO de-listing frequency, and this phenomenon coincides with Hensler, Rutherford and Springer (1997) studies that used a much earlier sample data period of 1975 to 1984. As discussed in the previous chapter, this suggests a non-monotonic distribution in the IPO delisting frequencies of the venture backed IPOs and allows appropriate fit to a log-logistic functional form for the baseline hazard function in the AFT analysis.

For a proper comparison between the still in trading listed ventured backed issues and the already delisted venture backed IPO issues, selected descriptive statistics for the VC reputation proxy measures and control variables are compiled for both still in trading and delisted venture backed IPO issues, presented in Table 3. A two-sample t-test assuming unequal variances are tested for the difference in means of the proxies as well as control variable measures between these two categories of IPO issues. Amongst the VC reputation proxy measures, it is found that the average VC firm age (16.97 years) backing the still in trading issues is larger than average VC firm age backing the non trading issues (15.70 years) and the difference is statistically significant. The VC market share and VC IPO share are slightly lower (2.62%, 8.85% respectively) for the venture backed companies that are still in trading when compared to non trading companies (2.65%, 10.22% respectively), they are not highly significant and hence these differences cannot be verified as definite. The average IPO size of the still in trading issues is significantly larger than the defunct issues with a difference of 9.977 million USD and the difference statistically significant; likewise the still in trading issues have been listed for a longer average duration than the defunct issues (9.87 years versus 5.79 years) and the difference statistically significant. There is similar evidence in literature on the long term over-performance of bigger IPO issues when compare against smaller IPO issues (Levis, 1993). This underscores the importance of IPO size as a control variable for the VC reputation proxy measures effect on the IPO issues' long term performance. The significant difference between the still in trading and defunct issues highlights the already known finding from the previous data tables that the IPO delisting frequencies peaks early after the IPO listing (3 years) and decreases after that.

Another important control variable to be controlled, the underwriter reputation proxied by Carter-Manaster scale, is shown be of higher reputation level for still in trading venture backed IPO issues than the delisted venture backed issues, and their differences are highly significant. This is in good agreement with the general findings in literature that there is less underperformance for IPO issues underwritten by more reputable underwriters due to lower under-pricing and hence these issuers achieved better expected long term performance (R. Carter & Manaster, 1990; R. B. Carter et al., 1998; Loughran, 2004). In this case, it is shown by lower attrition rate in terms of de-listing rate for our sample set. This highlights the importance of controlling for the underwriter reputation effect in the regression model. Also notable is the average asset size before offering for the still in trading issues are larger than the delisted issues (though not statistically significant). Other proposed control variables, including the technology indicator and road show success, show no significant difference between the still in trading and defunct issues.

3.2 Operating Performance of VC Backed IPOs versus Non VC Backed IPOs

To achieve the purpose of this study in investigating the venture capital reputation effect on the companies' long-run performance, it needs to be first preceded with the test on our sample set of IPOs that VC's active involvement in their portfolio of IPO companies, when compared against non VC backed IPOs, does provide value-add in monitoring and managerial services which allow these companies to experience superior post-IPO operating performance.

To address this issue, cross-sectional regression analysis is conducted with the post-IPO operating performance metrics (ROA, ROE and market-to-book) as the dependent variables and VC involvement (VC) [a binary variable with VC = 0 for non venture backed issues and VC =1 as venture backed issues], underwriter reputation, IPO size, age and technology flag on the IPO company (binary indicator) as the independent variables. These control variables used as covariates have previously been explained in Chapter 2. Newey-West heteroskedasticity robust and autocorrelation consistent (HAC) methodology will be applied to the cross-sectional ordinary least squares (OLS) estimates to minimize the standard errors of the coefficient estimates.

Table 4 shows the results of the parameter estimates and associated t-statistics with the aforementioned model:

$$ROA / ROE / Market-to-Book = \beta_o + \beta_1 VC + \beta_2 Underwriter + \beta_3 Size + \beta_4 Age + \beta_5 Tech + \varepsilon \tag{3.1}$$

On both long term operating performance measures ROA and ROE, the VC's involvement in bringing the company public is consistently positive and statistically significant in effecting these companies to perform better than the non venture backed companies, even after controlling for other control variables that potentially influence post-IPO operating performance. The market-to-book value is also associated with positive and significant VC involvement in the IPO issues, implying that the market recognizes the VC monitoring and value-add. These findings are not surprising, given that many research findings have concluded similar findings, such as Jain & Kini paper (Bharat A. Jain & Kini, 1995) that found the monitoring and reorganization services rendered by VCs to have a value-adding effect on venture backed companies' superior post-issue operating performances. Brav & Gompers study (Brav & Gompers, 1997) also found that the venture backed IPO issues do not suffer from underperformance due to its larger IPO size and there are stronger investors' preference to invest in these venture backed issues, especially by institutional investors rather than individual investor. Field's study (Field, 1996) has shown that long-run IPO performance is positively related to institutional holdings and this might explain the superior performances of venture backed IPO issues.

Likewise, this test also matches literature findings that superior long-run performances are positively associated with the quality of underwriters (R. B. Carter et al., 1998) proxied by the Carter-Manaster reputation scale. It is suggested that IPO issues underwritten by more reputable underwriters are less information asymmetric and suffer from less under pricing in such issues and hence are associated with higher initial returns. The superior long term operating performances are also positively and significantly associated with technology issues, and can be explained by the research findings that technology issues are usually highly information asymmetric (i.e. high technology companies with high market to book ratios) and its potential for maximum returns in investment are the highest (P. Gompers & Lerner, 2001). The association of operating performance with the IPO size and company age is uncertain from the outcome of this test.

These findings correlate with the broad literature that long term operating performances and market-to-book ratio are positively associated to venture backing, underwriter's reputation and technology issues. This permits us to further segregate and test for the VC reputation's effect in influencing the IPO companies' long-run performance and survivorship. I expect to see that through the more reputable VCs' advisory, managerial and professionalization skills, they will provide more value-add than less reputable VCs to transform the IPO companies into better long term performers and survivors.

3.3 VC Reputation and Characteristics of Issuers Brought to IPO Market

To learn more about the characteristics of the companies that are brought to the IPO market, cross-sectional examinations of the differences in the company characteristics backed by VCs of differing VC reputation proxy values are conducted on the sample set of venture backed IPO issues. As the reputation proxies are all left censored at zero, censored logistic regressions are applied to the following model for each of three previously defined VC reputation proxies (VC market share, VC IPO share and VC firm age):

$$VC\_\mathrm{Re}\,putation = \beta_o + \beta_1 Underwriter + \beta_2 AssetsBeforeIPO + \beta_3 Size + \beta_4 Age + \beta_5 Tech + \varepsilon \qquad \textbf{(3.2)}$$

Table 5 displays the results of this regression test. The IPO issuers backed by more reputable VCs tend to be underwritten by more reputable investment banks, and the results are consistent and significant across all three VC reputation proxy measures in our study. This seems to imply that the more reputable VCs might have preferential access to more established and higher quality underwriting services for bringing their supported entrepreneurial companies public. This also hints at the inter-organizational network effect that Stuart, Hoang and Hybels (Stuart, Hoang, & Hybels, 1999) discussed in their paper that better venture capitalist tend to function with more prominent affiliates and strategic partners, which potentially helps its supported companies to gain an edge during the going public process.

It's also not surprising that the higher ranked VCs tend to be significantly associated with companies with smaller asset size and operates in the technology sector, as the coefficients for company asset size prior to IPO are estimated to be negative (and statistically significant) and estimated to be positive (and statistically significant) for technology companies. Small technology companies tend to be riskier in terms of being highly information asymmetric, and have capital intensive research and development operations. They usually are asset deficient and have low and uncertain cash flows. Hence, more reputable VCs, perceptibly to more savvy and skilful in its screening, staging and monitoring process, are thought to be more able than their less reputable peers to identify high, positive net value opportunities in young, entrepreneurial companies with new, promising technologies. More reputable VCs also tend to invest in young companies with shorter operating histories, but this finding is not highly statistically significant.

As most of these characteristics have significant explanatory power on the VC reputation proxy measures, this highlights the importance of controlling for these issuer characteristics in our analysis of the VC reputation proxy effect on the post-IPO performances of the venture backed companies, and the results explained in the next section.

3.4 VC Reputation and Issuer Long-run Issuer Performance

In this section, test results for association of long-run operating performance of venture backed IPO companies with the proposed VC reputation proxy measures are presented. The objective is to determine if the proposed VC reputation proxies have explanatory powers on the company's post-IPO operating performances and to measure the relative effectiveness of our proposed reputation measures; that any one of the three VC reputation proxies is significantly better and consistent than the others in its effect on the long-run operating performance of the companies.

3.4.1 Test on Issuer Long-Run Industry Adjusted ROA/ROE

I postulated that the post-IPO operating performance of IPO issuers backed by more reputable VCs will be superior to ones backed by less reputable VCs. To test this hypothesis, we used the following regression specification for the industry-adjusted ROA and ROE against our three proposed VC reputation proxy measures and control variables:

$$ROA/ROE = \beta_o + \beta_1 VC\_\mathrm{Re}\,putation + \beta_2 Roadshow + \beta_3 Underwriter + \beta_4 Size + \beta_5 Age + \beta_6 Tech + \varepsilon \qquad \textbf{(3.3)}$$

The underwriter reputation, IPO size and technology indicator are shown in previous section to be important as control variables and are included in this regression model to allow better segregation of the VC reputation effect in the test. We also included IPO road show success indicator and company age as defined in Chapter 2 to be possible critical factors to the issuers' post-IPO performance and are the additional control variables. Natural logarithm of the IPO size (in dollar value) and age (in years) are used. This test is conducted sequentially for each of the VC reputation proxy of VC market share, VC IPO Share and VC firm age to allow relative explanatory powers of the VC reputation proxy measures to be compared against one another by keeping the aforementioned control variables constant. An OLS regression is carried out on the proposed model and the standard errors adjusted for Newey-West HAC corrections. The coefficient estimates and the associated p-values are presented in panel A of table 6B. While all three reputation proxies showed that better VC reputation rankings are positively associated with better post-IPO industry adjusted ROA of venture backed companies, only VC market share and VC IPO share are statistically significant (within 5% level) in its parameter estimates while VC firm age isn't. With the explained variance highest for VC market share followed by VC IPO Share and lastly VC firm age (5.27%, 4.09% and 3.41% respectively), this implies that the explanatory powers of VC market share may be greater than that of VC IPO share and VC firm age. Also within expectations, higher ROA on the post-IPO issuer is also significantly associated with more reputable underwriters and smaller IPO size. As shown in table 6A, the pair-wise Pearson's correlation between VC reputation proxies and underwriter reputation is low, and the correlations are -0.126, 0.055 and 0.149 for VC IPO share, VC firm age and VC market respectively. Hence the explanatory powers of VC reputation measures on operating performance are not a result of the VC reputation proxies merely acting as close substitutes for underwriter reputation. The VC reputation proxies tested allude to the superior value-add provided by reputable VCs in its advisory and intermediation services provided to their supported IPO issues have beneficial effects in the long-run profitability growth of these companies.

Likewise for the test on industry adjusted ROE, OLS regression is conducted with Newey-West HAC adjustments on the standard errors and the coefficient estimates as well as p-values are posted in panel B of table 6B. It shows similar results of VC reputation's influence on the long-run ROE of the post-IPO issues with all the VC proxies having positive effect on the long-run issuer ROE in the post-IPO. VC market share as VC reputation proxy have the greatest explanatory powers in it effect on long-run issuer ROE when compare to VC IPO Share and VC firm age as its coefficient estimate is most statistically significant (within 1% level as compared to 5% and 10% level for VC IPO share and VC firm age) and has the biggest explained variance (4.68%). VC IPO share as VC reputation proxy is second most effective (3.96%) in its explanatory powers of its effect on long-run ROE of the issuer while VC firm age, like the previous test on long-run ROA, has the weakest explanatory powers (3.29%). The long-run issuer ROE is positively associated with underwriter's reputation, though only the regression model with VC market share as VC reputation proxy shows statistical significance for this underwriter reputation effect within 10 percent level. Also similar to previous test on long-run ROA, the long-run post issue ROE is associated with smaller IPO size and the coefficient estimates significant within 10 percent level for all three regression models.

3.4.2 Test on Issuer Long-Run Market-to-Book Ratio

Panel C on Table 6B shows the coefficient estimates and its associated p-values from the OLS regression with Newey-West HAC corrections on the standard errors. The regression specification is summarized as below:

$$\begin{aligned} Market-to-Book &= \beta_o + \beta_1 VC\_Reputation + \beta_2 Roadshow + \beta_3 Underwriter \\ &+ \beta_4 Size + \beta_5 Age + \beta_6 Tech + \varepsilon \end{aligned} \quad \textbf{(3.4)}$$

Again, we tested for all three proposed VC reputation proxy measures of VC market share, VC IPO share and VC firm age on the long-run market-to-book of post-IPO company. For all three VC reputation proxies, it is shown that better VC reputation rankings are associated with higher market-to-book ratio. All three coefficient estimates of the VC reputation proxies are significant within 10 percent level. The model with VC market share as VC reputation proxy has the highest explanatory powers (4.89%) followed by VC firm age (4.07%) and VC IPO age (3.57%). Like the previous two tests, the underwriter reputation effect is not trivial in explaining the higher market-to-book ratio from more reputable underwriting of the IPO issue. Larger IPO sizes are also significantly associated with lower market-to-ratios. As already explained in Table 6A, the correlation between underwriter reputation and IPO size with the three proposed VC reputation proxies are shown to be relatively low. Hence, this shows that the VC reputation proxies have reasonable explanatory powers to permit the inference that the more reputable VCs provide higher value-add to its supported companies, reduce information asymmetry to the public investors which result in higher valuations in the form of higher long-run market to book ratios, and this suggest optimism on the future growth potential of these companies backed by more reputable VCs.

3.5 Summary

Table 6B's panel A,B and C have shown that all three VC reputation proxy measures to have positive influence on the venture backed companies' post-IPO long-run operating performance and market-to-book ratio, though on varying degree of explanatory powers. VC market share have the greatest explanatory powers on the operating performance and market-to-book ratio, followed by VC IPO share and finally VC firm age. In terms of economic significance, VC market share is the VC reputation proxy with greatest explanatory powers and after controlling for other issuer characteristics in the regression model, our model predicts that for one standard deviation increase in VC market share, it will result in 6.2% increase in long-run ROA increase, 8.9% increase in long-run ROE and 13.7% increase for long-run market-to-book ratio. Hence, VC market share association with post-IPO issuer performance has clear economic implications. For VC IPO share and VC firm age, they are also economically significant in its relation to superior long-run operating performance, albeit with lower explanatory powers.

It is noteworthy to recognize that so far two different facets of the companies' long-run performance have been looked into: average profitability and future growth potential. From the regression tests, the significance of the different control variables cannot be understated as the most critical variables such as underwriter reputation and IPO size are consistent with literature understanding that the underwriting quality adds value to the long-run operating performance and market-to-book ratio (R. B. Carter et al., 1998) and that larger IPO size is associated with lower issuer performance (Ivanov et al., 2008). For other control variables such as firm age and technology, the overall association is inconclusive, but it is shown that the market associates technology companies with higher future growth potential, as the technology indicator is statistically significant and positively related to higher market-to-book ratio for all three models of different VC reputation proxies.

Chapter 4: Robustness Test

The VC reputation proxy measures are shown to have positive and significant association with superior post-IPO issue operating performance, especially for VC market share which have been shown to have a non trivial economic significance. In this chapter, we subject these VC reputation proxies to robustness test in order to assess the strength of our findings even after controlling for self selection bias.

4.1 Heckman Two Stage Correction Method for Self Selection Bias

Our previous findings of the VC reputation proxies being significant determinants of superior operating performance could potentially be a self selection effect of more reputable VCs having better access to more promising investment opportunity set[8], as already argued in papers by Lee and Wahal (Lee & Wahal, 2004) and Sorensen (Sorenson, 2006). Hence, the reputable VCs' association with superior operating performance may be due to its access to better quality business ventures which it is able to invest, rather than through the VCs' ability to add value through its advisory, intermediation and professionalization services.

In Ivanov, Krishnan, Masulis & Singh (2008) working paper, they argue that the issuer pre-IPO asset size, number of VC partners and offer price revisions to be good

[8] Lee and Wahal (2004) used matching methods that endogenize the receipt of venture financing in order to miminize selectivity bias in their examination of the role of venture capital backing in the under pricing of IPOs. They find venture capital backed IPOs experience larger first-day returns than comparable non-venture backed IPOs. Sorenson (2006) is able to find that the selectivity effect is almost twice as important as influence for companies backed by more experienced VCs to go public

instrumental variables for capturing this self selection effect as these factors correlate with underlying firm quality at IPO date but are later unrelated in the post-IPO performance. As we are concerned only with the post-IPO long term performance, these factors proved to be difficult to control for in the selection of higher quality opportunity sets by more reputable VCs. However, in view of the importance to validate the value of reputable VC value-add and development of their portfolio of start-up companies, sensitivity test on the VC selection and screening of their invested companies is performed.

A two step modified Heckman (Heckman, 1979) procedure is applied to control the VC selection process. The first step of the procedure allows us to capture the likelihood of a positive outcome of the dependent variable which is the higher than median rank VC reputation proxy measure (VC_Rep*) in our test. This step is accomplished via a logit regression as similarly performed in Ivanov, Krishnan, Masulis & Singh's paper (2008) by regressing the dependent variable on the issuer characteristics:

$$VC\_\mathrm{Re}\,p^* = \beta_o + \beta_1 Underwriter + \beta_2 Size + \beta_3 Age + \beta_4 Tech + \varepsilon \qquad \textbf{(4.1)}$$

VC_Rep* is a binary indicator which shows 1 for higher than median rank VC reputation proxy measure and 0 otherwise. The parameter estimates are then used to compute the Inverse Mills' Ratio for each of the three proposed VC reputation proxy measures, which is defined as ratio of the probability density function over the cumulative distribution function of a distribution. In its formulaic form, it can be defined as:

$$E(x \mid x > \alpha) = \mu + \sigma\left[\frac{\phi((\alpha-\mu)/\sigma)}{1-\Phi((\alpha-\mu)/\sigma)}\right] \quad \textbf{(4.2a)}$$

and

$$E(x \mid x < \alpha) = \mu + \sigma\left[\frac{-\phi((\alpha-\mu)/\sigma)}{1-\Phi((\alpha-\mu)/\sigma)}\right] \quad \textbf{(4.2b)}$$

Where x is a random variable distributed normally with mean μ and variance σ^2, α is a constant, $\phi(.)$ denotes the standard normal density function, and $\Phi(.)$ denotes the standard cumulative distribution function. The terms expressed within brackets [.] are the Inverse Mills' Ratio (Greene, 2003).

The second step will involve adding the Inverse Mills' Ratio as an additional independent variable (InverseMillsRatio) to the general regression models in equation (3.3) and (3.4) of the effect of VC reputation proxy measures on long-run operating performance and market-to-book ratio. The appended regression specification can be expressed as follows:

$$\begin{gathered} ROA/ROE/Market-to-Book = \beta_o + \beta_1 VC\_Reputation + \beta_2 Roadshow + \\ \beta_3 Underwriter + \beta_4 Size + \beta_5 Age + \beta_6 Tech + \beta_7 InverseMillsRatio + \varepsilon \end{gathered} \quad \textbf{(4.3)}$$

The Inverse Mills' Ratio controls for the probability that more reputable VCs select higher quality business ventures, and hence corrects for the self selection bias on the original model which is without the inclusion of this additional explanatory variable.

4.2 Test Results

Table 7A represents the first stage regression estimates of the Heckman self-selection bias correction procedure using logit regression and converged using quadratic hill climbing methodology. All three models with different VC reputation proxy measures have reasonable explanatory powers and hence appropriate as a prediction model for the Inverse Mills' Ratio computation.

Table 7B represents the second stage regression estimates of the Heckman procedure with the general regression model augmented with an additional explanatory variable (equation 4.3), and that is the Inverse Mills' Ratio as computed from the parameter estimates in the first stage. As before, this regression model is conducted using OLS estimates with Newey-West HAC adjustment on standard errors to minimize any potential heteroskedasticity and autocorrelation. The result estimates of the regression of long-run operating performances ROA, ROE and market-to-book ratio against the three proposed VC reputation proxy measures are presented sequentially in panel A, B and C. Each of the coefficient estimates of the Inverse Mills' Ratio on all three VC reputation measures model is negatively associated with the long-run performances and is statistically significant. This implies that the VC selectivity and sorting issue of reputable VCs having better access to higher quality entrepreneurial companies is present and this coincides with literature findings (Lee & Wahal, 2004; Sorenson, 2006). Despite the presence of the VC selectivity, there is higher value-add in the skills of more reputable VCs due to its stronger association with better long-run operating performance and market-to-book ratio. The interaction coefficients of the VC reputation measures have positive effect on the long-run performance measures and are statistically significant within 5% level for VC market share and within 10% level for VC IPO share, while VC firm age is significant within 10% level for its positive association with ROE and market-to-book but not ROA. These results showed that via VC selectivity, experienced VCs invest in better companies, through a deliberate process of matching between VCs and start-up companies. Start-up companies needing VC capital care about the value-add that can be provided by the VCs, and when faced with multiple offers, these companies routinely turn down the VC with the best financial offer in favor of a VC that is more established (Hsu, 2004). However, this does not discount the influence that the more reputable VCs do add value in other ways to contribute to a better performing company in the long-run, as test results using the proposed VC reputation proxy measures, primarily VC market share, are able to significantly capture some of these latent information. It may be that reputable VCs, apart from acting as mere financial intermediary, also helped in building the supported companies' organization, provide management know-how and professionalizes the outfit (Thomas & Manju, 2002; V, Ljungqvist, & Lu, 2007). These value-adding measures go a long way in making the companies competitive and fit for the long-run.

On another note, the inclusion of the Inverse Mills' Ratio does not affect the issuer characteristics' influence on the long term operating performance and market-to-book ratio, as critical control variables such as underwriter reputation remained positively associated to better long term performance of the companies and in most of the test series, the coefficient estimates are statistically significant. Similar to previous series of tests without the self selection bias correction, the long term performance of a VC backed company is negatively associated to the IPO size offered and the coefficient estimates statistically significant.

Chapter 5: VC Reputation and Issuer Long-run Survivorship

Thus far, this paper has been dealing with the long term profitability and growth potential in terms of long-run industry operating performances (ROA & ROE) and market-to-book ratio. The issue of long-run survivorship of a company in the post-IPO, which is the likelihood that the company will suffer from an event of severe financial distress and de-list for negative reasons, have not been discussed so far.

The aftermarket survivorship of an IPO is not new in literature, and our methodology explained in section 2.4 to utilize survival analysis with hazard function to predict company failure are represented in studies such as Keasey, McGuinness & Short (1990) and Lane, Looney & Wansley (1986), which respectively argued for the use of survival analysis in company failures in the former while the latter applied the methodology onto analysis of bank failures. The application of AFT model as the baseline hazard function for the survival analysis has been done by Hensler, Rutherford & Springer (1997) in their survivorship studies of aftermarket IPOs and by Jain & Kini (2000) in their survival profiling of VC backed companies versus non VC backed companies in the aftermarket. Even though the use of AFT modeling has been widely adopted, this paper's application of AFT model to study VC reputation effect on the long-run survivorship of its portfolio of companies in the after market is novel.

I re-iterate the two advantages of using this methodology to study the long-run survivorship of VC backed companies' post-IPO survivorship. Firstly, it avoids the problems arising from the cross sectional models such as multiple discriminant analysis and logistic regression of only able to predict whether an event will occur but not when it will occur. Survival analysis hazard models are able produce estimates of probable time to failure, rather than merely providing probability estimates of failure over the specified period of our event study. Secondly, survival analysis allows assessment of the conditional probability of failure given that the firm has survived up till the present time, and our proposed models are able to deal with censored data which represents scenarios where the company failure has yet to occur at the end of our study period, given that companies have widely differing listing and delisting time periods. The survivorship study of VC backed companies in the post-IPO period has in each point of time a large proportion of firms that have gone public and are still in listing. Hence using survival analysis, it can serve as a valid platform to compare between firms that have listed and operated in the public space at different point and length of time (B. A. Jain & Kini, 2000).

The appeal of applying AFT model as the baseline hazard function in this survival analysis study is that, it can model the effect of the covariate value changes on hazard probability for different time periods according to the length of post-IPO trading time of the individual VC backed company. Hence, the effect of varying covariate values does not necessarily have a proportional effect on time to failure (de-listing), but can accelerate or decelerate depending on the importance of the specific independent variable and its length of listed period (Kalbfleisch, 2002). Our usage of the log-logistic functional form for the baseline hazard function is also appropriate, as already shown in Figure 1, that the de-listing frequencies of the VC backed companies is non-monotonic due to its peaking between the second and third year of IPO listing and the failure rate decreases thereafter. This provides empirical justification for the use of the log-logistic functional distribution[9].

5.1 Survivorship Test Model - AFT

In our model, I apply the natural logarithm of the response variable which in this case is the natural logarithm of the time to delisting of the individual companies in years, labeled Ln (H_t). The matrix of covariates respectively contains the binary form of the VC reputation proxies (Taking 1 if reputation proxy value is above the median value and 0 otherwise), underwriter reputation, natural logarithm of IPO size (millions), natural logarithm of company age, technology indicator, IPO road show success indicator and finally, a binary indicator to represent business expansion or contraction at the time which the IPO is listed. All these variables have been defined in Chapter 2 earlier and more details are available in Appendix A. The baseline hazard function, which was specified in equation (2.7) to take a log logistic form, is abbreviated here as H_o and σ is the ancillary scale parameter. For simplification, we will represent our model in a linear form as follows:

$$\begin{aligned} Ln(H_t) &= \beta_o + \beta_1 VC\_Reputation + \beta_2 Roadshow + \beta_3 Underwriter + \beta_4 Size \\ &+ \beta_5 Age + \beta_6 Tech + +\beta_7 Bcycle + \varepsilon + \sigma Ln(H_o) \end{aligned} \quad \textbf{(5.1)}$$

Where

[9] Hensler et. al. (1997) notes that the usage of the log – normal distribution is also possible, but this model does not easily accommodate censored data such as dealt in our current sample set. The log-logistic model is hence considered as an appropriate substitute.

$H_0(t) = \lambda\rho(\lambda t)^{\rho-1} \big/ (1+(\lambda t)^{\rho})$, $\lambda = e^{X\beta}$, $\rho = 1/\sigma$ and t is the individual sample time to failure in years.

The shape of the hazard function is affected by ρ as the point of maximum probability of failure occurs earlier in time as ρ decreases (or as σ increases).The model parameters are estimated by maximum likelihood method using Newton-Raphson algorithm for convergence and the significance of the individual coefficient estimates tested using a χ^2-statistic.

5.2 Survivorship Test for IPOs Listing 1985-2007

Table 8 summarizes the estimation results for the full sample set of the IPO duration in study from 1985 -2007. The above median VC market share reputation proxy (when VC_Reputation =1) is highly significant (within 1 % level) in predicting longer time to delisting with its positive coefficient estimates and VC IPO share also shows the same trend with lower statistical significance (within 10% level). Unexpectedly, this is shown to be vice versa for above median VC firm age as it predicts shorter time to delisting for VC backed IPOs. On the effect of control variables, the underwriter reputation, which is critical in predicting long-run operating performance success, is shown to have positive economic significance for both models with VC reputation proxies using VC market share and VC IPO share, but has negative economic implications for VC age. The coefficient estimates are all statistically insignificant. The IPO size seems to have a negative effect on the companies' time to delisting for all models and coefficient estimates statistically significant. Likewise, for all VC reputation proxy models, the longer the companies has been around and if they are technologically inclined, the longer the companies will be able to survive; the coefficient estimates are statistically significant for company age factor and statistically insignificant for technology company indicator. The pre-IPO road show success seems to be another critical factor in predicting long-run survivorship as the interaction terms are positive and statistically significant in their coefficient estimates for all three models. A positive business cycle is negatively associated with company time to delisting but is statistically insignificant for all three models. The statistical insignificance is not surprising as from Jan 1985 to Dec 2007, there has been only total period of 16 months of business contractions on two separate occasions as defined by NBER which leads to very few sample points with negative business cycles, and a longer period of analysis which takes in accounts more sample points of business up and down-cycles; can then the business cycle effect on venture backed company delisting time be tested more vigorously. The ancillary scale parameter σ, is largest for VC IPO share, followed by VC market share and VC firm age, which implies the order of attaining maximum probability of time to failure first reached by the respective VC reputation proxy models. Unlike linear regression analysis, this coefficient estimates from the AFT model do not lend themselves to simple interpretation apart from the usage that it allows the general inference of its effect on the company's post-IPO survival time.

Figures 3(a) – 3(c) illustrate the cumulative failure percentage of VC backed IPO firms versus time (years) for the respective models using only VC reputation proxies of VC market share (TIPOREP), VC IPO share (TVCREP) and VC firm age (TVCAGE) as model parameters in the AFT hazard function. Two curves are plotted for each figure, one for above median VC reputation proxy and the other for equal or below median VC reputation and labeled as 1 or 0 respectively. As again, VC market share is the most consistent in predicting probability of failure as it shows that the above median VC reputation curve is consistently less risky in de-listing throughout the study period when compare against the cumulative failure curves of other VC reputation proxies'.

The maximum cumulative failure percentage attained by the equal or below median VC market share proxy is modeled to be 89.9% and for above median VC market proxy to be 87.1%. 25% of companies are expected to delist in 6.3 years and 7.2 years respectively for the equal or below the median VC market share IPO company and above the median VC market share IPO company; for 50% delisting at 9.7 years and 11.0 years respectively and for 75% delisting at 14.9 years and 16.9 years respectively. This shows that the VC with higher VC market share reputation proxy measurement tends to add more longevity to the company trading in public space and has positive implications on the value-add a more reputable VC can provide in their professionalization and management skills to build a strong organization for the venture backed company to survive longer in the aftermarket. Figure 3(b) shows that the VC IPO share has little or insignificant effect on the cumulative failure percentage plots with failure time as both curves for above median reputation and below or equal median reputation trend closely to each other. Figure 3(c) for VC firm age shows a direct opposite effect of what has been shown for VC market share, with above median VC firm age supported companies having significantly higher cumulative failure percentage versus time trend.

5.3 Survivorship Test for IPOs Listing 1985-1996 and 1997-2007

Section 3.1 summary statistics have confirmed what have already been publicly known as the technology "bubble" in the late 1990s where venture backed companies listed from 1997 -2000 have an abnormally high percentage of de-listings for within the first few years of the post-IPO trading period. This was explained to be a phenomenon of simultaneously having high levels of uncommitted investment capital being held by VCs and comparatively too few sound business venture opportunities which resulted in overvaluations and unsustainable prices for investments in mediocre quality companies during that period (P. Gompers & Lerner, 2000; P.A Gompers & Lerner, 2004). There were severe IPO under pricings from reduced incentives on the part of the companies' principal investors, such as VCs, company insiders and investment banks, to hold on to the public stock in post-IPO once the lock-up period is over as these new listed companies hit skyrocketing valuations soon after they go public. The VC investors may also have been overly optimistic in these companies to perform well in the public markets (Alexander Ljungqvist, 2003) that they have no misgivings in paying a high price for these companies and then to relinquish ownership as soon as the lock up period is over in the post-IPO for quick returns.

With this understanding, this section splits the overall testing period into two different time frames and applies the same AFT hazard model for testing. The first testing period, which we termed as the pre-technology bubble period, is from 1985 – 1996, while the second testing period, which we termed as the technology bubble period (which also includes the post-technology bubble period), is from 1997 – 2007. The testing results and figures are shown for the pre-technology bubble period in Table 9 and Figures 4(a) – 4(c); and results for technology bubble period in Table 10 and Figures 5(a) -5(c).

Table 9 shows the parameter estimates for the pre-technology bubble period. The above median VC reputation proxies are positively and highly significant for both models with VC market share (higher statistical significance within 1% level) and for VC IPO share (lower statistical significance within 5% level). This implies that from 1985 – 1996, IPO companies with VC backing of higher than median reputation level (based on the two measures) are more likely to remain listed for a longer period of time than IPO companies backed by equal or lower than median reputation measure. Similar to previous section, the model using VC firm age as VC reputation proxy shows an opposite result with shorter listing time for companies backed by VCs with longer operating history. Unlike the full sample period tested in the previous section, the effect of the underwriter reputation is consistently positive and highly significant on longer venture company post-IPO survivorship for all VC reputation models, which matches our understanding that the underwriter reputation add intangible value in terms of providing critical after market services in market-making and stabilization (B. A. Jain & Kini, 2000). Similar to our finding in previous section, on all VC reputation proxy models, IPO size has a negative and statistically significant effect while company age has a positive and statistically significant on the company's listing period. All of the parameter estimates with high statistical significance are within 1% level. Technology driven companies have a positive effect of the listing period but the coefficient estimates are not statistically significant. Road show successes are shown to have negative effect on the listing period but this might have be negated by the highly significant positive effect of underwriter's reputation as previously explained. Business cycle impact on company listing times, like previous test on the full sample period, is negative but statistically insignificant. The ancillary scale parameter *σ,* has the same order as the previous section with the largest for VC IPO share, followed by VC market share and VC firm age, and this implies the order of maximum probability of time to failure to be first attained by the respective VC reputation proxy models.

Comparing against Table 10, which shows results estimated for technology bubble period from 1997-2007, some interesting comparisons emerge. Instead of having positive effect on the VC backed companies' listing period, the estimation models show that the above median VC market share and VC IPO share to have a negative but statistically insignificant effect on listing period of the companies, while for VC firm age, it has a negative effect on the company survivorship and coefficient estimates statistically significant. This implies that during the technology bubble of the late 1990s, even higher than median reputation VCs are not spared in making unsound investment decisions by being overly optimistic in their judgments on mediocre quality companies. The value-add in their advisory services to these companies are unable to overcome their earlier than expected delisting from the public markets, i.e. the well accepted idea of VC certification hypothesis to reduce information asymmetry to public investors as a signal of quality (Megginson & Weiss, 1991) during the technology bubble might not have been as effective. Underwriter reputation also has a negative but statistically insignificant effect on the delisting period of the VC backed companies, which is another signal of failure in the certification hypothesis due to reputable underwriters underestimating the risks and quality of the venture backed companies during this bubble period. This phenomenon is atypical as Loughran and Ritter (2004) pointed out that, historically, prestigious investment banks do not underwrite offerings by high-risk issuer. IPO size, consistent to the previous period, has a negative and statistically significant effect on the survival period of the companies and the pre-IPO road show success also has a positive and significant influence on the companies' survival in the after market. Technology companies, unlike in the pre-technology bubble period, are seen to have a shorter survival times but the coefficient estimates are not statistically significant. The business expansion cycle has a positive by statistically insignificant effect on the company listing times. The ancillary scale parameters σ, are also estimated to be much larger during the technology bubble period compared to pre-technology bubble period, as an example, σ is measured to be 0.3627 and 0.0982 respectively in the two periods for the AFT model tested on VC market share. This means that VC backed companies in the technology bubble period consistently reach the maximum probability of time to failure much earlier and are hence expected to have a much steeper delisting rate than VC backed companies in the pre-technology bubble period.

In comparing the cumulative failure percentage of VC backed IPO firms versus time (years) of the respective estimated AFT hazard models using only VC reputation proxy for the pre-technology bubble and technology bubble period, the survival probabilities between this two periods can again be cross-analyzed. Figures 4(a)–(c) and 5(a)–(c) illustrate respectively the failure probability for pre-technology bubble and during the technology bubble period for VC market share (TIPOREP), VC IPO share (TVCREP) and VC firm age (TVCAGE) as model parameters in the AFT hazard function. In the pre-technology bubble period, Figures 4(a) and 4(b) show that the above median reputation curves (TIPOREP =1, TVCREP =1) trends below the equal or below median reputation curves (TIPOREP =0, TVCREP =0), implying that the above median reputation VC backed IPO companies are delisted later in the post-IPO. This trend is seen to be reversed for the technology bubble period in Figures 5(a) and 5(b), where above median reputation VC backed companies are delisted earlier than equal or below median reputation VC backed companies. If we compare the rate at which companies are delisted for the two periods using the AFT model estimates with the most consistent VC reputation measure of VC market share; for above median reputation VC backed companies, it takes 15.6, 17.7 and 19.8 years respectively for 25%, 50% and 75% of the companies listed in the pre-technology bubble period to be expected to fail, while it takes 5.0, 7.6 and 11.4 years respectively for 25%, 50% and 75% of the companies listed during the technology bubble period to fail. These findings are also fungible across VC IPO share and VC firm age as VC reputation models and the large differences in survival rates of the VC backed companies based on AFT model do highlight the contrasting qualities of the venture backed companies invested by above median reputation VCs across these two periods. This phenomenon, as earlier explained, may be a result of the effects in the excessive amount of investment capital raised from the VC funds that created a "money chasing after deals" scenario where exorbitant prices have been paid to acquire a stake in the diminishing investment opportunity set (P. Gompers & Lerner, 2000); and in the reduced incentives for the VCs to properly monitor their business ventures as there are ample opportunities to taking profit once the lock up period is over, owing to the fact that technology companies routinely attained high valuations soon after going public during the technology bubble period (Alexander Ljungqvist, 2003).

5.4 Survivorship Test for Top Quartile versus Lowest Quartile and 3rd Quartile versus 2nd Quartile VCs

To further test the sensitivity of the VC reputation proxies in its effect on long-run survivorship of the VC backed companies, we further sub-divided the sample data set for the full period and grouped them into quartiles based on their individual VC reputation proxy values. Essentially, we created three different sets of quartile groupings based on the three proposed VC reputation proxy rankings and crossed tested using the same AFT hazard model. The quartiles for the individual reputation proxies are cut off based on their magnitude of the VC reputation proxy values at the 75th percentile, 50th percentile and 25th percentile. The AFT hazard modeling is then conducted by comparing against the top quartile versus the lowest quartile rankings and the 3rd quartile versus the 2nd quartile rankings for each of the VC reputation proxy models. This is carried out by replacing the VC reputation proxy binary variable in the general model as 1 for top quartile ranking VC reputations and 0 for the lowest quartile ranking VC reputations in the first test, likewise for the second test the VC reputation proxy binary variable is 1 if the VC reputation rankings are in the 3rd quartile and 0 if the VC reputation rankings are in the 2nd quartile. The two tests, conducted for all three VC reputation proxy models, can serve as a sensitivity test on the magnitude of VC reputation proxy measures and its influence on the long-run survivorship of the IPO companies.

The results for the two tests are shown in Table 11 (top versus lowest quartile IPOs) and Table 12 (third versus second quartile IPOs) from the AFT modeling of company delisting time with the respective VC reputation proxies and the control variables as presented in equation 5.1. The respective test of top versus lowest quartile IPOs and third versus second quartile IPOs are shown respectively in Figures 6(a)–(c) and 7(a)–(c) representing cumulative failure percentage versus time using only the individual VC reputation proxies of VC market share (TIPOREP), VC IPO share (TVCREP) and VC firm age (TVCAGE) as independent variables in the AFT modeling.

For model with VC market share as reputation proxy, it can be seen in both Table 11 and 12 that the respective higher ranked quartiles have a positive effect on the long-run survivorship of their VC backed companies in the aftermarket, and the coefficient estimates are of high statistical significance (within 1% level). This means the respective top quartile and 3^{rd} quartile ranked VCs with higher VC market share do have greater influence on their companies' survivorship than the 2^{nd} quartile and lowest quartile ranked VCs. Compared against the model with VC IPO share as the VC reputation proxy, the higher ranked quartiles are also consistent in having positive influence on the long-run survivorship of the VC backed companies as both tests revealed positive coefficient estimates. However, the first test coefficient estimate is statistically significant (within 5% level) and second test coefficient estimate is statistically insignificant for the model tested with VC IPO share. The relatively lower statistical significance for using VC IPO share in both test estimates showed that the sensitivity of using VC IPO share in predicting long-run survivorship of companies is lower compared to VC market share when the magnitude factor of the VC reputation proxy is considered. On the test model with VC firm age as reputation proxy, the higher quartile ranked VC has a negative and significant effect on the listing period of the IPO companies. On control variables' effect on survivorship, the underwriter reputation is negative but statistically insignificant; IPO size, pre-IPO road show success are similar to earlier findings that the former has negative and significant effect on company listing time while the latter has positive and significant effect. Technology companies are shown to list longer but the effect is statistically insignificant. The effect of business cycles is mixed and statistically insignificant for all tests.

The cumulative failure percentage versus time figures also indicated the greater sensitivity of VC market share as reputation proxy measure when compared to VC IPO share. For both top versus lowest quartile and 3rd versus 2nd quartile tests, the cumulative failure curves of Figures 6(a) and 7(a) are distinct and distinguishable for VC market shares as VC reputation proxy model with the higher ranked quartile curve trending below the lower ranked quartile curve throughout the test period. The same cannot be said for VC IPO share as VC reputation proxy model in Figures 6(b) and 7(b) as the higher ranked quartile cumulative failure curve trends very closely to the lower quartile curve in both tests and are almost indistinguishable. In the top versus lowest quartile VC reputation test with VC market share, 25% of companies are expected to delist within 7.0 and 6.0 years for the respective companies backed by top and bottom quartile VC market share VCs, for 50% expected delisting in 10.9 and 9.4 years respectively and, for 75% expected delisting in 17.0 and 14.7 years respectively. For the same test with VC IPO share, the 25% expected delisting are 7.0 and 6.8 years for respective companies backed by top and bottom quartile VC IPO share VCs, for 50% expected delisting in 10.6 and

10.2 years respectively, for 75% expected delisting in 15.8 and 15.2 years respectively. The differences of delisting time of companies backed by the top and bottom quartile ranked reputable VCs are larger for VC market share as VC compared to VC IPO share as reputation proxy, and these results are also consistent when the same comparison is done between 3rd versus 2nd quartile VC reputation test. Hence, VC market share can be argued to be more sensitive and effective than VC IPO share as a VC reputation proxy when its magnitude effect is taken in account to on the long-run survival studies of the VC backed company.

Chapter 6: Conclusion

The role that VCs participate in the private equity sector is a topic of considerable academic interest especially in the influence on their invested companies' aftermarket performance. Earlier studies have empirically tested and validated the importance of VCs in its ability to add value to its supported companies in the after market that allowed these companies to perform better in terms of superior operating performance (Bharat A. Jain & Kini, 1995) and longer survival times (B. A. Jain & Kini, 2000). The certification value offered by VCs in the going public process signals the quality to the company through reduction in information asymmetry to the external investors (Megginson & Weiss, 1991; Stuart et al., 1999), hence providing a reasonable basis for external investors to have confidence in the future growth prospects and profitability of the newly listed company. However, these earlier studies treated all VCs homogeneously without the granularity of distinguishing the VCs by reputation levels and have mostly examined the association between key IPO characteristic and indicator of VC backing. This provided the motivation in my study to further refine the effect of VC value-add to its portfolio of supported companies by introducing three proposed VC reputation proxies; namely VC market share, VC IPO share and VC firm age and study its influence on the venture backed company's long-run operating performance and survivorship in the aftermarket.

The "Keiretsu" effect of VCs having interorganizational affiliations with prominent exchange partners such as reputable strategic alliance partners and organizational equity investors can provide the start up companies backed by well connected VCs a competitive edge in the pre and post going public process over the other companies without such backings (Stuart et al., 1999). In this study, the more reputable VCs in our VC reputation proxy measures are found to be positively related to more reputable underwriters, implying that the value-add obtained by companies backed by more reputable VCs does not only come from the advisory and intermediation services provided by the VCs, but also from the expected higher quality underwriting activities rendered by more reputable underwriters with close ties to the more reputable VCs. This can make or break a start-up company as good quality underwriters can provide better value-add in critical pre and post-IPO activities such as pricing, allocation, market making and analyst coverage (Krigman, Shaw, & Womack, 2001).

I find that the proposed VC reputation proxies all have positive effect on long-run operating performance and amongst these proxies, VC market share to be the most effective and strongest in its explanatory powers. As more reputable VCs usually has access to superior investment opportunity set and may have been able to invest in higher quality start-up companies at a lower price in the first place (Hsu, 2004), we also tested the VC reputation proxies for robustness after controlling for self selection. By including an additional Inverse Mills' Ratio as explanatory variable to control for the selectivity bias, the VC reputation proxy effect is not trivial in explaining its association to the positive long term operating performance of their invested companies. We also find that more reputable VCs are associated with IPO issuers with greater future growth potential, as the more reputable VCs have positive and statistical significant effect on the long-run market to book ratio for all three regression models and the effect is significant even after accounting for self selection bias. This may be explained by the better organizational and professionalization skills provided by the more reputable VCs in their advisory services on their portfolio companies that allowed these companies to be able to build a more effective organization and management team (Thomas & Manju, 2002); which possibly have helped the company better and more efficiently managed their day-to-day operations, hence translating into superior long-run operating performances and survivorship.

I applied hazard analysis on the companies' time to failure (delisting) as the dependent variable using AFT as the baseline hazard model on the three proposed VC reputation proxies and the critical control variables as covariates. I find that VC market share and VC IPO share has a consistent and positive effect on its invested companies listing time in the post-IPO, and VC market share have stronger explanatory powers compared to VC IPO share. By splitting the sample period to pre-technology bubble period and technology bubble period, the effect of the VC reputation proxies is negative and statistically insignificant on the company's long-run survivorship in the latter period and this result contrasts strongly with the findings in the former period of VC reputation proxies (except VC firm age) having a statistically significant positive effect on the VC supported companies' survivorship. Taking the cumulative failure rate of 50%, companies with above median VC market share backing survive 10.1 years longer when the company is listed during the pre-technology bubble period versus being listed during the technology bubble period. This highlights the excessive optimism on the part of VCs during the era when elevated valuations on newly listed technology companies are common place. This might have reduce incentives for cautious VC screening on their invested companies as they can take profit soon after the lock-up period is over, even though severe IPO under pricings were rampant (Alexander Ljungqvist, 2003). Coupled with the excessive uncommitted investment capital from the VC fund raising, this might have resulted in reputable VCs paying high and unsustainable prices for mediocre quality companies (P. Gompers & Lerner, 2000) that are not able survive as long as the higher quality companies invested in the pre-technology bubble period.

Finally, by sub-dividing the sample set into quartiles according to the magnitude of the VC reputation proxies and crossed-compared for survival times using the hazard analysis, it is re-affirmed that VC market share is the more effective reputation proxy, as both tests for top versus lowest quartile VC reputation and 3rd versus 2nd quartile VC reputation effects on the company long-run survivorship, the above median VC market share coefficient estimates are positive and have greater statistical significance in its effect on longer post-IPO listing times for the VC invested companies.

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Appendix A
Definition of Variables

IPO Long Term Performance Measures	*Description*
ROA	ROA is the industry-adjusted rate of return on assets, defined as Net Income (NIQ) divided by Total Assets (ATQ) minus industry median ROA, and taking average for first three years following the IPO. Each IPO issuer is matched to their respective sample of companies based on the 4 digit SIC code, by deducting the sample companies' median ROA off IPO issuing company's ROA to account for the industry effects. If the IPO issuing company do not survive beyond 3 years, the maximum number of quarters data available in is taken and matched against the industry median ROA for the same number of quarters to account in the attempt to minimize survivorship bias. The data, NIQ and ATQ, are taken off the Compustat Quarterly Database
ROE	ROE is the industry-adjusted rate of return on outstanding equity, defined as Net Income (NIQ) divided by the Total Common Shares Outstanding (CSHOQ) minus the industry median ROE, and taking average for the first three years following the IPO. Each IPO issuer is matched to their respective sample of companies based on the 4 digit SIC code, by deducting the sample companies' median ROE off IPO issuing company's ROE to account for the industry effects. If the IPO issuing company do not survive beyond 3 years, the maximum number of quarters data available in is taken and matched against the industry median ROE for the same number of quarters to account in the attempt to minimize survivorship bias.The data, NIQ and CSHOQ, are taken off Compustat Quarterly Database
Market-to-Book	Market-to-book value is calculated as the ratio of the market value of equity to book value of equity. The market value of equity is defined as number of shares outstanding (CSHOQ) multiplied by its closing stock price for prior quarter (PRCCQ). The book value of equity is defined as total common/ordinary equity (CEQQ) plus net deferred balance sheet income taxes (TXDBQ), minus carrying value of preferred stock (Data 55).Each IPO issuer is matched to their respective sample of companies based on the 4 digit SIC code, by deducting the sample companies' median Market-to-Book off IPO issuing company's Market-to-Book to account for the industry effects. If the IPO issuing company do not survive beyond 3 years, the maximum number of quarters data available in is taken and matched against the industry median Market-to-Book for the same number of quarters to account in the attempt to minimize survivorship bias. . Data CSHOQ, PRCCQ, CEQQ, TXDBQ and carrying value of preferred stock (Data 55) [in database of the old data format] are also taken off Compustat Quarterly Database

VC Reputation Proxy	*Description*
VC Market Share	The market share of a VC is based on the dollar value of IPO deals that the VC backed in the 3 calendar years immediately preceding each IPO, as a proportion of the dollar value of all VC-backed IPOs in the same period. Each VC associated with an IPO is given full credit for the gross issue size of the IPO. For example, for IPOs made in 1999, it is the dollar market share of the IPO market for a VC in the years 1996-1998. Data is taken off Security Data Corporation Global New Issues Database.
VC IPO Share	The share of VC-backed IPOs is defined as the number of IPO deals that the VC backed in the 3 calendar years immediately preceding each IPO, as a proportion of all VC-backed IPOs in the same period. Data is taken off Security Data Corporation (SDC) Global New Issue Database.
VC Age	The age of the VC computed from the date of its incorporation to the IPO date. Data is taken off SDC Global New Issue Database and completed via internet search when data is not readily available.

Control Variables	*Description*
Underwriter	The lead underwriter reputation score as quantified by the Carter-Manaster scale, modified by Ritter and made available on his web site: *http://bear.cba.ufl.edu/ritter/rank.xls*
Age	The natural log of the age (in years) of the issuer at the time of the computed from the date of incorporation to the date of the offering. Data is taken off SDC Global New Issue Database and completed via internet search when data is not readily available.
Assets Before IPO	The natural log of the IPO issuer's total assets at the end of the quarter immediately prior to the IPO date.
Size	The natural log of the IPO gross proceeds from the offering. Data is taken off SDC Global New Issue Database.
Tech	A binary indicator to indicate that the issuing IPO is from a technology intensive industry: marked as 1 for technology based companies and 0 otherwise based on SDC database assignments.
Roadshow	A tercile indicator takes on the value of 1, 2 or 3 depending on whether the offer price is below, within or above the initial filing range respectively. Data is taken off SDC Global New Issue Database.
Bcycle	A binary indicator to indicate if the IPO is issued during a business contraction or expansion cycle as determined by National Bureau of Economic Research (NBER) on NBER's website: http://wwwdev.nber.org/cycles/cyclesmain.html.The indicator is 0 for IPOs issued during the former period and 1 for IPOs issued the latter period.

Appendix B

Technology Intensive Businesses Based on Security Data Corporation's Classification

('Y' in columns means that the NAICS defined major industry contains the SDC classified high technology business)

	NAICS Major Industries/ SIC Codes																									
	Agriculture	*Electric Service*	*Healthcare*	*Leisure*	*Manufacturing*											*Mortgage Bank*	*Other Services*	*Pers/Bus/ Rep Svc*		*Radio/TV/ Telecom*	*Real Estate*	*Retail*			*Wholesale*	
High Tech Industry (SDC Classfication)	18	49	80	78	27	28	30	32	33	34	35	36	37	38	39	61	82	73	87	48	65	52	57	59	50	51
Advanced Manufacturing												Y														
Alarm Systems												Y														
All Biotechnology Research																			Y							
All General Technology												Y														
Applications Software					Y						Y	Y		Y				Y	Y				Y		Y	
Artificial Organs/Limbs														Y												
Biological/Chemical Pro						Y																				
Biotech Instruments/Equ			Y			Y					Y			Y												
Blood Derivatives						Y																				
CAD/CAM/CAE/Graphics System											Y	Y						Y								
CD Rom Drives											Y															
Cellular Communications & Network Systems												Y						Y		Y						
Computer Consulting Services																	Y	Y							Y	
Data Communications											Y	Y						Y		Y						
Data Processing Service			Y								Y						Y	Y	Y							
Database Software/Programmes																		Y								
Disk Drives											Y	Y						Y								
Drug Delivery System						Y								Y												
Drugs/Pharmaceuticals						Y																				
General Med. Instrument						Y								Y												
General Pharmaceuticals						Y								Y					Y					Y		Y
Genetically Eng. Prod	Y		Y			Y																				
Healthcare Services			Y											Y												Y
Internet Services & Software		Y		Y	Y						Y	Y				Y	Y	Y	Y	Y	Y	Y	Y	Y		Y
In-Vitro Diagnostic Process						Y								Y					Y							
Lab Equipment														Y												
Lasers(Excluding Medical)											Y	Y														
Mainframes & Super Computers											Y	Y														
Medical Imaging Systems														Y												
Medical Lasers														Y												
Medical Monitoring Systems			Y											Y												

Medicinal Chemicals					Y																	
Messaging Systems											Y								Y			
Microcomputers										Y			Y									
Microwave Communication											Y								Y			
Modems											Y						Y					
Monitors/Terminals										Y	Y											
Networking Systems (LAN)										Y	Y		Y				Y		Y			
Nuclear Medicines					Y																	
Nuclear													Y									
Operating Systems																	Y					
Other Biotechnology			Y		Y								Y					Y				
Other Computer Systems										Y	Y			Y			Y					
Other Electronics						Y	Y			Y	Y						Y					
Other Peripherals										Y	Y		Y				Y					
Other Software										Y	Y					Y	Y					
Over-The-Counter Drugs					Y																	
Portable Computers										Y												
Precision/Measuring Equipment & Testing			Y							Y		Y	Y									
Printed Circuit Boards										Y	Y											
Printers										Y												
Process Control Systems										Y	Y		Y				Y					
Programming Services										Y						Y	Y					
Rehabilitation Equipment					Y								Y									
Research & Development			Y		Y								Y					Y				
Robotics									Y	Y	Y											
Satellite Communication											Y						Y		Y			
Search,Detection,Navigation												Y	Y									
Semiconductors										Y	Y		Y				Y					
Software										Y							Y					
Superconductors											Y											
Surgical Instruments			Y		Y								Y									
Telecommunications Equipment								Y		Y	Y						Y		Y			
Telephone Interconnect											Y						Y		Y			
Turnkey Systems Communications																	Y					
Utilities/File Mgmt Software																	Y					Y
Vaccines/Specialty Drug					Y																	
Workstations										Y												

Table 1
Industrial Composition of Venture-backed IPOs with High Tech and Non High Tech Split

Table 1 provides the industrial composition of venture-backed IPOs with High Tech and Non High Tech Splits for our IPO sample set from 1985 to 2007, extracted from Security Data Corporation (SDC) Global New Issues database. It has a viable set of 1876 IPOs brought to public over this period and the major industries are defined using the NAICS classification.

SIC Code	*SIC Major Group*	*High Tech*	*(%)*	*Non High Tech*	*(%)*	*Grand Total*	*(%)*
13	Oil & Gas Extraction	-	-	11	*3.1%*	11	*0.6%*
15	Building Construction General Contractors & Operative Builders	-	-	3	*0.8%*	3	*0.2%*
17	Construction Special Trade Contractors	-	-	4	*1.1%*	4	*0.2%*
20	Food & Kindred Products	-	-	9	*2.5%*	9	*0.5%*
22	Textile Mill Products	-	-	4	*1.1%*	4	*0.2%*
23	Apparel & Other Finished Products Made From Fabrics & Similar Materials	-	-	5	*1.4%*	5	*0.3%*
24	Lumber & Wood Products, Except Furniture	-	-	1	*0.3%*	1	*0.1%*
25	Furniture & Fixtures	-	-	1	*0.3%*	1	*0.1%*
26	Paper & Allied Products	-	-	4	*1.1%*	4	*0.2%*
27	Printing, Publishing, & Allied Industries	3	*0.2%*	4	*1.1%*	7	*0.4%*
28	Chemicals & Allied Products	253	*16.7%*	8	*2.2%*	261	*13.9%*
30	Rubber & Miscellaneous Plastics Products	1	*0.1%*	1	*0.3%*	2	*0.1%*
31	Leather & Leather Products	-	-	2	*0.6%*	2	*0.1%*
32	Stone, Clay, Glass, & Concrete Products	1	*0.1%*	3	*0.8%*	4	*0.2%*
33	Primary Metal Industries	1	*0.1%*	4	*1.1%*	5	*0.3%*
35	Industrial & Commercial Machinery & Computer Equipment	92	*6.1%*	10	*2.8%*	102	*5.4%*
36	Electronic & Other Electrical Equipment & Components, Except Computer Equipment	208	*13.7%*	9	*2.5%*	217	*11.6%*
37	Transportation Equipment	1	*0.1%*	5	*1.4%*	6	*0.3%*
38	Measuring, Analyzing, & Controlling Instruments; Photographic,Medical & Optical Goods; Watches & Clocks	177	*11.7%*	10	*2.8%*	187	*10.0%*
39	Miscellaneous Manufacturing Industries	1	*0.1%*	2	*0.6%*	3	*0.2%*
40	Railroad Transportation	-	-	1	*0.3%*	1	*0.1%*
41	Local & Suburban Transit & Interurban Highway Passenger Transportation	-	-	1	*0.3%*	1	*0.1%*
42	Motor Freight Transportation & Warehousing	-	-	3	*0.8%*	3	*0.2%*
44	Water Transportation	-	-	1	*0.3%*	1	*0.1%*
45	Transportation By Air	-	-	2	*0.6%*	2	*0.1%*
47	Transportation Services	-	-	4	*1.1%*	4	*0.2%*
48	Communications	66	*4.3%*	22	*6.1%*	88	*4.7%*
49	Electric, Gas, & Sanitary Services	1	*0.1%*	12	*3.4%*	13	*0.7%*
50	Wholesale Trade-durable Goods	4	*0.3%*	17	*4.7%*	21	*1.1%*
51	Wholesale Trade-non-durable Goods	3	*0.2%*	7	*2.0%*	10	*0.5%*
52	Building Materials, Hardware, Garden Supply, & Mobile Home Dealers	1	*0.1%*	1	*0.3%*	2	*0.1%*
53	General Merch&ise Stores	-	-	7	*2.0%*	7	*0.4%*
54	Food Stores	-	-	4	*1.1%*	4	*0.2%*
55	Automotive Dealers & Gasoline Service Stations	-	-	5	*1.4%*	5	*0.3%*
56	Apparel & Accessory Stores	-	-	8	*2.2%*	8	*0.4%*
57	Home Furniture, Furnishings, & Equipment Stores	7	*0.5%*	6	*1.7%*	13	*0.7%*
58	Eating & Drinking Places	-	-	16	*4.5%*	16	*0.9%*
59	Miscellaneous Retail	16	*1.1%*	28	*7.8%*	44	*2.3%*
60	Depository Institutions	-	-	1	*0.3%*	1	*0.1%*
61	Non-depository Credit Institutions	1	*0.1%*	4	*1.1%*	5	*0.3%*
65	Real Estate	2	*0.1%*	1	*0.3%*	3	*0.2%*
72	Personal Services	-	-	2	*0.6%*	2	*0.1%*
73	Business Services	590	*38.9%*	40	*11.2%*	630	*33.6%*
75	Automotive Repair, Services, & Parking	-	-	4	*1.1%*	4	*0.2%*
78	Motion Pictures	3	*0.2%*	4	*1.1%*	7	*0.4%*
79	Amusement & Recreation Services	-	-	2	*0.6%*	2	*0.1%*
80	Health Services	37	*2.4%*	28	*7.8%*	65	*3.5%*

SIC Code	*SIC Major Group*	*High Tech*	*(%)*	*Non High Tech*	*(%)*	*Grand Total*	*(%)*
82	Educational Services	6	*0.4%*	7	*2.0%*	13	*0.7%*
83	Social Services	-	-	5	*1.4%*	5	*0.3%*
87	Engineering, Accounting, Research, Management, & Related Services	43	*2.8%*	14	*3.9%*	57	*3.0%*
95	Administration Of Environmental Quality & Housing Programs	-	-	1	*0.3%*	1	*0.1%*
	Grand Total	**1518**	***100.0%***	**358**	***100.0%***	**1876**	***100.0%***

Table 2
Distribution of Venture Backed High Tech and Non High Tech Firms That Failed Y Years After IPO Issuance

Table 2 illustrates the distribution of the delisted venture backed IPOs for high tech and non high tech firms in a cross sectional view for the IPO issue year versus period (number of years, Y) after the IPO is launched. A grand total of 768 IPO delistings (for negative reasons) was documented for study period, which constitutes 40.4% of the total venture backed IPOs in sample study (1876 IPOs).

			Distribution of Venture Backed High Tech and Non High Tech Firms that Failed Y Years after IPO																											
IPO Year	**Hi Tech/ Non Hi Tech**	**Grand Total**	**Y = 1**	***(%)***	**Y = 2**	***(%)***	**Y = 3**	***(%)***	**Y = 4**	***(%)***	**Y = 5**	***(%)***	**Y = 6**	***(%)***	**Y = 7**	***(%)***	**Y = 8**	***(%)***	**Y = 9**	***(%)***	**Y = 10**	***(%)***	**Y = 11**	***(%)***	**Y = 12**	***(%)***	**Y = 13**	***(%)***	**Y > 13**	***(%)***
1985	Hi Tech	**6**	-	-	1	*1.0%*	-	-	1	*1.2%*	-	-	-	-	-	-	-	-	1	*2.6%*	1	*3.6%*	-	-	-	-	-	-	2	*4.6%*
	Not Hi Tech	**7**	-	-	-	-	-	-	-	-	4	*4.8%*	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	3	*6.8%*
1986	Hi Tech	**16**	-	-	1	*1.0%*	1	*1.0%*	-	-	1	*1.2%*	1	*1.7%*	2	*3.4%*	1	*2.9%*	2	*5.3%*	-	-	2	*8.7%*	1	*4.2%*	-	-	4	*9.1%*
	Not Hi Tech	**12**	-	-	3	*3.1%*	-	-	-	-	3	*3.6%*	1	*1.7%*	1	*1.7%*	-	-	-	-	-	-	-	-	-	-	-	-	4	*9.1%*
1987	Hi Tech	**22**	4	*5.5%*	1	*1.0%*	-	-	1	*1.2%*	-	-	-	-	2	*3.4%*	1	*2.9%*	1	*2.6%*	1	*3.6%*	1	*4.3%*	2	*8.3%*	2	*15.4%*	6	*13.6%*
	Not Hi Tech	**9**	-	-	-	-	-	-	-	-	-	-	1	*1.7%*	-	-	-	-	2	*5.3%*	1	*3.6%*	2	*8.7%*	1	*4.2%*	-	-	2	*4.6%*
1988	Hi Tech	**9**	-	-	-	-	2	*2.0%*	-	-	-	-	-	-	-	-	2	*5.9%*	-	-	-	-	-	-	1	*4.2%*	2	*15.4%*	2	*4.6%*
	Not Hi Tech	**3**	1	*1.4%*	-	-	1	*1.0%*	-	-	-	-	-	-	1	*1.7%*	-	-	-	-	-	-	-	-	-	-	-	-	-	-
1989	Hi Tech	**6**	-	-	-	-	1	*1.0%*	-	-	1	*1.2%*	-	-	-	-	-	-	1	*2.6%*	-	-	-	-	-	-	1	*7.7%*	2	*4.6%*
	Not Hi Tech	**7**	2	*2.7%*	-	-	-	-	1	*1.2%*	-	-	1	*1.7%*	2	*3.4%*	-	-	-	-	-	-	-	-	1	*4.2%*	-	-	-	-
1990	Hi Tech	**8**	-	-	-	-	1	*1.0%*	-	-	1	*1.2%*	-	-	1	*1.7%*	-	-	-	-	2	*7.1%*	1	*4.3%*	1	*4.2%*	1	*7.7%*	-	-
	Not Hi Tech	**7**	-	-	1	*1.0%*	-	-	-	-	-	-	1	*1.7%*	1	*1.7%*	1	*2.9%*	-	-	-	-	-	-	-	-	-	-	3	*6.8%*
1991	Hi Tech	**43**	-	-	-	-	5	*5.0%*	4	*4.9%*	6	*7.2%*	4	*6.8%*	8	*13.6%*	3	*8.8%*	3	*7.9%*	2	*7.1%*	2	*8.7%*	1	*4.2%*	1	*7.7%*	4	*9.1%*
	Not Hi Tech	**12**	3	*4.1%*	1	*1.0%*	1	*1.0%*	1	*1.2%*	1	*1.2%*	-	-	2	*3.4%*	1	*2.9%*	-	-	-	-	-	-	1	*4.2%*	-	-	1	*2.3%*
1992	Hi Tech	**45**	-	-	3	*3.1%*	8	*8.0%*	2	*2.4%*	5	*6.0%*	4	*6.8%*	1	*1.7%*	4	*11.8%*	8	*21.1%*	1	*3.6%*	-	-	3	*12.5%*	1	*7.7%*	5	*11.4%*
	Not Hi Tech	**21**	-	-	1	*1.0%*	5	*5.0%*	1	*1.2%*	2	*2.4%*	-	-	2	*3.4%*	2	*5.9%*	2	*5.3%*	-	-	2	*8.7%*	1	*4.2%*	-	-	3	*6.8%*
1993	Hi Tech	**55**	3	*4.1%*	4	*4.1%*	2	*2.0%*	5	*6.1%*	6	*7.2%*	11	*18.6%*	4	*6.8%*	4	*11.8%*	1	*2.6%*	7	*25.0%*	1	*4.3%*	4	*16.7%*	1	*7.7%*	2	*4.6%*
	Not Hi Tech	**19**	1	*1.4%*	2	*2.0%*	1	*1.0%*	4	*4.9%*	1	*1.2%*	3	*5.1%*	3	*5.1%*	2	*5.9%*	-	-	1	*3.6%*	-	-	1	*4.2%*	-	-	-	-
1994	Hi Tech	**52**	1	*1.4%*	7	*7.1%*	4	*4.0%*	7	*8.5%*	12	*14.5%*	3	*5.1%*	6	*10.2%*	2	*5.9%*	1	*2.6%*	3	*10.7%*	1	*4.3%*	1	*4.2%*	3	*23.1%*	1	*2.3%*
	Not Hi Tech	**13**	-	-	1	*1.0%*	2	*2.0%*	3	*3.7%*	3	*3.6%*	-	-	1	*1.7%*	-	-	1	*2.6%*	-	-	2	*8.7%*	-	-	-	-	-	-
1995	Hi Tech	**79**	5	*6.8%*	15	*15.3%*	9	*9.0%*	15	*18.3%*	7	*8.4%*	6	*10.2%*	7	*11.9%*	1	*2.9%*	6	*15.8%*	4	*14.3%*	1	*4.3%*	2	*8.3%*	1	*7.7%*	-	-
	Not Hi Tech	**15**	-	-	-	-	4	*4.0%*	-	-	2	*2.4%*	1	*1.7%*	2	*3.4%*	1	*2.9%*	2	*5.3%*	-	-	-	-	3	*12.5%*	-	-	-	-
1996	Hi Tech	**32**	3	*4.1%*	4	*4.1%*	6	*6.0%*	6	*7.3%*	2	*2.4%*	2	*3.4%*	1	*1.7%*	1	*2.9%*	2	*5.3%*	2	*7.1%*	3	*13.0%*	-	-	-	-	-	-
	Not Hi Tech	**33**	3	*4.1%*	4	*4.1%*	10	*10.0%*	5	*6.1%*	-	-	3	*5.1%*	1	*1.7%*	5	*14.7%*	1	*2.6%*	-	-	1	*4.3%*	-	-	-	-	-	-
1997	Hi Tech	**22**	1	*1.4%*	2	*2.0%*	3	*3.0%*	5	*6.1%*	3	*3.6%*	-	-	-	-	1	*2.9%*	1	*2.6%*	2	*7.1%*	4	*17.4%*	-	-	-	-	-	-
	Not Hi Tech	**20**	3	*4.1%*	5	*5.1%*	3	*3.0%*	2	*2.4%*	5	*6.0%*	1	*1.7%*	-	-	-	-	-	-	1	*3.6%*	-	-	-	-	-	-	-	-
1998	Hi Tech	**7**	4	*5.5%*	1	*1.0%*	-	-	-	-	-	-	-	-	1	*1.7%*	1	*2.9%*	-	-	-	-	-	-	-	-	-	-	-	-
	Not Hi Tech	**12**	1	*1.4%*	1	*1.0%*	1	*1.0%*	1	*1.2%*	1	*1.2%*	2	*3.4%*	1	*1.7%*	1	*2.9%*	3	*7.9%*	-	-	-	-	-	-	-	-	-	-
1999	Hi Tech	**60**	13	*17.8%*	18	*18.4%*	6	*6.0%*	6	*7.3%*	8	*9.6%*	4	*6.8%*	5	*8.5%*	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Not Hi Tech	**10**	3	*4.1%*	1	*1.0%*	2	*2.0%*	2	*2.4%*	-	-	1	*1.7%*	1	*1.7%*	-	-	-	-	-	-	-	-	-	-	-	-	-	-
2000	Hi Tech	**62**	16	*21.9%*	11	*11.2%*	14	*14.0%*	5	*6.1%*	7	*8.4%*	6	*10.2%*	3	*5.1%*	-	-	-	-	-	-	-	-	-	-	-	-	-	-

	Not Hi Tech	**5**	2	*2.7%*	1	*1.0%*	-	-	1	*1.2%*	-	-	1	*1.7%*	-	-	-	-		-	-	-	-	-	-	-	-	-	-	-
2001	Hi Tech	**4**	-	-	3	*3.1%*	-	-	1	*1.2%*	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Not Hi Tech	**2**	-	-	-	-	-	-	1	*1.2%*	-	-	1	*1.7%*	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
>2002	Hi Tech	**16**	3	*4.1%*	4	*4.1%*	6	*6.0%*	-	-	2	*2.4%*	1	*1.7%*	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Not Hi Tech	**7**	1	*1.4%*	2	*2.0%*	2	*2.0%*	2	*2.4%*	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Grand Total		**758**	**73**	***100.0%***	**98**	***100.0%***	**100**	***100.0%***	**82**	***100.0%***	**83**	***100.0%***	**59**	***100.0%***	**59**	***100.0%***	**34**	***100.0%***	**38**	***100.0%***	**28**	***100.0%***	**23**	***100.0%***	**24**	***100.0%***	**13**	***100.0%***	**44**	***100.0%***

Table 3
Selective Descriptive Statistics for Listed versus Delisted Venture Backed IPOs

Table 3 presents selected descriptive statistics for the selected VC reputation proxy measures (*VC Age, VC Market Share* and *VC IPO Share*) and control variables which characterizes the IPO companies (Asset size, company age, number of years traded, underwriter reputation, IPO road show success and technology indicator), compiled for both still in trading and delisted venture backed IPO issues. A two-sample t-test assuming unequal variances are tested for the difference in means of the reputation proxies as well as control variable measures between these two categories of IPO issues

Variable	IPOs Still Trading (N=1118)		IPOs Delisted (N=758)		Mean Difference	t-stat		Unit of Variable
	Mean	*Std. Dev.*	*Mean*	*Std. Dev.*				
VC Reputation: VC Age	16.971	6.629	15.700	7.513	1.271	3.726	***	Years
VC Reputation: VC Market Share	2.620%	0.021%	2.650%	0.019%	-0.030%	-0.303		Percentage
VC Reputation: VC IPO Share	8.850%	0.192%	10.220%	0.209%	-1.370%	-1.445	*	Percentage
IPO Size	56.880	71.847	46.903	59.115	9.977	3.281	***	USD Millions
Asset Size Before Offering	77.720	298.855	68.012	223.470	9.709	0.718		USD Millions
Company Age at Listing	8.315	7.422	8.400	8.648	-0.085	-0.150		Years
Years Traded	9.867	5.190	5.794	4.060	4.073	19.011	***	Years
Underwriter Reputation	8.168	1.364	7.943	1.498	0.225	3.299	***	Carter-Manaster 9-point scale
High Technology Firm	0.254	0.436	0.262	0.440	-0.007	-0.354		Binary
Road Show Success	2.095	0.772	2.092	0.731	0.002	0.069		1- Below Filing Range 2- Within Filing Range, 3 - Above Filing Range

*,**,*** denote coefficient estimates significantly differ from zero at 10,5 and 1% levels respectively

Table 4
Impact of VC Presence in IPOs (Jan 1985 – Dec 2007)

Table 4 shows the results of the parameter estimates and associated p-values from ordinary least squares estimation based on standard errors robust to heteroskedasticity and autocorrelation consistent from Newey-West adjustments. The general regression model:

$$ROA / ROE / Market-to-Book = \beta_o + \beta_1 VC + \beta_2 Underwriter + \beta_3 Size + \beta_4 Age + \beta_5 Tech + \varepsilon$$

Where the dependent variable *ROA* , *ROE* or *Market-to-Book* ratio is regressed against *VC*, a binary indicator signaling VC involvement (VC equals 1 indicates IPO with VC backing and equals 0 otherwise) in the IPO and other control variables (*Underwriter, Size, Age* and *Tech*) as listed in Appendix A. The regressions are estimated for a total of 4012 VC backed (1876 IPOs) and non VC backed IPOs (2136 IPOs) completed in the period 1985-2007.

	VC	*UNDERWRITER*	*SIZE*	*AGE*	*TECH*	*Adjusted* R^2
Model 1 **ROA**	0.546*** (0.000)	0.288** (0.051)	0.005*** (0.003)	-0.394** (0.040)	0.473*** (0.010)	**5.25%**
Model 2 **ROE**	0.280** (0.037)	0.410* (0.070)	0.042** (0.031)	-0.469 (0.183)	0.156** (0.021)	**4.74%**
Model 3 **Market-to-Book**	1.254** (0.024)	0.388** (0.017)	-0.031** (0.019)	0.077* (0.058)	2.330*** (0.010)	**3.40%**

*,**,*** denote coefficient estimates significantly differ from zero at 10,5 and 1% levels respectively p-values in parentheses

Table 5
Cross sectional Regression of VC Reputation Proxies on Control Variables

Table 5 presents coefficient estimates and in parentheses, the associated p-values on heteroskedasticity consistent standard errors adjusted for industry clustering where the dependent variable measuring alternative VC reputation measures (*VC age, VC Market Share* and *VC IPO Share*), *VC_Reputation*, is regressed on IPO issue variables listed below. The equation below estimated with censored logistic regression:

$$VC\_\mathrm{Re}\,putation = \beta_o + \beta_1 Underwriter + \beta_2 AssetsBeforeIPO + \beta_3 Size + \beta_4 Age + \beta_5 Tech + \varepsilon$$

All the issuer characteristics as regressants (*Underwriter, Assets Before IPO, Size, Age* and *Tech*) are defined in Appendix A. The regressions are estimated over 1876 VC-backed IPOs completed in the 1985-2007 period.

	UNDERWRITER	*ASSETS BEFORE IPO*	*SIZE*	*AGE*	*TECH*	*Adjusted R^2*
Model 1 VC Age	0.149** (0.018)	-0.493*** (0.006)	-0.917*** (0.002)	-0.621 (0.132)	0.612*** (0.009)	**18.23%**
Model 2 VC Market Share	0.050* (0.064)	-0.084*** (0.010)	-0.050 (0.020)	-0.054* (0.071)	0.134*** (0.006)	**23.73%**
Model 3 VC IPO Share	0.023** (0.014)	-0.002* (0.072)	-0.022* (0.088)	-0.005* (0.069)	0.095*** (0.001)	**27.84%**

*,**,*** denote coefficient estimates significantly differ from zero at 10,5 and 1% levels respectively. p-values in parentheses

Table 6A
Pair-wise Pearson's Correlation between VC Reputation and Control Variables

Table 6A shows the pair-wise Pearson's correlation between alternative VC reputation measures and the IPO issuer characteristics. They are estimated over 1876 VC-backed IPOs completed in the 1985-2007 period.

	VC Market Share	*VC IPO Share*	*VC Firm Age*
Underwriter	0.149	0.126	0.055
Size	0.203	0.081	0.162
Age	-0.079	0.131	0.034
Technology	-0.016	-0.056	-0.026
Roadshow	0.141	-0.011	0.053

Table 6B

Cross sectional Regression of VC Reputation Proxies on Long-run Operating Performance

This table presents coefficient estimates and in parentheses associated p-values based on standard errors which are robust to heteroskedasticity and industry clustering. The post-IPO long-run match-adjusted *ROA, ROE* and *Market-to-Book* ratio, purged of any survivorship bias, is regressed on one of the alternative VC reputation measures, *VC_Reputation*, using the following OLS regression specification:

$$ROA / ROE / Market - to - Book = \beta_o + \beta_1 VC\_\mathrm{Re}\,putation + \beta_2 Roadshow + \beta_3 Underwriter + \beta_4 Size + \beta_5 Age + \beta_6 Tech + \varepsilon$$

And the results are presented in panel A, B and C for the respective dependent variable of *ROA, ROE* and *Market-to-Book* ratio. The VC reputation proxies (*VC Market Share, VC IPO Share* and *VC Age*) and the control variables as regressants (*Underwriter, Size, Age, Tech* and *Roadshow*) are defined in Appendix A. The regressions are estimated over 1876 VC-backed IPOs completed in the 1985-2007 period.

Panel A: ROA

	VC Rep	*UNDERWRITER*	*SIZE*	*AGE*	*TECH*	*ROADSHOW*	*Adjusted R^2*
Model 1 VC Market Share	0.209** (0.017)	0.040*** (0.005)	-0.395* (0.069)	0.301** (0.012)	-0.743 (0.540)	0.152* (0.088)	**5.27%**
Model 2 VC IPO Share	0.348** (0.041)	0.186* (0.098)	-0.289** (0.046)	0.311 (0.201)	0.587* (0.054)	-0.136 (0.168)	**4.09%**
Model 3 VC Age	0.120 (0.129)	0.367*** (0.010)	-0.364* (0.077)	-0.207** (0.045)	0.409 (0.155)	-0.450 (0.113)	**3.41%**

Panel B: ROE

	VC Rep	*UNDERWRITER*	*SIZE*	*AGE*	*TECH*	*ROADSHOW*	*Adjusted R^2*
Model 1 VC Market Share	0.554*** (0.008)	0.440* (0.052)	-0.246* (0.096)	-0.101 (0.622)	1.054 (0.175)	0.095* (0.056)	**4.68%**
Model 2 VC IPO Share	0.215** (0.046)	0.107 (0.264)	-0.251* (0.081)	-0.356 (0.712)	0.101* (0.083)	-0.670* (0.064)	**3.96%**
Model 3 VC Age	0.207* (0.061)	0.108 (0.352)	-0.300* (0.093)	-0.363 (0.144)	0.932 (0.193)	-0.157 (0.433)	**3.29%**

*,**,*** denote coefficient estimates significantly differ from zero at 10,5 and 1% levels respectively. p-values in parentheses

Panel C: Market-to-Book

	VC Rep	*UNDERWRITER*	*SIZE*	*AGE*	*TECH*	*ROADSHOW*	*Adjusted R^2*
Model 1 VC Market Share	1.329* (0.088)	0.693* (0.056)	-0.765*** (0.002)	0.252** (0.048)	1.738* (0.090)	0.016 (0.380)	**4.89%**
Model 2 VC IPO Share	0.733** (0.042)	0.726** (0.044)	-0.356* (0.063)	-0.494 (0.318)	0.237** (0.030)	0.081 (0.549)	**3.57%**
Model 3 VC Age	0.104* (0.056)	0.780** (0.013)	-0.859* (0.090)	-0.588 (0.728)	1.230** (0.029)	0.032 (0.220)	**4.07%**

*,**,*** denote coefficient estimates significantly differ from zero at 10,5 and 1% levels respectively. p-values in parentheses

Table 7A

Correction for Self Selection Bias - Stage 1 Cross sectional Regression to Obtain Inverse Mills' Ratio

This table presents the first stage of the two-stage-Heckman regression coefficients and in parentheses its associated *p-values*. In this first stage, a logit regression is estimated for the likelihood of having a highly ranked VC, based on VC reputation proxies (*VC Market Share, VC IPO Share* and *VC Age*) of VC backed deals above the median. The associated p-values are based on standard errors robust to heteroskedasticity and industry clustering. The first stage regression equation is:

$$VC\_Rep^* = \beta_o + \beta_1 Underwriter + \beta_2 Size + \beta_3 Age + \beta_4 Tech + \varepsilon$$

Where *VC_Rep** is a binary variable that equals 1 if VC reputation proxy measurement > median VC reputation proxy measurement and 0 otherwise. The VC reputation proxies (*VC Market Share, VC IPO Share* and *VC Age*) and the control variables as regressants (*Underwriter, Size, Age, Tech* and *Roadshow*) are defined in Appendix A. The regressions are estimated over 1876 VC-backed IPOs completed in the 1985-2007 period.

	ASSET	*SIZE*	*AGE*	*TECH*	*INTERCEPT*	*Adjusted R^2*
Model 1	-0.051**	0.402	-0.376*	0.156**	-0.851**	**6.80%**
	(0.022)	(0.135)	(0.080)	(0.035)	(0.031)	
VC Market Share*						
Model 2	-0.040*	0.508	-0.430*	0.096*	-1.818***	**6.22%**
VC IPO Share*	(0.062)	(0.117)	(0.069)	(0.057)	(0.001)	
Model 3	-0.044*	0.679**	-0.137	0.048*	-1.431***	**5.56%**
VC Age*	(0.059)	(0.015)	(0.173)	(0.087)	(0.002)	

*,**,*** denote coefficient estimates significantly differ from zero at 10,5 and 1% levels respectively. p-values in parentheses

Table 7B
Correction for Selection Bias - Stage 2 Cross sectional Regression of Long-run Operating Performances on VC Reputation (Inclusive of Inverse Mills Ratio)

This table presents the second stage of the two-stage-Heckman regression coefficients and in parentheses its associated *p-values* based on standard errors which are robust to heteroskedasticity and industry clustering. The *Inverse Mills' Ratio* estimated from the first stage regression is used as an additional independent variable to the following second stage OLS regression specification:

$$ROA / ROE / Market-to-Book = \beta_o + \beta_1 VC\_\mathrm{Re}putation + \beta_2 Roadshow + \beta_3 Underwriter + \beta_4 Size + \beta_5 Age + \beta_6 Tech + \beta_7 InverseMillsRatio + \varepsilon$$

And the results are presented in panel A, B and C for the respective dependent variable of *ROA, ROE* and *Market-to-Book* ratio. The VC reputation proxies (*VC Market Share, VC IPO Share* and *VC Age*) and the control variables as regressants (*Underwriter, Size, Age, Tech* and *Roadshow*) are defined in Appendix A. The regressions are estimated over 1876 VC-backed IPOs completed in the 1985-2007 period.

Panel A: ROA

	VC Rep	***UNDERWRITER***	***SIZE***	***AGE***	***TECH***	***ROADSHOW***	***INVERSE MILLS RATIO***	***Adjusted R^2***
Model 1 VC Market Share	0.388** (0.041)	0.165** (0.014)	-0.427 (0.245)	0.584* (0.074)	-0.300 (0.364)	0.447** (0.031)	-0.103* (0.100)	**5.99%**
Model 2 VC IPO Share	0.218* (0.074)	0.358* (0.082)	-0.537** (0.038)	0.443 (0.479)	0.384 (0.164)	-0.662 (0.324)	-0.108** (0.043)	**4.59%**
Model 3 VC Age	0.09 (0.121)	0.307* (0.080)	-0.203* (0.060)	0.451** (0.032)	0.629 (0.147)	-0.164* (0.099)	-0.215** (0.037)	**3.80%**

Panel B: ROE

	VC Rep	***UNDERWRITER***	***SIZE***	***AGE***	***TECH***	***ROADSHOW***	***INVERSE MILLS RATIO***	***Adjusted R^2***
Model 1 VC Market Share	0.395** (0.033)	0.246* (0.067)	-0.771** (0.049)	-0.991 (0.498)	0.590* (0.095)	0.138 (0.139)	-1.094*** (0.000)	**9.66%**
Model 2 VC IPO Share	0.292** (0.012)	0.245 (0.136)	-0.274* (0.061)	-0.706 (0.220)	0.140* (0.069)	0.140 (0.102)	-1.020* (0.065)	**8.79%**
Model 3 VC Age	0.022* (0.055)	0.156** (0.049)	-0.415* (0.069)	-0.811* (0.083)	0.236 (0.111)	-0.419 (0.346)	-0.530*** (0.008)	**6.61%**

*,**,*** denote coefficient estimates significantly differ from zero at 10,5 and 1% levels respectively. p-values in parentheses

Panel C: Market-to-Book

	VC Rep	*UNDERWRITER*	*SIZE*	*AGE*	*TECH*	*ROADSHOW*	*INVERSE MILLS RATIO*	*Adjusted R^2*
Model 1 VC Market Share	0.264** (0.023)	0.900** (0.012)	-1.445* (0.060)	0.591 (0.562)	1.168 (0.133)	0.127* (0.062)	-2.591* (0.095)	**5.75%**
Model 2 VC IPO Share	0.405* (0.081)	1.011*** (0.010)	-0.559** (0.046)	-0.683 (0.387)	0.216** (0.050)	0.333* (0.059)	-1.386* (0.097)	**4.98%**
Model 3 VC Age	0.069* (0.098)	0.971 (0.197)	-1.017* (0.082)	-0.347 (0.495)	0.997** (0.039)	0.279** (0.040)	-1.256* (0.083)	**4.82%**

*,**,*** denote coefficient estimates significantly differ from zero at 10,5 and 1% levels respectively. p-values in parentheses

Table 8

Survivorship Test for Above Median Reputation VC (VC Rep =1) versus Below Median Reputation VC (VC Rep =0) - 1985 -2007

Table 8 presents the accelerated failure time model (AFT) regression coefficients and in parentheses its associated *p-values* based on maximum likelihood estimation method using Newton-Raphson algorithm for convergence and the individual coefficient estimates tested using a χ^2-statistic. The simplified linear representation of the regression specification:

$$Ln(H_t) = \beta_o + \beta_1 VC\_\mathrm{Re}\,putation + \beta_2 Roadshow + \beta_3 Underwriter + \beta_4 Size + \beta_5 Age + \beta_6 Tech + +\beta_7 Bcycle + \varepsilon + \sigma Ln(H_o)$$

Where *Ln(H$_t$)* is natural logarithm of the time to delisting of the individual companies in years, $H_0(t) = \lambda\rho(\lambda t)^{\rho-1} \big/ (1+(\lambda t)^{\rho})$, $\lambda = e^{X\beta}$, $\rho = 1/\sigma$ and t is the individual sample time to failure in years. The *VC_Reputation* is a binary variable that equals 1 if VC reputation proxy measurement > median VC reputation proxy measurement and 0 otherwise. The VC reputation proxies (*VC Market Share, VC IPO Share* and *VC Age*) and the control variables as regressants (*Underwriter, Size, Age, Tech*, *Roadshow and Bcycle*) are defined in Appendix A. The regressions are estimated over 1431 VC-backed IPOs completed in the 1985-2007 period.

	VC Rep	*UNDERWRITER*	*SIZE*	*AGE*	*TECH*	*ROADSHOW*	*BCYCLE*	*INTERCEPT*	*Ancillary Scale, σ*	*Log Likelihood*
Model 1	0.1458***	0.0163	-0.0055***	0.0042*	0.0585	0.1053***	-0.0535	2.4943***	**0.3577**	**-1071.87**
VC Market Share	(0.000)	(0.204)	(0.000)	(0.075)	(0.122)	(0.000)	(0.615)	(0.000)		
Model 2	0.0552*	0.0074	-0.0056***	0.0055**	0.0575	0.1152***	-0.0519	2.4534***	**0.3598**	**-1060.47**
VC IPO Share	(0.100)	(0.560)	(0.000)	(0.021)	(0.131)	(0.000)	(0.631)	(0.000)		
Model 3	-0.3814***	-0.0011	-0.0048***	0.0046**	0.0538	0.1189***	-0.0341	2.5482***	**0.3451**	**-1025.94**
VC Age	(0.000)	(0.927)	(0.000)	(0.039)	(0.143)	(0.000)	(0.742)	(0.000)		

*,**,*** denote coefficient estimates significantly differ from zero at 10,5 and 1% levels respectively. p-values in parentheses.

Table 9

Survivorship Test for Above Median Reputation VC (VC Rep =1) versus Below Median Reputation VC (VC Rep =0) - 1985 -1996

Table 9 presents the accelerated failure time model (AFT) regression coefficients and in parentheses its associated *p-values* based on maximum likelihood estimation method using Newton-Raphson algorithm for convergence and the individual coefficient estimates tested using a χ^2-statistic. The simplified linear representation of the regression specification:

$$Ln(H_t) = \beta_o + \beta_1 VC\_Reputation + \beta_2 Roadshow + \beta_3 Underwriter + \beta_4 Size + \beta_5 Age + \beta_6 Tech + +\beta_7 Bcycle + \varepsilon + \sigma Ln(H_o)$$

Where $Ln(H_t)$ is natural logarithm of the time to delisting of the individual companies in years, $H_0(t) = \lambda\rho(\lambda t)^{\rho-1} / (1+(\lambda t)^{\rho})$, $\lambda = e^{X\beta}$, $\rho = 1/\sigma$ and t is the individual sample time to failure in years. The *VC_Reputation* is a binary variable that equals 1 if VC reputation proxy measurement > median VC reputation proxy measurement and 0 otherwise. The VC reputation proxies (*VC Market Share, VC IPO Share* and *VC Age*) and the control variables as regressants (*Underwriter, Size, Age, Tech*, *Roadshow and Bcycle*) are defined in Appendix A. The regressions are estimated over 478 VC-backed IPOs completed in the 1985-1996 period.

	VC Rep	*UNDERWRITER*	*SIZE*	*AGE*	*TECH*	*ROADSHOW*	*BCYCLE*	*INTERCEPT*	*Ancillary Scale, σ*	*Log Likelihood*
Model 1	0.1049***	0.0215***	-0.0019***	0.0038***	0.0271	-0.0391*	-0.0309	2.7636***	**0.0982**	**-369.10**
VC Market Share	(0.000)	(0.001)	(0.000)	(0.008)	(0.229)	(0.091)	(0.599)	(0.000)		
Model 2	0.0411**	0.0300***	-0.0020***	0.0049***	0.0272	-0.0379**	-0.0337	2.7385***	**0.1017**	**-358.99**
VC IPO Share	(0.048)	(0.000)	(0.000)	(0.001)	(0.246)	(0.015)	(0.578)	(0.000)		
Model 3	-0.1511***	0.0260***	-0.0016***	0.0056***	0.0326	-0.0293**	-0.0566	2.8536***	**0.0931**	**-385.53**
VC Age	(0.000)	(0.000)	(0.000)	(0.007)	(0.126)	(0.047)	(0.315)	(0.000)		

*,**,*** denote coefficient estimates significantly differ from zero at 10,5 and 1% levels respectively. p-values in parentheses.

Table 10

Survivorship Test for Above Median Reputation VC (VC Rep =1) versus Below Median Reputation VC (VC Rep =0) - 1997 -2007

Table 10 presents the accelerated failure time model (AFT) regression coefficients and in parentheses its associated *p-values* based on maximum likelihood estimation method using Newton-Raphson algorithm for convergence and the individual coefficient estimates tested using a χ^2-statistic. The simplified linear representation of the regression specification:

$$Ln(H_t) = \beta_o + \beta_1 VC\_\mathrm{Re}putation + \beta_2 Roadshow + \beta_3 Underwriter + \beta_4 Size + \beta_5 Age + \beta_6 Tech + +\beta_7 Bcycle + \varepsilon + \sigma Ln(H_o)$$

Where *Ln(H$_t$)* is natural logarithm of the time to delisting of the individual companies in years, $H_0(t) = \lambda\rho(\lambda t)^{\rho-1} / (1+(\lambda t)^{\rho})$, $\lambda = e^{X\beta}$, $\rho = 1/\sigma$ and t is the individual sample time to failure in years. The *VC_Reputation* is a binary variable that equals 1 if VC reputation proxy measurement > median VC reputation proxy measurement and 0 otherwise. The VC reputation proxies (*VC Market Share, VC IPO Share* and *VC Age*) and the control variables as regressants (*Underwriter, Size, Age, Tech*, *Roadshow and Bcycle*) are defined in Appendix A. The regressions are estimated over 953 VC-backed IPOs completed in the 1997-2007 period.

	VC Rep	*UNDERWRITER*	*SIZE*	*AGE*	*TECH*	*ROADSHOW*	*BCYCLE*	*INTERCEPT*	*Ancillary Scale, σ*	*Log Likelihood*
Model 1	-0.0118	-0.0037	-0.0029***	0.0003	-0.0053	0.1549***	0.0194	1.8889***	**0.3627**	**-766.01**
VC Market Share	(0.774)	(0.826)	(0.000)	(0.926)	(0.912)	(0.000)	(0.872)	(0.000)		
Model 2	-0.0948	-0.0087	-0.0027***	-0.0011	-0.0054	0.1554***	0.0126	1.9574***	**0.3626**	**-763.42**
VC IPO Share	(0.221)	(0.6037)	(0.000)	(0.698)	(0.909)	(0.000)	(0.9167)	(0.000)		
Model 3	-0.2808***	0.0024	-0.0027***	0.0006	-0.0068	0.1546***	-0.0194	1.9860***	**0.3550**	**-741.09**
VC Age	(0.000)	(0.883)	(0.000)	(0.839)	(0.884)	(0.000)	(0.8711)	(0.000)		

*,**,*** denote coefficient estimates significantly differ from zero at 10,5 and 1% levels respectively. p-values in parentheses.

Table 11
Survivorship Test for Top Quartile Reputation VC (VC Rep =1) versus Lowest Quartile Reputation VC (VC Rep = 0) - 1985 -2007

Table 11 presents the accelerated failure time model (AFT) regression coefficients and in parentheses its associated *p-values* based on maximum likelihood estimation method using Newton-Raphson algorithm for convergence and the individual coefficient estimates tested using a χ^2-statistic. The simplified linear representation of the regression specification:

$$Ln(H_t) = \beta_o + \beta_1 VC\_\mathrm{Re}putation + \beta_2 Roadshow + \beta_3 Underwriter + \beta_4 Size + \beta_5 Age + \beta_6 Tech + +\beta_7 Bcycle + \varepsilon + \sigma Ln(H_o)$$

Where $Ln(H_t)$ is natural logarithm of the time to delisting of the individual companies in years, $H_0(t) = \lambda\rho(\lambda t)^{\rho-1} \big/ (1+(\lambda t)^{\rho})$, $\lambda = e^{X\beta}$, $\rho = 1/\sigma$ and t is the individual sample time to failure in years. The *VC_Reputation* is a binary variable that equals 1 if the VC reputation proxy measurement is within top quartile reputation VC scale and 0 if the VC reputation proxy measurement is within lowest quartile reputation VC scale. The VC reputation proxies (*VC Market Share, VC IPO Share* and *VC Age*) and the control variables as regressants (*Underwriter, Size, Age, Tech*, *Roadshow and Bcycle*) are defined in Appendix A. The regressions are estimated over 711VC-backed IPOs filtered for the regression requirement and completed in the 1985-2007 period.

	VC Rep	***UNDERWRITER***	***SIZE***	***AGE***	***TECH***	***ROADSHOW***	***BCYCLE***	***INTERCEPT***	***Ancillary Scale, σ***	***Log Likelihood***
Model 1	0.1855***	-0.0104	-0.0047***	0.0023	0.0642	0.0860**	-0.0648	2.4188***	**0.3765**	**-533.04**
VC Market Share	(0.000)	(0.549)	(0.000)	(0.480)	(0.249)	(0.013)	(0.637)	(0.000)		
Model 2	0.1131**	-0.0084	-0.0041***	0.0057*	0.0750	0.0621**	0.0093	2.4257***	**0.3395**	**-524.01**
VC IPO Share	(0.015)	(0.579)	(0.000)	(0.077)	(0.152)	(0.046)	(0.950)	(0.000)		
Model 3	-0.6181***	0.0187	-0.0050***	-0.0032	0.0007	0.1130***	-0.1635	2.6931***	**0.3824**	**-520.25**
VC Age	(0.000)	(0.299)	(0.000)	(0.358)	(0.991)	(0.001)	(0.2876)	(0.000)		

*,**,*** denote coefficient estimates significantly differ from zero at 10,5 and 1% levels respectively. p-values in parentheses.

Table 12
Survivorship Test for 3rd Quartile Reputation VC (VC Rep =1) versus 2nd Quartile Reputation VC (VC Rep = 0) - 1985 -2007

Table 11 presents the accelerated failure time model (AFT) regression coefficients and in parentheses its associated *p-values* based on maximum likelihood estimation method using Newton-Raphson algorithm for convergence and the individual coefficient estimates tested using a χ^2-statistic. The simplified linear representation of the regression specification:

$$Ln(H_t) = \beta_o + \beta_1 VC\_\mathrm{Re}putation + \beta_2 Roadshow + \beta_3 Underwriter + \beta_4 Size + \beta_5 Age + \beta_6 Tech + +\beta_7 Bcycle + \varepsilon + \sigma Ln(H_o)$$

Where *Ln(H$_t$)* is natural logarithm of the time to delisting of the individual companies in years, $H_0(t) = \lambda\rho(\lambda t)^{\rho-1} / (1+(\lambda t)^{\rho})$, $\lambda = e^{X\beta}$, $\rho = 1/\sigma$ and t is the individual sample time to failure in years. The *VC_Reputation* is a binary variable that equals 1 if the VC reputation proxy measurement is within third quartile reputation VC scale and 0 if the VC reputation proxy measurement is within lowest quartile reputation VC scale. The VC reputation proxies (*VC Market Share, VC IPO Share* and *VC Age*) and the control variables as regressants (*Underwriter, Size, Age, Tech*, *Roadshow and Bcycle*) are defined in Appendix A. The regressions are estimated over 721VC-backed IPOs filtered for the regression requirement and completed in the 1985-2007 period.

	VC Rep	*UNDERWRITER*	*SIZE*	*AGE*	*TECH*	*ROADSHOW*	*BCYCLE*	*INTERCEPT*	*Ancillary Scale, σ*	*Log Likelihood*
Model 1	0.1054**	-0.0259	-0.0071***	0.0055	0.0604	0.1339***	0.0097	2.2171***	**0.3371**	**-544.37**
VC Market Share	(0.018)	(0.175)	(0.000)	(0.108)	(0.238)	(0.000)	(0.9546)	(0.000)		
Model 2	0.0267	-0.0036	-0.0079***	0.0063**	0.0765*	0.1619***	-0.0316	2.3981***	**0.3283**	**-548.72**
VC IPO Share	(0.485)	(0.806)	(0.000)	(0.026)	(0.055)	(0.000)	(0.792)	(0.000)		
Model 3	-0.1736***	-0.0222	-0.0037***	0.0039	0.0812*	0.1154***	0.1139	2.3794***	**0.2909**	**-531.54**
VC Age	(0.000)	(0.1612)	(0.000)	(0.157)	(0.062)	(0.000)	(0.3897)	(0.000)		

*,**,*** denote coefficient estimates significantly differ from zero at 10,5 and 1% levels respectively. p-values in parentheses.

Figure 1

Industry Composition for Venture Backed High Tech and Non High Tech IPOs (1985-2007), Sample Size = 1876 IPOs

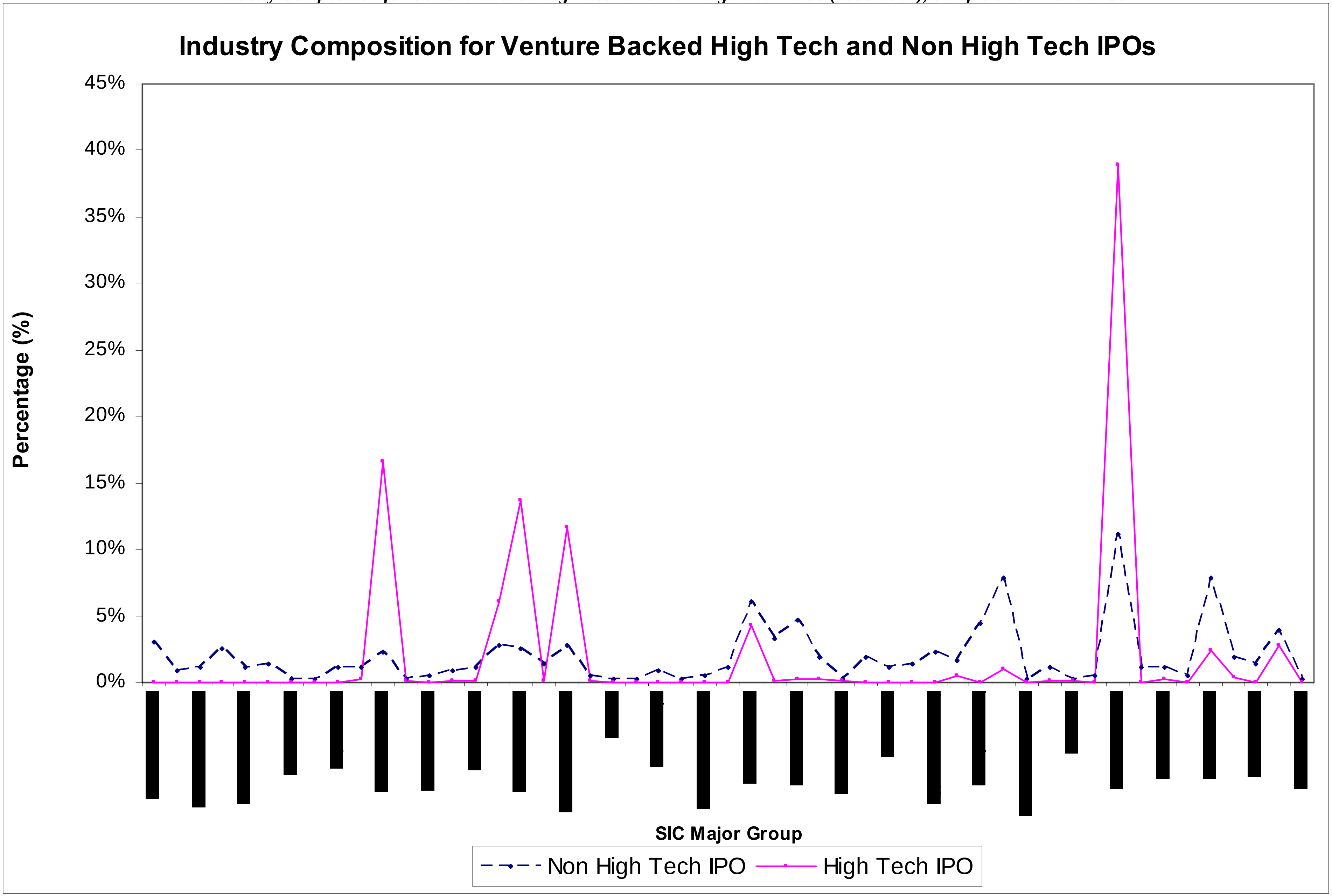

Figure 2
IPO Delisting Frequency By Quarter for Venture Backed IPOs (1985 -2007), Sample Size = 1876 IPOs

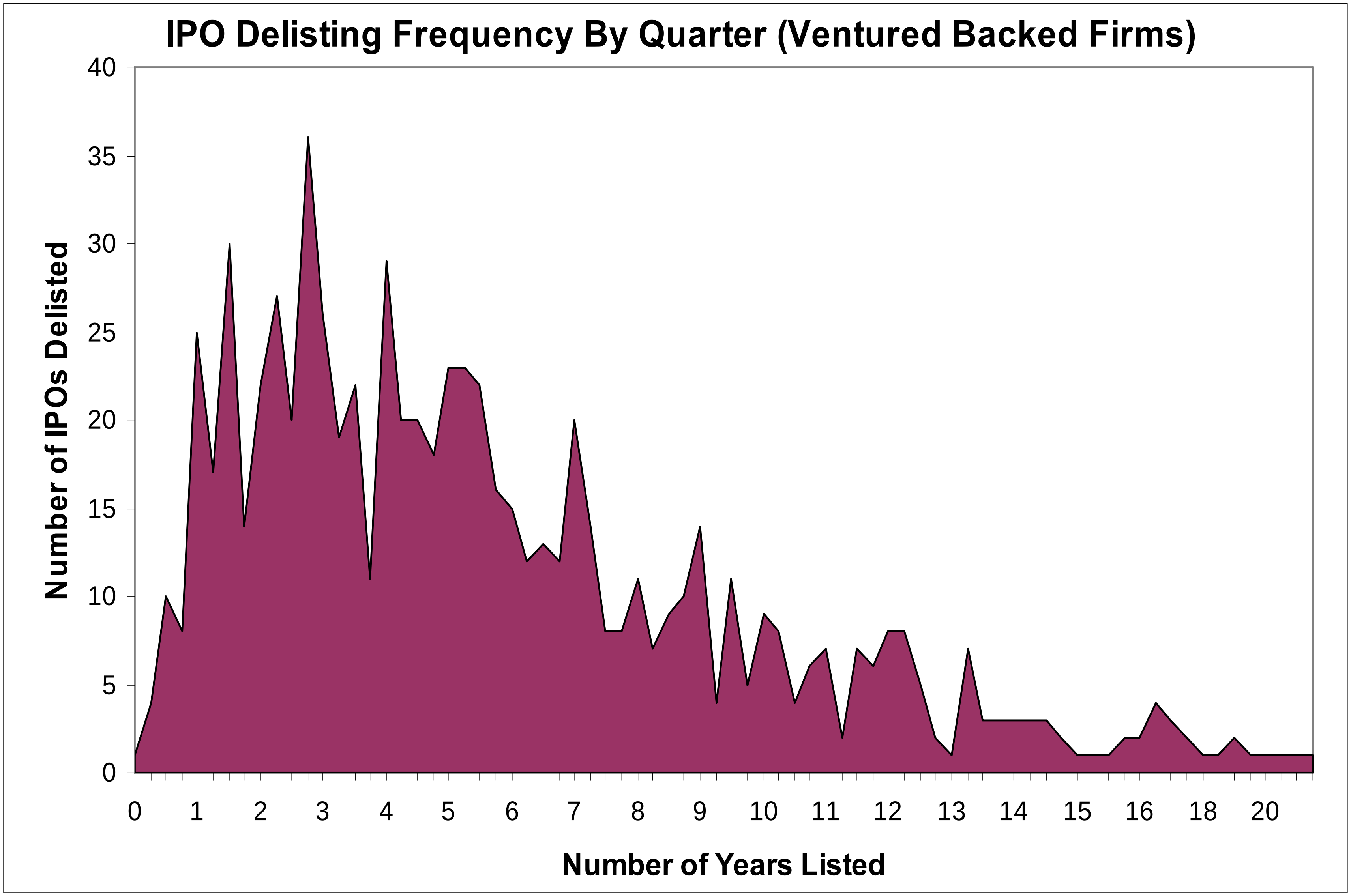

Figure 3(a)-(c)
Cumulative density function (CDF) curves estimated from the AFT modeling for 1985-2007, Sample size =1431 IPOs (Matches Test in Table 8)

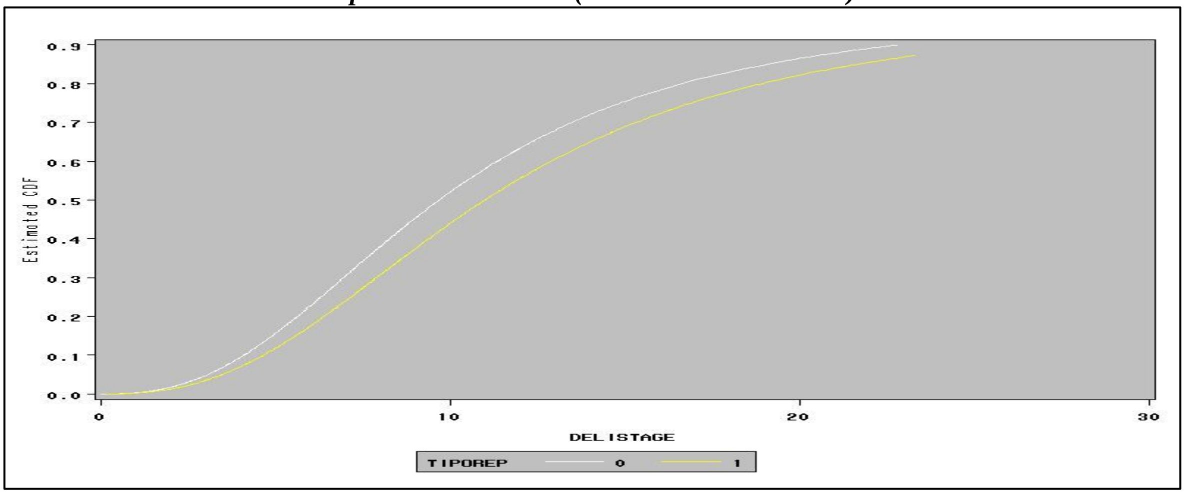

Figure 3(a) Comparison By VC Market Share as Reputation Proxy

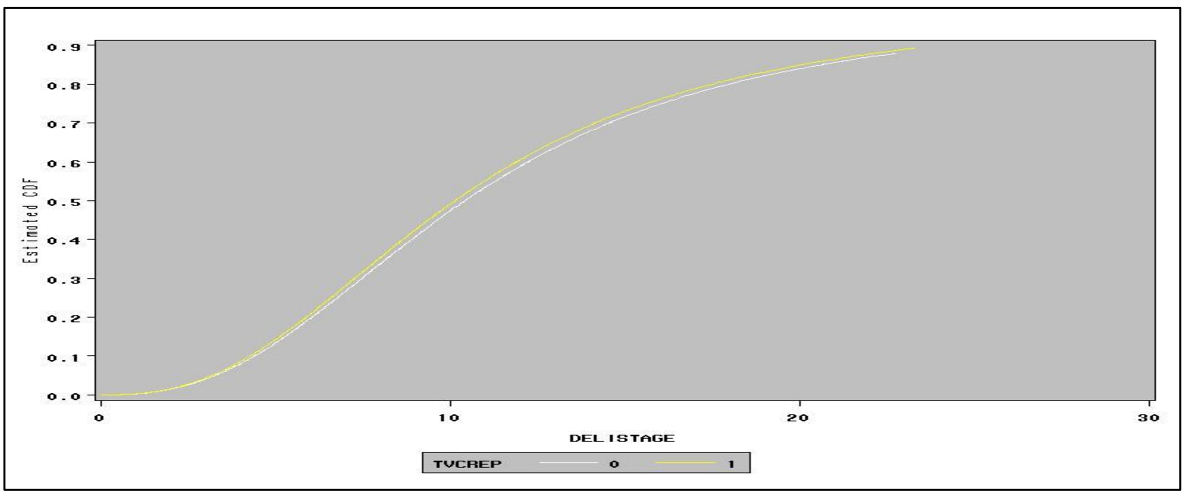

Figure 3(b) Comparison By VC IPO Share as Reputation Proxy

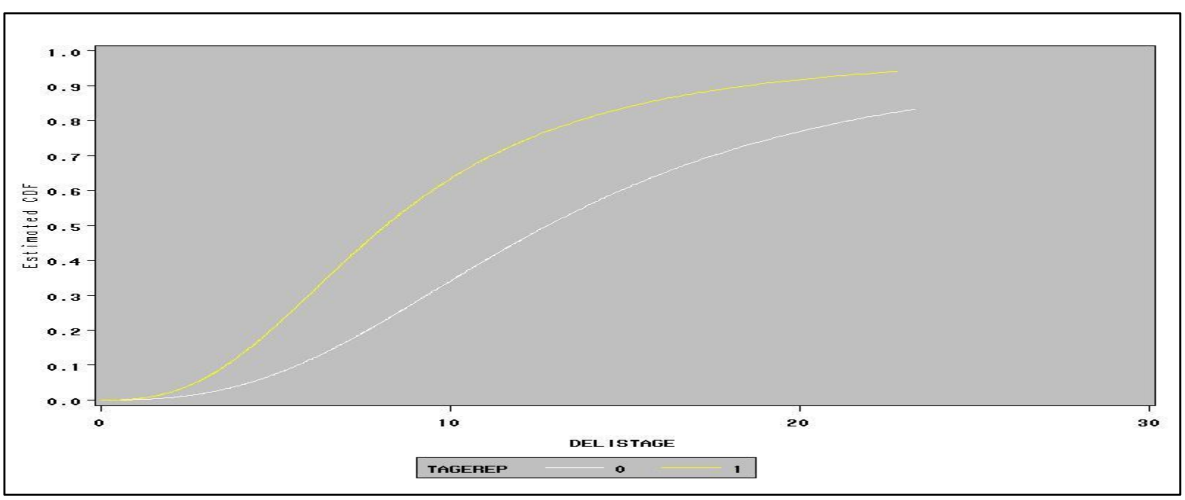

Figure 3(c) Comparison By VC Age as Reputation Proxy

Figure 4(a)-(c)
Cumulative density function (CDF) curves estimated from the AFT modeling for 1985-1996, Sample size = 478 IPOs (Matches Test in Table 9)

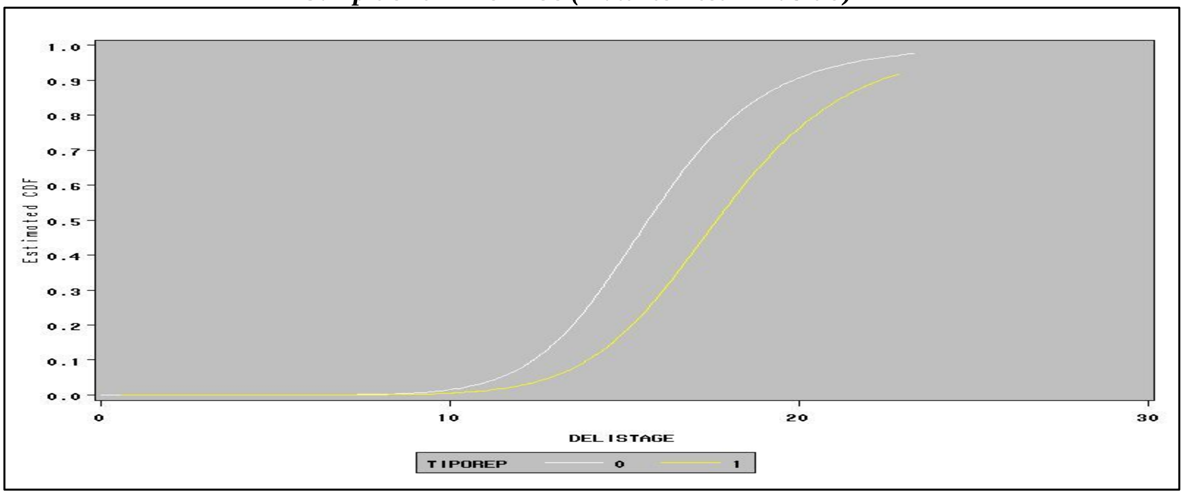

Figure 4(a) Comparison By VC Market Share as Reputation Proxy

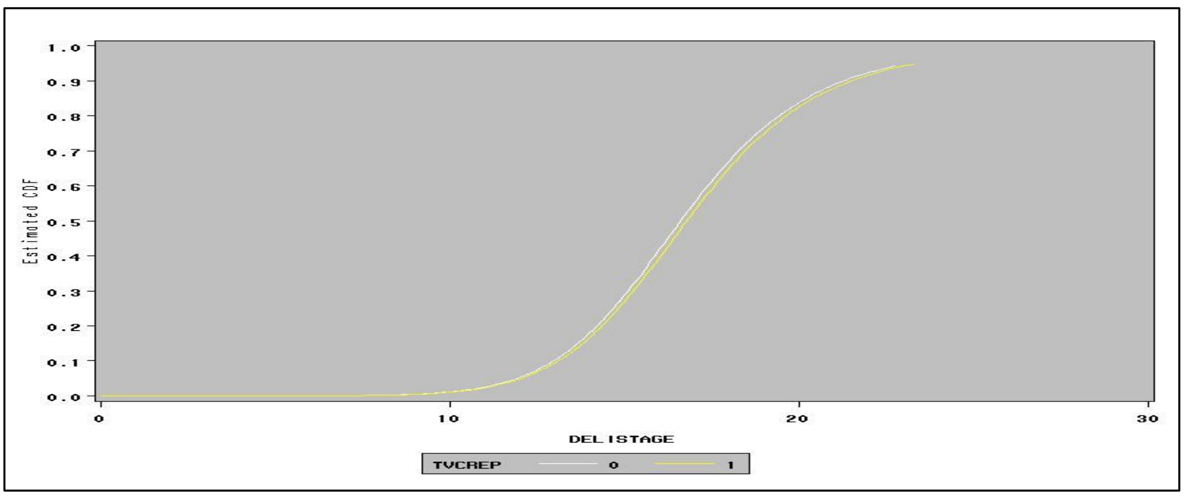

Figure 4(b) Comparison By VC IPO Share as Reputation Proxy

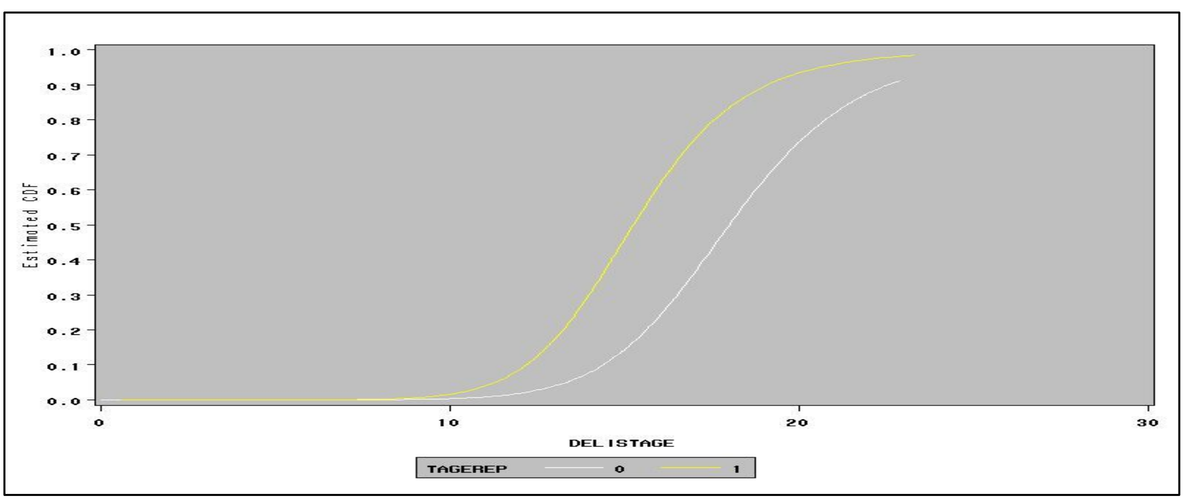

Figure 4(c) Comparison By VC Age as Reputation Proxy

Figure 5(a)-(c)
Cumulative density function (CDF) curves estimated from the AFT modeling for 1996-2007, Sample size = 953 IPOs (Matches Test in Table 10)

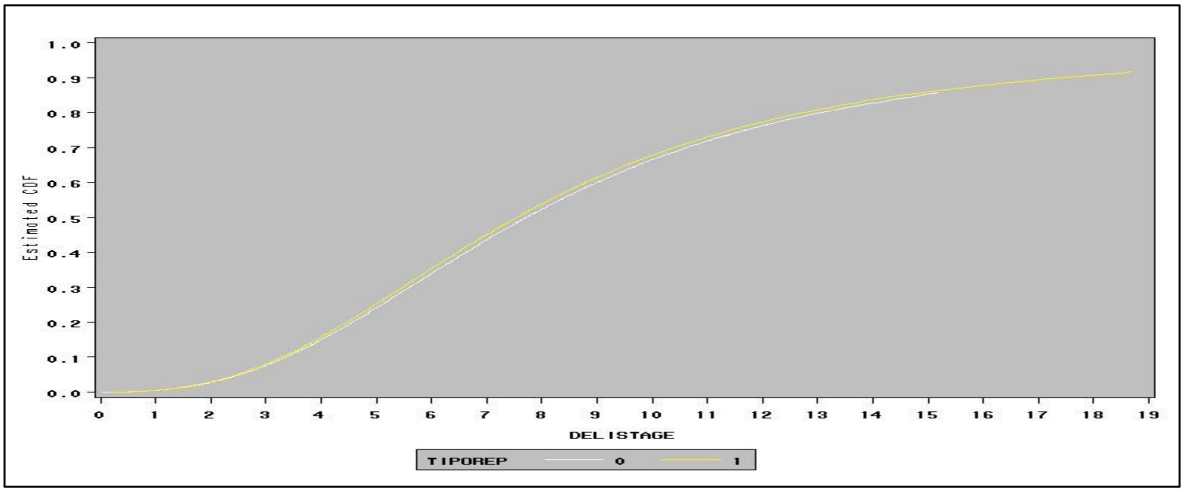

Figure 5(a) Comparison By VC Market Share as Reputation Proxy

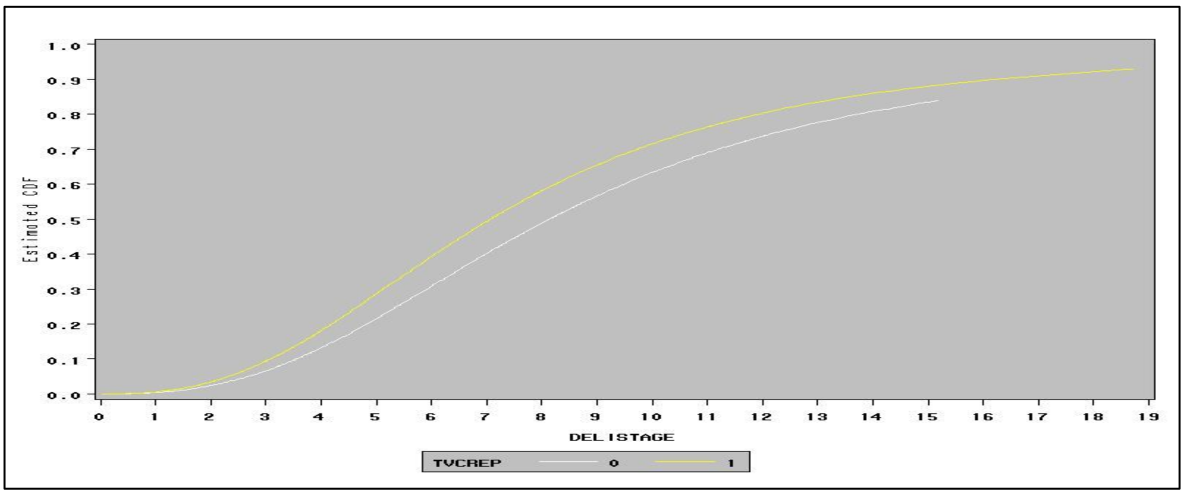

Figure 5(b) Comparison By VC IPO Share as Reputation Proxy

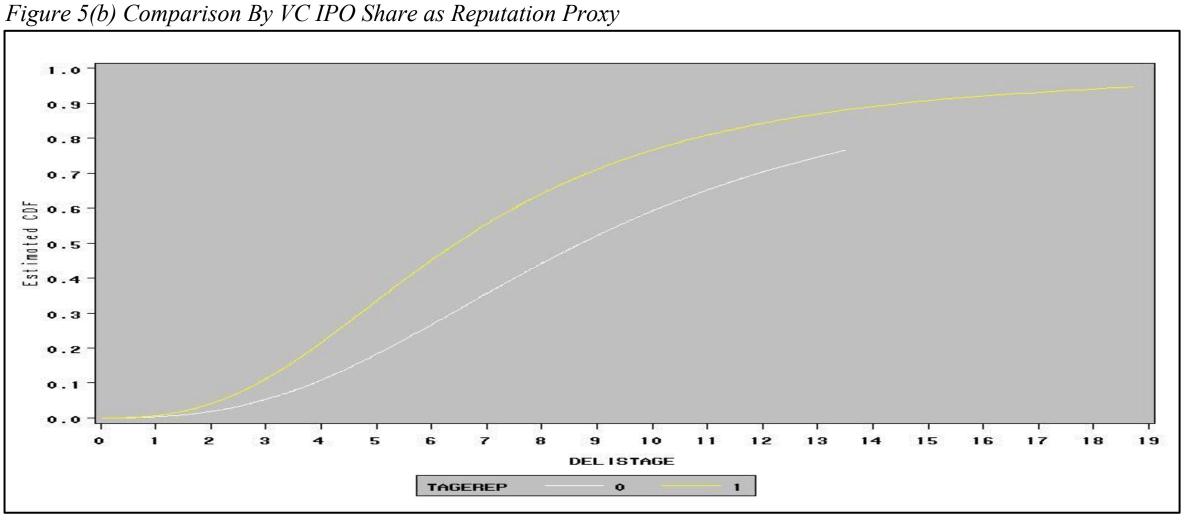

Figure 5(c) Comparison By VC Age as Reputation Proxy

Figure 6(a)-(c)
Cumulative density function (CDF) curves estimated from the AFT modeling for 1985-2007 for top and bottom quartile VC reputation IPOs , Sample size = 711 IPOs (Matches Test in Table 11)

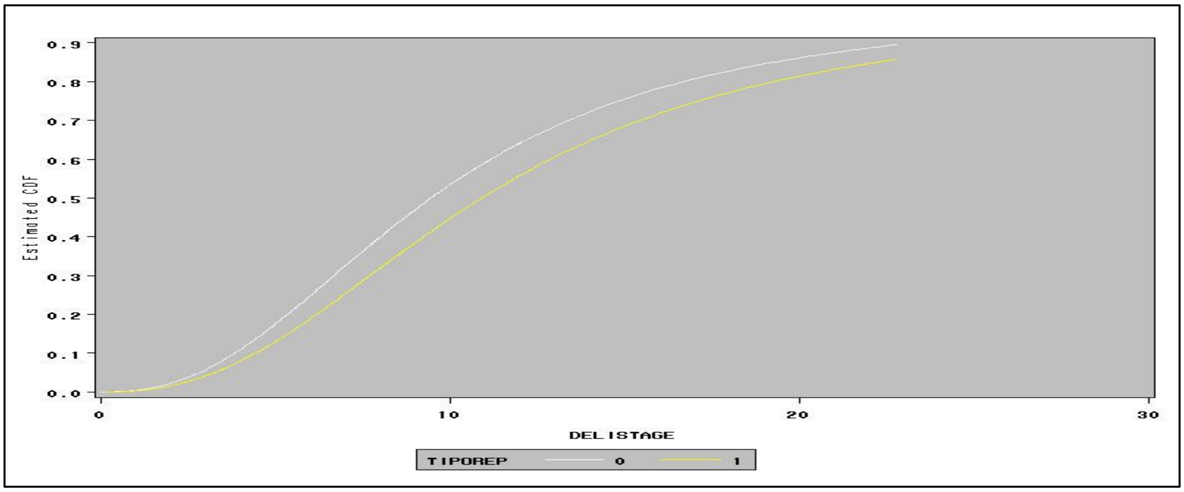

Figure 6(a) Comparison By VC Market Share as Reputation Proxy

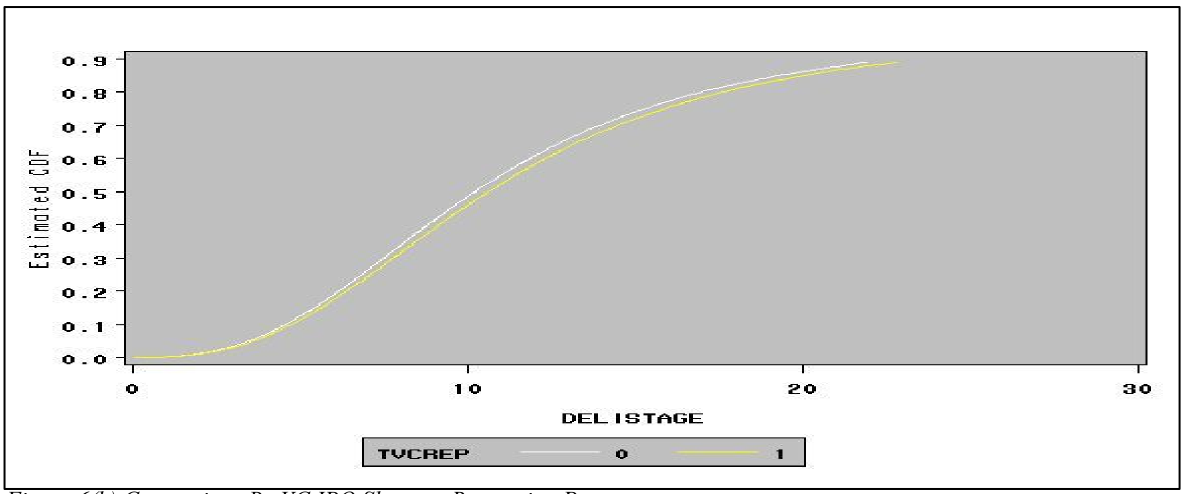

Figure 6(b) Comparison By VC IPO Share as Reputation Proxy

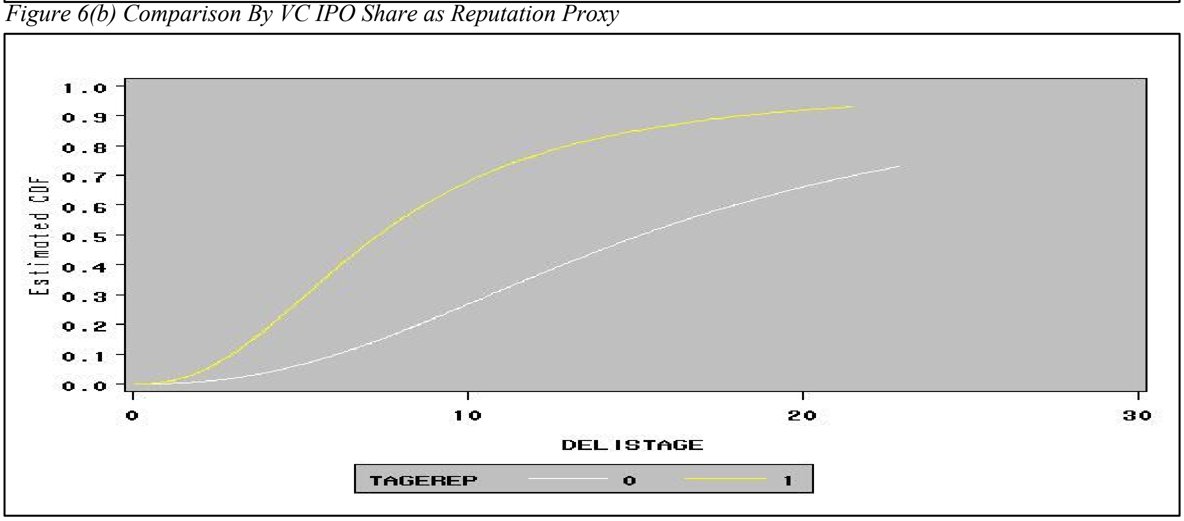

Figure 6(c) Comparison By VC Age as Reputation Proxy

Figure 7(a)-(c)
Cumulative density function (CDF) curves estimated from the AFT modeling for 1985-2007 for third and second quartile VC reputation IPOs , Sample size = 721 IPOs (Matches Test in Table 12)

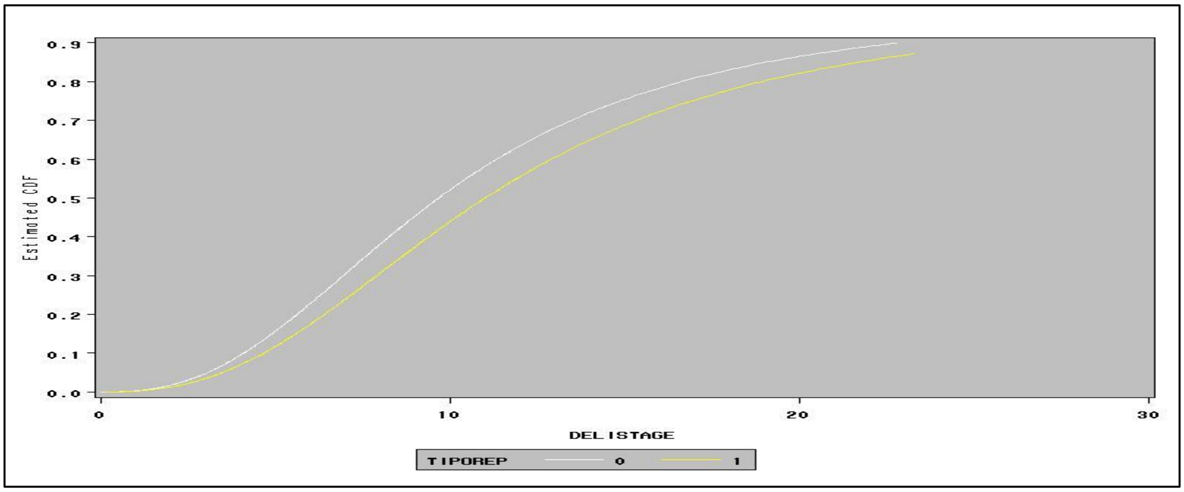

Figure 7(a) Comparison By VC Market Share as Reputation Proxy

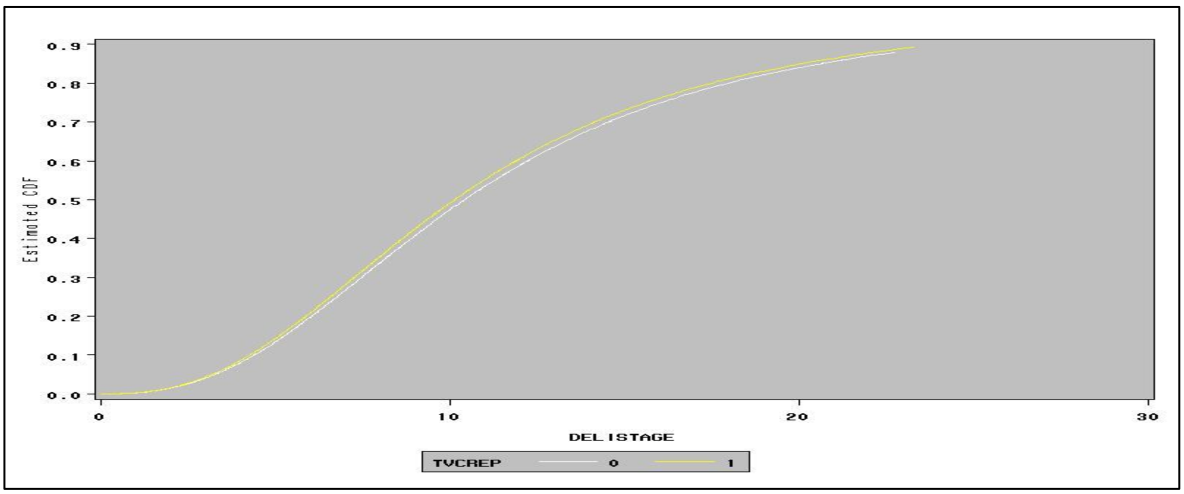

Figure 7(b) Comparison By VC IPO Share as Reputation Proxy

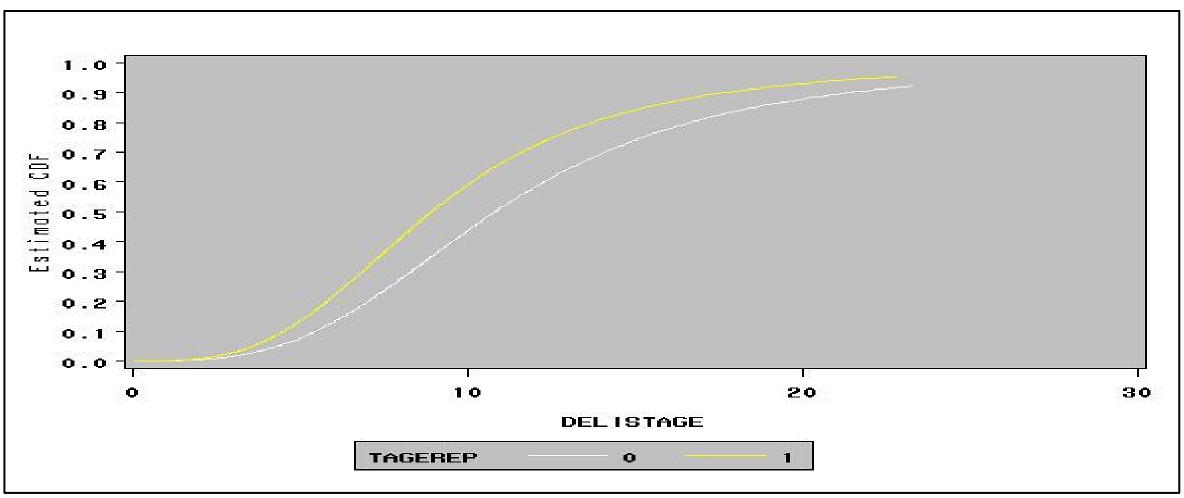

Figure 7(c) Comparison By VC Age as Reputation Proxy