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Debt Financing of High-Growth Startups

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Abstract:
We study the business model of venture debt firms, specialized institutions that provide loans to high-growth startups. Venture debt represents an apparent contradiction with traditional debt theory since startups have negative cash flows and lack tangible assets to secure the loan. Yet, we estimate that the U.S. venture debt industry provides at least one venture debt dollar for every seven venture capital dollars invested. We aim to provide the first empirical evidence on the determinants of the lending decision. Building on existing field interviews and case studies, we design a choice experiment of the lending decision and conduct experiments with 55 senior venture lenders. We find support for the hypothesis that backing by venture capital firms substitutes for startups' cash flow. Furthermore, we illustrate the signaling effect of patents and their role as collateral to facilitate the lending decision.

Keywords: Venture capital; startups; patents
Jel codes: G24 ; O31

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1. Introduction

Entrepreneurial ventures play a central role in the economy. They foster technological development and drive competition and economic growth. However, entrepreneurs are usually liquidity constrained, making external capital essential to the entrepreneurial process (Evans and Jovanovic, 1989). For these reasons, the financing of new ventures has attracted strong interest in the management, finance and entrepreneurship literature. Much of the literature emphasizes the prominent role of venture capital in addressing the financing needs of high-tech startups, where moral hazard problems are particularly acute (see Berger and Udell, 1998; Carpenter and Petersen, 2002; Tykvova, 2007; de Bettignies, 2008). As a result, scholars studying new venture financing have devoted considerable attention to the understanding of venture capitalists (VCs).

A new phenomenon in the financing of new ventures is the emergence of venture debt, which we define as loans to high-growth startups that are usually at the pre-revenue stage.[2] The rise of venture debt not only goes against received wisdom in entrepreneurial finance but it also appears puzzling from the viewpoint of traditional debt theory. High-growth firms do not meet the traditional banking standards known as 'belt and suspenders' – the ability to repay a loan either from operating cash flow or, alternatively, from the value of underlying assets (Hardymon and Leamon, 2001).[3] As a matter of fact, new ventures often have negative cash flows and lack tangible assets to secure the loan. Yet, according to our estimates, the U.S. venture debt industry provided at least US$ 3 billion in loans to new ventures in 2010, which is about one venture debt dollar for every seven venture capital dollars invested. Well-known U.S. companies that used venture debt include Facebook, YouTube and Amazon.com.

Venture debt, which usually comes on top of venture capital, is an equity-efficient way to raise money. The money provided allows the startup to exceed or hit more milestones and raise the next equity funding round at a higher valuation, thereby reducing overall dilution to both management and investor teams. Yet, despite the size of the venture debt industry and its advantage for the entrepreneurs and the VCs, scholarly research on the lending activity is scarce and confined to case studies and field interviews. Some authors have studied a particular lending transaction (Crawford, 2003; Roberts et al., 2008), while some others have looked more broadly at the business model of venture lenders (VLs) relying on

[2] We use the terms 'debt' and 'loan' interchangeably.
[3] Venture debt can be used to finance growth or the purchase of new equipment. Loans made to finance new equipment are not so puzzling as the underlying asset can be taken as collateral. In this paper, we focus on loans to finance growth.

qualitative research methods (Mann, 1999; Hardymon and Leamon, 2001; Hardymon et al., 2005; Ibrahim, 2010).

We aim to provide the first empirical evidence on the determinants of the venture lending decision. More precisely, we study the characteristics which influence the probability that a startup will obtain venture debt. This analysis represents an important building block in the emerging theory of venture lending. In deriving the hypotheses, we devote particular attention to connecting lessons learned from qualitative research with theories of new venture financing. To test the hypotheses, we develop choice experiments which model a realistic venture lending decision and conduct them with 55 senior venture lenders. Our findings yield empirical evidence that venture debt firms rely on non-traditional criteria to evaluate repayment capacity. In particular, we find strong support for the hypothesis that backing by a VC company substitutes for startup cash flow. We also illustrate the importance of the signaling effect of patents and their role as collateral to facilitate the lending decision.

With these findings we make two contributions to management theory. First, we unravel the – at first glance – puzzling venture debt business model by showing that VC backing and patents provide the 'belt and suspenders' that lenders typically require. Second, we find empirical support for the recent argument that patents play an important role in supporting startups to secure financing. Overall, our industry estimates suggest that we have put the focus on an important facet of new venture financing that has so far not been the subject of thorough empirical research.

2. Determinants of the venture lending decision

The existing qualitative research suggests three dimensions on which venture lending activity can be studied: the assessment of repayment capacity, the need for collateral and the importance of equity warrants. The two first dimensions are reminiscent of traditional lending activity while the latter is more peculiar to the VC activity.

2.1 Repayment capacity

Traditional lenders usually assess the repayment capacity on the basis of operating cash flows, a prime factor of credit worthiness (Carey and Hrycay, 2001). However, most of the companies that receive venture debt are at the pre-revenue stage and consequently have negative cash flows – they can 'burn' millions in conducting R&D and building complementary assets. Lenders thus have to rely on alternative sources to evaluate the startup's repayment capacity. A critical factor that they look at is whether the startup has received backing by a VC firm (Mann, 1999). VC backing is beneficial to lenders in two ways: it provides them with a positive signal about the startup's future prospects and it increases the startup repayment capacity.

First, VC backing signals the quality of the project to the lender. High-tech startups are typically risky ventures and VCs have been shown to be particularly skilled at screening promising projects (Chan, 1983; Amit et al., 1998). In addition to the 'quality tag' provided by VCs, VLs and VCs usually know each other well through their frequent interactions. Such social ties may also act as an information transfer mechanism that further reduces the risk of the investment (Batjargal and Liu, 2004; Shane and Cable, 2002).

Second, lenders rely on the VC's capacity to make or attract a follow-on round of financing. VC-backed companies typically go through several rounds of venture financing (Gompers, 1995) which provide cash that can be used to pay back the loan. While some startups might have revenues at the time of the loan application, or might be able to obtain revenues in the near future, most startups are not close to receiving positive cash flows. High-tech startups generally can take 3–5 years to develop their product so the most likely source of cash in VC-backed ventures is the next equity round (see Hardymon et al., 2005; Roberts et al., 2008 for case-study evidence on lenders' reliance on VC). Ibrahim (2010:1184) even goes a step further by arguing that the VC and the VL engage in an implicit contract that the VC repays the loan. These arguments suggest that VC backing may substitute for cash flow (Mann, 1999; Ibrahim, 2010). We hypothesize:

HYPOTHESIS 1. *VC backing substitutes for cash flow in the venture lending decision.*

2.2 Collateral

Much like traditional commercial loan agreements, collateral is an important aspect of venture debt agreements. It usually takes the form of a first lien on all assets, meaning that the lender can take and sell or hold the property of a debtor to satisfy the company's debt (Hardymon et al., 2005). The importance of collateral is well understood in the theoretical literature and has been illustrated in empirical studies (e.g., Gan, 2007; Leeth and Scott, 1989). Collateral not only increases the lender's return from a loan (Stiglitz and Weiss, 1981) but is also used as a mechanism to enforce loan contracts (Barro, 1976). Most high-growth startups, however, do not have tangible assets. Their most likely tradable asset is their intellectual property, in particular patents (Mann, 1999).

Patents represent assets that can be liquidated and as such can be used as collateral (see, e.g., Crawford, 2003, Hardymon et al., 2005 and Ibrahim, 2010 for case study evidence that patents are used as collateral in venture lending transactions).[4] The liquidation value of patents lies in the fact that they can be enforced to exclude others from using the underlying invention. On the one hand the patent serves to facilitate technology licensing, i.e. licensing of the underlying invention to some entity that aims to commercialize the technology (e.g. Arora et al., 2001; Gans et al., 2008; Lamoreaux and Sokoloff, 2001). On the other hand the exclusion right per se can be traded either to potential competitors or to non-practicing entities (Reitzig et al., 2007). As the risk of inadvertent patent infringement is very high in at least some industries (see Bessen and Meurer, 2008), non-practicing entities trying to acquire exclusion rights in the market for patents give patents a considerable liquidation value.

From the investor point of view, the holding of patents also reduces information asymmetries by signaling a new venture's chances of success (see e.g. Long, 2002; Wagner and Cockburn, 2010). Patents may have a direct effect on firm performance by protecting market niches from competitors (see e.g. Mann, 2005; Cockburn and MacGarvie, forthcoming) or an indirect effect by informing investors about the discipline and expertise of the startup, as well as the novelty and the quality of its technology (Häussler et al., 2009; Hsu and Ziedonis, 2008). We use the term 'signaling' in a broad way to refer to both the direct and indirect effects of patents.

HYPOTHESIS 2A. *Offering patents as collateral increases the chance of getting venture debt, on top of the signaling effect conveyed by patents.*

Since most of the startups lack tangible collateral, they could offer intangible assets in the form of patents as a substitute for tangible assets (Ibrahim, 2010). Thus, we hypothesize:

HYPOTHESIS 2B. *Patents substitute for tangible assets in the venture lending decision.*

[4] One might wonder why VCs allow VLs to take a lien on all assets. An interviewee explained that in practice there is no tension between VCs and VLs regarding collateralized assets. In the case of bankruptcy the VC will usually try to liquidate all company assets (in accordance with the VL) to pay back the loan. If the VC fails the VL will try to liquidate the collateralized assets on its own.

2.3 Equity warrants

Equity warrants convey the right to purchase shares at a stated price within a given time period (e.g., Hardymon et al., 2005; Roberts et al., 2008). Economic theory suggests a strong rationale for the use of warrants. The lending activity is subject to a principal–agent problem that results in agency cost. Because the principal (lender) cannot monitor the agent's (entrepreneur's) actions and the agent has different objectives than the principal, the pursuit of a self-maximizing strategy by the entrepreneur will conflict with the interest of the lender. In particular, the lender is typically more risk averse than the entrepreneur. Should the startup fail, the cost of failure would be shared between the entrepreneur and the lender whereas in case of success, the entrepreneur would reap all the benefits. The principal–agent problem is likely to be exacerbated in high tech startups given the entrepreneur's strong incentives to take on risky behavior and the high risk of failure associated with new ventures. The economic literature suggests that warrants can be used by lenders to align the interests of the principal with those of the agent (Green, 1984; Jensen and Meckling, 1976). The provision of warrants rewards the lender for the risky behavior of the entrepreneur thereby better aligning his objectives with those of the entrepreneur and reducing agency cost. A second rationale for the use of warrants is the increase in returns that they provide to lenders. They are a way to get a share of any upside created, thereby better rewarding lenders for the risk they are taking. Everything else being equal, VLs should prefer loans that come with warrants. Thus, we hypothesize:

HYPOTHESIS 3. *Equity warrants increase the chance of getting venture debt.*

Given that a venture loan may come with equity warrants, it may look similar to convertible debt, which is widely used by VCs. These two instruments are, however, different. Convertible debt is expected to be converted into equity in a subsequent financing round and usually comes with a low coupon rate. By contrast, venture debt is a loan that has to be paid back, much like a traditional business loan; the warrant comes on top of the loan and generally represents a minor stake.

3. Empirical approach

To shed some light on the venture debt industry and to test our hypotheses, we conducted a survey among U.S. venture lenders in November 2010. Most notably, we asked survey participants about the characteristics of their loan portfolio and conducted choice experiments to understand the determinants of the venture lending decision.

3.1. Population

We identified the population of venture lenders operating in the United States in two steps. First, we identified companies active in the industry, and second, we indentified venture lending experts within each company.

The first stage of the identification process involved listing all the potential providers of venture debt, loosely defined as institutions providing loans to new ventures. To this end, we searched the academic literature for the key players (Hardymon et al. 2005; Ibrahim, 2010) and performed a broader search on specialized press, online fora and directories (including the professional network LinkedIn and the Private Equity and Venture Capital Directory published by PSEPS Ltd) for smaller players. We then browsed each company's website or asked directly for evidence that the company actually provides venture debt. We ultimately identified 80 U.S. institutions likely to provide venture debt financing. These institutions were of two types: (usually specialized) private equity shops such as Horizon Technology Finance and banks with an entrepreneurial finance branch such as Silicon Valley Bank.

In the second step we identified individual venture lenders within each company. We restricted the data collection exercise to senior positions, specifically looking for people at the level of CEO, Vice-President, Partner, Managing Director and the like. When the company website did not provide information on employees, we searched for employee names in public reports, presentations, and interviews on venture debt-related topics. We identified 529 venture lenders with correct email addresses, that is, about 6.6 venture lenders per company. After one reminder email, we obtained choice data from 55 venture lenders across 31 companies, leading to a response rate of 10% (or 39% if computed at the company level). The list of companies that took part in the survey is available in Appendix A.

3.2. Descriptive statistics

Our questionnaire contained questions aimed at evaluating the experience of respondents as well as general questions on the venture lending business model.

First, we asked about the level of experience with the venture lending activity on a 5-point Likert scale ranging from 'not experienced' to 'very experienced'. Eleven of the respondents saw themselves as experienced (score of 4) in venture lending while 44 saw themselves as very experienced (score of 5). The 'expert' status of the respondents was corroborated by their number of years of experience in financing new ventures, which averages 13.82 years.

Second, we asked respondents about the characteristics of their company's loan portfolio. As these questions were asked at the end of the survey questionnaire, we have information only from the 42 respondents (from 24 different companies) that completed the whole questionnaire. On average the lending companies in our sample had 87 outstanding loans with a maturity of 28 months and an interest rate of 11.5%. Each loan had an average size of US$ 3.5 million. Taking these figures together we can derive original market size estimates for the venture debt industry. The currently outstanding loans by the 24 companies in our data set come close to US$ 7 billion.[5] As our sample includes the biggest U.S. venture lenders, our population market size estimate should come close to the actual industry market size, although it should underestimate the true amount of loans since not all lenders participated in our survey. Calculated by year, the estimate is in the range of the US$ 1–5 billion figure discussed in Ibrahim (2010): the venture lending firms in our sample provides about US$ 3 billion per year (7*12/28) in 2010. In comparison, the VC industry invested about US$ 22 billion in the same year.[6] In other words, the venture debt industry provides about one dollar for every seven dollars invested by VCs.

Third, to understand the benefits of venture lending for all stakeholders we asked the participating VLs why they provide venture debt and how it benefits startups and VCs. Table 2 provides descriptive statistics of the potential benefits of venture debt. Venture lenders mainly aimed at obtaining interest payments, but also aimed at obtaining equity warrants. The latter finding is somewhat surprising because it contradicts qualitative research that describes obtaining warrants as a nice bonus (Ibrahim, 2010). Rather, our results suggest that the motive for obtaining an equity share is en par with the motive for obtaining interest payments. Concerning startups, VLs saw the major advantage being that venture debt avoids the dilution of startups' equity shares, but VLs only somewhat agreed with the proposition that startups do not obtain enough money from VCs. Hence, our results point to equity-efficient financing as the major advantage of venture lending for startups. This is also the main advantage for VCs: from the lenders' perspective, venture capitalists profit the most from venture debt through an increase in their internal rate of return (by limiting equity dilution). Regarding other benefits to VCs, there was less

[5] The estimates of portfolio characteristics seem to be very reliable. We obtained data from 10 venture lending companies with at least two survey participants. For these 10 firms, the within-firm correlation of the number of loans is 0.979 and the within-firm correlation of the average amount of loans is 0.794.
[6] Source: US National Venture Capital Association. http://www.nvca.org

agreement on the proposition that venture debt gives venture capitalists more time to evaluate startups. Finally, lenders agreed that venture debt reduces the limitation of VC's funds.

Table 2: Benefits of venture debt lending from various perspectives

	strongly disagree	somewhat disagree	indifferent	somewhat agree	Strongly agree
Your company lends to new ventures because it aims to…					
…obtain interest payments	0	0	1	4	50
…obtain an equity share via warrants	0	0	2	9	44
Venture debt is important for new ventures because…					
…venture debt avoids dilution of the equity shares held by startups' owners	0	0	0	11	30
…startups do not obtain enough financing from venture capitalists to reach milestones	2	8	6	18	7
Venture debt is important for venture capital firms because…					
…venture debt provides the VC more time to evaluate the startup's worthiness for a follow-on VC round	3	13	5	14	6
…venture debt improves the VC's internal rate of return.	0	0	4	19	18
…venture debt reduces the limitation of funds.	2	1	5	19	14

3.3. Experimental design

To test our hypotheses we conduct a choice-based conjoint analysis (see Green and Srinivasan 1990), also known as discrete choice experiments.[7] In a choice-based conjoint approach, each participant is presented with multiple 'choice sets', each containing multiple alternatives. In every choice set participants have to choose their most and least preferred alternative. As the alternatives are described by several attributes with different levels, the choices of the participants can be analyzed to reveal their preferences on attribute levels.

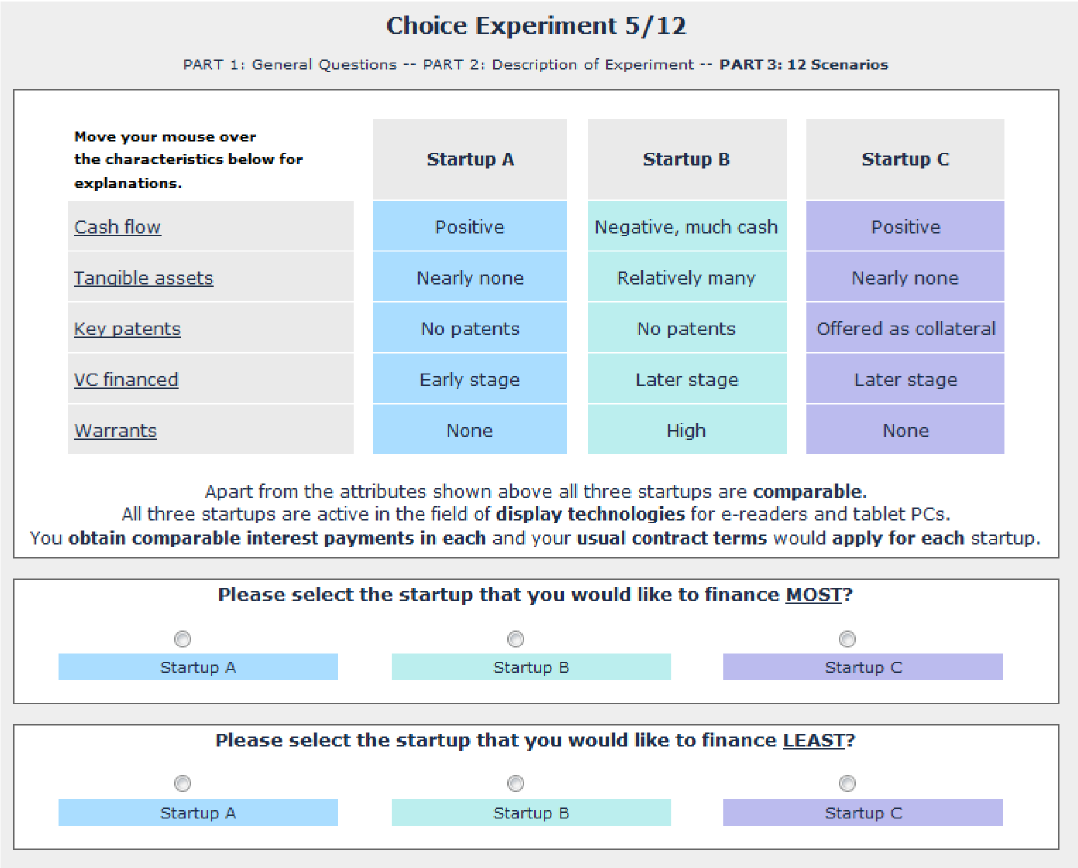
For the purpose of our analysis, we set up a choice experiment where venture lenders must consider providing a loan to three rapid growth startups. For each choice set, participants are asked to choose the startup that they would like to finance most and the one they would like to finance least, based

[7] A discrete choice experiment or choice-based conjoint analysis is a state-of-the art research method prevalent in marketing research. While being less known in management research, it has already been applied to the analysis of VC financing decisions (e.g. Franke et al., 2006) due to its unique advantage of allowing realistic modelling of investment decisions.

on five attributes describing important startup characteristics on three levels each. A respondent's preference for each attribute level is then determined indirectly by estimating its impact on the probability that the presented alternative is chosen. With a suitable experimental design, this method also allows us to test for substitution effects between startup characteristics in a venture lending decision. As analyzing and selecting startups is a core task of day-to-day business in the venture debt industry, discrete choice experiments provide a natural way of testing our hypotheses.

The most important design issue in a choice-based conjoint approach is making the experiments as realistic as possible while keeping them manageable for respondents. In order to define the levels of each attribute, we conducted several interviews with venture lenders and experts on new venture financing. Eventually, we chose to let the survey participants see 12 choice sets, each containing three startups described by five attributes: operating cash flow of the startup; its tangible assets; its patents; the amount of warrants offered; and whether the startup had VC backing or not. All other potential characteristics are comparable among the three startups. All startups were engaged in developing display technologies for e-readers and tablet PCs, a subfield of information technology where venture debt is said to be frequently observed (e.g. Ibrahim, 2010). The venture lender obtains a comparable interest payment for each startup. Figure 1 shows a choice experiment as presented to survey participants.

Figure 1: Sample choice experiment



The pretests that we conducted confirmed that the number of choice tasks was burdensome but manageable and that the attribute levels and setup of the experiment were realistic and understandable. With five attributes at three levels each, 3^5=243 possible combinations exist (the full-fractional design). As we needed to estimate main and interaction effects in ‘only’ 12 choice sets, we relied on an efficient fractional-factorial design generated by computerized search (Yu et al., 2009). To avoid potential attrition biases, we used five versions of the resulting design randomly assigned to survey participants where the order of choice sets and the order of startup characteristics were randomly varied.

As each attribute is described by three levels, we dummy coded each attribute into two dummy variables indicating the deviation from the reference value. To ensure convenient interpretation of coefficient estimates, we used the value with the (presumably) lowest benefit as a reference for each attribute. Table 3 shows all attributes and their levels. The respective reference level is always the first level of the attribute.

Table 3: Attributes and attribute levels

Attribute	Attribute levels
Cash flow	Negative, few cash available Negative, much cash availble Positive
Tangible assets (usable as collateral)	Nearly none Some Relatively many
Key patents	No patents Patents available, but not offered as collateral Patents available, and offered as collateral
VC financed	No VC-backing Early-stage VC backing Later-stage VC backing
Warrants	None Medium High

3.4. Estimation method

By asking participants to identify the two startups they would finance most and least out of three, we obtained a complete ranking of alternatives for each choice set. An estimation method for analyzing such rank-ordered data was first introduced by Beggs et al. (1981) and Chapman and Staelin (1982). In this method the ranking of three alternatives is decomposed into a choice of the best alternative out of all three, and a subsequent choice of the second-best alternative out of the remaining two. Thus, in our experiments, each participant makes up to 24 choices – 12 choices from sets of three alternatives each and 12 choices from sets of two alternatives each, obtained after the respondent has picked his or her best alternative from a set of three. In a second step, the decomposed data is fitted with McFadden’s (1974) conditional logit model.

Employing a conditional logit estimator on repeated choice data, or even decomposed repeated choice data is questionable in light of the assumption of independence of irrelevant alternatives (iia) underlying this model. The iia assumption implies that the error terms of each respondent’s choice of alternatives are assumed to be independently and identically distributed (iid). With subjective choice data this assumption is likely to be violated, because the preferences of one person should translate into similar choice patterns in different choice sets (Hausman and Wise, 1978; Layton, 2000). Thus, unobserved preference heterogeneity among respondents making multiple choices leads to correlation among error terms, violating the iia assumption of conditional logit (Layton, 2000). We thus employ mixed logit models (also called random coefficient models), extensions of conditional logit models. Mixed logit models avoid the need for the iia assumption (Brownstone and Train, 1999; McFadden and Train 2000; Revelt and Train 1998) by estimating individual coefficient vectors, hence implicitly controlling for individual-specific effects.

Following Revelt and Train (1998), Hole (2007) and Fischer and Henkel (2010), we describe the utility of alternative j in choice set t for respondent n as a linear additive function of the alternative's characteristics, described by the vector x_{njt}, while β_n is a vector of participant-specific coefficients. The ε_{njt} are error terms that are assumed to be iid extreme value, independent of x_{njt} and β_n.

$$U_{njt} = \beta_n^{'} x_{njt} + \varepsilon_{njt}$$

Conditional on the participant-specific coefficient vector β_n, the probability that participant n selects alternative i from choice set t is given by:

$$L_{nit}(\beta_n) = \frac{\exp[\beta_n' x_{nit}]}{\sum_{j=1}^{J} \exp[\beta_n' x_{njt}]}$$

The probability of the observed sequence of 24 choices conditional on β_n is then given by:

$$S_n(\beta_n) = \prod_{t=1}^{T} L_{ni(n,t)t}(\beta_n)$$

where $i(n,t)$ denotes the alternative chosen by participant n in choice t. Finally, the unconditional probability of the observed sequence of choices is derived by integrating the conditional probability over the distribution of β. $f(\beta \mid \theta)$ describes the density of β, θ denoting the parameters of the distribution:

$$P_n(\theta) = \int S_n(\beta) f(\beta \mid \theta) d\beta$$

The log-likelihood function $LL(\theta) = \sum_{n=1}^{N} \ln P_n(\theta)$ to be maximized in a mixed logit model does not have a closed form solution. Revelt and Train (1998) proposed a procedure for simulating the likelihood function value, which Hole (2007) implemented in the STATA mixlogit command that we use.

4. Results

The estimation results are presented in Table 4. Model 1a reports the results of the traditional rank-ordered logit specification, which we present as a robustness check, while Model 1b reports the results of the correct rank-ordered mixed logit specification that we interpret in the following. The results of both models are comparable, making clear that our results are not driven by the choice of the estimation method. Because both specifications are non-linear, we test hypotheses on the estimated coefficients (Greene, 2010) as a first step, but offer a deeper analysis of the average marginal effects at the end of the section (e.g. Norton et al., 2004; Hoetker, 2007).

Table 4: Coefficient estimates – Main model

Dependent variable: ranking	**Model 1a** Rank-ordered Logit		**Model 1b** Rank-ordered mixed logit	
Main effects:				
Negative cash flow but still much cash available (base: negative cash flow, few cash available)	1.154***	(.273)	2.465***	(.483)
Positive cash flow (base: negative cash flow, few cash available)	2.118***	(.249)	3.706***	(.560)
Few tangible assets (base: nearly none)	1.026***	(.264)	1.615**	(.527)
Relatively many tangible assets (base: nearly none)	1.129***	(.261)	1.914**	(.695)
Patents available but not offered as collateral (base: no patents)	.416**	(.131)	.511**	(.270)
Patents available and offered as collateral (base: no patents)	1.210***	(.184)	2.106***	(.410)
VC financed now in early stage (base: no VC backing)	2.135***	(.299)	3.397***	(.396)
VC financed now in later stage (base: no VC backing)	1.963***	(.306)	3.868***	(.450)
Medium warrants (base: no warrants)	.941***	(.183)	1.740***	(.318)
High warrants (base: no warrants)	1.383***	(.193)	2.683***	(.422)
Substitution effects:				
VC backing (early and later stage) X Negative cash flow but still much cash available	-.660**	(.239)	-1.296***	(.399)
VC backing (early and later stage) X Positive cash flow	-.481**	(.164)	-.805**	(.314)
Patents available and offered as collateral X Few tangible assets	-.244	(.239)	-.272	(.377)
Patents available and offered as collateral X Relatively many tangible	.191	(.167)	.178	(.358)
Respondents / Choices	55	2,825	55	2,825
LL / Mc Faddens Pseudo-R²	-726.80	.282	-643.10	.365
Wald test / p-value	232.15	.000	182.54	.000

Notes: Standard errors are shown in parentheses (one-sided tests for hypotheses, two-sided tests for controls). Standard errors clustered on respondents in rank-ordered logit model, robust standard errors in rank-ordered mixed logit model. * $p < 0.1$, ** $p < 0.01$, *** $p < 0.001$.

All startup attributes (main effects) are significantly different from zero at all levels, confirming that only relevant characteristics have been included in the experimental design. We do find support for Hypothesis 1 that VC backing substitutes for cash flow: the interaction effect of VC backing and cash flows is negative and statistically significant for both negative and positive cash flows. In other words, having VC backing reduces the impact that cash flows have on the lending decision.

As far as the effect of patents is concerned (Hypotheses 2a and 2b), we find that holding key patents increases the probability of receiving venture debt, which we interpret as evidence of the signaling effect of patents to venture lenders. In addition, the likelihood that a firm receives the loan significantly increases if the patent portfolio is offered as collateral, supporting Hypothesis 2a. However, the coefficients of the respective interaction terms are not significant, leading to a rejection of Hypothesis 2b. In other words, we find no evidence of a substitution effect between tangible and intangible assets that are used as collateral.

Finally, we find support for Hypothesis 3. As hypothesized, the probability that a startup will obtain venture debt financing increases with the amount of warrants being offered.

The substitution effect between cash flows and VC backing is a remarkable – and strong – result that deserves further attention. The models presented in Table 5 enable us to delve deeper into the analysis of the substitution effect by differentiating between early- and late-stage backing. Again, we first present a traditional rank-ordered logit specification as a robustness check, but interpret only Model 2b, the correct mixed logit specification.

Table 5: Coefficient estimates – Extended model

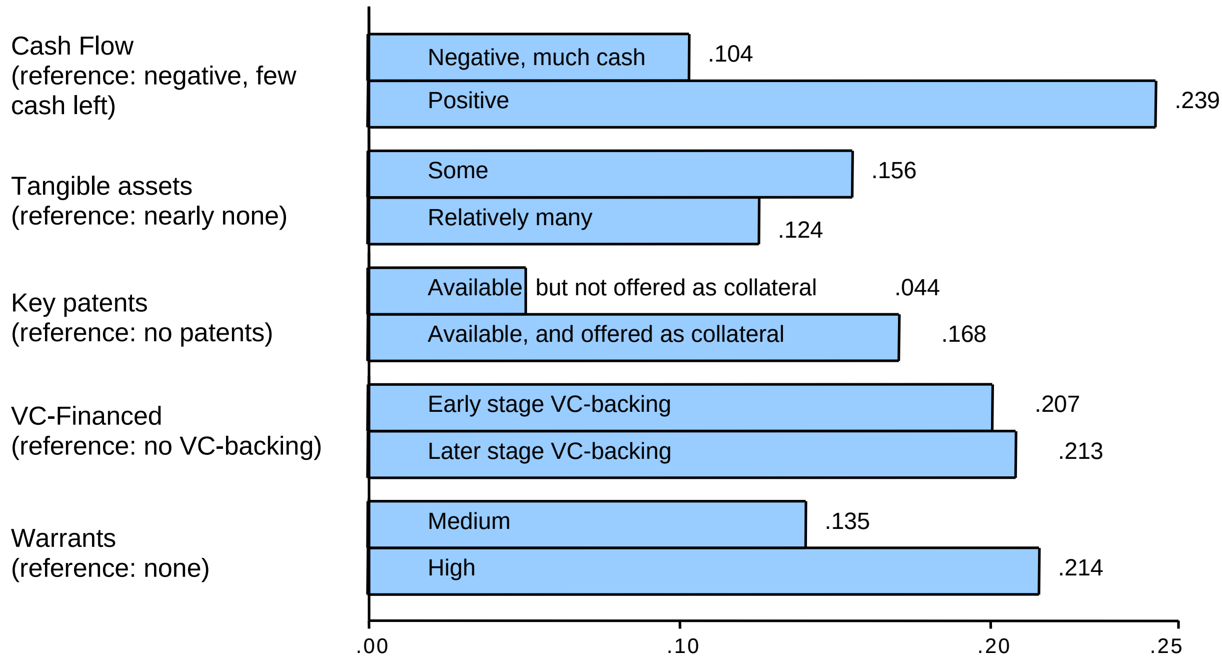
Dependent variable: ranking	Model 2a Rank-ordered Logit		Model 2b Rank-ordered mixed logit	
Main effects:				
Negative cash flow but still much cash available (base: negative cash flow, few cash available)	.995**	(.316)	1.992**	(.608)
Positive cash flow (base: negative cash flow, few cash available)	2.153***	(.274)	3.272***	(.600)
Few tangible assets (base: nearly none)	1.346***	(.347)	1.981**	(.687)
Relatively many tangible assets (base: nearly none)	1.183***	(.267)	1.515**	(.726)
Patents available but not offered as collateral (base: no patents)	.480***	(.141)	.513**	(.263)
Patents available and offered as collateral (base: no patents)	1.203***	(.191)	2.126***	(.395)
VC financed now in early stage (base: no VC backing)	2.143***	(.288)	3.567***	(.530)
VC financed now in later stage (base: no VC backing)	1.389**	(.463)	2.608**	(.905)
Medium warrants (base: no warrants)	.757***	(.209)	1.581***	(.467)
High warrants (base: no warrants)	1.348***	(.236)	2.449***	(.471)
Substitution effects:				
VC backing early stage X Negative cash flow but still much cash available	-.768**	(.409)	-1.887**	(.726)
VC backing early stage X Positive cash flow	-.844**	(.270)	-1.306**	(.664)
VC backing later stage X Negative cash flow but still much cash available	-.217	(.506)	-.140	(.790)
VC backing later stage X Positive cash flow	-.116	(.260)	-.171	(.410)
Patents available and offered as collateral X Few tangible assets	-.372*	(.255)	-.535	(.590)
Patents available and offered as collateral X Relatively many tangible assets	.197	(.305)	-.229	(.498)
Respondents / Choices	55	2,825	55	2,825
LL / Mc Faddens Pseudo-R^2	-726.05	.283	-641.86	.366
Wald test / p-value	259.63	.000	212.43	.000

Notes: Standard errors are shown in parentheses (one-sided tests for hypotheses, two-sided tests for controls). Standard errors clustered on respondents in rank-ordered logit model, robust standard errors in rank-ordered mixed logit model. * $p < 0.1$, ** $p < 0.01$, *** $p < 0.001$.

The results provided in Table 5 are by and large comparable to the previously discussed results. The specification leads to very interesting insights into the role of VC backing though. While the interaction coefficients associated with early-stage backing are negative and significant, the interaction coefficients associated with late-stage backing are not statistically significant. This result suggests that only early-stage VC backing substitutes for cash flows

In order to provide an in-depth interpretation of the effects shown in Table 5, Figure 2 presents the average marginal effects of the main effects in Model 2b and Figure 3 presents the average marginal effects of the substitution effects in Model 2b. Such an analysis is necessary because rank-ordered logit and rank-ordered mixed logit models are non-linear models in which the effect size of interest not only depends on the estimated coefficient, but also on the coefficient estimates and the values of all other variables in the model (Huang and Shields, 2000; Norton et al., 2004; Hoetker, 2007). The average marginal effects are the difference in predicted probability of switching a dummy variable (coding an attribute level as deviation from the respective reference level) from 0 to 1. As this difference in predicted probabilities depends on the choice set, i.e. the startups that were competing for venture debt financing, we calculated the difference in predicted probabilities for every single possible combination of startups that could compete for financing (see Fischer and Henkel, 2010). Eventually, the results presented are the difference in predicted probabilities averaged over all $3^5*3^5*3^4$ = 4.7 million possible combinations.

Figure 2: Average marginal effects of the main effects



The results presented in Figure 2 confirm the important role of (positive) cash flows. High-growth startups with positive cash flow are a real gem and lenders' preferences for such come as no surprise. The probability of these startups obtaining venture debt financing is on average 23.9 percentage points higher than that of a startup with negative cash flow and little cash remaining (the reference level). Offering a high level of warrants is the second most important criterion. More than a 'nice bonus' (Ibrahim, 2010:1183), warrants seem key to the venture lending business model, with a probability increase of 13.5

percentage points for a medium amount of warrants and 21.4 percentage points for a high amount of warrants. Early- and late-stage VC backing also play an important role in the lender's decision. Interestingly, offering key patents as collateral is more important to the lender than offering tangible assets. Related to this, the amount of tangible assets seems not to matter to lenders as the difference between 'some' and 'relatively many' assets is not statistically significant at the 10% probability threshold.

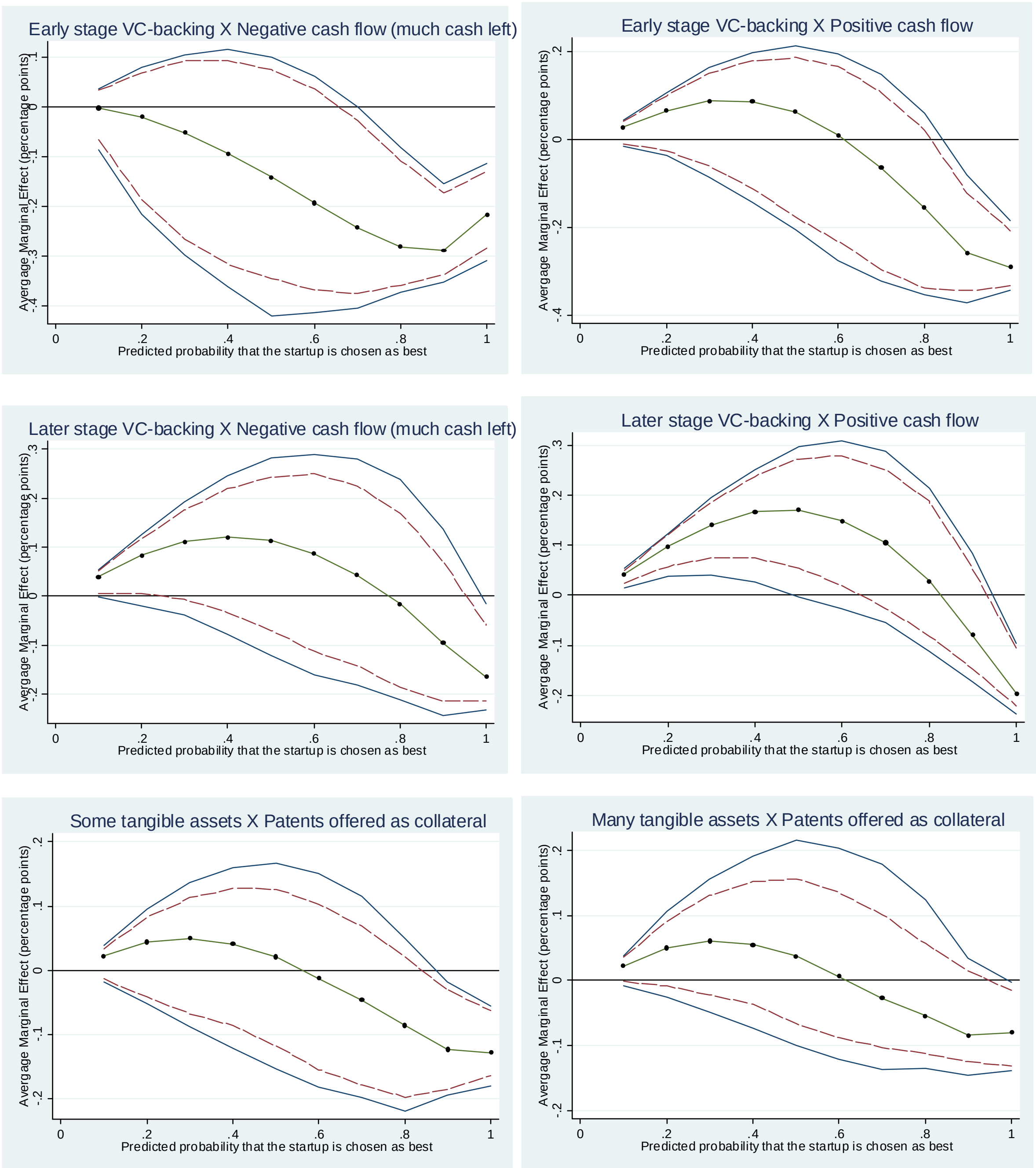
A detailed analysis of the average marginal effects of the interaction terms is presented in Figure 3, following the methodology proposed by Fischer and Henkel (2010). The figure contains a graph for each interaction term in the model, showing the predicted probability that a startup will obtain venture debt financing on the x-axis and the difference in predicted probabilities when an interaction dummy is switched from 0 to 1 on the y-axis. These plots enable us to assess how the size of the interaction effect varies with the probability that a startup obtains venture debt financing, which depends on its characteristics and the startups that it is competing with. As in the calculation of the average marginal effects of the main terms, we calculate the size of the interaction effect for every possible combination of startup characteristics. We then plot the average interaction effect in each of ten ranges of predicted probability (0%–10%, 10%–20% …) that the startup will obtain venture debt financing. To be able to assess the significance of the interaction effect, we also calculate and present 90% (full lines in graphs) and 80% (broken lines in graphs) confidence intervals.[8] Since our hypotheses are directed, the confidence intervals indicate significance of one-sided hypotheses tests at the 5% and the 10% significance level, respectively.

Figure 3 shows a strong interaction effect between early-stage VC backing and negative cash flow (top-left panel), the effect being particularly strong when the startup already has a high chance of obtaining venture debt financing. We observe a similar pattern in the interaction between early stage VC backing and positive cash flow (top-right panel). When it comes to the interaction between for later stage VC backing and cash flow, the interaction term later stage VC backing and positive cash flow (middle right panel) is most interesting. On a low probability that a startup obtains venture debt financing, VC-backing and cash flow are complements to each other. However, on a high probability that a startup will receive venture debt financing both are substitutes for each other, yielding an interaction term that is in total not significantly different from zero. When we analyze the interaction between tangible assets and

[8] We used 100 draws from the distribution of the originally estimated coefficient vector to calculate the confidence intervals. The STATA code to calculate the interaction effects is based on the code developed by Fischer and Henkel (2010).

offering patents as collateral (bottom panel), we find a significant substitution effect only when there is a high probability that a startup receives venture debt.

Figure 3: Average marginal effects of the interaction effects



Notes: Full line indicates 90% confidence intervals, broken line indicates 80% confidence intervals.

5. Discussion

This paper takes a close look at venture debt, an area which has received little attention in the literature to date. To the best of our knowledge, this paper is the first to provide a quantitative overview of the venture debt market and to empirically study the venture lending decision criteria. Our findings have implications for the theory of new venture financing and for the literature on innovation research more broadly.

Our results provide empirical support for the argument that the venture debt business model can be reconciled with existing theory. The importance of warrants in venture lending is consistent with the high agency costs that exist between the lender and the entrepreneur in high-growth ventures (Green, 1984). Furthermore, we have provided empirical evidence that VC backing substitutes for cash flow and that intangible assets in the form of patents are taken as collateral, thereby providing the ‘belt and suspenders’ that traditional lenders typically require (Hardymon and Leamon, 2001). Interestingly the substitution effect between VC backing and cash flows is much stronger for early-stage startups. While VCs and venture lenders seem to have a symbiotic relationship, as argued by Mann (1999), the finding that the substitution effect between VC-backing and cash flow is moderated by startup stage supports the argument that there is no implicit contract between VCs and venture lenders to pay back the loan. If such an implicit promise existed (Ibrahim, 2010) we would expect to observe a substitution effect independent on startup stage. An explanation for the moderation by startup stage which we observe is that the probability of cash infusion by the VC is stronger in early stages than in later stages of VC backing. VCs do not want to earn a reputation within the entrepreneurial community for not supporting their portfolio firms, especially in early stages where a strong commitment by the VC is expected (Hardymon et al., 2005). VC commitment in early-stage investments is also emphasized in Roberts et al. (2008), who report that early-stage venture capital firms usually follow their investments at least through a second or third round (see also Puri and Zarutskie, forthcoming, for empirical evidence that VCs help keep firms alive in the early part of firms’ lifecycle). Hence, our findings suggest that venture lenders simply bet on follow-up cash infusions by VCs, for which the probability is higher in early stage startups, and do not rely on an implicit contract with VCs. This finding assists in unraveling the apparent puzzle of the venture lending business model, by articulating the simple economic rationales behind venture lending decisions.

The paper also contributes to the literature on innovation research, in particular research on the effects of patents on innovative activity (see e.g. Kulatilaka and Lin, 2006). Our empirical setting allows us to disentangle two different ways in which patents help finance innovative activity. First, the results of our choice experiment provide evidence that the mere holding of patents significantly increases the probability that a firm will receive a venture loan, which we interpret as evidence of the signaling effect of patents. The signaling effect of patents can work in two ways: patents can secure a market niche and thus increase the chance of a startup's success (Cockburn and MacGarvie, forthcoming); and they can signal technological excellence and a team's professionalism (Häussler et al., 2009; Hsu and Ziedonis, 2008). Second, most notably, our empirical findings also suggest a role played by patents that has received little attention in the literature: we find that offering patents as collateral has a strong effect on the probability of obtaining venture debt. This finding shows that patents not only act as a signal to potential investors, but also represent an asset per se that can be liquidated and therefore serve as collateral, similarly to tangible assets. The general lack of substitutability between tangible assets and patents could be explained by the great deal of tacit knowledge that is usually needed to exploit the invention, such that ownership of the patent does not imply ownership of the invention (i.e. the residual rights of control of intangible assets are difficult to transfer). Discussions with industry experts support that view: the intellectual property is often bundled with the team of engineers when it is transferred to another party. Interestingly, patents and tangible assets are perfect substitutes only when the startup already has a high probability of obtaining venture debt. A potential explanation for this finding is that startups that already have a high probability of obtaining venture debt are very promising startups from the venture lenders point of view. As far as the high probability of obtaining venture debt results from performance-related startup characteristics (like cash flow or VC backing) these startups could also hold patents protecting promising inventions, making them easier to liquidate. The venture debt industry sets an encouraging precedent of the use of patents as collateral to finance innovative activity. The potential of patent-backed loans on the growth of innovations in general is substantial, as demonstrated by Amable et al. (2010). In this respect the liquidation capabilities developed by VLs should be of interest to traditional banks, given the growing importance of intangible assets to firm valuations in general.

Our study comes with some limitations offering opportunities for further research. First, although we are confident that we selected the most important characteristics identified by qualitative research, the choice experiment approach implies that we can only study a limited set of startup characteristics. During this research we learned that VLs perform a great deal of due diligence on their own. Hence, future research could investigate the effect of other startup characteristics, such as valuation, market size or the quality of the management team, on the lending decision. Similarly, much as Shane and Cable (2002) have shown that that the strength of ties between entrepreneurs and investors matters in explaining venture finance decisions, we suspect that the history of VC–VL interactions and the VC's reputation play a central role in the venture lending decision and the terms of the venture debt agreement. Second, the empirical setting for our study was startups operating in IT, because qualitative research proposed that venture debt is the most prevalent in IT. Insofar as we do not expect our hypotheses to be industryspecific, our conclusion can be generalized to other industries. Our findings regarding the signaling and the collateral effects of patents are likely to be stronger in some industries (such as biotech or pharmaceuticals) and weaker in others where patents are not essential. Finally, we have studied venture debt taking a lender's perspective. A promising avenue for further research would be to analyze the circumstances in which it is optimal for entrepreneurs and VCs to take on venture debt, thus allowing for normative guidance to startup owners on financing decisions.

Our results are particularly valuable to entrepreneurs in innovative startups. Many startups do not take patents because they are expensive (Graham et al., 2009), especially for startups at the prerevenue stage. Our results suggest that the signaling and the collateral effects are additional factors that firms should take into account when considering whether to apply for patent. Similarly, our results add a new element to the list of effects that VCs have on new ventures (see e.g. Hellmann and Puri, 2000). Having a VC onboard impacts the funding capacity of startups by facilitating access to venture debt. Overall, the economic importance of venture debt should not be underestimated. This is true not only at the startup level, given the equity-efficient money that venture debt provides, but also economy-wide, given the size of the industry.

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Appendix A

Aegis Capital Group LLC

Agility Capital LLC

BFI Business Finance

BlueCrest Capital Finance, LP

Comerica

Culver Capital Group

Eastward Capital Partners LLC

Escalate Capital Partners

Gold Hill Capital Management LLC

Harris & Harris Group Inc

Hercules Technology Growth Capital Inc

Horizon Technology Finance

InnoVentures Capital Partners

Leader Ventures

Leasing Technologies International Inc

Lighthouse Capital Partners Inc

Madison Development Corporation

MCG Capital Corp

MMV Financial

Noble Venture Finance

ORIX Venture Finance

Oxford Finance corporation

Pearl Street Capital Group

Pinnacle Ventures

RCC Ventures LLC

Sand Hill Capital

Square 1 Bank

SVB Capital

US Capital Partners

Velocity Financial Group

Wellington Financial LP