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Debt financing of high-growth startups: The venture lending business model

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Abstract

We study the business model of venture lendin g firms, specialized institutions that provide loans to high-growth start-ups. Venture debt is in apparent contradiction with traditional debt theory since start-ups have negative cash flows and lack tangible assets to secure the loan. Yet, we estimate that the U.S. venture debt industry provided at least US$ 3.8 billion in loan to start-ups in 2010, which is about 1 venture debt dollar for every 6 venture capital dollars invested. We aim to provide the first empirical assessment of how the venture debt lending business model works. Building on existing field interviews and case studies, we design a choice experiment of the venture lending decision and conduct experiments with 55 venture debt lenders. Most notably, we find that backing by venture capital firms substitutes for cash flows. Furthermore, we illustrate the importance of offering patents as collateral for obtaining venture debt.

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Debt financing of high-growth startups: The venture debt business model [1]

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We study the business model of venture debt firms, specialized institutions that provide loans to high-growth start-ups. Venture debt is in apparent contradiction with traditional debt theory since start-ups have negative cash flows and lack tangible assets to secure the loan. Yet, we estimate that the U.S. venture debt industry provided at least US$ 3 billion in loan to start-ups in 2010, which is about 1 venture debt dollar for every 7 venture capital dollars invested. We aim to provide the first quantitative empirical analysis of the venture debt business model. 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. Our findings yield empirical evidence that venture debt firms rely on non-traditional criteria to evaluate repayment capacity. Most notably, we find that backing by venture capital firms substitutes for start-ups' cash flows only for early stage startups. Furthermore, we illustrate the effect of offering patents as collateral on top of the patents' signaling effect to tap venture debt financing.

1. Introduction

Entrepreneurial ventures play a central role in the economy. They foster technological development and drive competition and economic growth. However, most entrepreneurs are liquidity constrained, making external capital essential to the entrepreneurial process (Evans and

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Jovanovic, 1989). For these reasons, the financing of new ventures has attracted strong interest in the management, finance and entrepreneurship literature. Much of the attention has been devoted to the study of venture capitalists (VCs), which provide equity to high-growth start-ups in high tech fields (see e.g. Schmidt, 2002; Shane and Cable, 2002; Batjargal and Liu, 2004; Tykvova, 2007; de Bettignies, 2008 for recent studies in the field).

A new phenomenon in the financing of new ventures is the emergence of venture debt firms (or venture lenders, VLs), which provide loans to high-growth start-ups.[2] Such loans are different from convertible debt widely used by VCs. In particular, convertible debt is meant to be converted into equity in the next financing round, whereas venture debt is a loan that has to be paid back, much like a traditional business loan. The rise of venture debt 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). 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 loan to new ventures in 2010, which is about 1 venture debt dollar for every 7 venture capital dollars invested. Well-known U.S. companies that used venture debt include Facebook, YouTube and Amazon.com.

Venture debt, which comes on top of venture capital, is an equity-efficient way to raise money: The money provided allows the start-up 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 investors teams. In addition, even though venture debt usually comes with warrants, lenders only take a small equity stake in the company. Yet, despite the size of the venture debt industry and its advantage for the entrepreneurs and the VCs, existing research 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 other have looked more broadly at the business model of VLs relying on qualitative research methods (Mann, 1999; Hardymon and Leamon, 2001; Hardymon et al, 2005; Ibrahim, 2010). A thorough, quantitative understanding of the determinants that allow new ventures to tap this increasingly important source of money is key for scholars, investors and entrepreneurs alike. With this paper, we aim to provide the first quantitative evidence on the determinants of the venture lending decision. More precisely, we study what startup characteristics influence the probability that a start-up obtains venture debt. We derive our hypotheses by drawing on theories of new venture financing and connecting it with existing qualitative research. To test the hypotheses, we develop choice experiments which model a realistic venture lending decision and conduct them with 55 senior venture lenders. To the best of our knowledge, this paper is the first to empirically test the emerging theory of venture lending. Our findings yield empirical evidence that venture debt firms rely on non-traditional criteria to evaluate repayment capacity in line with extant qualitative research. Going beyond existing works and extending our understanding of venture lending, we show that backing by venture capital firms substitutes for start-ups' cash flows only for early stage startups. Furthermore, we illustrate the importance of offering patents as collateral in the lending decision, a finding that emphasizes an often overlooked role of patents in fostering innovation.

[2] We use the terms "debt" and "loan" interchangeably.

2. The venture debt business model

The venture lending activity is the provision of loans to high-growth startups. Such loans appear puzzling from the view point of 'traditional' debt theory since high-growth startups have no track record, virtually no repayment capacity and only limited collateral to secure the loan.[3] The repayment capacity is usually assessed on the basis of operating cash flows, a prime factor of credit worthiness (Carey & Hrycay, 2001). The importance of collaterals 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 they are also used as a mechanism to enforce loan contracts (Barro, 1976). In the following, we discuss how VLs evaluate the firm repayment capacity and the role of collateral. We also discuss equity warrants, which are prevalent in venture debt agreements.

2.1 Repayment capacity

Most of the companies that receive venture debt are at the prerevenue stage and consequently have negative cash flows – they can burn millions for conducting R&D and building complementary assets. Lenders thus have to rely on alternative sources to evaluate the start-ups repayment capacity. A critical factor that they look at is whether the start-up 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 start-up's future prospects and it increases the start-up repayment capacity.

First, VC backing signals the quality of the project to the lender. High tech start-ups are 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 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 capacity to make or attract a follow-on round of financing. VC-backed companies typically go through several rounds of venture financing 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 start-ups 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 conclude an implicit contract that the VC repays the loan. These arguments suggests that VC backing may substitute for cash flows (Mann, 1999; Ibrahim, 2010). We hypothesize:

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

[3] Venture debt can be used to finance growth capital or the purchase of new equipments. Loans to finance new equipments is not so puzzling as the underlying asset can be taken as collateral. In this paper, we focus on loans to finance growth capital.

2.2 Collaterals

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). Most high-growth start-ups, however, do not have tangible assets. Their most likely tradable asset is their intellectual property, in particular patents (Mann, 1999).

From the investor point of view, the holding of patents reduces information asymmetries by signaling new ventures likely chances of success (see e.g. Cockburn and Wagner, 2010). Patents may have a direct effect on firms' performance by protecting market niches from competitors (see e.g. Cockburn and MacGarvie, forthcoming) or an indirect effect by informing investors about the discipline and expertise of the start-up 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.

Patents also 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 at commercializing 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, 2007) non-practicing entities trying to acquire exclusion rights on the "market for patents" give patents a considerable liquidation value.

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 start-ups lack tangible collaterals, 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.*

2.3 Equity warrants

Equity warrants convey the right to purchase shares of stock at a stated price within a given time period (e.g., Hardymon et al., 2005; Roberts et al., 2008). VLs often take warrant as a way to get a piece of any upside created, to be rewarded for the risk they are taking. 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 (the lender) cannot

[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 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.

monitor the agent's actions (the entrepreneur) and the agent has different objectives than the principal, the pursue 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 start-up 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 these of the agents (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 these of the entrepreneur and reducing agency cost. Thus, we hypothesize:

HYPOTHESIS 3. *The more equity warrants the higher the chance of getting venture debt.*

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 U.S. in two steps: First, we identified companies active in the industry, and second, we indentified the targeted participants within each company.

The first stage of the identification process consisted in listing all the potential providers of venture debt, loosely defined as institutions providing loans to new ventures. To this aim, we searched the academic literature for the key players (Hardymon et al. 2005; Ibrahim, 2010) and performed a broader search on specialized press, online forums 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.

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 employees name 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 from 31 companies, leading to a response rate of 10% (or 39% if computed at the company level). 42 venture lenders completed all 12 experiments. 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". 11 of the respondents see themselves as experienced (score of 4) in venture lending while 44 see themselves as very experienced (score of 5). The "expert" status of the respondents is corroborated with 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 only information from the 42 respondents (from 24 different companies) that completed the whole questionnaire. On average the lending companies in our sample have 87 outstanding loans with a maturity of 28 months and an interest rate of 11.5%. Each loan has 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 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; eventually it should underestimate the true amount of loans since not all lenders participated in our survey. Calculated by year, the estimate is the US$ 1–5 billion figure discussed in Ibrahim (2010): the venture lending firms in our sample provide about US$ 3 billion per year (7*12/28). In comparison, the VC industry invested about US$ 22 billion in 2010.[6] In other words, the venture debt industry provides about 1 dollar for every 7 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 potential benefits of venture debt. Venture lenders mainly aim at obtaining interest payments, but also aim at obtaining equity warrants. The latter finding is somewhat surprising because it contradicts qualitative research that describes obtaining warrants as nice bonus (Ibrahim, 2010). Our results rather suggest that the motive to obtain an equity share is en par with the motive to obtain interest payments. Concerning startups, VLs see the major advantage that venture debt avoids the dilution of startups' equity shares, but only somewhat agree 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. From the lenders' perspective, venture capitalists profit strongest from venture debt by increasing their internal rate of return (by reducing equity dilution), while there is less agreement on the proposition that venture debt gives venture capitalists more time to evaluate startups. Finally lenders agree that venture debt reduces the limitation of VC's funds.

[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

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

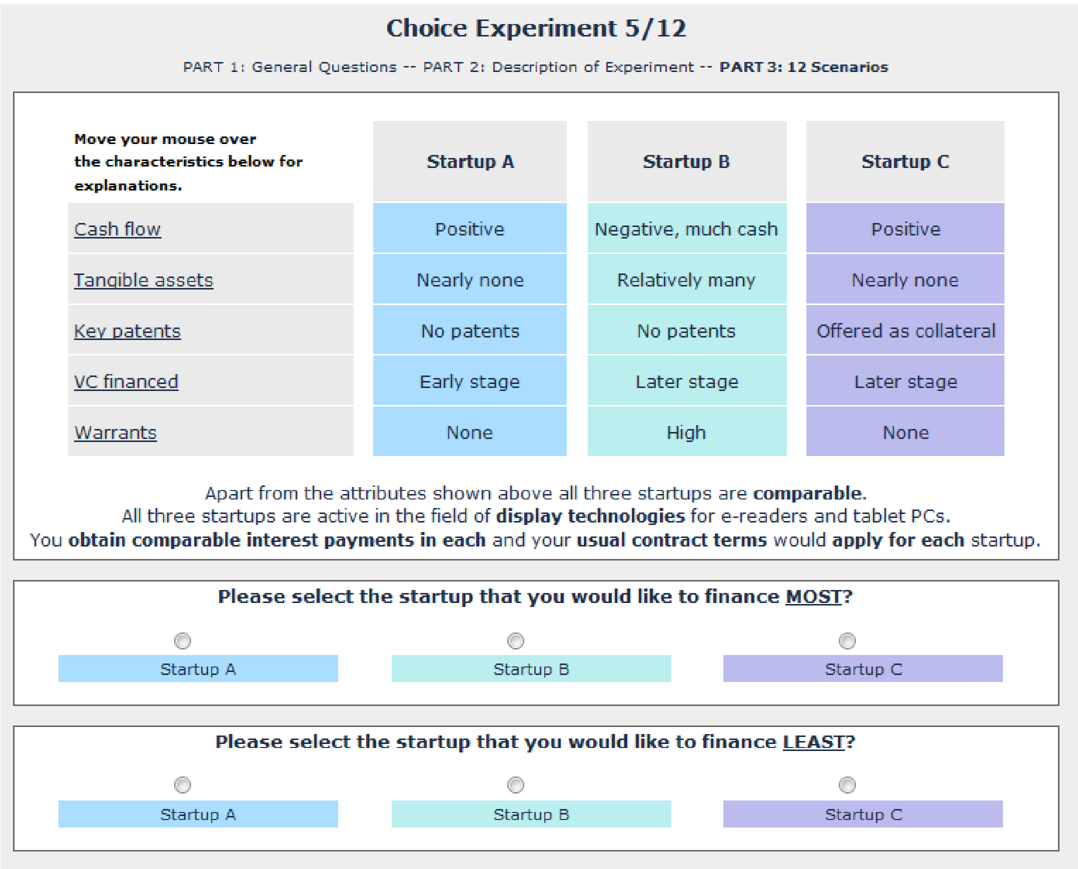
To test our hypotheses, we conduct a choice-based conjoint analysis (see Green and Srinivasan 1990), also known as discrete choice experiments.[7] In a choice-based conjoint approach, each participant sees multiple choice sets, each containing multiple alternatives. In every choice set participants have 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. In each choice-set, participants choose the startup that they would like to finance most and the one they would like to finance least, based on five attributes describing important startup characteristics on three levels each. Respondents' 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 start-ups 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.

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

The most important issue in a choice-based conjoint approach is to make the experiments as realistic as possible while keeping them manageable for respondents. To do so, we drew on existing qualitative research on venture debt that identified important characteristics of startups in a venture lending decision. 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 5 characteristics: operating cash flow of the startup, its tangible assets, its patents, the amount of warrants offered and whether the startup has VC backing or not. All other potential characteristics are comparable among the three startups. All startups develop 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 mechanisms 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 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 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	Nearly none
(usable as collateral)	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 start-ups they would finance most and least out of three, we obtained a complete ranking of alternatives for each choice set. An estimation method to analyze 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 that do not require the iia assumption (Brownstone and Train, 1999; McFadden and Train 2000; Revelt and Train 1998).

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 ß. $f(\beta \mid \theta)$ 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 only as a first step on the estimated coefficients (Greene, 2010), but offer a deeper analysis of the average marginal effects as well (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	.191	(.167)	.178	(.358)
Respondents / Choices	55	2,825	55	2,825
LL / Mc Faddens Pseudo-R	-726.80	.282	-643.10	.365
Wald test / p-value	232.15	.000	182.54	.000

Notes: Standard errors are 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 to receive venture debt, which we interpret as evidence of the signaling effect of patents to venture lenders. In addition, the likelihood that the 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. We find no evidence of a substitution 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 models presented in Table 5 enable us to delve deeper into the analysis of the substitution effect between VC backing and cash flow by differentiating between early- and late-stage backing. Again, we present first 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

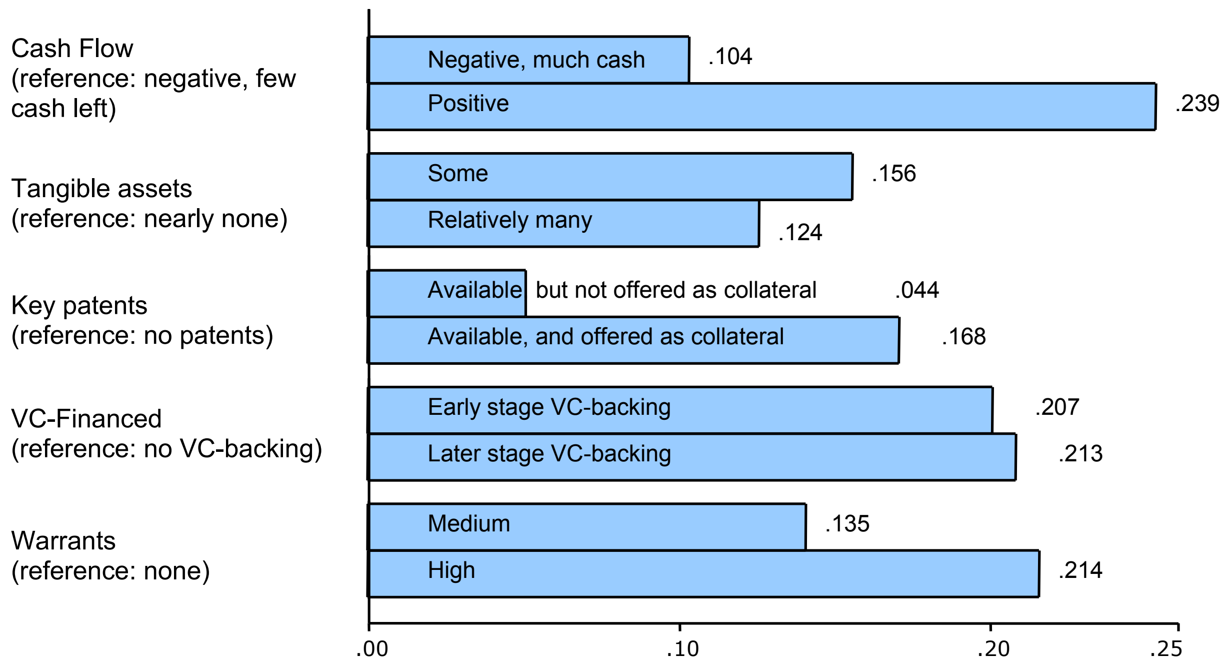
	Model 2a		**Model 2b**	
Dependent variable: ranking	**Rank-ordered Logit**		**Rank-ordered mixed logit**	
Main effects:				
Negative cash flow but still much cash available (base: negative cash flow, few cash available)	.995**	(.316)	1.992**	(.608)
Positive cash flow (base: negative cash flow, few cash 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	.197	(.305)	-.229	(.498)
Respondents / Choices	55	2,825	55	2,825
LL / Mc Faddens Pseudo-R	-726.05	.283	-641.86	.366
Wald test / p-value	259.63	.000	212.43	.000

Notes: Standard errors are 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. 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). Following Fischer and Henkel (2010), we define the average marginal effect as 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. Eventually, the results presented are the difference in predicted probabilities (for a dummy variable its marginal effect) averaged over all $3^5*3^5*3^4$ = 4.7 million possible combinations.[8]

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 start-ups with positive cash flows are a real gem and lenders' preference comes as

[8] To perform the analysis of main and interaction effects, we relied on the STATA code developed by Fischer and Henkel (2010).

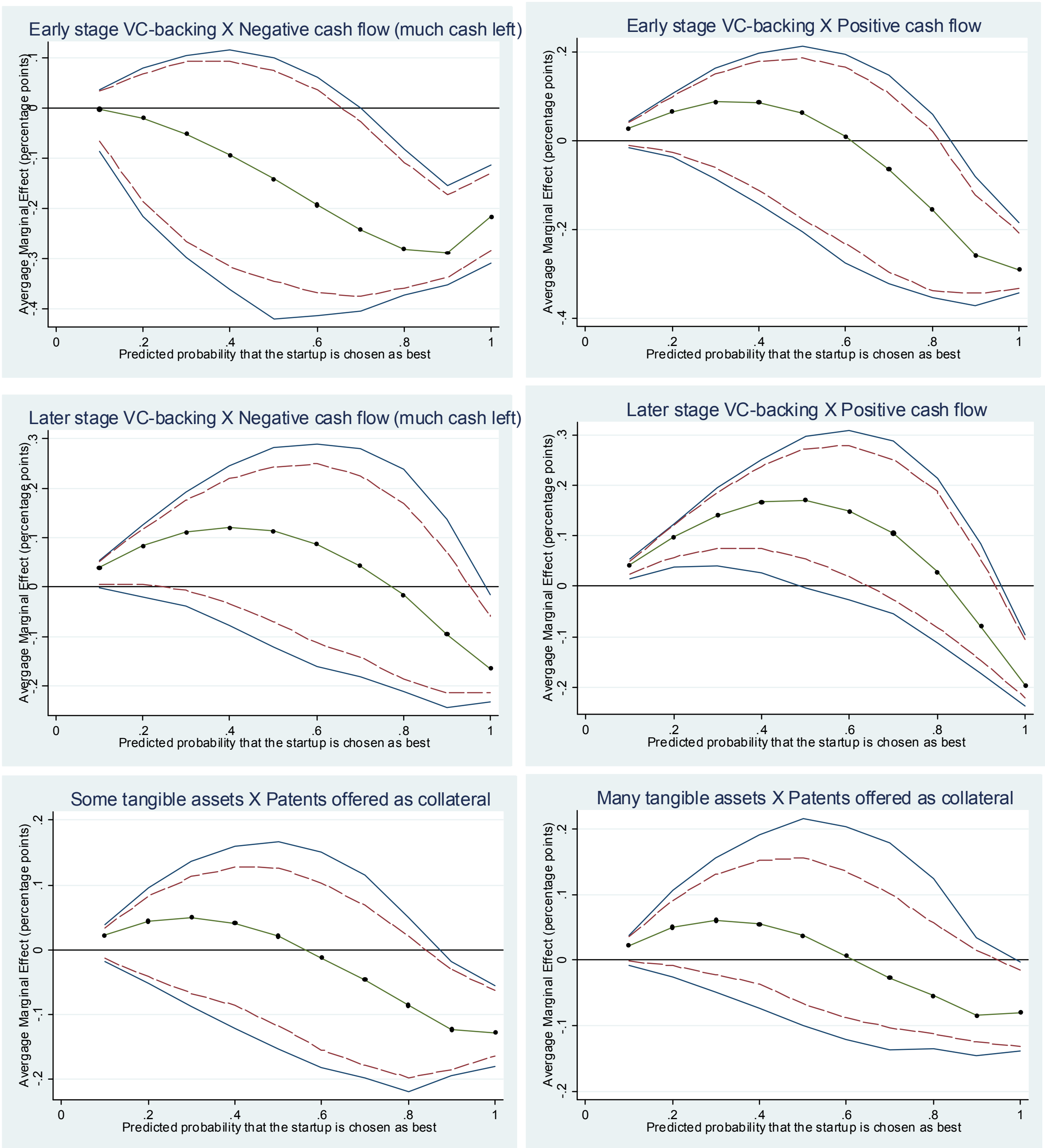
no surprise. The probability of obtaining venture debt financing is on average 23.9 percentage points higher than for a startup with negative cash flow and few cash left (the reference level). Offering a high level of warrants is the second most important criterion. More than a "nice bonus" (Ibrahim, 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.

In particular if interaction terms are the subject of analysis in non-linear model, as in our case, a detailed analysis of the average marginal effects of the interaction terms is warranted (Norton et al., 2004; Hoetker, 2007). Hence, we present the average marginal effects of the interaction effects in Model 2b in Figure 3, as proposed by Fischer and Henkel (2010). It 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 start-up 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.[9] 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 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 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 to each other, yielding an interaction term that is in total not significantly different from zero. When we analyze the interaction between tangible assets and offering patents as collateral (bottom panel), we find a significant substitution effect when there is a high probability that a startup receives venture debt.

[9] 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).

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, which has received little attention in the literature on new venture financing. 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 results have implications for the theory of new venture financing and for the literature on innovation research more broadly.

Regarding the theory of new ventures financing, our results provide empirical support for the argument that the venture debt business model can be reconciled with existing theory. The strong importance of warrants 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 lenders typically require (Hardymon and Leamon, 2001). In particular these two latter results have strong implications for our understanding of new venture financing and innovation research.

It is intriguing that the substitution effect between VC backing and cash flows is much stronger for early-stage start-ups. 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 start-up stage supports the argument that there is no implicit contract between VCs and venture lenders to pay back the loan. If VCs implicitly promise to pay back the loan (Ibrahim, 2010) we would expect to observe a substitution effect independent on start-up stage. An explanation for the moderation by start-up stage we observe is related to the fact that the probability of cash infusion of 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 stage where a strong commitment of the VC is expected (Hardymon et al., 2005; Ibrahim, 2010). 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 finding suggests that venture lenders simply bet on follow up cash infusions by VCs which probability is higher for early stage start-ups and do not rely on an implicit contract to pay back the loan with VCs. This finding adds to unravel the apparently puzzling venture lending business model, by supporting simple economic rationales behind venture lending decisions.

The paper also contributes to the literature on innovation research, in particular to the debate on the effects of patents on innovative activity. Our empirical setting allows us to disentangle two different ways patents help finance innovative activity. First, the results of our choice experiment provide evidence that the more holding of patents significantly increases the probability that a firm will receive venture debt, 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 startups' success (Cockburn and MacGarvie, forthcoming); and they can signal technological excellence and the teams' professionalism (Häussler et al., 2009; Hsu and Ziedonis, 2008). Second, most notably, our empirical findings also suggest a role of patents that has received little attention in the literature: we find a strong effect of offering patents as collateral on the probability to obtain venture debt. This finding shows that patents not only serve 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. 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 should also hold patents protecting promising inventions making them easier to liquidate. The general lack of substitutability between tangible assets and patents could be explained by the lack of separability of the patent from the inventor and the great transaction costs in the market for patents (Arora et al., 2001). Yet, 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 in firms' value 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, we included only a limited set of startup characteristics in our experiments. 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 start-ups' characteristics such as valuation, market size or the quality of the management team on the lending decision. Similarly, much like Shane and Cable (2002) have shown that that the strength of ties between entrepreneurs and investors matters in explaining venture finance decision, we suspect the history of VC-VL interactions and the VC reputation to play a strong role on the venture lending decision and the terms of the venture debt agreement. Second, the empirical testbed for our study were startups operating in IT, because qualitative research proposed that venture debt is the most prevalent in IT. An extension of the current work includes testing whether the results can be generalized to other industries in which startups operate and to carve out industry contingencies. Finally, we have only studied venture debt taking a lender's perspective. A promising avenue of further research is to analyze when it is optimal for entrepreneurs and VCs to take venture debt and to be able to offer start-ups owners with normative guidance on financing decisions.

Our results are particularly valuable to entrepreneurs in innovative start-ups. Venture debt allows them to raise money by leveraging existing resources with unsuspected or difficult-to-realize value such as VC backing and patents. This is particularly true for pre-revenue start-ups, for which patents and VC backing are their only valuable asset. At the same time, venture debt does not dilute the equity shares of existing investors and entrepreneurs that comes with commonly employed additional VC financing rounds. It is thus vital for entrepreneurs (and investors) to understand how venture debt works and how to obtain it. Our results also yield that the economic importance of venture debt should not be underestimated. We find that VLs provide startups with at minima 1 additional dollar for every 7 dollars provided by VCs. Economy-wide, this additional supply of money allows bringing more innovations to the market.

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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