Financial Distress Risk in Initial Public Offerings: How Much Do Venture Capitalists Matter?

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JEL classification: G23, G24, G32, G33
Keywords: Venture capital, Financial distress risk, Bankruptcy, IPOs

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Abstract

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Financial Distress Risk in Initial Public Offerings: How Much Do Venture Capitalists Matter?

Are venture capital (VC)-backed Initial Public Offering (IPO) firms less financialy distressed than other IPO firms? And, if so, do VCs contribute to the financial markets stability? Furthermore, does the lower level of an IPO financial distress only depend on VCs' screening ability or on VC' investments effect too? And is there a relationship between the VCs' value-added intensity and the level of an IPO firm financial distress? These questions have long been empirically debated, but have recently picked up impetus after the 2008-2009 financial crisis which emphasized the need for regulators to keep the risk-taking of financial institutions and public companies at reasonable levels.

There are at least three arguments supporting the idea that VCs contribute to financial markets stability by bringing public firms that show a lower risk of financial distress over the post-IPO period. Firstly, VCs undertake an intensive screening and selection process in order to pick "winning firms" that have favorable future business perspectives (e.g., Gompers and Lerner, 2001; Baum and Silvermann, 2004; Chemmanur, *et al.*, 2011). The screening process involves selecting firms with specific characteristics that should lead to a lower risk of financial distress over the post-investment period (*screening effect*). The selection of firms with a low risk of financial distress should be even more pronounced in the case of bank-affiliated VCs, which are likely to be more risk-adverse than other VCs. As suggested by various studies (Manigart, *et al.*,2002; Croce, *et al.*, 2014) bank-affiliated VCs have less pressure to maximize returns because they do not have to raise funding from third parties. Secondly, VCs supply portfolio firms with the needed equity capital to expand their business. In so doing they enable firms to have a robust capital structure to avoid the burdens of inside collateral and principal and interest payments (*financial effect*). Finally, VCs are also builders of "winning firms" because they add value to portfolio firms by providing them with coaching (e.g., Jain and Kini, 1995; Hellmann and Puri, 2002), effective monitoring (e.g., Lerner, 1995; Kaplan and Strömberg, 2003), and valuable business contacts (e.g., Hsu, 2006; Lindsey, 2008). As a result, the level of financial soundness of firms brought public with VC-backing is likely to be higher than that of non-VC-backed firms, even though their financial soundness at the VC's investment date was analogous to that of non-VC-backed firms (*value-added effect*).

Despite the arguments discussed above, the nature of the relationship between the VC-backing and the IPOs' risk of financial distress may be unclear since there are at least two explanations for expecting a significant portion of economic success obtained by VCs derives from bringing public riskier firms. The first explanation is related to the *certification effect* (Megginson and Weiss, 1991), according to which VCs make it easier for portfolio firms to obtain third part resources, such as bank debt financing (Croce *et al.*, 2014). The presence of a multi-billion dollar venture debt market[1] that accounts for a substantial percentage of the capital raised each year by VC-backed firms corroborates the certification effect and shows that VC financing and debt financing coexist in reality. This is particularly important because if the use of debt delays the dilutive effects of an increase in the number of shares—resulting in decreases in both the firm's performance and the VC's internal rate of return--this can induce a higher risk of financial distress (e.g., Kaplan and Stein, 1993).

[1] Venture debt is a type of debt financing provided to VC-backed firms by specialized lenders to fund working capital or capital expenses. Unlike traditional bank loans, venture debt is available to startups and growth firms that do not have positive cash flows or significant assets to use as collateral. Although quantitative data about venture debt industry are hard to come by, it is a common idea that venture debt is a common piece of start-up capital structures (Ibrahim, 2010). It joined well-known VC-backed companies such as Google and Facebook that have taken venture debt as part of their capital structure to gain first-to-market advantage and to maximize shareholder value.

The second explanation relates to the *grandstanding hypothesis* proposed by Gompers (1996). Since a large part of a VC firm's reputation come from its ability to bring portfolio firms public, and from the fact that establishing reputation is critical for future fundraising, VCs might have an incentive to bring firms they back public too quickly. This would be particularly enticing for low reputation VCs. Thus, these portfolio firms can end up with high risk of financial distress as a result of having gone public prematurely.

Ultimately, in the presence of contrasting predictions about the role of VC backing in IPOs, whether VC-backed firms are less financial distressed than other firms is an empirical puzzle that we seek to solve in this study by analyzing a sample of 1,593 US IPOs between 1990 and 2007, about 27.5% (438) of which are VC-backed IPOs. Following several papers (among others, Coles *et al.*, 2006; Tyknova and Borrell, 2012) we use the *Z-score* (Altman, 1968) as our primary measure of the firm's risk of financial distress. We find that VC-backed companies on average exhibit a higher *Z-score*, meaning that, all else equal, these firms are characterized by a lower risk of financial distress than are non-VC-backed portfolio companies. As a robustness check, we also conduct univariate analyses employing alternative measures of risk for financial distress, such as *ZM-score* (Zmijewski, 1984), *O-score* (Ohlson, 1980), and *Equity ratio* (e.g., Dushnitsky and Lenox, 2006). We find that our results are analogous to the ones we observe using the *Z-score* measure.

We next estimate OLS regressions, where a firm's financial distress-risk measure is a function of a dummy variable for VC-backing and various other firm-specific characteristics, macroeconomic variables, and industry and state dummies. Consistent with the univariate analysis, we strongly document differential risks of financial distress between VC- and non-VC-backed IPOs, which is robust to all the financial distress measures used. This result, however interesting on its own, makes imperative determination of whether the lower risk of financial distress risk for VC-backed IPOs comes from the VCs' screening role only, or from the financial effect and value-added effect as well (henceforth, we will use "treatment effect" to refer to both financial effect and value-added effect). The use of OLS estimations does not allow us to address this issue because the provision and receipt of venture funding represents the result of an endogenous choice by firms and VCs, which is reflected not only in the investment by VCs but also in their eventual exit from the backed firm. This suggests a nonrandom distribution and characteristics of VC-backed IPOs (Lee and Wahal, 2004). Thus, we employ a matching technique, where the one-to-one nearest neighbor is matched without replacement (Heckman *et al.*, 1997), which allows us to control for observed heterogeneity among treated and untreated firms, represented by the characteristics included in the matching process. This approach starts with the estimation of a logit model for the endogenous choice variable (VC=1 for VC backing, 0, otherwise) with a vector of *X* variables (we use age, size, 2-digit SIC code dummies, headquarter-state dummies). Then, the predicted probability is used as the propensity score and each VC-backed IPO is matched with the non-VC-backed IPO with the closest propensity score. Once controlled for selection bias, we estimate OLS regressions. Consistent with our previous results documenting the positive effects of the role of VC-backing in IPOs, we find a negative causal effect of VC financing on the risk of financial distress for firms receiving such financing. In so doing, we document the VC-backed IPOs are less financial distressed than other IPOs because of the treatment effects.

Since the propensity score matching analysis is not without flaws (specifically, it does not control for the effect of unobserved factors) we perform two robustness tests in order to check the resilience of our results. First, we include in the OLS specification the lagged dependent variable to predict the current year's value of the dependent variable (e.g., Baum and Silverman, 2004; Tykvová and Borrell, 2012). Indeed, if VC funding is itself a result of unobserved factors related to financial distress risk, controlling for lagged financial distress risk should eliminate spurious effects resulting from such endogeneity. One again, we document a negative causal relationship between the VC backing and the risk of financial distress for IPO firms.

Second, while restricting the analysis to the VC-backed IPOs, we examine the effect of VC investments intensity (measured through both the length of the investment and the presence or absence of a VC Syndication) on the level of a firm's financial distress and find that the level of financial distress declines as VC investments intensity increases. This result, which is resilient to all the financial distress measures, enables us to provide further evidence in favor of the treatment effect hypothesis.

The rest of this paper is organized as follows: the next section contains the research design. Section 2 discusses the empirical methodology. Section 3 presents the empirical results, and the final section concludes.

1. Research design

1.1 Data and Sample

Our sample consists of US VC- and non-VC-backed IPOs that went public between 1990 and 2007. The final sample is the sum of several steps which are described as follows. First, we obtain the information of whether a firm has been subject to a VC financing from THOMSON ONE database which contains information on mergers and acquisitions, VC and buy-out transactions, and VC investor's exit route. This first step concludes with obtaining a long list of 2,413 VC-backed IPOs. Second, we exclude financial firms – banks, insurance companies, pension funds, etc. – due to the fact that they are not directly comparable to industrial and other service firms (among others, Mazzola and Marchisio, 2002; Anderson and Reeb, 2003, and Martinez, Stohr, and Quiroga, 2007), nonprofit companies – social clubs, sports clubs, and schools – (among others, Martinez, Stohr, and Quiroga, 2007) and finally IPOs with an offer price of less than $5.00 and amount offered of less than $3 million (e.g., Megginson and Weiss, 1991; Jain and Kini, 1994; Lee and Wahal, 2004). As a result, our sample is reduced to 942 VC-backed firms. Third, by using the ticker symbol, we match the rest of the sample with COMPUSTAT, which contains detailed information from balance sheets and profit/loss accounts for US IPOs, and extract the accounting data of related companies. The procedure rejects an additional 357 VC-backed IPOs due to not having a valid ticker symbol. Fourth, leaving unchanged the queries regarding amount offered, offer price, industrial sectors and listing year, we extract all the rest of IPOs in COMPUSTAT, this represents our potential universe of untreated sample of non-VC-backed IPOs. Fifth, we exclude companies for which we do not find complete accounting information even just for a fiscal year after the listing (the sample includes financial data for five years after the listing). The decision to exclude these kinds of firms exposes us to a trade-off between sample size and balancing of sample. On one hand, the non-exclusion of IPOs affected by missing value and without accounting information allows us to have a bigger sample in term of number of individuals. On the other, this excludes the possibility to have a balanced panel data. Another issue is associated with the relation between the time dimension (i.e., how many years after the IPO we want to investigate) and the probability to have a panel data with missing value and/or without accounting information. It is obvious that these factors move in the same direction. By considering these aspects, we opt for a balanced data panel without missing values and accounting information. Finally, because the firm's foundation year which is needed to calculate the age, is not available on COMPUSTAT, we supplement this lack in two different ways. For VC-backed IPOs, we extract this information from THOMSON ONE; for non-VC-backed IPOs, we hand-construct the age variable seeking the firm's foundation year, via ticker symbol, on FACTIVA database, which contains information mainly related to historical market data and financial news archives. As a result, our final sample consists of 1,593 IPOs: 438 VC- and 1,155 non-VC-backed IPOs.

1.2 Endogenity issues and descriptive statistics

Panel A of Table 2 shows the industry distribution of VC-backed IPOs across 2-digit SIC codes that represent about 27.5% of the total sample. Consistent with previous studies (e.g., Megginson and Weiss, 1991; Lee and Wahal, 2004), we find significant variation across industries, from a minimum of one or two units (e.g., SIC code 51) to a maximum of 88 units (i.e. 20.09%), relative to the VC-backed IPOs subsample (SIC code 73). We also find that VC-backed IPOs are concentrated in absolute terms. In fact, just five sectors represented by SIC codes 73, 36, 28, 38 and 35 (i.e., (a) Business services; (b) Electronic and other Electrical Equipment and Components, except Computer Equipment; (c) Chemicals and Allied Products; (d) Measuring, Analyzing, and Controlling Instruments; Photographic, Medical and Optical Goods; Watches and Clocks; and (e) Industrial and Commercial Machinery and Computer Equipment; respectively), make up over 50% of the VC-backed IPOs subsample.

Panel B shows the sample distribution by State in which the firm is headquartered. As shown, also in this case, the data is highly concentrated. Just four States, i.e. California (32.65%), Texas (4.57%), New York City (4.57%) and Massachusetts (10.50%), represent over 50% of VC-backed IPOs subsample.

Panel C shows the sample distribution of VC- and non-VC-backed IPOs for each calendar year. The distribution is consistent with the "hot issue market theory" (among others, Ibbotson and Jaffe, 1975; Ritter, 1984) according to which the firms choose the timing to go public in a non-random manner. In fact, they prefer to go public in a market period that isparticularly favorable (periods of upper trend). Consistent with this theory, it is noted the high number of VC- and non-VC-backed IPOs listed over 1999-2000 and 2007. An additional consideration should be made at the level of a firms' characteristics. Table 1 shows statistics related to the IPO fiscal year's total assets (in $ million), book value of equity, revenue, age, market value and Capex ratio. Consistent with other studies in this field (among others, Megginson and Weiss, 1991; Lee and Wahal, 2004), VC-backed IPOs are younger and smaller with lower book values of equity, lower revenues, and smaller assets.

Since VC-backed IPOs are concentrated in certain sectors and geographic areas and show different characteristics compared to non VC-backed IPOs, the idea of VC financing as the result of a random process cannot be shared. A selection bias arises because firms have the chance to ask for VC funding (see Bertoni *et al.*, 2012a, b), and equally, VC investors can pick up their target firms from a huge group of possible investable firms.

Insert Table 1 about here

Insert Table 2 about here

1.3 Propensity score matching

To measure VCs effect on firms' financial distress risk after the IPO, we observe differences in the outcomes, record both VC- and non-VC-backed IPOs on relevant variables able to predict the financial distress risk (see section 2.1).

One crucial aspect in the construction of the counterfactual sample is the selection of a valid control group. Many sample distribution statistics shown in Table 2 are in line with previous US studies addressing VC. More specifically, some authors (e.g.,Gompers and Lerner,2000; and Megginson,2004) report similar industry and geographic concentrations, while others (e.g., Megginson and Weiss, 1991; Bradley and Jordan, 2002; Lee and Wahal, 2004) highlight differences in characteristics of VC- and non-VC-backed IPOs. This is, consistent with the belief that VCs tend to specialize both to sector and geographic area. We employ a methodology which takes into account endogenous choice in a matching context, allowing causal inference in non-experimental settings. We define y_1 as a one-year measure of financial distress risk for an IPO firm with VC backing, y_0 as a one-year measure of financial distress risk for the same IPO firm without VC backing, and "VC", dummy variable, which is set on 1 for VC-backed IPO firms and zero otherwise. Our interest is focused on the difference $y_1 - y_0$, but this result is unobservable for a single firm because, simply, a firm either receivesVC backing or not. Therefore, the most important information comes from estimating the average VC effect at population level. In formal terms, we are interested to $E(y_1 - y_0|VC = 1, X)$ that is equal to:

$$E(y_1 - y_0|VC = 1, X) = E(y_1|VC = 1, X) - E(y_0|VC = 1, X)$$

where X is a set of variables that represent the firms and industry characteristics. Unfortunately, as mentioned so far, VCs tend to specialize to both sector and industry, without considering the screening and selection process done in order to choose the best target firm (see Kaplan and Strömberg, 2004). Consequently, VC investments are not random, and randomization of treatment is unrealizable. So, applying this procedure means coming across a bias, formally defined as:

$$b(X) = E(y_0|VC = 1, X) - E(y_0|VC = 0, X)$$

To solve this bias issue, Rosenbaum and Rubin (1983) propose the propensity score approach. This method requires the estimation of a logit model for the endogenous choice variable (VC=1 for VC backing, zero otherwise) with a vector of X variables. In other words, the purpose of this matching approach is to find a comparable firm that has similar characteristics of VC-backed IPO firm but with the unique difference that VCs have no equity position on it. The procedure that we employ is described as follows. First, we choose the endogenous dependent variable on the propensity score model which is the dummy variable VC. Second, we choose the independent variables of the model: Age, Total Assets, Industry dummies based on 2- digit SIC code, firms' headquarter-state dummies. Third, we run a logit regression, based on the accounting data in the year of the IPO, to calculate the firms' propensity score. As a result, we obtain 1,593 value of propensity scores: one for each firm. Finally, after imposing a strict radius equal to ±0.01 propensity score unit and by applying the "radius matching" criterion (see Becker and Ichino, 2002), for each VC-backed firm we choose the matching firm, which fall within the radius just described, utilizing the procedure without replacement (among others, Heckman, Ichimura, and Todd, 1997). This methodology permits us to match each VC-backed IPO with one or more non-VC-backed IPO(s). However, in our case, we never find more than one matching firm for each VC-backed IPO. This leads to a state that in our case, the "radius matching" is exactly equivalent to the "nearest-neighbor matching" methodology. In addition, we check whether the matching procedure is able to balance the distribution of the relevant variables in both the control and VC group (balancing property)[2]. Formally, the matching criterion can be written as follows:

$$C = \underbrace{\{p_j | \quad \|p_i - p_j\| \leq r\}}_{Radius\ Matching} \overset{in\ our\ case}{\triangleq} \underbrace{\min_j \|p_i - p_j\|}_{Nearest-Neighbor\ Matching}$$

where C is the control firm; i is VC-backed IPO firm; j is non-VC-backed IPO firm; r is the radius. Consequently, we obtain a sample composed of 316 VC- matched with 316 non-VC-backed IPO firms. This strict selection criterion which we adopt leads us to exclude 122 companies (i.e., 438 minus 316) because no one comparable is found[3].

In addition, as a further control, we employ a matching process with replacement that is based on a kernel estimator that uses a distribution to specify weights. Specifically, we use a Gaussian Kernel distribution where each VC-backed IPO is matched with one or more non-VC-

[2] Becker and Ichino (2002) p. 359: "[…] Lemma 1. Balancing of pretreatment variables given the propensity score. If $p(X)$ is the propensity score, then $D \perp X \mid p\,(X)$. (D in our case is equal to VC).
Lemma 2. Unconfoundedness given the propensity score. Suppose that assignment to treatment is unconfounded; i.e., $y_1, y_0 \perp D \mid X$. Then assignment to treatment is unconfounded given the propensity score, i.e., $y_1, y_0 \perp D \mid p(X)$.
If the Balancing Hypothesis of Lemma 1 is satisfied, observations with the same propensity score must have the same distribution of observable (and unobservable) characteristics independently of treatment status. In other words, for a given propensity score, exposure to treatment is random and therefore treated and control units should be on average observationally identical. Any standard probability model can be used to estimate the propensity score. […]"

[3] In other words, no one comparable falls in the range imposed by us.

backed IPOs, however, with the propensity score approach, calculating the difference between the financial distress risk measures of a VC-backed IPO and the matched of non-VC backed IPO(s). We use bootstrapped standard errors to conduct statistical inference. The bootstrapping is based on 50 replications. We also calculate selection-bias-adjusted 95% confidence intervals. The results are shown in Table 3.

Insert Table 3 about here

2 Empirical methodology

2.1 Financial Distress Risk Measures

Aside from the *Equity Ratio* variable, all the financial distress risk measures used in this study are the result of a maximum-likelihood estimation (MLE)[4] of the so-called conditional logit model, this is the case for the Zmijewski (1984) and Ohlson (1980) models, and multiple discriminant analysis (MDA)[5], this is the case for theAltman (1968) model. The decision to use three different models comes from taking into account three different aspects. First, the

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[4] Assume that X_n is a vector of predictors for the *n*-th observation; assume that δ is a set of unknown parameters and assume that $P(X_n;\ \delta)$ is the probability of bankruptcy corresponding to given values of X_i and δ. The log-likelihood function of any specific outcomes is given by:

$$l(\delta) = \sum_n (P) ln[X_n; \delta] + \sum_n (1 - P)\, ln[1 - X_n; \delta]$$

now, the assessment parameters are estimated for equation by maximizing the log-likelihood function i.e. by solving $\max_\delta l(\delta)$

[5] Discriminant analysis is used to classify cases into one or more groups of populations on the basis of a set variables measured on each case. The populations are known by the scholar to be distinct and to which each individual belongs. the *discriminant function* is the linear combination of the independent variables that will best discriminate between the *a priori* identified groups. Discrimination is achieved by finding the linear combination that maximizes the differences between the groups. With *n* observations and *p* independent variables, $1 < i < p$ and $1 < k < m$, the *discriminant function*, can be written as follows:

$$Z = \alpha + v_1 X_{1k} + v_2 X_{2k} + \dots + v_n X_{nk}$$

where *Z* is the discriminant *Z*-score calculated using the *j-th* discriminant function on the *k-th* observation; α is the intercept, v_i is the discriminant weight for independent variable *i*, and *Xij* is the *i-th* independent variable measured on the *k-th* observation. In general, this technique is most used for more-than-two groups. Vice versa, *logistic regression* is most common when there are only two groups.

simplicity of computation. In fact, all three measures primarily use accounting data which are easily retrieved from the COMPUSTAT. Second, as argued by Zmijewski (1984) p.59, studies *"typically estimate financial distress prediction models on nonrandom samples. Estimating models on such samples can result in biased parameter and probability estimates if appropriate estimation techniques are not used"*[6]. Thus, we use Zmijewski model which is calibrated to a random sample in order to deal with this phenomena. Finally, a potential disadvantage by utilizing Zmijewski or Ohlson's model is that they do not consider any market transactions (e.g., price) data of the firms. To cover this aspect as a further financial distress measure, we use the *Z-score* model by Altman (1968) which incorporates the market capitalization, computed as a product between number of share per stock price recorded at the end of each fiscal year. In sum, we use four financial distress risk measures which can be described as follows:

Z-score model (Altman,1968),

$$Z - score = 1.2 \underbrace{\left(\frac{WC}{TA}\right)}_{X_1} + 1.4 \underbrace{\left(\frac{\mathrm{RE}}{TA}\right)}_{X_2} + 3.3 \underbrace{\left(\frac{EBIT}{TA}\right)}_{X_3} + 0.6 \underbrace{\left(\frac{MC}{TL}\right)}_{X_4} + 1.0 \underbrace{\left(\frac{TR}{TA}\right)}_{X_5}$$

with *WC* being working capital; *TA* total assets; *RE* retained earnings; *EBIT* earnings before interest and taxes; *MC* market capitalization; *TL* total liabilities; and *TR* total revenue. The five sub-ratios which form this score reflect: X_1, the measure of the net liquid assets of the firm relative to the total capitalization. Working capital is defined as the difference between current assets and current liabilities; X_2, the measure of cumulative profitability over time. It provides an

[6] In other words, Zmijewski states that previous studies are affected by at least two kinds of biases. The first bias results from oversampling distressed firms compared to non-distressed firms, having, in this way, a final sample poorly near the reality *(choice-based sample biases).* The second bias results from using a complete data sample selection criterion. But, notoriously the data for distressed firms are often incomplete *(sample selection biases).*

estimate of how companies face the risk of default. This measure implicitly takes into account the age of the firm since older firms probably show a higher value of this ratio; X_3, the operating efficiency apart from tax and leveraging factors. Altman states that *"this ratio appears to be particularly appropriate for studies dealing with corporate failure. Insolvency in a bankruptcy sense occurs when the total liabilities exceed a fair valuation of the firm's assets with value determined by the earning power of the assets"*; X_4, this measure indicates that when the *MC* tends to approach or become smaller of the total debt, the firm becomes insolvent and eventually bankrupt; X_5, measure of management's capability of a firm to generate profits, *ceteris paribus*, to its peers. An higher value of the *Z-score* indicates a less financial distress risk[7].

ZM-score model (Zmijewski, 1984),

$$ZM - score = -4.336 - 4.513\left(\frac{NI}{TA}\right) + 5.679\left(\frac{TL}{TA}\right) + 0.004\left(\frac{CA}{CL}\right)$$

with *NI* being net income; *TA* being total assets; *TL* total liabilities; *CA* current assets; and *CL* current liabilities. A higher *Zmijewski-score* value indicates a higher financial distress risk.

O-score model (Ohlson, 1980),

[7] Altman defines the following zones of discrimination: Z > 2.99 safe zone; 1.81 < Z < 2.99 gray zone; Z < 1.81 distress zone.

$$O - score = -1.32 - 0.407\log(TA) + 6.03\left(\frac{TL}{TA}\right) - 1.43\left(\frac{WC}{TA}\right) + 0.076\left(\frac{CL}{CA}\right)$$
$$- 1.72\, D_{TL-TA} - 2.37\left(\frac{NI}{TA}\right) - 1.83\left(\frac{FFO}{TL}\right) + 0.285\, D_{LOSS}$$
$$- 0.521\left(\frac{NI_t - NI_{t-1}}{|NI_t| + |NI_{t-1}|}\right)$$

with *TA* being total assets; *TL* total liabilities; *WC* working capital; *CL* current liabilities; *CA* current assets; D_{TL-TA} being a dummy variable which takes value 1 if total liabilities are higher than total assets, 0 otherwise; *NI* being net income; FFO being funds from operations; and D_{LOSS} being a dummy variable which takes value 1 if the company realized a net loss in the last two years, zero otherwise. An higher *O-score* value is associated with a higher financial distress risk.

Equity ratio,

$$Equity\ ratio = \frac{EQ}{TA}$$

Equity ratio (exactly equivalent to *Leverage*$^{-1}$) is simply the book value of total equity *(EQ)* normalized by total asset *(TA)*. As argued by Andrade and Kaplan (1998), a high level of leverage is one of the primary causes of financial distress. So in this study, we use the *Equity ratio* as a further variable in order to complete the picture of financial distress risk measures. A higher value of the *Equity ratio* indicates a lower financial distress risk.

Insert Table 4 about here

2.2 *Specification models*

In order to correctly evaluate the impact of VC financing on a company's financial distress risk, we base the multivariate analysis on two steps which differ depending on the sample composition. Specifically, we first run a *OLS* on the panel data for estimating the *model 1* which is specified as follows:

Model 1 $$y_{i,t} = \alpha + \beta_1 VC_i + \delta X_{i,t} + \varepsilon_{i,t}$$

where *i* denotes a firm (*i* = 1, 2, …, 1,593). In our first round of the analysis, we consider the full sample as an experimental setting (i.e., 1,593 IPOs) composed of 438 VC-backed IPOs and 1,155 non-VC-backed IPOs selected and reported in the data and sample section; *t* denotes the time dimension represented by the five fiscal years after the listing year (*t* = 0, 1, 2, 3, 4, 5), *y* denotes the financial distress risk measures (i.e., *Z-score, ZM-score, O-score, Equity ratio*); *VC* is a dummy variable which is set to 1 for VC backed IPOs firms and 0 otherwise; *X* is a vector of control variables; and ε is the random error term. Second, we attempt to deal with the endogeneity concern, that affect our initial sample (see section 1.2), by estimating the *model 1* using, in an experimental setting, a subsample composed of 316 VC-backed IPOs matched with 316 non-VC-backed IPOs (see section 1.3 for a deeper explanation). The variables definitions are reported in appendix (see Table A1).

3 Econometric results

3.1 Impact of VC backing on IPO firm financial distress risk

Table 5 presents the results of estimating the impact of VC backing on the risk of financial distress on IPO firms by using the *OLS* regression model. The dependent variables are *Z-score* (*columns I* and *II*), *Equity ratio* (*columns III* and *IV*), *ZM-score* (*columns V* and *VI*) and

O-score (*columns VII* and *VIII*), respectively. As highlighted in Table 1, high values of *Z-score* and *Equity Ratio* are associated with a low risk of financial distress, whereas high values of *ZM-score* and *O-score* are associated with a high risk of financial distress. *Columns I*, *III*, *V* and *VII* report the results of estimating *model 1*, where the risk of financial distress on a firm is a function of a dummy variable for VC-backed IPOs, various other firm-specific characteristics, and macroeconomic-specific variation. *Columns II*, *IV*, *VI* and *VIII* report estimations obtained by adding to the baseline regression specification the *Industry* and *State* dummy variables.

Insert Table 5 about here

We find that several factors are statistically significant drivers of the risk of financial distress on IPO firms. Specifically, financial distress measures are negatively influenced (at the 5% confidence level or less) by firm size, the growth rate of GDP, and positively influenced (at the 5% confidence level or less, except for *O-score*) by firm age. Also unsurprisingly, the set of dummy variables describing the industrial sectors and the territorial differences contribute to explain the IPO firms risk of financial distress. In contrast the coefficient of *Capex* is almost never significant.

In regards to the impact of VC backing on the risk of financial distress of IPO firms, we find, in line with the univariate analysis, that VC-backed IPO firms exhibit significantly lower risk of financial distress to that of other IPOs (at the 1 % confidence level or less). In terms of *Z-score* and *Equity ratio*, the coefficient of *VC* variable is positive (e.g., in *columns II and IV:* 3.503 and 0.082, respectively) and highly significant (*in columns II and IV*: 4.96 and 5.03, respectively). In terms of *ZM-score* and *O-score*, the coefficient of the *VC* variable is negative (e.g., in *columns VI and VIII*: -0.658 and -0.685, respectively) and significant (in *columns VI and VIII*: -4.19 and -3.89, respectively). As such, our earlier empirical results are consistent with both the screening hypothesis and the treatment effect hypothesis (financial effect plus value-added effect).

Once documented that VC-backed IPO firms display a lower risk of financial distress than other IPOs, the second step of our analysis has been aimed to satisfy the need for the determination of whether this result comes from the VCs' screening role or the treatment effect (or from both).

Following various papers (among others, Lee and Wahal, 2004; Chemmanur *et al*., 2011; Croce *et al*., 2013) to properly evaluate the treatment effect in OLS estimation, or net of the screening effect, we implement the propensity score matching-based analysis which allows us to control for observed heterogeneity among treated (i.e. VC-backed firms) and untreated firms (i.e. non-VC-backed firms), represented by the characteristics included in the matching process. As highlighted in the section 1.3, a matching estimator contributes to solve the selection bias problem by pickingeach VC-backed firm that received VC financing in year *t*, the non-VC-backed firm that in the same year t had the most similar probability (i.e., the closest propensity score) of receiving VC. Table 6 presents the results of the propensity score matching-based analysis.

Insert Table 6 about here

One again for each dependent variable of interest, we estimate two OLS specifications, one with (*columns II, IV, VI* and *VIII*) and another without (*columns I, III, V* and *VII*) *Industry* and *State* dummy variables. Newly, in terms of *Z-score* and *Equity ratio* the coefficient of VC variable is positive (e.g., in *column II and IV:* 3.311 and 0.112, respectively) and highly significant (in *column II and IV*: 3.22 and 4.17, respectively), whereas in terms of *ZM-score* and *O-score* the coefficient of *VC* is negative (e.g., in *column VI and VIII*: -0.923 and -0.862, respectively) and significant (in *column VI and VIII*: -3.19 and -3.07, respectively). Thus, the coefficients of *VC* variable maintain their significance after being controlled for observed heterogeneity among VC-backed firms and non VC-backed firms. That is, the lower risk of financial distress of VC-backed IPO firms depends not only on the VCs' screening ability but also on the financial and non-financial services they provide to the backed firms. As observed by Chemmanur *et al.,* 2011, one possible limitation of the propensity score matching analysis is that it does not control for the effect of unobserved factors (such as a brilliant business idea) on the selection of firms that get VC financing. As such, in the next section we perform a couple of robustness checks in order to further confirm our results about the impact of VC backing on the risk of financial distress of IPOs.

3.2 Robustness checks

In this section we perform two additional robustness checks in an attempt to confirm our earlier results about the effects of VC investments on IPO firms.

First, we estimate the OLS with one lagged value of the dependent variable in an attempt to account for the possibility that our empirical models of IPO firms' financial distress risk suffer from specification bias due to unobserved heterogeneity. The results are reported in Table 7.

Insert Table 7 about here

Inclusion of the lagged dependent variable results in a loss of 1,351 observations reducing the sample from 8,487 to 7,136 observations, and in an increase in the explanatory power of the OLS regressions (e.g., the R^2 of the OLS regression in *column I* is 0.2700, much more than the value of 0.0280 reported in *column I* of Table 5), even if the effects of VC backing on the risk of financial distress remain substantially unchanged. Indeed, except for the results reported in *column 2*, the dependent variables are influenced by *VC* variable at the 1% confidence level or less. Therefore, also these results are consistent with the treatment effect hypothesis.

Second, we restrict the analysis to the VC-backed firms and specify a linear model to verify whether the firm's financial distress varies across IPO firms according to the effectiveness of VC investments. Indeed, if the VC treatment effect hypothesis is true, then we expect that among VC-backed firms characterized by a higher VC investment's intensity exhibit a lower risk of financial distress. Following various papers (among others, Jain and Kini, 1995; Wang *et al.*, 2003; Tian, 2012), we measure the intensity of a VC investment through two indicators: (a) the length of time between the induction of the first VC on the board of directors and the IPO (*LI*), and (b) the VC Syndication dummy (*Syndication*)[8], i.e., a variable assuming the value of 1 for firms in which pre-IPO shareholding were two or more VC investors.

The idea behind the use of *LI* is that the longer the investment period, the greater the opportunities VCs have to add value to portfolio firms and influence their actions. Furthermore, we use *Syndication* because when VC investors form a Syndicate to co-invest in a project, Syndicate members who have heterogeneous skills, information, industry expertise, and networks can provide a broad range of inputs for entrepreneurial firms (Tian, 2012).

[8] The data are hand collected from IPO prospectuses (for the year of the offering), retrieved from filing section of Thomson ONE. We set the dummy variable *Syndication* on 1 if at the time of offering there are more than one VCs with equity position in the target firm, and 0 otherwise.

Insert Table 8 about here

Table 8 reports OLS estimations for each dependent variable of interest. As expected *LI* displays a positive correlation with the *Z-score* and *Equity ratio* (at the 10% confidence level or less), and a negative correlation with *ZM-score* and *O-score* (at the 1% confidence level or less). Even *Syndication* shows a positive correlation with the *Z-score* and *Equity ratio* (at the 5% confidence level or less), and a negative correlation with *ZM-score* (at the 10% confidence level or less), though its relationship with *O-score* is negative but not significant.

Overall, we are able to confirm the idea that the greater the VC investments intensity, the lower the risk of a IPO firm financial distress. As a consequence, once again, we report findings suggesting the existence of a negative causal relationship between the VC financing and the risk of financial distress for firms receiving such financing.

4. Conclusions

Many empirical studies have investigated the effect of VC investments on portfolio firms, principally in terms of growth, efficiency, profitability, innovation, and probability of going public. Our paper adds to the empirical evidence by analyzing the effects of VC investments on the risk of financial distress of portfolio firms. Specifically, we use a sample of 1,593 US IPOs between 1990 and 2007 to examine whether after going public VC-backed IPO firms are less financially distressed than other ones, and report two main results.

First, while controlling for other determining factors of a firm's risk of financial distress (e.g., size and age), we find that among IPO firms, those with VC backing exhibit a lower risk of financial distress. This result, which can be consistent with either the screening hypothesis or the treatment hypothesis (or both), is resilient to all the financial distress measures used (i.e., Z-score; ZM-score; O-score; and Equity ratio). Second, we disentangle the screening and treatment effects of VC backing by using propensity score matching. We find that the lower risk of financial distress of VC-backed IPO firms depends both on how VC investors select their investments (screening ability), and on the business support (financial and non-financial) they provide to a portfolio firm. This result is resilient to a number of robustness tests performed to check for possible limitations of the propensity score matching analysis.

Our study contributes both to academic research and to recent policy discussions about the increasing risk of financial markets by analyzing the impact of VC investments on an IPO's risk. Policymakers and regulators are afraid that IPOs may produce adverse effects on the financial system as a whole by transferring too much risk from entrepreneurs and institutional investors to retail investors, thus causing contamination effects when huge firms fail not long after the IPO. Investors share the same concerns as regulators even if for different reasons. We provide evidence that the VC industry represents an effective tool to mitigate these worries and provides valuable support for financial market stability.

References

Altman, E. I. 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance* 23: 589-609.

Anderson, R. C., and D. M. Reeb. 2003. Founding-family ownership and firm performance: evidence from the S&P 500. *Journal of Finance* 58: 1301-1327.

Andrade, G., and S. N. Kaplan. 1998. How costly is financial (not economic) distress? Evidence from highly leveraged transactions that became distressed. *Journal of Finance* 53: 1443-1493.

Baum, J. A., and B. S. Silverman. 2004. Picking winners or building them? Alliance, intellectual, and human capital as selection criteria in venture financing and performance of biotechnology startups. *Journal of Business Venturing* 19: 411-436.

Becker, S. O., and A. Ichino. 2002. Estimation of average treatment effects based on propensity scores. *The Stata Journal* 2: 358-377.

Bertoni, F., A. Croce, and M. Guerini. 2012. How and when venture capital affects the investment of portfolio firms *(SSRN Scholarly Paper No. ID 2149544). Social Science Research Network. Retrieved from SSRN: http://ssrn.com/abstract=2149544*.

Bertoni, F., D. D'Adda, and L. Grilli. 2012. Cherry picking or frog kissing? The matching process between investors and entrepreneurial ventures in thin venture capital markets *(SSRN Scholarly Paper No. ID 2138247). Social Science Research Network. Retrieved from http:// papers.ssrn.com/abstract=2138247.*

Bradley, D. J., and B. D. Jordan. 2002. Partial adjustment to public information and IPO underpricing. *Journal of Financial and Quantitative Analysis* 37: 595-616.

Chemmanur, T. J., K. Krishnan, and D. K. Nandy. 2011. How does venture capital financing improve efficiency in private firms? A look beneath the surface. *Review of Financial Studies* 24: 4037–90.

Coles, J. L., N. D. Daniel, and L. Naveen. 2006. Managerial incentives and risk-taking. *Journal of Financial Economics* 79: 431-468.

Croce, A., D. D'Adda, and E. Ughetto. 2014. Venture capital financing and the financial distress risk of portfolio firms: How independent and bank-affiliated investors differ. *Small Business Economics, forthcoming*.

Croce, A., J. Martí, and S. Murtinu. 2013. The impact of venture capital on the productivity growth of European entrepreneurial firms:'Screening'or 'value added'effect? *Journal of Business Venturing* 28: 489-510.

Dushnitsky, G., and M. J. Lenox. 2006. When does corporate venture capital investment create firm value? *Journal of Business Venturing* 21: 753-772.

Gompers, P. A. 1996. Grandstanding in the venture capital industry. *Journal of Financial Economics* 42: 133-156.

Gompers, P., and J. Lerner. 2000. Money chasing deals? the impact of fund inflows on private equity valuations. *Journal of Financial Economics* 55: 281–325.

Gompers, P., and J. Lerner. 2001. The venture capital revolution. *Journal of Economic Perspectives* 15: 145-168.

Heckman, J. J., H. Ichimura, and P. E. Todd. 1997. Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *Review of Economic Studies* 64: 605-654.

Hellmann, T., and M. Puri. 2002. Venture capital and the professionalization of start-up firms: Empirical evidence. *Journal of Finance* 57: 169-197.

Hsu, D. H. 2006. Venture capitalists and cooperative start-up commercialization strategy. *Management Science* 52: 204-219.

Ibbotson, R., J. Jaffe. 1975. ‘‘Hot issue’’ markets. *Journal of Finance* 30: 1027-1042.

Ibrahim, D. M. 2010. Debt as venture capital. *University of Illinois Law Review*, 1169.

Jain, B. A., and O. Kini. 1994. The post-issue operating performance of IPO firms. *Journal of Finance* 49: 1699-1726.

Jain, B. A., and O. Kini. 1995. Venture capitalist participation and the post-issue operating performance of IPO firms. *Managerial and Decision Economics* 16: 593-606.

Kaplan, S. N., and J. C. Stein. 1993. The evolution of buyout pricing and financial structure. Working Paper No. 3695, National Bureau of Economic Research.

Kaplan, S. N., and P. Strömberg. 2003. Financial contracting theory meets the real world: An empirical analysis of venture capital contracts. *Review of Economic Studies* 70: 281-315.

Kaplan, S. N., and P. E. Strömberg. 2004. Characteristics, contracts, and actions: Evidence from venture capitalist analyses. *Journal of Finance* 59: 2177-2210.

Lee, P. M., and S. Wahal. 2004. Grandstanding, certification and the underpricing of venture capital backed IPOs. *Journal of Financial Economics* 73: 375-407.

Lerner, J. 1995. Venture capitalists and the oversight of private firms. *Journal of Finance* 50: 301–18.

Lindsey, L. 2008. Blurring firm boundaries: the role of venture capital in strategic alliances, *Journal of Finance* 63: 1137–68.

Manigart, S., K. De Waele, M. Wright, K. Robbie, P. Desbrières, H. J. Sapienza, and A. Beekman. 2002. Determinants of required return in venture capital investments: a five-country study. *Journal of Business Venturing* 17: 291-312.

Martínez, J. I., B. S. Stöhr, and B. F. Quiroga. 2007. Family ownership and firm performance: Evidence from public companies in Chile. *Family Business Review* 20: 83-94.

Mazzola, P., and G. Marchisio. 2002. The Role of Going Public in Family Businesses' Long-Lasting Growth: A Study of Italian IPOs. *Family Business Review* 15: 133-148.

Megginson, W. L. 2004. Toward a global model of venture capital? *Journal of Applied Corporate Finance* 16: 89-107.

Megginson, W. L., and K. A. Weiss. 1991. Venture capitalist certification in initial public offerings. *Journal of Finance* 46: 879-903.

Ohlson, J. A. 1980. Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research* 19: 109-131.

Rosenbaum, P. R., and D. B. Rubin. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika* 70: 41-55.

Ritter, J. R. 1984. The “hot issue” market of 1980. *Journal of Business* 57: 215-240.

Tian, X. 2012. The role of venture capital syndication in value creation for entrepreneurial firms. *Review of Finance* 16: 245-283.

Tykvová, T., and M. Borell. 2012. Do private equity owners increase risk of financial distress and bankruptcy? *Journal of Corporate Finance* 18: 138-150.

Wang, C. K., K. Wang, and Q. Lu. 2003. Effects of venture capitalists’ participation in listed companies. *Journal of Banking and Finance* 27: 2015-2034.

Zmijewski, M. E. 1984. Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research* 22: 59-82.

Table 1. Summary statistics in the IPO calendar year of VC- and non-VC-backed IPOs

This table shows the summary characteristics of VC- and non-VC-backed firms in the IPO calendar year. Panel A provides means and medians of various characteristics of VC- and non-VC-backed IPOs, along with associated Wilcoxon statistics and t-statistics. *Total assets*, *revenue*, *book value* and *market value* are in millions of dollars. *Age* is the number of years from the founding date to the IPO date. *Capex ratio*, which is the ratio between the capital expenditures and the total assets, is in percent. Panel B, C, D and E provide means and medians of financial distress risk indicators (*Z-score*, *Equity ratio*, *ZM-score* and *O-score*, respectively) for VC- and non-VC-backed IPOs. Means and medians are measured considering both the full sample period (1990-2007) and various subperiods.

	VC- backed IPOs			non-VC- backed IPOs			T-test	Wilcoxon test
	Mean	Median	N	Mean	Median	N	(P-value)	(P-value)
Panel A: Characteristics of VC backed and non-VC backed IPOs								
Total Assets	562.86	109.79	438	1,166.51	104.37	1,155	0.0074	0.5755
Revenue	459.70	60.09	438	863.68	86.33	1,155	0.0154	0.0004
Age	9.83	7.00	438	19.31	8.00	1,008	0.0000	0.0019
Capex Ratio	5.90	3.70	437	8.70	4.90	1,136	0.0000	0.0000
Book Value	289.67	78.11	438	512.58	53.23	1,155	0.0359	0.0016
Market Value	1,323.13	350.65	438	1,307.32	200.46	1,155	0.9543	0.0000
Panel B: Time series distribution of Z-score								
1990-2007	23.39	9.44	438	13.33	4.63	1,155	0.0093	0.0000
Subperiods								
1990-1993	14.05	9.18	62	8.24	5.02	219	0.0001	0.0000
1994-1997	16.90	9.48	81	10.72	5.12	410	0.0114	0.0000
1998-2002	46.77	12.60	124	24.37	4.33	319	0.0956	0.0000
2003-2007	12.89	8.39	171	6.87	3.32	207	0.0000	0.0000
Panel C: Time series distribution of Equity ratio								
1990-2007	0.69	0.77	438	0.57	0.61	1,155	0.0000	0.0000
Subperiods								
1990-1993	0.73	0.77	62	0.57	0.59	219	0.0000	0.0000
1994-1997	0.70	0.79	81	0.59	0.62	410	0.0006	0.0000
1998-2002	0.74	0.83	124	0.57	0.64	319	0.0000	0.0000
2003-2007	0.65	0.71	171	0.51	0.53	207	0.0000	0.0000

(continued)

Table 1. *Continued*

Panel D: Time series distribution of ZM-score

1990-2007	-2.27	-2.70	438	-1.62	-2.06	1,155	0.0002	0.0000
Subperiods								
1990-1993	-2.89	-3.04	62	-2.00	-2.29	219	0.0002	0.0001
1994-1997	-2.37	-2.81	81	-1.97	-2.17	410	0.2743	0.0204
1998-2002	-2.06	-2.49	124	-1.01	-1.94	319	0.0166	0.0068
2003-2007	-2.14	-2.62	171	-1.47	-1.55	207	0.0024	0.0004

Panel E: Time series distribution of O-score

1990-2007	-0.97	-1.41	438	0.14	-1.29	1,155	0.3445	0.1009
Subperiods								
1990-1993	-1.83	-2.16	62	-1.16	-1.29	219	0.1174	0.0554
1994-1997	-0.73	-1.26	81	-0.78	-1.29	410	0.9281	0.7984
1998-2002	0.64	-0.46	124	2.96	-1.22	319	0.5734	0.0841
2003-2007	-1.93	-2.08	171	-1.02	-1.35	207	0.0650	0.0153

Table 2. Distribution and characteristics of VC- and non-VC-backed IPOs

Panel A shows the distribution of VC- and non-VC- backed IPOs across two-digit SIC codes. Panel B shows the geographic distribution of VC- and non-VC- backed IPOs. Panel C shows the time-series distribution of VC- and non-VC- backed IPOs in each calendar year. In the same panel, the average VC investment duration, split per calendar year, is reported.

Panel A

2-digit SIC code	Total number of IPOs	Total IPOs cumulative %	VC-backed IPOs	VC- backed IPOs cumulative %	non-VC-backed IPOs	non-VC-backed IPOs cumulative %
73	269	16.89	88	20.09	181	15.67
36	162	27.06	66	35.16	96	23.98
28	151	36.53	65	50.00	86	31.43
38	124	44.32	50	61.42	74	37.84
35	94	50.22	31	68.49	63	43.29
48	94	56.12	19	72.83	75	49.78
13	48	59.13	5	73.97	43	53.51
37	37	61.46	7	75.57	30	56.10
87	36	63.72	12	78.31	24	58.18
50	33	65.79	4	79.22	29	60.69
33	32	67.80	6	80.59	26	62.94
59	32	69.81	13	83.56	19	64.59
49	29	71.63	3	84.25	26	66.84
20	27	73.32	3	84.93	24	68.92
58	27	75.02	5	86.07	22	70.82
80	25	76.59	3	86.76	22	72.73
44	24	78.09	4	87.67	20	74.46
51	23	79.54	2	88.13	21	76.28
Others (over 40 sectors)	326	100.00	52	100.00	274	100.00
Total	1,593	100.00	438	100.00	1,155	100.00

(continued)

Table 2. *Continued*

Panel B

State	Total number of IPOs	Total IPOs %	Total IPOs cum. %	VC backed IPOs	VC backed IPOs %	non-VC-backed IPOs	non-VC-backed IPOs %
CA	274	17.20	17.20	143	32.65	131	11.34
TX	129	8.10	25.30	20	4.57	109	9.44
NY	96	6.03	31.32	20	4.57	76	6.58
MA	86	5.40	36.72	46	10.50	40	3.46
FL	58	3.64	40.36	8	1.83	50	4.33
NJ	52	3.26	43.63	13	2.97	39	3.38
IL	45	2.82	46.45	15	3.42	30	2.60
PA	38	2.39	48.84	8	1.83	30	2.60
GA	34	2.13	50.97	10	2.28	24	2.08
MN	32	2.01	52.98	9	2.05	23	1.99
OH	32	2.01	54.99	2	0.46	30	2.60
CO	29	1.82	56.81	6	1.37	23	1.99
VA	29	1.82	58.63	6	1.37	23	1.99
CT	26	1.63	60.26	12	2.74	14	1.21
WA	26	1.63	61.90	12	2.74	14	1.21
MI	25	1.57	63.47	5	1.14	20	1.73
NC	23	1.44	64.91	6	1.37	17	1.47
MD	22	1.38	66.29	12	2.74	10	0.87
AZ	20	1.26	67.55	5	1.14	15	1.30
TN	20	1.26	68.80	4	0.91	16	1.39
MO	19	1.19	69.99	5	1.14	14	1.21
NV	15	0.94	70.94	1	0.23	14	1.21
IN	14	0.88	71.81	3	0.68	11	0.95
Other States	449	28.19	100.00	67	15.30	382	33.07
Total	1,593	100.00	-	438	100.00	1,155	100.00

Table 2. *Continued*

Panel C

Year IPO	Total number of IPOs	Total IPOs %	Total IPOs cum. %	non-VC-backed IPOs	non-VC-backed IPOs %	VC backed IPOs	VC backed IPOs %	VC Investment Duration (avg. in years)
1990	23	1.44	1.44	14	1.21	9	2.05	4.74
1991	58	3.64	5.08	47	4.07	11	2.51	4.41
1992	88	5.52	10.61	69	5.97	19	4.34	5.21
1993	112	7.03	17.64	89	7.71	23	5.25	6.46
1994	87	5.46	23.10	74	6.41	13	2.97	5.06
1995	106	6.65	29.76	91	7.88	15	3.42	5.57
1996	163	10.23	39.99	132	11.43	31	7.08	3.93
1997	135	8.47	48.46	113	9.78	22	5.02	5.91
1998	107	6.72	55.18	97	8.40	10	2.28	4.31
1999	141	8.85	64.03	101	8.74	40	9.13	3.23
2000	138	8.66	72.69	88	7.62	50	11.42	4.45
2001	31	1.95	74.64	19	1.65	12	2.74	4.78
2002	26	1.63	76.27	14	1.21	12	2.74	5.35
2003	20	1.26	77.53	11	0.95	9	2.05	5.06
2004	69	4.33	81.86	39	3.38	30	6.85	5.75
2005	87	5.46	87.32	54	4.68	33	7.53	5.83
2006	90	5.65	92.97	54	4.68	36	8.22	5.89
2007	112	7.03	100.00	49	4.24	63	14.38	5.11
Total	1,593	-	-	1,155	-	438	100.00	-

Table 3. Differences between VC backed (438 firms) and non-VC backed IPOs (1,155 firms)

This table presents selection bias adjusted average indices measuring financial distress differences between VC- and non VC-backed IPO firms, their standard errors and 95% confidence intervals. Each VC- backed IPO is matched with one or many control IPOs using the propensity score (in the calendar year). The estimate of propensity score is based on the logarithm of total assets, the logarithm of age, two-digit SIC code dummies, and headquarter-state dummies. Bootstrapped standard errors are based on 50 replications. Bias-adjusted 95% confidence intervals appear below the standard errors.

	Z-score	Equity ratio	ZM-score	O-score
		Full Sample (1990-2007)		
ATT	3.803	0.128	-1.229	-1.695
Standard Error	0.819	0.022	0.239	0.226
Bias-adjusted confidence interval (95%)	[2.327;5.799]	[0.077;0.164]	[-1.807; -0.850]	[-2.107; -1.104]
Obs. treatment	2,567	2,567	2,567	2,567
Obs. control	5,204	5,204	5,204	5,204
T-statistic	4.641	5.816	-5.141	-7.504
		Subperiod (1990-1993)		
ATT	-4.051	0.087	-0.874	-3.625
Standard Error	3.732	0.027	0.211	1.495
Bias-adjusted confidence interval (95%)	[-15.360; 1.092]	[0.043; 0.127]	[-1.217; -0.577]	[-8.555; -1.961]
Obs. treatment	319	319	319	319
Obs. control	467	467	467	467
T-statistic	-1.086	3.249	-4.146	-2.424
		Subperiod (1994-1997)		
ATT	4.072	0.065	-1.012	-1.471
Standard Error	2.819	0.022	0.287	0.715
Bias-adjusted confidence interval (95%)	[-2.737; 8.463]	[0.0364; 0.099]	[-1.521; -0.318]	[-2.679; -0.035]
Obs. treatment	444	444	444	444
Obs. control	741	741	741	741
T-statistic	1.444	2.952	-3.522	-2.058
		Subperiod (1998-2002)		
ATT	7.766	0.209	-2.274	-2.001
Standard Error	2.950	0.071	0.701	0.757
Bias-adjusted confidence interval (95%)	[3.919; 14.936]	[-0.017; 0.302]	[-3.988; -1.186]	[-3.316; -0.429]
Obs. treatment	700	700	700	700
Obs. control	1,016	1,016	1,016	1,016
T-statistic	2.633	2.924	-3.247	-2.642

(continued)

Table 3. ***Continued***

		Subperiod (2003-2007)		
ATT	5.351	0.134	-1.227	-1.765
Standard Error	1.348	0.062	0.386	0.531
Bias-adjusted confidence interval (95%)	[3.952; 10.492]	[0.059; 0.257]	[-2.264; -0.606]	[-4.273; -1.185]
Obs. treatment	888	888	888	888
Obs. control	828	828	828	828
T-statistic	3.968	2.172	-3.182	-3.323

Table 4. Median values and median changes from the calendar year to five years later for VC- and non-VC-backed IPOs. Analysis 1 to 1 with control sample chosen on the basis of propensity score

This table shows medians of the indices measuring financial distress – *Z-score*, *ZM-score*, *O-score*, *Equity ratio* – for a sample of US VC backed firms went public between 1990-2007 and for the respective control IPOs firms sample. The variables are presented for a time horizon of six years, starting from the year that firms went public (i.e., t=0) to five years after. The changes (i.e., $(X_{t+i} – X_{t=0}) / X_{t=0}$; with X = *Z-score* , *ZM-score*, *O-score*, *Equity ratio* and *i* = 1…5) are measured from the year that firms went public through the fifth year following each it (year 0 to years 1, 2, 3,4 and5). It tests for the equality of distributions (Wilcoxon–Mann–Whitney rank sum test) between the two groups of firms. Moreover, it tests whether the changes are significantly different from zero (denoted by asterisks) by using a Wilcoxon signed-ranks test for medians. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

	Values						Changes				
	Z-score *(lower values indicate a larger distress)*										
Year (divestment year=0)	t= 0	t=1	t=2	t=3	t=4	t=5	0/1	0/2	0/3	0/4	0/5
(1) VC-backed sample	8.83	5.61	4.71	4.17	3.80	3.69	-0.24***	-0.35***	-0.43***	-0.47***	-0.53***
(2) Control Sample	6.97	4.42	3.47	3.24	3.11	3.01	-0.16***	-0.34***	-0.43***	-0.47***	-0.52***
Wilcoxon test (1) vs. (2)	0.0811	0.2095	0.2307	0.0628	0.0658	0.0320	0.4110	0.5879	0.4950	0.8747	0.7917
No. Observ. (1)	316	316	316	316	316	316	316	316	316	316	316
No. Observ. (2)	316	316	316	316	316	316	316	316	316	316	316
	ZM-score *(higher values indicate a larger distress)*										
Year (divestment year=0)	t= 0	t=1	t=2	t=3	t=4	t=5	0/1	0/2	0/3	0/4	0/5
(1) VC-backed sample	-2.62	-2.26	-2.05	-2.16	-2.00	-2.04	-0.06***	-0.11***	-0.11***	-0.16***	-0.21***
(2) Control Sample VC	-2.55	-2.05	-1.77	-1.53	-1.57	-1.47	-0.08***	-0.18***	-0.27***	-0.30***	-0.33***
Wilcoxon test (1) vs. (2)	0.5109	0.3349	0.2553	0.0060	0.0155	0.0033	0.6608	0.4194	0.0028	0.0317	0.3664
No. Observ. (1)	316	316	316	316	316	316	316	316	316	316	316
No. Observ. (2)	316	316	316	316	316	316	316	316	316	316	316

(continued)

Table 4. *Continued*

O-score *(higher values indicate a larger distress)*											
Year (calendar year t=0)	t= 0	t=1	t=2	t=3	t=4	t=5	0/1	0/2	0/3	0/4	0/5
(1) VC-backed sample	-1.49	-1.28	-1.22	-1.37	-1.51	-1.30	-0.03	-0.06	-0.09**	-0.13***	-0.24***
(2) Control Sample VC	-1.47	-0.93	-0.74	-0.58	-0.48	-0.67	-0.06*	-0.19***	-0.31***	-0.38***	-0.31***
Wilcoxon test (1) vs. (2)	0.2336	0.0961	0.0480	0.0003	0.0006	0.0010	0.3750	0.1518	0.0225	0.0867	0.3534
No. Observ. (1)	316	316	316	316	316	316	316	316	316	316	316
No. Observ. (2)	316	316	316	316	316	316	316	316	316	316	316
Equity ratio *(Lower values indicate a larger distress)*											
Year (calendar year t=0)	t= 0	t=1	t=2	t=3	t=4	t=5	0/1	0/2	0/3	0/4	0/5
(1) VC-backed sample	0.74	0.71	0.68	0.66	0.64	0.62	-0.02***	-0.04***	-0.07***	-0.08***	-0.09***
(2) Control Sample VC	0.70	0.65	0.62	0.58	0.58	0.56	-0.01**	-0.03***	-0.08***	-0.08***	-0.13***
Wilcoxon test (1) vs. (2)	0.0836	0.0718	0.2656	0.0473	0.1783	0.0193	0.3627	0.3327	0.5735	0.6892	0.3431
No. Observ. (1)	316	316	316	316	316	316	316	316	316	316	316
No. Observ. (2)	316	316	316	316	316	316	316	316	316	316	316

Table 5. Impact of VC on firm's financial distress: Results from OLS regressions

The dependent variables are *Z-score* (columns I and II), *Equity ratio* (columns III and IV), *ZM-score* (columns V and VI) and *O-score* (columns VII and VIII). *Age* is the Natural logarithm of the firm age; *Size* is the natural logarithm of the total asset; *Capex* is Capital expenditures normalized by total assets; *VC* is a dummy variable which is set at 1 when firms are backed by a VC investor and 0 otherwise; *GDP* is the GDP growth rate between two consecutive years. *State* and *Industry* dummies are included in estimates reported in columns II, IV, VI and VIII. Estimates are derived from OLS regressions with robust clustered standard errors. T-statistics are reported in round brackets. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Sample: 438 VC backed IPOs Vs. 1,053 control IPOs

	lower values(dep.var.)indicate larger distress				*higher values(dep.var.)indicate larger distress*			
	Z-score		Equity ratio		ZM-score		O-score	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
VC	6.241***	3.503***	0.173***	0.082***	-1.246***	-0.658***	-1.215***	-0.685***
	(7.60)	(4.96)	(5.93)	(5.03)	(-4.71)	(-4.19)	(4.41)	(-3.89)
Age	-2.334***	-2.762***	-0.057***	-0.076***	0.175**	0.411***	-0.104	0.209
	(-6.08)	(-5.81)	(-6.36)	(-4.76)	(2.33)	(3.27)	(-1.18)	(1.43)
Size	1.491***	2.387***	0.078**	0.108**	-1.113***	-1.346***	-1.735***	-1.966***
	(2.72)	(3.38)	(2.22)	(2.35)	(-3.84)	(-3.57)	(-5.57)	(-4.83)
Capex	-16.367**	-10.678	-0.442	-0.291	1.889	1.134	2.637	2.309
	(-2.52)	(-1.25)	(-0.97)	(-0.49)	(0.62)	(0.28)	(0.494)	(0.45)
GDP	2.293***	2.269***	0.049***	0.047***	-0.538***	-0.510***	-0.527***	-0.487***
	(8.52)	(8.70)	(3.04)	(3.00)	(-3.45)	(-3.37)	(-3.54)	(-3.41)
_cons	-2.101	-10.751	0.078	0.152	6.175***	10.008	10.854***	12.616**
	(-0.60)	(-1.42)	(0.35)	(0.44)	(3.15)	(1.28)	(5.37)	(2.36)
State dummies	No	Yes	No	Yes	No	Yes	No	Yes
Industry dummies	No	Yes	No	Yes	No	Yes	No	Yes
No. of ob.	8,487	8,487	8,487	8,487	8,487	8,487	8,487	8,487
No. of firms	1,593	1,593	1,593	1,593	1,593	1,593	1,593	1,593
Adj R squared	0.0280	0.0434	0.0143	0.0253	0.0303	0.0414	0.0570	0.0714

Table 6. Results from OLS regressions after control for selection bias through a propensity score method

The dependent variables are *Z-score* (columns I and II), *Equity ratio* (columns III and IV), *ZM-score* (columns V and VI) and *O-score* (columns VII and VIII). *Age* is the Natural logarithm of the firm age; *Size* is the natural logarithm of the total assets; *Capex* is Capital expenditures normalized by total assets; *VC* is a dummy variable which is set at 1 when firms are backed by a VC investor and 0 otherwise; *GDP* is the GDP growth rate between two consecutive years. *State* and *Industry* dummies are included in estimates reported in columns II, IV, VI and VIII. Estimates are derived from OLS regressions with robust clustered standard errors. T-statistics are reported in round brackets. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Sample: 316 VC backed IPOs Vs. 316 non-VC backed-IPOs

	lower values(dep.var.)indicate larger distress				*higher values(dep.var.)indicate larger distress*			
	Z-score		Equity ratio		ZM-score		O-score	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
VC	3.346***	3.311***	0.111***	0.112***	-0.866***	-0.923***	-0.768***	-0.862***
	(3.48)	(3.22)	(4.17)	(4.01)	(-3.13)	(-3.19)	(-2.85)	(-3.07)
Age	-3.329***	-3.602***	-0.077***	-0.091***	0.208	0.481**	-0.259*	0.082
	(-5.42)	(-4.99)	(-5.10)	(-4.14)	(1.41)	(2.31)	(-1.65)	(0.39)
Size	1.735**	2.356***	0.068*	0.087**	-1.192***	-1.368***	-1.850***	-1.971***
	(2.53)	(2.97)	(1.88)	(2.12)	(-3.38)	(-3.38)	(-5.66)	(-5.29)
Capex	-4.541	8.182	0.133	0.399***	-3.262	-4.097	-4.336**	-3.702
	(-0.82)	(1.10)	(1.19)	(2.82)	(-1.34)	(-1.18)	(-2.29)	(-1.45)
GDP	2.715***	2.878***	0.057**	0.060**	-0.672**	-0.690**	-0.610**	-0.624**
	(6.68)	(6.93)	(2.09)	(2.17)	(-2.34)	(-2.36)	(-2.42)	(-2.44)
_cons	-0.999	-13.991**	0.165	-0.056	6.842***	8.462**	12.064***	10.728***
	(-0.23)	(-1.99)	(0.65)	(-0.16)	(2.60)	(2.35)	(5.09)	(3.23)
State dummies	No	Yes	No	Yes	No	Yes	No	Yes
Industry dummies	No	Yes	No	Yes	No	Yes	No	Yes
No. of ob.	3,729	3,729	3,729	3,729	3,729	3,729	3,729	3,729
No. of firms	632	632	632	632	632	632	632	632
Adj R squared	0.0346	0.0636	0.0209	0.0544	0.0467	0.0759	0.0984	0.1362

Table 7. Results from OLS regressions whit one lagged value of dependent variable

The dependent variables are *Z-score* (columns I and II), *Equity ratio* (columns III and IV), *ZM-score* (columns V and VI) and *O-score* (columns VII and VIII). *Lag. Dep. Var.*is the dependent variable lagged. *Age* is the Natural logarithm of the firm age; *Size* is the natural logarithm of the total asset; *Capex* is Capital expenditures normalized by total assets; *VC* is a dummy variable which is set at 1 when firms are backed by a VC investor and 0 otherwise; *GDP* is the GDP growth rate between two consecutive years. *State* and *Industry* dummies are included in estimates reported in columns II, IV, VI and VIII. Estimates are derived from OLS regressions with robust clustered standard errors. T-statistics are reported in round brackets. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Sample: 438 VC backed IPOs Vs. 1,155 control IPOs

	lower values(dep.var.)indicate larger distress				*higher values(dep.var.)indicate larger distress*			
	Z-score		Equity ratio		ZM-score		O-score	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Lag. Dep. Var.	0.468***	0.460***	0.613***	0.607***	0.513***	0.506***	0.569***	0.561***
	(6.14)	(6.05)	(6.74)	(6.79)	(4.23)	(4.21)	(6.95)	(6.97)
VC	2.334***	0.848	0.100***	0.040***	-0.890***	-0.447***	-0.893***	-0.468***
	(3.74)	(1.52)	(3.47)	(3.15)	(-3.65)	(-3.48)	(-3.33)	(-3.15)
Age	0.006	-0.291	-0.015***	-0.027***	0.004	0.142	-0.099	0.063
	(0.971)	(-1.27)	(-2.88)	(-2.59)	(0.07)	(1.58)	(-1.49)	(0.59)
Size	1.398***	1.879***	0.065**	0.086*	-0.797***	-0.967***	-1.099***	-1.192***
	(2.80)	(2.87)	(1.97)	(1.92)	(-3.08)	(-2.73)	(-3.57)	(-3.08)
Capex	-8.689***	-8.451**	-0.021	0.195	-0.484	-1.690	-0.480	-1.010
	(-2.95)	(-2.11)	(0.15)	(1.01)	(-0.28)	(-0.69)	(-0.03)	(-0.81)
GDP	1.115***	1.085***	0.033***	0.030***	-0.376***	-0.352***	-0.351***	-0.321***
	(5.87)	(6.07)	(2.62)	(2.65)	(-3.47)	(-3.46)	(-3.20)	(-3.21)
_cons	-8.661**	-18.333***	-0.264	-0.423	5.291***	12.201	6.951***	10.903*
	(-2.36)	(-2.71)	(-1.06)	(-1.08)	(2.86)	(1.35)	(3.58)	(1.70)
State dummies	No	Yes	No	Yes	No	Yes	No	Yes
Industry dummies	No	Yes	No	Yes	No	Yes	No	Yes
No. of ob.	7,136	7,136	7,136	7,136	7,136	7,136	7,136	7,136
No. of firms	1,593	1,593	1,593	1,593	1,593	1,593	1,593	1,593
Adj R squared	0.2700	0.2784	0.3052	0.3091	0.2508	0.2553	0.3099	0.3140

Table 8.The relationship between the intensity of VC value-adding services and the firm's financial distress: Results from OLS regressions
The dependent variables are *Z-score* (columns I and II), *Equity ratio* (columns III and IV), *ZM-score* (columns V and VI) and *O-score* (columns VII and VIII). *LI* is the length of the investment. *Age* is the Natural logarithm of the firm age; *Size* is the natural logarithm of the total asset; *Capex* is Capital expenditures normalized by total assets; *Syndication* is a dummy variable which is set on 1 if at the time of offering there are more than one VCs with equity position in the target firm, and 0 otherwise; *GDP* is the GDP growth rate between two consecutive years. *State* and *Industry* dummies are included in the estimates. Estimates are derived from OLS regressions with robust clustered standard errors. T-statistics are reported in round brackets. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively. Note that the number of firms (columns II, IV, VI and VIII) differs to 316 due to for 44 VC-backed IPOs the prospectus is missing. Consequently, the variable *Syndication* reports the same number of missing values.

Sample: 316 VC backed IPOs

	lower values(dep.var.)indicate larger distress				*higher values(dep.var.)indicate larger distress*			
	Z-score		Equity ratio		ZM-score		O-score	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
LI	2.196**		0.054***		-0.558***		-0.818***	
	(2.43)		(5.42)		(-6.31)		(-7.00)	
Syndication		2.709**		0.038***		-0.274**		-0.104
		(2.43)		(2.13)		(-1.84)		(-0.46)
Age	-5.472***	-6.298***	-0.070***	-0.037***	0.106	-0.253**	-0.347	-0.887***
	(-5.23)	(-4.30)	(-6.23)	(-3.31)	(1.05)	(-2.12)	(-1.61)	(-3.47)
Size	0.658	1.368***	-0.035***	-0.036***	-0.170***	-0.140**	-0.796***	-0.799***
	(1.51)	(2.56)	(-6.00)	(-4.98)	(-2.67)	(-2.01)	(-10.54)	(-9.22)
Capex	4.091	1.882	0.232**	0.234**	-1.575*	-1.601*	-1.218	-1.579
	(0.46)	(0.19)	(2.28)	(2.09)	(-1.81)	(-1.69)	(-0.87)	(-1.04)
GDP	1.912***	1.796***	0.014***	0.013***	-0.155***	-0.145***	-0.102**	-0.099**
	(5.59)	(5.01)	(3.21)	(2.78)	(-4.37)	(-3.95)	(-2.30)	(-2.10)
_cons	6.798**	2.961	0.978***	0.869***	-1.733***	-0.760	2.057***	3.479***
	(2.32)	(0.81)	(21.88)	(15.46)	(-3.60)	(-1.27)	(2.99)	(4.35)
State dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of ob.	1,884	1,621	1,884	1,621	1,884	1,621	1,884	1,621
No. of firms	316	272	316	272	316	272	316	272
Adj. R squared	0.0939	0.0983	0.3203	0.3115	0.2249	0.2218	0.3359	0.3399

Appendix

Table A1. Description of variables

Variables	Symbol	Description
Dependent variables		
Financial distress indicator 1	*Z-score*	Altman's model (1968) to predict financial distress. A higher Z-score value indicates a lower financial distress risk[a]
Financial distress indicator 2	*ZM-score*	Zmijewski's model (1984) to predict financial distress. A higher ZM-score value indicates a higher financial distress risk[a]
Financial distress indicator 3	*O-score*	Ohlson's model (1980) to predict financial distress. A higher O-score value indicates a higher financial distress risk[a]
Financial distress indicator 4	*Equity ratio*	Book value of total equity normalized by total assets. A higher Equity ratio value indicates a lower financial distress risk[a]
Independent variables		
VC backing	*VC*	Dummy variable which is set at 1 when firms are backed by a VC investor and 0 otherwise[b]
Length of PE investment	*LI*	Natural logarithm of the number of years between the investment time and the divestment time[b]
VC Syndication	*Syndication*	Dummy variable which is set on 1 if at the time of offering there are more than one VCs with equity position in the target firm, and 0 otherwise[c]
Size	*Size*	Natural logarithm of the total asset[a]
Age	*Age*	Natural logarithm of the firm age[b,d]
Capital expenditures	*Capex*	Capital expenditures normalized by total assets [a]
GDP growth rate	*GDP*	The GDP growth rate between two consecutive years[e]
Industry dummies	*Industry*	A set of dummy variables describing the industrial sectors and each of which takes the value 1 if the firm operates in the corresponding sector, and zero otherwise [a]
State dummies	*State*	A set of dummy variables describing the territorial differences and each equal to 1 if the firm operates in the corresponding State, and zero otherwise [a]

[a] *Source*: COMPUSTAT
[b] *Source*: THOMSON ONE
[c] *Source*: IPO PROSPECTUS
[d] *Source*: FACTIVA
[e] *Source*: WORLD BANK