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Financial distress risk in initial public offerings: How much do venture capitalists matter?☆

William L. Megginson^{a,b,*}, Antonio Meles^c, Gabriele Sampagnaro^d, Vincenzo Verdoliva^e

^a University of Oklahoma, United States

^b King Fahd University of Petroleum and Minerals, Saudi Arabia

^c Second University of Naples, Italy

^d University of Naples Parthenope, Italy

^e Kingston University of London, United Kingdom

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ABSTRACT

Using a sample of 1593 US firms that go public between 1990 and 2007, we find that VC-backed IPOs experience less financial distress risk post-offering than do comparable non-VC-backed IPOs. After controlling for endogeneity, we find this is related to the screening done by VC-investors, who select firms with lower risk of financial distress and by VCs reducing risks when they finance portfolio firms. We find companies backed by more reputable VCs exhibit higher levels of financial distress risk even when they show superior operating performance, due to their highly levered capital structure and investment in relatively illiquid assets.

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1. Introduction

Are venture capital (VC)-backed Initial Public Offering (IPO) firms less financially distressed than other IPO firms, and if so, do VCs contribute to the financial stability of portfolio companies after the IPO? If VC investors do reduce financial risk of investee firms, is this risk-reduction caused by VCs' screening of portfolio companies, or by the direct effect of VC investments in reducing financial risk? Stated differently, is there a relationship between the VCs' value-added intensity and the level of a post-IPO firm's

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* Corresponding author at: Price College of Business, 307 West Brooks, 205A Adams Hall, The University of Oklahoma, Norman, OK 73019-4005, United States.

E-mail addresses: wmegginson@ou.edu (W.L. Megginson), antonio.meles@unina2.it (A. Meles), gabriele.sampagnaro@uniparthenope.it (G. Sampagnaro), V.Verdoliva@kingston.ac.uk (V. Verdoliva).

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financial distress? Finally, are certain types of VC firms (high reputation vs. low reputation and bank affiliated vs. independent) better at reducing the financial distress risk of investee firms than other ones? These questions have long been empirically debated, but have picked up impetus in the wake of the 2008–2009 financial crisis, which emphasized the need for managers and 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 market stability by bringing public firms that show a lower risk of financial distress during the post-IPO period. First, VCs undertake an intensive screening and selection process in order to pick “winning firms” that have favorable future business prospects (Amit et al. 1998; Gompers and Lerner, 2001; Baum and Silverman, 2004; Ueda, 2004; Casmatta and Haritchabalet, 2007; Chemmanur et al., 2011). The screening process involves selecting firms with specific characteristics that should lead to a lower risk of financial distress during 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 captive VCs (mainly bank-affiliated and corporate VCs), which tend to be more risk-averse than independent VCs (Manigart et al., 2002; Croce et al., 2015). Indeed, independent VCs have a high risk tolerance and pursuing higher capital gains preserves their future ability to raise funding from third parties. Captive VCs have less pressure to maximize investment returns because they can raise additional funds from the parent company they are affiliated with.

Second, VCs supply portfolio firms with the equity capital needed to expand their business, and enable firms to have a robust capital structure to meet any contracted principal and interest payments (*financial effect*) (Kaplan and Schoar, 2005; Croce et al., 2013). Finally, VCs are also builders of “winning firms” because they add value to portfolio firms by providing them with coaching (Jain and Kini, 1995; Hellmann and Puri, 2002; Chemmanur et al., 2011; Croce et al., 2013; Cumming et al., 2014), effective monitoring (Kaplan and Strömberg, 2003; Cumming, 2005; Cumming et al., 2014), and valuable business contacts (Hsu, 2006; Lindsey, 2008; Wang and Wang, 2012). 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 might well be analogous to that of non-VC-backed firms (*value-added effect*). This should be even more true for companies backed by high reputable VCs, as several studies (Lee and Wahal, 2004; Nahata, 2008; Krishnan et al., 2011) document that more reputable VCs are able to select better-quality firms and exhibit more active post-IPO involvement in the corporate governance of their investee firms.

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 reasons to expect VC backing to be associated with bringing riskier firms public. The first explanation is the *certification effect* (Megginson and Weiss, 1991), which predicts that VCs, especially those with a high reputation, make it easier for portfolio firms to obtain external financing, such as equity investment or bank debt financing (Croce et al., 2015). The presence of a multi-billion dollar venture debt market¹ 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—which will cause a decrease in both the firm’s performance and the VC’s internal rate of return—this can induce a higher risk of financial distress (Kaplan and Stein, 1993). In addition to allowing risky portfolio firms to access greater amounts of equity and debt financing than they could otherwise, prestigious VC backing also allows portfolio companies to access public capital markets earlier in their life cycles, when these companies are quite risky, than would otherwise be possible.

The second reason to expect that that VCs might be associated with very risky investee firms 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 companies public, and since establishing reputation is critical for future fundraising, VCs 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 financially distressed than are other firms and whether VC firm reputation is associated with lower financial distress risk by investee firms are empirical questions that we seek to answer by analyzing a sample of 1593 US IPOs between 1990 and 2007, about 27.5% (438) of which are VC-backed IPOs. Following several papers (Coles et al. (2006) and Tykrová and Borell (2012), among others) we use the *Z*’-score (Altman et al., 1995) 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). Results from these robustness tests are analogous to the ones we observe using the *Z*’-score measure.

We next estimate OLS regressions, testing whether a firm’s financial distress risk 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 document significantly different 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, emphasizes the need to determine whether the lower risk of financial distress risk for VC-backed IPOs comes from the VCs’ screening role

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, venture debt is commonly used for start-up capital structures (Ibrahim, 2010). VC-backed companies such as Google and Facebook have used venture in their capital structures to gain first-to-market advantage and to minimize the need to obtain expensive and scarce (at the time) external equity financing.

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 as the provision and receipt of venture funding represents the result of an endogenous choice by firms and VCs, as Sørensen (2007) clearly shows, which is reflected not only in the investment by VCs but also in their eventual exit. 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 (age, size, 2-digit SIC code dummies, headquarters-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 selection bias is controlled for, 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 due to 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 (Baum and Silverman, 2004; Tykvová and Borell, 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 relationship between 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 investment intensity (measured as 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 investment 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.

Since VC investments have favorable effects on the IPOs' risk of financial distress, and as various studies (e.g., Lee and Wahal, 2004; Krishnan et al., 2011) have pointed out that more reputable VCs are able to better solve their role compared to low reputable ones, it is really interesting to know what is the role of VC reputation in explaining post-IPO risk of financial distress. Using a reputation measure based on the VC firm's funding market share, we find that companies backed by more reputable VCs exhibit higher levels of financial distress risk than others. Furthermore, implementing a standard Heckman (1979) 2-step selection procedure we report results that are robust to the correction of selection bias possibly induced by VC firms' choice of investee companies. Since these results are somewhat unexpected, we analyze them further by decomposing the Z'' -score. Similar to Krishnan et al. (2011), we find that companies backed by more reputable VCs perform better than others. However, we document that this success comes, at least partially, from more aggressive investment (lower liquidity assets on total assets ratio) and financing policy (lower capital ratio). Indeed, greater investments in long-term assets and greater use of debt financing are associated with higher operating performance and profitability, respectively, but also higher risk of financial distress.

We perform an additional analysis by distinguishing and evaluating the impact of the different types of VCs. Following several studies (e.g., Croce et al., 2015), we split the VC-backed IPOs sample into firms backed by bank affiliated VCs and firms backed by independent VCs. We find that bank affiliated VC-backed IPOs are safer compared to independent VC-backed IPOs. This result suggests that bank affiliated VCs are interested in the long-term growth of their portfolio firms in order to yield synergies with their core banking business (Hellmann et al., 2008).

The last issue addressed in this paper is related to how the different risk of financial distress between VC-backed IPOs and non-VC-backed IPOs affects the cost of debt. In order to shed light on this issue we distinguish between the best and the worst firms. For example, concerning Z'' -score, firms are grouped into the three zones of discrimination identified by Altman et al. (1995): *Distress Zone*, *Grey Zone* and *Safe Zone*. The results suggest that as the financial risk decreases, the cost of debt decreases as well, though VC-backed IPOs always shows (i.e. for each class of financial distress risk) a lower cost of debt compared to other ones.

Our paper complements previous research on the role of VC backing in IPOs.² Existing studies find that investee firms are more likely to go public (Sørensen, 2007); obtain higher valuation and attract more reputable financial market players during the IPO process (Ivanov and Xie, 2010); show better performance in term of profitability (Jain and Kini, 1995), long-run market returns (Brav and Gompers, 1997), and innovation (Cumming, 2007; Caselli et al., 2009) over the post-IPO period. While this literature is consistent with the notion that VC- are better than non-VC-backed firms in many aspects, our paper shows for the first time that VC-backed firms have lower risk of financial distress. However, we are aware of the fact that, as with other research (Jain and Kini, 1995; Chemmanur et al., 2011), our study suffers from a lack of observational data on the behavior of VC-backed firms during the pre-IPO period.³

² Since there is a greater amount of information available for IPO firms, the impact on investee firms by VC investments exiting via IPOs have traditionally been more frequently studied in academic work than other VC investments (Cumming et al., 2006).

³ It is worth noting that we do not observe private firms' risk of financial distress risk because in the US, only the approximately 15,000 SEC registrants plus certain regulated entities and firms for which lenders or contracts impose such requirements have publicly available financial statements (Hope et al., 2013). Thus, financial data for U.S. private firms have not been widely accessible.

A recent paper by Croce et al. (2015) also investigates the relationship between VC investments and risk of financial distress for investee firms, demonstrating that VC-backed firms, particularly those backed by bank-affiliated VC investors, exhibit a significant increase in both debt exposure and risk of financial distress after the VC financing. Our study differs from theirs in several ways. First, Croce et al. (2015) focus on a relatively narrow sample of small and micro firms.⁴ Analyzing the role of VC in mitigating the risk of financial distress in IPO firms is fundamentally different from studying its impact on small and micro firms. Indeed, the risk of financial distress for IPO firms is of great importance given their large systemic relevance and the potential repercussion on financial market stability. Furthermore, the performance of an IPO firm has implications for a larger number of stakeholders (thousands of retail investors, institutional investors, underwriters, firm's auditors, financial analysts and board members). Second, Croce et al. (2015) focus on European VC-backed firms. We believe that analyzing the US VC market has the following strengths. First, US VC investments account for a large portion of the global VC industry and VCs invest much larger funds in the US than in Europe.⁵ As such, studies focused on US market suffer fewer generalization concerns than those focused on European market. Second, US VCs are more active, skilled and experienced than their European counterparts (Schwienbacher, 2008; Hege et al., 2009). As a consequence, their investment decisions should be more aligned with theoretical predictions and should help scholars to better explain differences in performance and risk of financial distress between VC- and non-VC-backed firms. Third, the Croce et al. (2015) study is limited to distinguishing between bank-affiliated and independent VCs, we also provide evidence on VC reputation, showing that the greater success of highly-reputable firms, widely documented by previous studies (e.g., Nahata, 2008), depends on more aggressive investment and financing policy.

This paper is organized as follows: Section 2 contains the research design. Section 3 discusses the empirical methodology. Section 4 presents the empirical results. Section 5 introduces further evidence on impact of VC's reputation on firm's financial distress risk and the final section concludes.

2. Research design

2.1. Data and sample

Our sample consists of VC- and non-VC-backed IPOs that went public on US markets between 1990 and 2007. We first determine 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 exit route. This yields an initial sample of 2413 VC-backed IPOs. Second, we exclude financial firms such as banks, insurance companies, and pension funds—due to the fact that they are not directly comparable to industrial and other service firms (Mazzola and Marchisio, 2002; Anderson and Reeb, 2003; Martínez et al., 2007); nonprofit companies—social clubs, sports clubs, and schools (Martínez et al., 2007); and IPOs with an offer price of less than \$5.00 and amount offered of less than \$3 million (Megginson and Weiss, 1991; Jain and Kini, 1994; Lee and Wahal, 2004). This yields a reduced sample of 942 VC-backed firms. Third, we match the rest of the sample with COMPUSTAT using the ticker symbol to extract accounting data for companies going public; this procedure rejects an additional 357 VC-backed IPOs lacking a valid ticker symbol. Fourth, we extract all other IPOs in COMPUSTAT meeting the data screens detailed above, which yields the potential universe of untreated sample of non-VC-backed IPOs. We then exclude companies for which we do not find complete accounting information for at least one fiscal year after the listing (the sample includes financial data for up to five years after the listing).

The decision to exclude firms without full data exposes us to a trade-off between sample size and panel balance. On one hand, the non-exclusion of IPOs affected by missing value and without accounting information would allow us to have a bigger sample in term of number of observations. On the other hand, this would exclude the possibility of having a balanced panel. There is also a trade-off between the number of years after the IPO to investigate and the probability of having a panel of data with missing value and/or without accounting information. Considering all these trade-offs, we opt for a balanced data panel without missing values and accounting information. Finally, because the portfolio company's foundation year—which is needed to calculate firm age—is not available in COMPUSTAT, we supplement this 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 using the firm's foundation year, via ticker symbol, on the FACTIVA database, which contains information mainly related to historical market data and financial news archives. As a result, our final sample consists of 1593 IPOs, 438 of which are VC-backed and 1155 are not.

Table 1 shows statistics on 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 (Megginson and Weiss, 1991; Lee and Wahal, 2004), VC-backed IPOs are younger and smaller than are non-VC-backed firms, and also have lower book values of equity, lower revenues, and smaller levels of total assets.

⁴ The authors use VICO dataset that contains information on new high-tech firms operating in several European countries (Belgium, Finland, France, Germany, Italy, Spain, and the United Kingdom). Descriptive statistics about Vico dataset are reported by various researchers. For example, Bertoni and Tykvová (2012) exhibit that the average sales of 159 VC-backed firms extracted by VICO is €3.782 million.

⁵ Over the period 2006–2013, the total amount of VC investments in the United States was about \$254.6 billion (on average, \$31.8 billion dollars per year) accounting for 67.8% of global VC investments. Over the same period in Europe the total amount of VC investments was about \$55.4 billion (on average, \$6.9 billion per year). Source of data: *Global Venture Capital Insights and Trends 2014*.

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, 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 sub-periods.

	VC- backed IPOs			non-VC- backed IPOs			T-test (P-value)	Wilcoxon test (P-value)
	Mean	Median	N	Mean	Median	N		
<i>Panel A: Characteristics of VC backed and non-VC backed IPOs</i>								
Total Assets	562.86	109.79	438	1166.51	104.37	1155	0.0074	0.5755
Revenue	459.70	60.09	438	863.68	86.33	1155	0.0154	0.0004
Age	9.83	7.00	438	19.31	8.00	1008	0.0000	0.0019
Capex (%)	5.90	3.70	437	8.70	4.90	1136	0.0000	0.0000
Book Value	289.67	78.11	438	512.58	53.23	1155	0.0359	0.0016
Market Value	1323.13	350.65	438	1307.32	200.46	1155	0.9543	0.0000
<i>Panel B: Time series distribution of Z''-score</i>								
1990–2007	8.00	6.50	438	5.25	4.11	1155	0.0000	0.0000
1990–1993	9.90	7.52	62	5.95	4.94	219	0.0000	0.0000
1994–1997	8.88	7.93	81	5.87	4.74	410	0.0028	0.0041
1998–2002	9.43	6.92	124	4.50	3.63	319	0.0054	0.0001
2003–2007	5.86	5.27	171	4.42	2.70	207	0.0775	0.0002
<i>Panel C: Time series distribution of Equity ratio</i>								
1990–2007	0.69	0.77	438	0.57	0.61	1155	0.0000	0.0000
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
<i>Panel D: Time series distribution of ZM-score</i>								
1990–2007	−2.27	−2.70	438	−1.62	−2.06	1155	0.0002	0.0000
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
<i>Panel E: Time series distribution of O-score</i>								
1990–2007	−0.97	−1.41	438	0.14	−1.29	1155	0.3445	0.1009
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

2.2. Endogeneity issues and descriptive statistics

Consistent with the fact that the VCs tend to have a special appetite both for certain sectors and geographic areas,⁶ the VCs' choice of target firm is not the result of a random selection process. Megginson and Weiss (1991, p. 882) underscore that "the cost and stringency of VC investment, as well as the sheer difficulty in obtaining it (venture capitalists typically fund less than one percent of all the proposals they receive), implies that only those firms which would benefit most from the services venture capitalists provide will be willing and able to accept such participation". This clearly indicates a selection bias both because only better firms, especially in terms of growth prospects, can seek VC funding (Bertoni et al., 2012) and because VC investors can pick their targets from a huge group of possible investable firms.

The industry distribution of our full sample of VC-backed and non-VC-backed IPOs across 2-digit SIC codes is presented in Panel A of Table 2. VC-backed IPOs represent about 27.5% of the total sample. In line with the text above and with previous studies (e.g., Megginson and Weiss, 1991; Lee and Wahal, 2004), our sample shows a high variability across industry, from a minimum of one or two IPOs (e.g., SIC code 51) to a maximum of 88 IPOs (SIC code 73), where, obviously, in this latter case, the VCs show major interest in investing. We also find that VC-backed IPOs are concentrated in absolute terms. In fact, five sectors represented by SIC codes 73, 36, 28, 38 and 35 make up over 50% of the VC-backed IPOs subsample. These are: (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.

Panel B shows the sample distribution by state in which the firm is headquartered. As expected, these data are highly concentrated, especially for VC-backed IPOs. Just four States—California (VC: 32.65%; non-VC: 11.34%), Texas (VC: 4.57%; non-VC: 9.44%), New York City (VC: 4.57%; non-VC: 6.58%) and Massachusetts (VC: 10.50%; non-VC: 3.46%)—represent over 50% of the VC-backed IPOs subsample and 30% of non-VC-backed IPOs, respectively. Panel C shows the sample distribution of VC- and non-VC-backed

⁶ Over the first quarter of 2015, in US, the total amount invested by Venture Capital funds was 13.4 billion dollars and about 80% of this (11.0 billion dollars) was concentrated among just four States: California, Massachusetts, New York and Texas. Source of data: National Venture Capital Association—NVCA.

Table 2

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

This table shows the distribution of VC- and non-VC-backed IPOs by characteristics. 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.

<i>Panel A</i>							<i>Panel B</i>						<i>Panel C</i>								
SIC code	Overall		VC		non-VC		State	Overall		VC		non-VC		IPO (year)	Overall		VC		non-VC		
	#	Cum. %	#	Cum. %	#	Cum. %		#	Cum. %	#	Cum. %	#	Cum. %		#	Cum. %	#	Cum. %	#	Cum. %	
73	269	16.89	88	20.09	181	15.67	CA	274	17.20	143	32.65	131	11.34	1990	23	1.44	9	2.05	14	1.21	
36	162	27.06	66	35.16	96	23.98	TX	129	25.30	20	37.22	109	20.78	1991	58	5.08	11	4.56	47	5.28	
28	151	36.53	65	50.00	86	31.43	NY	96	31.32	20	41.79	76	27.36	1992	88	10.61	19	8.90	69	11.25	
38	124	44.32	50	61.42	74	37.84	MA	86	36.72	46	52.29	40	30.82	1993	112	17.64	23	14.15	89	18.96	
35	94	50.22	31	68.49	63	43.29	FL	58	40.36	8	54.12	50	35.15	1994	87	23.10	13	17.12	74	25.37	
48	94	56.12	19	72.83	75	49.78	NJ	52	43.63	13	57.09	39	35.53	1995	106	29.76	15	20.54	91	33.24	
13	48	59.13	5	73.97	43	53.51	IL	45	46.45	15	60.51	30	41.13	1996	163	39.99	31	27.62	132	44.67	
37	37	61.46	7	75.57	30	56.10	PA	38	48.84	8	62.34	30	43.73	1997	135	48.46	22	32.64	113	54.46	
87	36	63.72	12	78.31	24	58.18	GA	34	50.97	10	64.62	24	45.81	1998	107	55.18	10	34.93	97	62.86	
50	33	65.79	4	79.22	29	60.69	MN	32	52.98	9	66.67	23	47.80	1999	141	64.03	40	44.06	101	71.60	
33	32	67.80	6	80.59	26	62.94	OH	32	54.99	2	67.13	30	50.40	2000	138	72.69	50	55.47	88	79.22	
59	32	69.81	13	83.56	19	64.59	CO	29	56.81	6	68.50	23	52.39	2001	31	74.64	12	58.21	19	80.86	
49	29	71.63	3	84.25	26	66.84	VA	29	58.63	6	69.87	23	54.38	2002	26	76.27	12	60.95	14	82.08	
20	27	73.32	3	84.93	24	68.92	CT	26	60.26	12	72.61	14	55.59	2003	20	77.53	9	63.01	11	83.03	
58	27	75.02	5	86.07	22	70.82	WA	26	61.90	12	75.35	14	56.80	2004	69	81.86	30	69.86	39	86.40	
80	25	76.59	3	86.76	22	72.73	MI	25	63.47	5	76.49	20	58.53	2005	87	87.32	33	77.39	54	91.08	
44	24	78.09	4	87.67	20	74.46	NC	23	64.91	6	77.87	17	60.00	2006	90	92.97	36	85.61	54	95.76	
51	23	79.54	2	88.13	21	76.28	MD	22	66.29	12	80.60	10	60.87	2007	112	100.00	63	100.00	49	100.00	
Others	326	100.00	52	100.00	274	100.00	AZ	20	67.55	5	71.74	15	62.17	Total	1593	-	438	-	1155	-	
Total	1593	100.00	438	100.00	1155	100.00	TN	20	68.80	4	82.65	16	63.56								
							MO	19	69.99	5	83.79	14	64.77								
							NV	15	70.94	1	84.02	14	65.98								
							IN	14	71.81	3	84.70	11	66.93								
							Others	449	100.00	67	100.00	382	100.00								
							Total	1593	-	438	-	1155	-								

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IPOs for each calendar year. The distribution is consistent with “hot issue markets” (Ibbotson and Jaffe, 1975; Ritter, 1984) influencing firms to go public at non-random times. Instead, both VC-backed and non-VC-backed companies prefer to go public during particularly favorable periods, when market valuations are rising sharply—as demonstrated by the high number of VC- and non-VC-backed IPOs listed during 1999 and 2007.

2.3. Propensity score matching

We now turn to estimating the effect of VC investments on firms' financial distress after the IPO. One crucial aspect in the construction of the counterfactual sample is the selection of a valid control group. Many sample statistics shown in Table 2 are in line with previous US studies addressing VC. Specifically, some authors (Gompers and Lerner, 2000; Megginson, 2004) report similar industry and geographic concentrations, while others (Megginson and Weiss, 1991; Bradley and Jordan, 2002; Lee and Wahal, 2004) highlight differences in characteristics of VC- and non-VC-backed IPOs. As already discussed, this is consistent with the belief that VCs tend to specialize both by sector and geographic area.

We employ a methodology that accounts for endogenous choice in matching, 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 define VC as a dummy variable set equal to 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 a firm either receives VC backing or does not. Therefore, the most important information comes from estimating the average VC effect at a full-sample level. In formal terms, we are interested in $E(y_1 - y_0 | VC = 1, X)$, which is equal to:

$$E(y_1 - y_0 | VC = 1, X) = E(y_1 | VC = 1, X) - E(y_0 | VC = 1, X) \tag{1}$$

where X is a set of variables that represent firm and industry characteristics. Unfortunately, as previously mentioned, VCs tend to specialize both by sector and industry, so we must control for the screening and selection process performed in order to choose the best target firm (Kaplan and Strömberg, 2004). Consequently, VC investments are not random, and randomization of treatment is unrealizable. So, applying this procedure means confronting a bias, formally defined as:

$$b(X) = E(y_0 | VC = 1, X) - E(y_0 | VC = 0, X) \tag{2}$$

To ameliorate this bias, 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 a VC-backed IPO firm, but differing in that VCs have no equity positions in it.

The procedure that we employ is as follows. First, we choose the endogenous dependent variable on the propensity score model, the dummy variable VC. Second, we choose the independent variables of the model: Age, Total Assets, Industry dummies based on 2- digit SIC code, and firms' headquarters-state dummies. Third, we run a logit regression, based on the accounting data in the year of the IPO, to calculate the firm's propensity score. As a result, we obtain 1593 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 (Becker and Ichino, 2002), for each VC-backed firm we choose the matching firm which falls within the radius just described, utilizing the procedure without replacement (Heckman et al., 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).⁷ Formally, the matching criterion can be written as follows:

$$C = \underbrace{\left\{ p_j \mid \left\| p_i - p_j \right\| \leq r \right\}}_{\text{Radius Matching}} \stackrel{\text{in our case}}{\cong} \underbrace{\min_j \left\| p_i - p_j \right\|}_{\text{Nearest-Neighbor Matching}} \tag{3}$$

where C is the control firm; i is VC-backed IPO firm; j is non-VC-backed IPO firm; and 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 leads us to exclude 122 companies (438 minus 316) because no comparable match is found. In other words, no one comparable falls in the range imposed by us.

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

⁷ 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; $y_1, y_0 \perp D \mid p(X)$. 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. [...]”.

Table 3

Differences between VC backed (438 firms) and non-VC backed IPOs (1155 firms).

This table presents selection bias adjusted average indices measuring financial distress differences between VC- and non VC-backed IPO firms (Average effect of Treatment on the Treated–ATT), their standard errors and 95% confidence intervals. Each VC- backed IPO is matched with one or many control IPOs using the Kernel matching method. The estimates are 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 by using Gaussian Kernel distribution. Bias-adjusted 95% confidence intervals appear below the standard errors.

	Z'-score	Equity ratio	ZM-score	O-score
<i>Full sample (1990–2007)</i>				
ATT	5.087	0.128	–1.229	–1.695
Standard Error	0.867	0.022	0.239	0.226
Bias-adjusted (95%)	[3.709; 6.839]	[0.077; 0.164]	[–1.807; –0.850]	[–2.107; –1.104]
Obs. treatment	2567	2567	2567	2567
Obs. control	5204	5204	5204	5204
T-statistic	5.864	5.816	–5.141	–7.504
<i>Sub-period (1990–1993)</i>				
ATT	–2.086	0.087	–0.874	–3.625
Standard Error	3.259	0.027	0.211	1.495
Bias-adjusted (95%)	[–11.779; 1.846]	[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	–0.640	3.249	–4.146	–2.424
<i>Sub-period (1994–1997)</i>				
ATT	4.469	0.065	–1.012	–1.471
Standard Error	1.341	0.022	0.287	0.715
Bias-adjusted (95%)	[2.793; 7.324]	[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	3.332	2.952	–3.522	–2.058
<i>Sub-period (1998–2002)</i>				
ATT	10.629	0.209	–2.274	–2.001
Standard Error	3.162	0.071	0.701	0.757
Bias-adjusted (95%)	[6.098; 19.077]	[–0.017; 0.302]	[–3.988; –1.186]	[–3.316; –0.429]
Obs. treatment	700	700	700	700
Obs. control	1016	1016	1016	1016
T-statistic	3.362	2.924	–3.247	–2.642
<i>Sub-period (2003–2007)</i>				
ATT	5.470	0.134	–1.227	–1.765
Standard Error	2.145	0.062	0.386	0.531
Bias-adjusted (95%)	[2.834; 12.121]	[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	2.550	2.172	–3.182	–3.323

one or more non-VC-backed IPOs, with the propensity score approach calculating the difference between the financial distress risk measures of a VC-backed IPO and the matched 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.

3. Empirical methodology

3.1. 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)⁸ of a conditional logit model, as used in the Zmijewski (1984) and Ohlson (1980) models, and

⁸ 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 by maximizing the log-likelihood function, i.e. by solving $\max_{\delta} l(\delta)$.

multiple discriminant analysis (MDA),⁹ as used by Altman et al. (1995).¹⁰ Two reasons motivate the use of these models. The first is simplicity of computation, since all three measures primarily use accounting data that are easily retrieved from 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.”¹¹ Thus we use the Zmijewski model, which is calibrated to a random sample in order to deal with these phenomena. In sum, we use four financial distress risk measures that can be described as follows. The *Z*’-score model (Altman et al., 1995) is estimated as

$$Z\text{'-score} = 6.56 \underbrace{\left(\frac{WC}{TA}\right)}_{X_1} + 3.26 \underbrace{\left(\frac{RE}{TA}\right)}_{X_2} + 6.72 \underbrace{\left(\frac{EBIT}{TA}\right)}_{X_3} + 1.05 \underbrace{\left(\frac{BV}{TL}\right)}_{X_4} \quad (4)$$

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 four sub-ratios that form this score reflect *X*₁, a measure of the net liquid assets of the firm relative to total capitalization. Working capital is defined as the difference between current assets and current liabilities. *X*₂ is the measure of cumulative profitability over time. It provides an estimate of how close companies are to default, with high values being far away from default and low values indicating danger. This measure implicitly takes into account the age of the firm, since older firms probably show a higher value of this ratio. *X*₃ is operating efficiency, apart from tax and leveraging factors. Altman (1968) 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.” Finally, *X*₄ measures when book value of total equity, *BV*, tends to approach or become smaller than total debt, after which the firm becomes insolvent and eventually bankrupt. As noted, a higher value of the *Z*’-score indicates a lower financial distress risk.¹² The *ZM*-score model (Zmijewski, 1984) is estimated as:

$$ZM\text{-score} = -4.336 - 4.513 \left(\frac{NI}{TA}\right) + 5.679 \left(\frac{TL}{TA}\right) + 0.004 \left(\frac{CA}{CL}\right) \quad (5)$$

where *NI* is net income; *TA* total assets; *TL* total liabilities; *CA* current assets; and *CL* current liabilities. A higher *Zmijewski*-score value indicates higher financial distress risk. The *O*-score model (Ohlson, 1980) is estimated as:

$$O\text{-score} = -1.32 - 0.407 \log(TA) + 6.03 \left(\frac{TL}{TA}\right) - 1.43 \left(\frac{WC}{TA}\right) + 0.076 \left(\frac{CL}{CA}\right) - 1.72 D_{TL-TA} - 2.37 \left(\frac{NI}{TA}\right) - 1.83 \left(\frac{FFO}{TL}\right) + 0.285 D_{LOSS} - 0.521 \left(\frac{NI_t - NI_{t-1}}{|NI_t| + |NI_{t-1}|}\right) \quad (6)$$

where *TA* is total assets; *TL* total liabilities; *WC* working capital; *CL* current liabilities; *CA* current assets; *D*_{TL-TA} is a dummy variable which takes value 1 if total liabilities are higher than total assets, and 0 otherwise; *NI* is net income; *FFO* funds from operations; and *D*_{LOSS} is a dummy variable taking a value of 1 if the company realized a net loss in the last two years, zero otherwise. A higher *O*-score value is associated with a higher financial distress risk. The *Equity ratio* is estimated simply as:

$$Equity\ ratio = \frac{BV}{TA} \quad (7)$$

This is equivalent to *Leverage*⁻¹ and is simply the book value of total equity (*BV*) normalized by total assets (*TA*). As argued by Andrade and Kaplan (1998), a high level of leverage is one of the primary causes of financial distress. The *Equity ratio* completes

⁹ 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 *X*_{*ij*} 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.

¹⁰ We use *Z*’-score that was introduced for both non-manufacturing and manufacturing sectors. The variables of the *Z*’-score are similar of those of *Z*-score model with the exclusion of the sales/total assets in order to filter the function from the possible distortion related to the sector. For this reason, we use *Z*’-score rather than *Z*-score that is solely limited to manufacturing corporations. However, as robustness check, we perform all the elaborations also on *Z*-score. The results are qualitatively the same.

¹¹ 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 matched with reality (*choice-based sample biases*). The second bias results from using a complete data sample selection criterion, where the data for distressed firms are notoriously incomplete (*sample selection biases*).

¹² Altman, Hartzell and Peck define the following zones of discrimination: *Z*’ > 2.6 safe zone; 1.1 < *Z*’ < 2.6 grey zone; and *Z*’ < 1.1, distress zone.

our measures of financial distress risk measures. A higher value of the *Equity ratio* indicates lower financial distress risk. The summary statistics of the four financial distress risk measures presented in this paragraph are reported in Table 4.

3.2. 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 that differ depending on the sample composition. Specifically, we first run OLS on the panel data for estimating the Model 1 which is specified as follows:

$$Model\ 1\ y_{i,t} = \alpha + \beta_1 VC_i + \delta X_{i,t} + \varepsilon_{i,t} \tag{8}$$

where *i* denotes a firm (*i* = 1, 2, ..., 1593). In our first round of the analysis, we consider the full sample as an experimental setting (1593 IPOs) composed of 438 VC-backed IPOs and 1155 non-VC-backed IPOs as reported in the data and sample section. Here *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 (*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 concerns that affect our initial sample (see Section 2.2), by estimating model 1 using a subsample composed of 316 VC-backed IPOs matched with 316 non-VC-backed IPOs, as described in Section 2.3. Variable definitions are reported in Appendix A as Table A1.

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*, *Equity ratio*, *ZM-score*, *O-score*—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*, *Equity ratio*, *ZM-score*, *O-score* 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 and 5). 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				
<i>Z'-score (lower values indicate a larger distress)</i>												
Year (divestment year = 0)	t _{0-t₅}	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	4.21	6.15	4.53	3.93	3.61	3.54	3.29	-0.11***	-0.20***	-0.21***	-0.23***	-0.26***
(2) Control Sample	3.57	5.47	4.06	3.51	3.19	2.92	2.58	-0.11***	-0.20***	-0.35***	-0.43***	-0.45***
Wilcoxon test (1) vs. (2)	0.0032***	0.4512	0.3565	0.2913	0.1635	0.2256	0.0530*	0.6950	0.6602	0.0474	0.0272	0.1733
No. Observations (1)	1896	316	316	316	316	316	316	316	316	316	316	316
No. Observations (2)	1896	316	316	316	316	316	316	316	316	316	316	316
<i>Equity ratio (lower values indicate a larger distress)</i>												
Year (divestment year = 0)	t _{0-t₅}	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	0.68	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	0.62	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)	0.0000***	0.0836*	0.0718*	0.2656	0.0473**	0.1783	0.0193**	0.3627	0.3327	0.5735	0.6892	0.3431
No. Observations (1)	1896	316	316	316	316	316	316	316	316	316	316	316
No. Observations (2)	1896	316	316	316	316	316	316	316	316	316	316	316
<i>ZM-score (higher values indicate a larger distress)</i>												
Year (divestment year = 0)	t _{0-t₅}	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	-2.20	-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	-1.83	-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)	0.0000***	0.5109	0.3349	0.2553	0.0060***	0.0155**	0.0033***	0.6608	0.4194	0.0028	0.0317	0.3664
No. Observations (1)	1896	316	316	316	316	316	316	316	316	316	316	316
No. Observations (2)	1896	316	316	316	316	316	316	316	316	316	316	316
<i>O-score (higher values indicate a larger distress)</i>												
Year (divestment year = 0)	t _{0-t₅}	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	-1.36	-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	-0.78	-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)	0.0000***	0.2336	0.0961*	0.0480**	0.0003***	0.0006***	0.0010***	0.3750	0.1518	0.0225	0.0867	0.3534
No. Observations (1)	1896	316	316	316	316	316	316	316	316	316	316	316
No. Observations (2)	1896	316	316	316	316	316	316	316	316	316	316	316

4. Econometric results

4.1. 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 noted, 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 a company's financial distress risk 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*, *State* and *Year* dummy variables.

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

Regarding 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 than do non-VC backed IPOs (at the 1% confidence level or less). In terms of *Z''-score* and *Equity ratio*, the coefficient of VC variable is positive (in columns II and IV: 2.537 and 0.086, respectively) and highly significant (in columns II and IV: 2.59 and 3.60, respectively). In terms of *ZM-score* and *O-score*, the coefficient of the VC variable is negative (in columns VI and VIII: -0.719 and -0.744, respectively) and significant (in columns VI and VIII: -3.35 and -3.14, 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).

Having documented that VC-backed IPO firms display a lower risk of financial distress than do other IPOs, the second step of our analysis aims to satisfy the need to determine whether this result comes from the VCs' screening role or the treatment effect (or from both). Following previous researchers (Lee and Wahal, 2004; Chemmanur et al., 2011; Croce et al., 2015), we implement the propensity score matching-based analysis to properly evaluate the treatment effect in OLS estimation, net of the screening, since this method allows us to control for observed heterogeneity among treated (VC-backed) and untreated (non-VC-backed) firms, represented by the characteristics included in the matching process. As highlighted in Section 2.3, a matching estimator contributes to solving the selection bias problem by picking, for each VC-backed firm that receives VC financing in year *t*, the non-VC-backed firm that in the same year *t* has the most similar probability (the closest propensity score) of receiving VC. Table 6 presents the results of the propensity score matching-based analysis.

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*, *Industry* and *Year* 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.

	lower values(dep.var.)indicate larger distress				higher values(dep.var.)indicate larger distress			
	<i>Z''-score</i>		<i>Equity ratio</i>		<i>ZM-score</i>		<i>O-score</i>	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
VC	5.157*** (4.58)	2.537*** (2.59)	0.173*** (5.93)	0.086*** (3.60)	-1.246*** (-4.71)	-0.719*** (-3.35)	-1.215*** (4.41)	-0.744*** (-3.14)
Age	-1.245*** (-3.21)	-2.555*** (-4.42)	-0.057*** (-6.36)	-0.074*** (-5.27)	0.175** (2.33)	0.414*** (3.78)	-0.104 (-1.18)	0.232* (1.80)
Size	5.586*** (4.34)	7.722*** (4.26)	0.078** (2.22)	0.116** (2.46)	-1.113*** (-3.84)	-1.439*** (-3.73)	-1.735*** (-5.57)	-2.077*** (-4.97)
Capex	-18.292 (-1.15)	-19.661 (-0.94)	-0.442 (-0.97)	-0.348 (-0.57)	1.889 (0.62)	1.873 (0.47)	2.637 (0.494)	3.294 (0.64)
GDP	2.368*** (4.40)	1.198*** (2.68)	0.049*** (3.04)	0.030** (2.25)	-0.538*** (-3.45)	-0.359*** (-2.85)	-0.527*** (-3.54)	-0.353*** (-2.90)
_cons	-33.621*** (-3.96)	-14.872 (-1.00)	0.078 (0.35)	0.537 (1.58)	6.175*** (3.15)	6.593 (0.85)	10.854*** (5.37)	8.217 (1.53)
State dummies	No	Yes	No	Yes	No	Yes	No	Yes
Industry dummies	No	Yes	No	Yes	No	Yes	No	Yes
Year dummies	No	Yes	No	Yes	No	Yes	No	Yes
No. of ob.	8487	8487	8487	8487	8487	8487	8487	8487
No. of firms	1593	1593	1593	1593	1593	1593	1593	1593
Adj R squared	0.0363	0.0611	0.0143	0.0310	0.0303	0.0484	0.0570	0.0792

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*, *Industry* and *Year* 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.

	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)
<i>VC</i>	2.414** (2.54)	4.763*** (2.68)	0.111*** (4.17)	0.143*** (3.46)	−0.866*** (−3.13)	−1.212*** (−2.97)	−0.768*** (−2.85)	−1.196*** (−3.05)
<i>Age</i>	−1.513** (−2.18)	−2.845*** (−2.85)	−0.077*** (−5.10)	−0.085*** (−4.15)	0.208 (1.41)	0.445** (2.32)	−0.259* (−1.65)	0.077 (0.39)
<i>Size</i>	5.684*** (3.62)	7.366*** (3.66)	0.068* (1.88)	0.099** (2.24)	−1.192*** (−3.38)	−1.517*** (−3.51)	−1.850*** (−5.66)	−2.120*** (−5.31)
<i>Capex</i>	−4.221 (0.51)	−0.005 (−0.00)	0.133 (1.19)	0.372*** (2.62)	−3.262 (−1.34)	−3.363 (−0.97)	−4.336** (−2.29)	−2.612 (−1.03)
<i>GDP</i>	2.605*** (3.31)	0.875 (1.34)	0.057** (2.09)	0.030 (1.40)	−0.672** (−2.34)	−0.411* (−1.83)	−0.610** (−2.42)	−0.352* (−1.77)
<i>_cons</i>	−31.704*** (−3.26)	−60.144*** (−5.31)	0.165 (0.65)	−0.385 (−1.56)	6.842*** (2.60)	12.695*** (4.46)	12.064*** (5.09)	14.146*** (4.49)
<i>State dummies</i>	No	Yes	No	Yes	No	Yes	No	Yes
<i>Industry dummies</i>	No	Yes	No	Yes	No	Yes	No	Yes
<i>Year dummies</i>	No	Yes	No	Yes	No	Yes	No	Yes
<i>No. of ob.</i>	3729	3729	3729	3729	3729	3729	3729	3729
<i>No. of firms</i>	632	632	632	632	632	632	632	632
<i>Adj R squared</i>	0.0457	0.0919	0.0209	0.0678	0.0467	0.0895	0.0984	0.1499

For each dependent variable of interest, we again estimate two OLS specifications, one with (*columns II, IV, VI and VIII*) and another without (*columns I, III, V and VII*) *Industry*, *State* and *Year* dummy variables. For the first time, the coefficient of *VC* variable in the Z' -score and *Equity ratio* regressions are highly significantly positive, whereas in terms of ZM -score and O -score the coefficients of *VC* are significantly negative. Thus, *VC* variable coefficients retain significance after controlling for observed heterogeneity among *VC*-backed firms and non *VC*-backed firms. In terms of economic significance, the regression analysis indicates that *VC* financing increases Z' -score of 2.414 units (*column I*). The economic significance is higher, at 4.763 Z' -score units, when we add *State*, *Industry* and *Year* dummy variables. The *Equity ratio* results suggest that *VC* financing increases its value of 11.1% (*column III*). As Z' -score case, the economic significance is higher, at 14.3% (*column IV*), when we add *State*, *Industry* and *Year* dummy variables. Consistently, *VC* financing reduces the bankruptcy probabilities of 86.6% (*column V*) and of 76.8% (*column VII*) for ZM -score and O -score, respectively. Once again, the economic significance is higher, at 121.2% (*column VI*) and 119.6% (*column VIII*) for ZM -score and O -score, respectively, when we add *State*, *Industry* and *Year* dummy variables.

Results discussed here suggest that the lower risk of financial distress of *VC*-backed IPO firms depends not only on the *VC*'s 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 Section 4.4 we perform robustness checks to further confirm our results about the impact of *VC* backing on the risk of financial distress of IPOs.

4.2. The risk of financial distress and the cost of debt

A question raised by the results of the previous section is whether or not the lower financial distress risk by *VC*-backed IPOs results in a lower cost of debt. In this section, we attempt to provide an answer by conducting a test on the sample chosen through propensity score approach. Table 7 reports medians of the *Interest Ratio* (total interest paid on total debt) both for *VC*-backed IPOs sample and for the respective control IPO firms. The analysis is conducted by distinguishing between the best and the worst firms. Specifically, concerning Z' -score, firms are grouped into three ranges on the basis of the three zones of discrimination identified by Altman et al. (1995). This is, firms that show a Z' -score <1.1 are grouped in the *Distress Zone*; between 1.1 and 2.6 in the *Grey Zone*; over 2.6 in the *Safe Zone*, that are defined as best firms. Since ZM -score and O -score are the result of a maximum-likelihood estimation of a conditional logit model and *Equity ratio* is simply a ratio between two variables, there have not been identified, for these three variables, discriminant zones as in the case of Z' -score. Considering that they are continuous variables, we overcome this issue by defining as *Best Firms* those that show a ZM -score and O -score among the first quartile of the respective distribution; and as *Worst Firms* those that show a ZM -score and O -score among the fourth quartile. Conversely, given that *Equity ratio* works in an opposite way—a higher value indicates a lower financial distress risk—we define as *Worst Firms* those that show an *Equity ratio* among the first quartile of the respective distribution; and as *Best Firms* those that show an *Equity ratio* among the fourth quartile. The results seem to suggest that as the financial risk increases, the cost of debt increases as well.

Table 7

Median values of Interest Ratio variable for VC- and non-VC-backed IPOs. Control sample chosen on the basis of propensity score approach. This table shows medians of the *Interest Ratio* (interest paid on total debt) for a sample of US VC backed firms went public between 1990–2007 and for the respective control IPO firms sample. The analysis is conducted by distinguishing between the best and the worst firms. Concerning Z'' -score, firms are grouped into three ranges on the basis of the three zones of discrimination identified by Altman. Instead, on the side of *Equity Ratio*, ZM -score and O -score, the analysis is conducted by comparing the first and the last quartile. Specifically, with regard to *Equity Ratio* variable, the first quartile highlights the worst firms and the last quartile the best firms in term of distress risk. Vice versa, with regard to ZM -score and O -score the first quartile highlights the best firms and the last quartile the worst firms in term of distress risk. It tests for the equality of distributions (Wilcoxon-Mann-Whitney rank sum test) between the two groups of firms. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

	VC-backed Sample (1)	Control Sample (2)	Wilcoxon test (1) vs. (2)
<i>Z''-score based analysis</i>			
	<i>Distress Zone: Z''-score < 1.1</i>		
<i>Interest Ratio</i>	4.99%	6.02%	0.0835*
<i>No. Observations</i>	461	463	
	<i>Grey Zone: 1.1 < Z''-score < 2.6</i>		
<i>Interest Ratio</i>	4.87%	5.57%	0.0917*
<i>No. Observations</i>	206	219	
	<i>Safe Zone: Z''-score > 2.6</i>		
<i>Interest Ratio</i>	3.23%	4.46%	0.0000***
<i>No. Observations</i>	984	941	
<i>Equity ratio based analysis</i>			
	<i>Worst firms: 1st Quartile–Equity ratio</i>		
<i>Interest Ratio</i>	4.89%	5.82%	0.0005***
<i>No. Observations</i>	408	497	
	<i>Best firms: 4th Quartile–Equity ratio</i>		
<i>Interest Ratio</i>	3.13%	4.52%	0.0195**
<i>No. Observations</i>	381	328	
<i>ZM-score based analysis</i>			
	<i>Best firms: 1st Quartile–ZM-score</i>		
<i>Interest Ratio</i>	2.13%	3.79%	0.0013***
<i>No. Observations</i>	395	342	
	<i>Worst firms: 4th Quartile–ZM-score</i>		
<i>Interest Ratio</i>	5.31%	6.02%	0.0716*
<i>No. Observations</i>	401	466	
<i>O-score based analysis</i>			
	<i>Best firms: 1st Quartile–O-score</i>		
<i>Interest Ratio</i>	2.29%	3.58%	0.0032***
<i>No. Observations</i>	413	343	
	<i>Worst firms: 4th Quartile–O-score</i>		
<i>Interest Ratio</i>	5.67%	6.20%	0.7650
<i>No. Observations</i>	352	444	

The results are resilient to all the financial distress risk measures used. In particular, on the side of Z'' -score, *Interest Ratio* is equal to 4.99% and 6.09% (significantly different at 10% level) along *Distress Zone* for VC- and non-VC-backed IPOs, respectively. As we move to *Safe Zone*, these values drop to 3.23% and 4.46% (significantly different at 1% level) for VC- and non-VC-backed IPOs, respectively. Similarly, *Interest Ratio* is equal to 5.31% and 6.02% (significantly different at 10% level) for *Worst Firms*, and 2.13% and 3.79% (significantly different at 1% level), for *Best Firms* for VC- and non-VC-backed IPOs, respectively, both based on ZM -score. For O -score, *Interest Ratio* is equal to 5.67% and 6.20% for *Worst Firms*, and 2.29% and 3.58% (significantly different at 1% level), for *Best Firms*, for VC- and non-VC-backed IPOs, respectively. We can thus conclude that after controlling for the level of financial distress risk, VC-backed IPOs always show lower *Interest Ratios* than do firms that are not. This phenomenon seems to be consistent with the certification hypothesis by Megginson and Weiss (1991).

4.3. Distinguishing between bank affiliated and independent VCs

In this section we evaluating the impact of the different types of VCs. Specifically, we split the VC-backed IPOs sample in two: firms backed by bank affiliated VCs and firms backed by independent VCs. In a case where a company going public is backed by VC syndication, we focus on the lead VC, the VC with the highest equity stake in an IPO company as of the listing date (Hochberg et al., 2007). Once the lead VC is identified from IPO PROSPECTUSES, we gather the information about its nature from THOMSON ONE. Hence, we build two dummy variables to distinguish between different VCs. Specifically, we set *Bank VC* to 1 when firms are backed by a bank affiliated VC and to zero otherwise. Conversely, we set *Independent VC* to 1 when firms are backed by independent VC and to zero otherwise. To account for selection bias issues discussed previously, we conduct the testing using the sample generated by the propensity score matching approach.¹³

¹³ For 37 VC backed IPOs, we are not able to retrieve information regarding VC type since this is listed as “Unknown” in THOMSON ONE. We exclude these firms from the analysis.

Table 8 presents the results of estimating the impact of VC type on the risk of financial distress of IPO firms using the baseline models of the previous section. Specifically, columns I, III, V and VII report the results of estimating the impact of being financed by bank affiliated VC on the risk of financial distress for IPO firms and various other firm-specific characteristics, and macroeconomic-specific variation. Conversely, columns II, IV, VI and VIII refer to the same estimations but the aim is to capture the impact of being financed by an independent VC.

Overall, the findings seem to confirm that VC-backed IPOs experience lower risk of financial distress than do non-VC backed IPOs, and this is the case both when firms are backed by bank affiliated VCs and by independent VCs. In terms of *Z'*-score and *Equity ratio*, the coefficient of *Bank VC* variable is positive (in columns I and III: 5.849 and 0.166, respectively) and highly significant (in columns I and III: 2.03 and 2.47, respectively). In terms of *ZM-score* and *O-score*, the coefficient of *Bank VC* variable is negative (in columns V and VII: -1.565 and -1.015, respectively) and significant, limited to *ZM-score* (in columns V and VII: -2.36 and -1.56, respectively). Equivalently, in terms of *Z'*-score and *Equity ratio*, the coefficient of *Independent VC* variable is positive (in columns II and IV: 3.473 and 0.098, respectively) and highly significant (in columns II and IV: 2.63 and 3.12, respectively). In terms of *ZM-score* and *O-score*, the coefficient of *Independent VC* variable is negative (in columns VI and VIII: -0.790 and -0.961, respectively) and significant (in columns VI and VIII: -2.61 and -3.15, respectively). As noted, the coefficients of *Bank VC* are higher compared to *Independent VC*, regarding the *Z'*-score and *Equity ratio* variables. The coefficients of *Bank VC* are lower compared to *Independent VC*, regarding *ZM-score* and *O-score* variables. At this stage, it is worth briefly discussing the economic significance of these figures. The *Z'*-score outcomes clearly suggest that, for VC-backed IPOs, being supported by bank affiliated VCs produces a *Z'*-score of 5.849 units versus only a 3.473 score when supported by independent VCs. Since a higher value of *Z'*-score indicates a lower financial distress risk, this suggests that bank affiliated VCs desire a lower level of financial distress risk more than do independent VCs.

As shown by Hellmann et al. (2008), bank affiliated VCs target their investments in a manner that yields synergy with the bank's core business. As such, they would be interested in engaging in a long-term relationship after the VC financing. Under these conditions, the hypothesis makes sense that bank affiliated VCs tend to prefer lower risk investee firms. In particular, Hellmann et al. (2008, p.514) find that "building a relationship at the early venture capital stage increases a bank's likelihood of providing a loan to the company at a later stage. [...] having made a venture capital investment significantly increases a bank's chances of financing that company in the loan market. [...] companies may benefit from this relationship through lower loan pricing".

4.4. Robustness check

This section presents the main results of two additional robustness checks that further investigate whether VC financing causally impacts the financial risk of VC-backed IPOs. First, we estimate OLS with one lagged value of the dependent variable to account for the possibility that our empirical models of IPO firms' financial distress risk suffer from specification bias due to

Table 8

Results from OLS regressions by distinguishing between bank affiliated and independent VCs.

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). *Bank VC* is a dummy variable which is set at 1 when firms are backed by a lead VC that is a bank affiliated investor and 0 otherwise; *Independent VC* is a dummy variable which is set at 1 when firms are backed by a lead VC that is an independent investor and 0 otherwise; *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; *GDP* is the GDP growth rate between two consecutive years. State, Industry and Year 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.

	<i>Z'</i> -score		<i>Equity ratio</i>		<i>ZM-score</i>		<i>O-score</i>	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
<i>Bank VC</i>	5.849** (2.03)		0.166** (2.47)		-1.565** (-2.36)		-1.015 (-1.56)	
<i>Independent VC</i>		3.473*** (2.63)		0.098*** (3.12)		-0.790*** (-2.61)		-0.961*** (-3.15)
<i>Age</i>	-3.592*** (-2.98)	-3.577*** (-2.98)	-0.099*** (-4.00)	-0.099*** (-4.00)	0.596*** (2.59)	0.592*** (2.59)	0.235 (1.00)	0.231 (0.99)
<i>Size</i>	8.259*** (3.60)	8.256*** (3.59)	0.119** (2.34)	0.119** (2.34)	-1.716*** (-3.47)	-1.717*** (-3.47)	-2.340*** (-5.13)	-2.334*** (-5.11)
<i>Capex</i>	-1.659 (-0.15)	-2.309 (-0.20)	0.384** (2.55)	0.366** (2.42)	-3.363 (-0.92)	-3.217 (-0.88)	-2.877 (-1.09)	-2.693 (-1.02)
<i>GDP</i>	0.919 (1.33)	0.922 (1.34)	0.032 (1.41)	0.032 (1.41)	-0.437* (-1.84)	-0.438* (-1.85)	-0.376* (-1.80)	-0.377* (-1.80)
<i>_cons</i>	-46.033** (-2.01)	-52.443** (-2.11)	0.132 (0.25)	-0.048 (-0.08)	7.818 (1.46)	9.333 (1.60)	11.142** (2.03)	12.771** (2.16)
<i>State dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Industry dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>No. of ob.</i>	3508	3508	3508	3508	3508	3508	3508	3508
<i>No. of firms</i>	595	595	595	595	595	595	595	595
<i>Adj. R squared</i>	0.0988	0.0990	0.0733	0.0735	0.0965	0.0965	0.1577	0.1585

unobserved heterogeneity. In unreported results, we find that the effects of VC backing on the risk of financial distress remain substantially unchanged.

Second, we restrict the analysis to 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, we would expect that VC-backed firms characterized by higher VC investment intensity should exhibit lower risk of financial distress. Following various papers (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 to the board of directors and the IPO (*LI*), and (b) the VC syndication dummy (*Syndication*),¹⁴ which is 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). Overall, our results, that are omitted here for sake of brevity, confirm the idea that the greater the VC investments intensity, the lower the risk that an IPO firm will encounter financial distress, again suggesting a negative causal relationship between VC financing and the risk of financial distress for firms receiving such financing.

5. The impact of VC's reputation on firm's financial distress risk

We next analyze the role of VC reputation in explaining post-IPO risk of financial distress. This issue is of special interest because previous studies (e.g., Krishnan et al., 2011) indicate that all VC firms are not equal: companies backed by more reputable VCs exhibit superior post-IPO operative performance compared to those backed by less reputable VCs. This result has a twofold explanation. First, VCs with a high reputation have a greater ability to select better-quality portfolio firms and provide them with more valuable advisory and monitoring services. Secondly, less reputable VCs can have strong incentives to “grandstand” by taking weak firms public too early (see Gompers, 1996; Lee and Wahal, 2004). As such, it appears imperative not only to observe how these companies perform after the IPO, but also determine their level of financial distress risk.

5.1. VC reputation measure

Taking inspiration from other studies that have investigated the impact of VC's reputation on portfolio firms (Megginson and Weiss, 1991; Nahata, 2008; Chemmanur et al., 2011; Krishnan et al., 2011), we measure VC's reputation using the market share of the amount of funds raised by the VC over the prior five-year rolling window.¹⁵ Specifically, we first calculate the cumulative funds raised for each VC firm in the five years prior to the listing of the corresponding backed firm, retrieving the data from THOMSON ONE. Second, we calculate the market share for each VC firm by dividing its cumulative funds raised by the total cumulative amount of funds raised. Finally, we construct a dummy variable, *VC Reputation*, which takes value 1 if the VC firm, for the corresponding time window, is among the top 50 VC firms for market share and zero otherwise. We define VC firms among the top 50 as *High Reputation* firms and the others as *Low Reputation* firms.

In a case where a company going public is backed by a VC syndication, we focus on the lead VC's reputation—the reputation of the VC with highest equity stake in the IPO company as of the listing date (Hochberg et al., 2007).¹⁶ However, our approach differs slightly from previous studies (Nahata, 2008; Chemmanur et al., 2011; Krishnan et al., 2011) that use the median value to classify VCs into high and low reputation classes. Our choice is motivated by the fact that VC fund-raising is highly concentrated among a few VC firms. This is clearly seen by observing the list of Top 100 VCs published annually by *Entrepreneur* magazine, where huge spread in terms of market share are observed between the first and hundredth VC firm. Consistently, we find that VC funds raised are highly concentrated among the top 50 VC firms in THOMSON ONE data. For example, in 2000 the cumulative value of funds raised in the five previous years by the first hundred VC firms is about 50% of the total funds raised by the entire VC industry, composed of about 3000 VC firms. This statistic remains substantially unchanged over time. Therefore, in the presence of such a concentrated industry, the use of median value as the parameter of discrimination between high and low reputable VC firms seems inappropriate.¹⁷ As the role of VC reputation in explaining post-IPO risk of financial distress can also depend on how large an equity stake the VC firm has in the IPO company at the listing date, we construct the variable *VC Reputation* × *Stake*, which is the product of *VC Reputation* and lead VC's *Stake* of equity in the portfolio firm as of the listing date.

5.2. Differences in outcomes among VC-backed firms: High and low reputation VCs

In this section, we investigate the differences in the financial distress risk measures between firms backed by high and low reputation VCs. Specifically, our investigation process proceeds as follows. First, we verify the quality of our VC's reputation

¹⁴ The data are hand collected from IPO PROSPECTUSES (for the year of the offering), retrieved from the filing section of THOMSON ONE. We set the dummy variable *Syndication* on 1 if at the time of offering there are more than one VC with equity position in the target firm, and 0 otherwise.

¹⁵ As empirically shown by Hochberg et al. (2014), the VCs' track record affect their capability to raise new funds. The explanation of this result arises by considering that limited partners (LPs) increase their appetite, propensity, to entrust new funds to general partners (GPs) on the basis of past success of these latter.

¹⁶ The information apt to identify the lead VC investor and its stake is retrieved from IPO PROSPECTUSES.

¹⁷ For example, Chemmanur et al. (2011) define VCs with a market share of funds raised being above the sample median as highly reputable and low reputation VCs as those below the sample median.

Table 9

Median values: High and Low reputation of VCs.

This table shows medians of the indices measuring financial distress—*Z*^{''}-score, *Equity ratio*, *ZM-score*, *O-score*—, *Z*^{''}-score sub-ratios (*W-Cap./Asset*, which is the ratio between working capital and total assets, *Ret. Earn./Asset*, which is the ratio between retained earnings and total assets, *EBIT/Asset*, which is the ratio between EBIT and total assets and *Book value/TL*, which is the ratio between book value and total liabilities), *ROA*, *EBITDA/Asset* and *Age* for a sample of US VC backed firms went public between 1990–2007. The analysis compares the outcomes of firms backed by high and low reputable VCs, based on the funds raised, that are classified as described in Section 5.2. The variables are based on a time horizon of six years, starting from the year that firms went public to five years after. It tests for the equality of distributions (Wilcoxon–Mann–Whitney rank sum test) between the two groups. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

					lower values indicate a larger distress		higher values indicate a larger distress	
<i>Panel A: VC reputation based on funds raised</i>								
	ROA	EBITDA/Asset	Age	Book Value	<i>Z</i> ^{''} -score	Equity ratio	ZM-score	O-score
(1) High-Reputation	0.09	0.15	11.00	161.65	2.54	0.51	−1.39	−0.94
(2) Low-Reputation	0.03	0.07	10.00	106.13	4.70	0.71	−2.43	−1.53
Wilcoxon test (1) vs. (2)	0.0000***	0.0000***	0.0022***	0.0038***	0.0062***	0.0000***	0.0000***	0.4027
No. Observ. (1)	234	234	234	234	234	234	234	234
No. Observ. (2)	990	990	990	990	990	990	990	990
<i>Z</i> ^{''} -score sub-ratios								
<i>Panel B: VC reputation based on funds raised</i>								
	<i>X</i> ₁ = <i>W-Cap./Asset</i>	<i>X</i> ₂ = <i>Ret. Earn./Asset</i>	<i>X</i> ₃ = <i>EBIT/Asset</i>	<i>X</i> ₄ = <i>Book value/TL</i>	<i>CL/CA</i>			
(1) High-Reputation	0.16	−0.02	0.09	1.04	0.56			
(2) Low-Reputation	0.44	−0.15	0.03	2.37	0.32			
Wilcoxon test (1) vs. (2)	0.0000***	0.0003***	0.0000***	0.0000***	0.0000***			
No. Observ. (1)	234	234	234	234	234			
No. Observ. (2)	990	990	990	990	990			

variable. We do so by analyzing the impact of VC reputation on firm financial performance. As suggested by Krishnan, Ivanov, Masulis, and Singh (2011, p. 1327), “more reputable VCs continue to have significant positive associations with a number of post-IPO long-run performance measures”. The authors interpret this evidence “as indicating that continued post-IPO support and development of portfolio firms by more reputable VCs positively affects their long-term performance”. Using two well-known measures of financial performance—ROA (Return on Assets) and EBITDA (Earnings Before Interest Taxes, Depreciation and Amortization) on Assets—we test the above proposition using our dataset. Panel A of Table 9 presents, among other results, the median value and Wilcoxon test for ROA and EBITDA/Assets for firms backed by high- and low-reputable VCs by considering the entire time window from IPO data to five fiscal years later. As shown, we find that the performance of firms backed by highly reputable VCs are significantly higher compared to those backed by low reputation VCs, with the difference being on average around 6% and 8%, respectively.¹⁸ These results are not novel (Krishnan et al., 2011) and, as such, should not need further interpretation. We refer to them merely as a test of the correctness of our VC reputation measure.

We next focus on the role of VC reputation in explaining post-IPO risk of financial distress. Panels A and B of Table 9 presents the median value and Wilcoxon test for the four measures of financial distress risk used in this study for firms backed by high and low reputation VCs by considering the entire time window from IPO date to five fiscal years later. As shown, we find that firms backed by highly reputable VCs experience a higher level of financial distress risk than do firms backed by low reputation VCs. This result is supported by the difference of median values being significantly different from zero, at the 1% level, for three of four financial distress risk measures.

Table 10 reports OLS estimations for each dependent variable of interest. In line with univariate analyses, we find that VC reputation negatively affects the financial distress risk of VC backed firms. Specifically, *VC Reputation* and *VC Reputation_x_Stake* display a negative correlation with the *Z*^{''}-score and *Equity ratio* (at the 1% confidence level) and a positive correlation with *ZM-score* and *O-score* (at the 5% confidence level or less).¹⁹ Focusing on *Z*^{''}-score outcomes suggests that being supported by high reputable VCs decreases *Z*^{''}-score of 2.336 units. Since higher values of *Z*^{''}-score indicate lower financial distress risk, this implies that lower VC reputation is associated with lower financial distress risk.

5.3. VC screening and VC impact on investee firms: disentangling the effects

The coefficient estimates in Table 10 may be affected by selection bias arising out of the likely matching of better portfolio companies with more reputable VC firms. As a result, the risk of financial distress of VC-backed firms may be attributable to their characteristics rather than VCs' reputation effect. In order to control for this kind of endogeneity, we use Heckman's

¹⁸ In unreported tests, we also run the regressions by considering as dependent variable both ROA and Ebitda/Assets. Consistent with expectations, we find that being backed by a highly reputable VC is strongly positive for a firm's operating performance. Specifically, we run the regressions once with dummy variable *VC Reputation* and once with variable *VC Reputation_x_Stake*, and the coefficients are always significantly different from zero at 1% level.

¹⁹ As a robustness check we also measure VC reputation using a dummy that takes value 1 if the VC firm, for the corresponding time window, is among the top 100 VC firms for market share and zero otherwise. The results, that are not reported for brevity, are substantially unchanged.

Table 10

The impact of VC's reputation on firm's financial distress risk: 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). *VC Reputation* is a dummy variable which is set on 1 when the VC is among the top 50 VC firms in terms of funds raised five years before the VC-backed firm listing. *VC Reputation* × *Stake* is the product between the *VC Reputation* and lead VC's *Stake* of equity in the portfolio firm as of the listing date. *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; *GDP* is the GDP growth rate between two consecutive years. *State*, *Industry* and *Year* 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.

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)
<i>VC Reputation</i>	-2.336*** (-3.25)		-0.246*** (-7.32)		1.302*** (5.32)		0.940*** (3.00)	
<i>VC Reputation</i> × <i>Stake</i>		-4.514*** (-3.02)		-0.439*** (-6.93)		2.371*** (5.21)		1.541** (2.43)
<i>Age</i>	-1.252*** (-2.61)	-1.219** (-2.52)	-0.029** (-2.42)	-0.0258** (-2.01)	-0.182 (-1.36)	-0.202 (-1.48)	-0.505*** (-2.83)	-0.522*** (-2.89)
<i>Size</i>	2.103*** (6.89)	2.092*** (6.76)	-0.031*** (-3.19)	-0.031*** (-3.00)	-0.196** (-2.10)	-0.200** (-2.09)	-0.879*** (-8.34)	-0.875*** (-8.03)
<i>Capex</i>	0.091 (0.02)	-0.590 (-0.15)	0.442*** (3.47)	0.364*** (3.01)	-3.163*** (-2.77)	-2.752** (-2.48)	-1.845 (-0.94)	-1.480 (-0.76)
<i>GDP</i>	0.241* (1.76)	0.246* (1.77)	0.013** (2.38)	0.013** (2.41)	-0.141*** (3.41)	-0.143*** (-3.41)	-0.149*** (-2.85)	-0.150*** (-2.83)
<i>_cons</i>	-7.547* (-1.67)	-11.486** (-2.10)	0.684*** (6.18)	0.165* (0.82)	0.138 (0.13)	4.228** (2.40)	-0.480 (-0.27)	10.670*** (4.50)
<i>State dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Industry dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>No. of ob.</i>	1213	1183	1213	1183	1213	1183	1213	1183
<i>Adj. R squared</i>	0.3868	0.3895	0.5198	0.5180	0.3838	0.3827	0.4836	0.4803

(1979) correction procedure. In a 1st step, a probit regression is estimated for the likelihood of a firm receiving funding from a more reputable VC. Specifically, *VC Reputation* represents the dependent variable. The instrumental variables (IVs) are *VC Firm Experience* and *Nearby Firm*. The reasons for inclusion of explanatory variables in the selection equation are as follows. We use *VC Firm Experience*, measured by the natural logarithm of the age of each VC firm, because reputation is at least partially based on experience (Nahata, 2008). We find that *VC Firm Experience* is significantly related to VC reputation, but is unrelated to issuer financial distress risk-measure. *Nearby Firm* is an indicator for an IPO firm whose headquarters is located in the same state as that of its lead VC firm. As highlighted by Krishnan et al. (2011), VCs have strong incentives to limit general partners' time commitment to an investee firm by reducing partner travel time. More reputable VCs should have greater ability to select VC investments located nearby and to require more distant portfolio firms to move nearby. While *VC Firm Experience* is significantly related to VC reputation, it is unrelated to issuer financial distress risk measures. The first step concludes by estimating the *Inverse Mills* ratio that is included in the following 2-step regression model:

$$y = \beta_0 + \beta_1 \text{Market Share VC Firm} + \beta_2 \text{Age} + \beta_3 \text{Size} + \beta_4 \text{Capex} + \beta_5 \text{GDP} + \sum \beta_i \text{State Dummies} + \sum \beta_j \text{Industry Dummies} + \beta_6 \text{Inverse Mills} + \varepsilon,$$

where *y* is the financial distress risk measure, and the *Market Share VC Firm* is the market share of the VC firm for funds raised five year prior to the listing of the corresponding backed firm. This is the endogenous covariate. The *Inverse Mills* ratio captures the likelihood that highly reputable VCs are more likely to select better quality portfolio firms compared to low reputation ones.

Table 11 presents 2-step Heckman (1979) regression coefficients. As is standard, all control variables in the second step equation are also included in the first step. According to our arguments the IVs are positively and significantly related to *VC Reputation*. The explanatory power of the first-stage models is sufficiently high, as the *Adjusted R squared* value is 27.52%. Since *Market Share VC Firm* continues to have significant negative associations with *Z'-score* and *Equity ratio* and significant positive association with *ZM-score* and *O-Score*, we conclude that the higher financial distress risk exhibited by companies backed by more reputable VCs is due to how these investors perform their monitoring role. The second step regressions also indicate VC selectivity does not matter, since the *Inverse Mills* ratio is statistically insignificant for all of the issuer financial distress risk measures.

5.4. Why are more reputable VCs associated with higher risk of financial distress?

Taken as a whole, the results discussed above are somewhat unexpected, because previous studies shed light on the benefits deriving from highly reputable VC investments. As such, we consider it appropriate to delve deeper into this issue by investigating

Table 11

VC Reputation and the issuer risk of financial distress: disentangling the screening and treatment effects.

This table presents 2-step Heckman (1979) regression coefficients and in parentheses associated *t*-statistics (i.e. *z*-statistics in the case of *probit* regression) based on standard errors that are robust to heteroskedasticity. In a 1st step, a *probit* regression is estimated for the likelihood of a firm receiving backing from a more reputable VC. Specifically, *VC Reputation* is set on 1 when the VC is among the top 50 VC firms in terms of funds raised five years before the VC-backed firm listing. The instrumental variables are *VC Firm Experience* and *Nearby Firm*. All the variables are defined in Appendix A. The *Inverse Mills* ratio estimated from the 1st-step regression is used in the following 2nd-step regression model:

$$y = \beta_0 + \beta_1 \text{Market Share VC Firm} + \beta_2 \text{Age} + \beta_3 \text{Size} + \beta_4 \text{Capex} + \beta_5 \text{GDP} + \sum \beta_i \text{State Dummies} + \sum \beta_j \text{Industry Dummies} + \beta_6 \text{Inverse Mills} + \varepsilon.$$

where *y* is the financial distress risk measures, and the *Market Share VC Firm* is the endogenous covariate. *, **, and *** denote coefficient estimates significantly different from 0 at the 10%, 5%, and 1% levels, respectively.

	<i>Pr(Reputable VC = 1)</i>	<i>Z''-score</i>	<i>Equity ratio</i>	<i>ZM-score</i>	<i>O-score</i>
	(I)	(II)	(III)	(IV)	(V)
<i>Market Share VC Firm</i>		−2.811*** (−3.45)	−0.165*** (−3.66)	1.033*** (3.41)	0.604 (1.63)
<i>VC Firm Experience</i>	0.822*** (9.92)				
<i>Nearby Firm</i>	0.638*** (3.04)				
<i>Age</i>	0.0240 (0.25)	−0.965* (−1.71)	−0.0381** (−2.32)	−0.0710 (−0.45)	−0.125 (−0.61)
<i>Size</i>	0.0946* (1.87)	2.001*** (6.78)	−0.0285*** (−2.85)	−0.191** (−2.13)	−0.971*** (−9.04)
<i>Capex</i>	2.628*** (3.06)	−1.413 (−0.34)	0.637*** (3.53)	−3.342** (−2.55)	−1.501 (−0.85)
<i>GDP</i>	0.0319 (1.00)	0.362** (2.45)	0.0173** (2.53)	−0.117** (−2.47)	−0.0688 (−1.07)
<i>Inverse Mills</i>		−1.126 (−1.27)	0.0180 (0.75)	0.164 (0.65)	−0.0622 (−0.20)
<i>State Dummies</i>	Yes	Yes	Yes	Yes	Yes
<i>Industry Dummies</i>	Yes	Yes	Yes	Yes	Yes
<i>_cons</i>	−4.158*** (−6.47)	−3.255 (−0.77)	−0.423 (−1.16)	6.021*** (2.67)	5.683** (2.42)
<i>No. of ob.</i>	729	723	723	723	723
<i>Adj R squared</i>	0.2752	0.2171	0.2956	0.2881	0.4239

the impact of VC reputation on the determinants of financial distress risk indicator.²⁰ Thus, we re-estimate the regression model in Table 10, after replacing the dependent variable with the components of *Z''-score*, one by one. As reported in Table 12, we find that *VC Reputation* is: (i) negatively correlated with the working capital on total assets ratio (at the 1% confidence level); (ii) negatively related with the retained earnings on total assets ratio (at the 10% confidence level); (iii) positively related with the *EBIT* on total assets ratio (at the 10% confidence level or less); (iv) negatively related to capital ratio (at 1% confidence level).

In summary, according to Krishnan et al. (2011), we find that companies backed by more reputable VC-backed firms perform better than others, but we also document that this success comes, at least partially, from more aggressive investment (lower proportion of current assets on total assets) and financing policy (lower capital ratio). Indeed, the greater the investments in long-term assets and the use of debt financing, the higher the operating performance and shareholders' profitably, but also the higher the risk of financial distress. As such, while our additional evidence seems to be consistent with the certification theory (Megginson and Weiss, 1991), which predict that companies backed by more reputable VCs are more likely to obtain external financing, such as bank debt financing.²¹

6. Conclusions

Our paper analyzes the effects of VC investments on the risk of financial distress of portfolio firms. Using a sample of 1593 US IPOs between 1990 and 2007, we examine whether VC-backed IPO firms are less financially distressed after going public than others and whether the risk of financial distress varies across investee firms according to reputation and type of VC firms. We present several results.

First, after controlling for other determinants of a firm's risk of financial distress such as size and age, we find VC backed IPOs exhibit a lower risk of financial distress than do non-VC backed IPOs. This result, which can be consistent with either the screening hypothesis or the treatment hypothesis, or both, is robust to all the financial distress measures used (*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, and find that the lower risk of financial distress of VC-backed IPO firms depends both on how VC investors select

²⁰ We warmly thank Edward Altman for this precious suggestion.

²¹ Leaving unchanged the criteria discussed along the paragraph 5, we construct an addition measure of VC' reputation based on the assets under management (AUM) and replicate all the analysis presented. The results are qualitatively the same. We do not present them here for brevity reasons but they are available upon request.

Table 12

The impact of VC's reputation on the Z"-score components: Results from OLS regressions.

The dependent variables are *W-Cap./Asset*, which is the ratio between working capital and total assets (columns I and II), *Ret. Earn./Asset*, which is the ratio between retained earnings and total assets (columns III and IV), *EBIT/Asset*, which is the ratio between EBIT and total assets (columns V and VI) and *Book value/TL*, which is the ratio between book value and total liabilities (columns VII and VIII). *VC Reputation* is a dummy variable which is set on 1 when the VC is among the top 50 VC firms in terms of funds raised five years before the VC-backed firm listing. *VC Reputation* × *Stake* is the product between the *VC Reputation* and lead VC's *Stake* of equity in the portfolio firm as of the listing date. *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; *GDP* is the GDP growth rate between two consecutive years. *State*, *Industry* and *Year* 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.

	<i>W-Cap./Asset</i>		<i>Ret. Earn./Asset</i>		<i>EBIT/Asset</i>		<i>Book value/TL</i>	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
<i>VC Reputation</i>	-0.149*** (-5.26)		-0.179* (-1.69)		0.040* (1.69)		-0.996*** (-3.22)	
<i>VC Reputation</i> × <i>Stake</i>		-0.303*** (-5.75)		-0.283 (-1.38)		0.092** (2.14)		-2.114*** (-3.05)
<i>Age</i>	-0.052*** (-4.05)	-0.049*** (-3.72)	-0.063 (-0.85)	-0.059 (-0.80)	0.074*** (6.58)	0.073*** (6.54)	-1.145*** (-4.74)	-1.143*** (-4.71)
<i>Size</i>	-0.039*** (-4.38)	-0.037*** (-4.11)	0.624*** (10.78)	0.623*** (10.62)	0.077*** (8.17)	0.077*** (7.98)	-0.186* (-1.82)	-0.200* (-1.94)
<i>Capex</i>	-0.391*** (-4.07)	-0.437*** (-4.56)	1.566** (2.50)	1.516** (2.43)	0.009 (0.09)	0.020 (0.20)	-2.392 (-1.28)	-2.667 (-1.42)
<i>GDP</i>	0.011** (2.37)	0.011** (2.41)	0.044** (2.18)	0.045** (2.20)	0.009** (2.55)	0.009** (2.51)	-0.031 (-0.44)	-0.031 (-0.42)
<i>_cons</i>	0.504*** (4.13)	0.743*** (4.18)	-2.663*** (-4.56)	-4.874*** (-5.44)	-0.481*** (-3.56)	-0.549*** (-3.41)	1.004 (0.36)	3.071 (1.10)
<i>State dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Industry dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>No. of ob.</i>	1213	1183	1213	1183	1213	1183	1213	1183
<i>Adj. R squared</i>	0.4411	0.4416	0.5323	0.5302	0.5243	0.5180	0.4155	0.4155

their investments (screening ability), and on the business support (financial and non-financial) they provide to a portfolio firm. This result is robust to checks for possible limitations of the propensity score matching analysis. Third, we find that as the financial risk decreases the cost of debt decreases as well, though VC-backed IPOs always show a lower cost of debt compared to others. Fourth, we find that companies backed by more reputable VCs exhibit higher levels of financial distress risk even when they show superior operating performance. This result, which is robust to the correction of selection bias concerns, appears related to VCs' capital structure choices (high use of debt) and investment selection (illiquid asset choices). Finally, we find that bank affiliated VC-backed IPOs are safer compared to independent VC-backed IPOs, consistent with the idea that bank affiliated VCs are interested in a long-term success of their portfolio firms in attempt to yields synergies with the banking core business.

Our study contributes to recent policy discussions about the increasing risk of financial markets. 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. We show instead that the VC industry represents an effective tool to mitigate these worries and provides valuable support to financial market stability.

Appendix A

Table A1

Description of variables.

Variables	Symbol	Description
<i>Dependent variables</i>		
Financial distress indicator 1	Z"-score	Altman et al. model (1995) to predict financial distress. A higher Z"-score value indicates a lower financial distress risk ^a
Financial distress indicator 2	ZM-score	Zmijewski 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 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
<i>Independent variables</i>		
VC backing	VC	Dummy variable which is set at 1 when firms are backed by a VC investor and 0 otherwise ^b

(continued on next page)

Table A1 (continued)

Variables	Symbol	Description
Length of PE investment	<i>LI</i>	Natural logarithm of the number of years between the investment time and the divestment time ^b
VC Nature	<i>Bank VC</i>	Dummy variable which is set at 1 when firms are backed by a lead VC that is a bank affiliated investor and 0 otherwise ^b
VC Nature	<i>Independent VC</i>	Dummy variable which is set at 1 when firms are backed by a lead VC that is an independent investor and 0 otherwise ^b
VC Syndication	<i>Syndication</i>	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
VC Reputation	<i>VC Reputation</i>	An indicator variable for highly ranked lead VCs that takes value 1 if the VC firm, for the corresponding time window, is among the top 50 VC firms for market share (funds raised) and zero otherwise
VC firm Stake	<i>Stake</i>	Lead VC's stake of equity in portfolio firm as of the listing date ^c
Market share VC Firm	<i>Market share VC Firm</i>	Market share of VC firm for funds raised five year prior the listing of the corresponding backed firm ^b
Interaction VC Reputation and Stake	<i>VC Reputation_x_Stake</i>	Product between <i>VC Reputation</i> and <i>Stake</i> ^b
<i>Independent variables</i>		
Size	<i>Size</i>	Natural logarithm of the total asset ^a
Age	<i>Age</i>	Natural logarithm of the firm age ^{b,d}
Capital expenditures	<i>Capex</i>	Capital expenditures normalized by total assets ^a
GDP growth rate	<i>GDP</i>	The GDP growth rate between two consecutive years ^e
Industry dummies	<i>Industry dummies</i>	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	<i>State dummies</i>	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
Year dummies	<i>Year dummies</i>	A set of dummy variables each equal to 1 if the firm went public in corresponding in the corresponding Year, and zero otherwise ^a
<i>Instrumental variables</i>		
VC Firm Experience	<i>VC Firm Experience</i>	Natural logarithm of VC firm age measured as the difference between VC backed firm IPO date minus VC firm incorporation date ^b
VC firm–VC backed firm distance	<i>Nearby Firm</i>	An indicator variable that takes the value of 1 if the lead VC is headquartered in the same state as the issuer, and 0 otherwise ^{b,c}

^a Source: COMPUSTAT.

^b Source: THOMSON ONE.

^c Source: IPO PROSPECTUS.

^d Source: FACTIVA.

^e Source: WORLD BANK.

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