Venture debt financing and the development of startups: Disentangling treatment from selection effects

Carlos Krause, Jörn Block, Alexandra Moritz

Abstract

This article is the first study that examines how venture debt (VD) financing influences startup development and disentangles whether this influence can be credited to the treatment effect or selection effect of VD investors. Therefore, we examine whether VD investors are "making winners" or "picking winners". We use a sample comprising 64 identified VD investors with 2,950 funding rounds with VD participation of 1,431 US-based and VD-backed startups since 2009. We analyze events such as "subsequent funding round", "trade sale", and "IPO" as a measure of startup development following VD and venture capital (VC) funding rounds with the application of a two-step Heckman and counterfactual model. We find that VD investors on the one hand seem to select better portfolio companies, but on the other hand, also have a direct positive treatment effect on a startup's development.

Introduction

Venture debt (VD) is a growing phenomenon reaching a new record high in aggregated deal value of $26.4bn worldwide in 2019 with an average overall stake in the entrepreneurial finance landscape of 10.3% of the yearly aggregated deal value of venture capital (VC) for the last 10 years. Although VD has already been invented in the 70s, surprisingly little attention was given to this phenomenon by scholars. The scarce literature investigating VD focuses on the general business model? of VD investors (Ibrahim, 2010; Hesse et al., 2016; Veena Iyer, 2020), the selection criteria of VD investors (Hardymond et al., 2005; Chuat et al., 2011; de Rassenfosse & Fischer, 2016; Tykvová, 2017) and the role of patents for VD investors (Fischer & Ringler, 2014; Hesse & Lutz, 2016; Hochberg et al., 2018).

However, although VD becomes more and more important to the startup financing market, little is known about the influence of VD on a startup's development. We tap into this research gap by investigating how VD-backed startups develop after their VD funding rounds. This question is important to answer because it helps both practitioners and scholars with the rationale of VD-funding.

Previous studies that examined VD mainly focused on the selection criteria VD investors use for their decision to invest in a startup. Their results show that several startup characteristics are important in the VD investor's selection process: The involvement of an intermediary (e.g., VC), the reputation of an involved VC, the presence of equity warrants and patents, the deployability of patents, and family involvement (e.g., Hardymond et al., 2004; Chua et al., 2011; Fischer & Ringler, 2014; de Rassenfosse & Fischer, 2016; Hesse & Lutz, 2016; Hochberg et al., 2018). However, it remains unclear how VD and their selection of startups are linked to the startup's development. Research investigating how debt strategies can be used by companies and how they affect their performance (Ross, 1977; Flannery, 1986; Harris & Raviv, 1990) does not consider startups. Ultimately, they find that debt can hurt and boost competitive performance depending on the industry concentration and competitive position of the respective company (Campello, 2006). However, these studies cannot be used to explain the influence of VD on startup development since VD is used in the special context of entrepreneurial finance and has very different characteristics.

Contributing to the VD research stream, we are the first study that addresses how VD affects startups by examining the following research questions: First, do VD-backed startups develop better than their non-VD-backed counterparts? Second, if this is the case, is this positive association mainly attributable to the ability of VD investors to select companies with higher development prospects ("selection effect"), or is it a consequence of the support they offer to portfolio firms ("treatment effect")? In other words, do VD investments have a positive treatment effect on portfolio firms beyond the selection effect?

To answer these research questions, we empirically analyze the impact of VD investments on the development of startups. Our data set is based on the database "Crunchbase" and comprises 2,950 US-based funding rounds of 1,431 VD funded companies by 64 VD investors since 2009. We compare these funding rounds with 79,066 funding rounds of solely VC-backed startups. As a proxy to measure the development of the startups we consider the different events that can follow the respective funding round: Subsequent funding, trade sale, IPO, and those without any events recorded ("nothing"). We use these events as the dependent variable and apply a two-step Heckman and counterfactual model.

The results of our study reveal that startups that received funding from VD investors experience more often trade sales and IPOs. This positive effect of VD on a startup's development is partially explained by the selection criteria of VD investors. In other words, although we find that VDs seem to select better portfolio companies, we still find a positive significant relationship between VD and a startup's development that can be explained with the treatment effect of VDs. Therefore, we can conclude that VD does provide an additional positive treatment effect compared to the positive treatment effect of VC, and the positive effect on the development of VD-backed startups is not completely based on the selection criteria of VD investors.

With our study, we provide several theoretical contributions. First, we are contributing to the growing VD literature (e.g., Ibrahim, 2010; Fischer & Ringler, 2014; de Rassenfosse & Fischer, 2016; Tykvová, 2017; Hochberg et al., 2018) by investigating which influence VD funding has on a startup's development. We show that VD-funded companies develop better than non-VD-funded companies. Second, we are contributing to the literature disentangling selection from treatment effects of financing options for startups (e.g., Aerts et al., 2007; Bertoni et al., 2011; Lee & Zhang, 2011; Croce et al., 2013; González-Uribe & Leatherbee, 2018; Bonini et al., 2019). Our study contributes to this research stream by examining VD as an alternative funding option for startups and shows that a better startup development can be contributed to both the selection and the treatment of VD investors. Third, we contribute to the broader research stream dealing with capital structure and the signaling effects of debt funding (Ross, 1977; Flannery, 1986; Harris & Raviv, 1990). We find empirical evidence that is consistent with the debt literature in a VD setting and show that high-quality startups are preferred by debt investors, in our case VD.

Additionally, we can derive practical implications from our study. We show that VD investors seem to offer a direct value-adding treatment to a startup. Thus, entrepreneurs do not only have a direct incentive to include VD-funding in their startup for less personal dilution of their shares but also to generate additional value for their startup and to improve their startup's development outcome.

The literature on the differences and influences of venture capital versus venture debt on startup development outcomes

Venture debt, venture capital, and value creation

Usually, VD is seen more as a complementary funding option in between rounds to extend the startup's runway, and that VD is built on an implicit contract between VC and VD investors where the VC implicitly guarantees the loan repayment (Ibrahim, 2010). However, as de Rassenfosse & Fischer (2016) pointed out, startups that receive VD are in a phase after initial insider financing provided by the startup team, family, friends, and angel investors and before access to public equity and debt markets. Based on this view, VD would be a direct substitute to VC as this is the phase where VC investors also start to provide funding to startups. Although equity is the primary funding for startups in that phase (Berger & Udell, 1998), startups in this phase have also been found to rely heavily on debt (Cassar, 2004). In line with this, practitioners from the VD space argue that they oftentimes are competing with VCs for the same deals (Source).

Since VD and VC differ not only fundamentally in their effect on the capital structure of the startups but also in how they handle and add value to their portfolio firms (Source), it is important to investigate the effect of VD and VC investors on the startup.

For that, we start by summarizing the findings of prior research investigating the value-added services that VD and VC investors offer that may influence a startup's development.

Venture capitalists and value-added services

Over the last decades, VCs have been praised for their positive impact on startup development (Lerner & Nanda, 2020).

As equity investors, VCs want to be actively involved in the development of a startup and want to offer more value-adding resources beyond money to their portfolio companies (Sapienza, 1992). Thereby, VCs can add value for startups via financial and business advice, as mentors and confidants to CEOs, and providing a network to other firms and professionals to the startup (Sapienza et al., 1996). Furthermore, VCs also show additional presence in the startup through strong monitoring processes (Gorman & Sahlman, 1989) and also do not offer the entrepreneurs the complete amount of money that is needed via one transaction but offer a staging investment process (Gompers, 1995). Therefore, VC-backed startups have to rely a lot on their VC investor after their initial investment and also have to tolerate the active involvement of their VC investor.

The positive effect of VC on a startup's performance, growth, and general development has been highlighted by various studies (e.g., Jain & Kini, 1995; Audretsch & Lehmann, 2004; Alemany & Marti, 2005; Engel & Keilbach, 2007; Puri & Zarutskie, 2012). Bertoni et al. (2011) disentangled the relationship between the ability of VCs to select better startups versus building better startups due to their value-adding impact. The authors conclude that VCs have indeed direct value-adding treatment effects that they offer to startups that improve their development. This positive treatment effect can be mainly contributed to two dimensions: The value-adding practices of VCs (Sapienza et al., 1996) and the positive signaling effect that a startup sends with the affiliation with an external equity provider (Plummer et al., 2016). In line with this finding, Lerner & Nanda (2020) pointed out that VC-backed startups comprise less than 0.5 percent of US-based startups that are born each year but represent nearly half of the entrepreneurial companies that go public.

Venture debt and value-added services

VD is structured in a way that VD investors provide debt and typically do not hold (substantial)equity. The debt part is similar to traditional bank loans in that the VD providers get common interest payment on the loan and the debt has to be repaid on a schedule. Due to the high information asymmetries between the VD providers and the entrepreneurs, the VD providers typically also ask for securities that can either be classic tangible securities (which oftentimes are not present for tech startups) or intangible in form of patents or other intellectual property. Additionally, VD investors also often rely on the implied security of an already involved VC investor that the startup will not default (Ibrahim, 2010). As these securities are typically imperative for the startup, the entrepreneurs have strong incentives to repay the loan. Thus, VD investors do not need to actively monitor their portfolio companies in a similar way as VCs do. However, in special cases, the VD investors can be able to monitor the startup's day-to-day activities on their accounts, cash-burn rates, or other accessible financial account data if the startup has its account managed by the VD investor. Hardymon et al. (2004) describe how this is an easy way for one of the largest and oldest VD players, Silicon Valley Bank, to monitor their portfolio companies. Although equity kickers are an incremental feature of VD that gives VD investors a small equity portion, they do not rely that much on the potential upsides of their portfolio companies (Ibrahim, 2010). As a result, VD investors typically do not want to get actively involved in the daily business of the entrepreneurs and to advise startups (de Rassenfosse & Fischer, 2016). However, VD investors often offer their help and advice if needed and entrepreneurs often actively seek their competencies.

Comparison of VDs and VCs influence on value creation

Based on these findings, the question arises as, whether VD can positively influence the development of startups. First, we can conclude that, in contrast to VCs, VD investors typically do not seek active involvement in their portfolio companies. Therefore, VD investors do not have the same level of "political cost" for the entrepreneur as the entrepreneur has more freedom in his decision-making processes and does not have to face a very influential board of directors. This allows entrepreneurs to work more independently and develop their businesses with fewer restrictions.

Second, prior research found that VC can be a tool for startups to signal their value to outsiders (Janney & Folta, 2006). On the other hand, established research has also shown that external debt can be a tool for a company to signal its quality (Ross, 1977). Additionally, in the startup world, third-party signals can unlock values of signals that would otherwise go unnoticed, especially if the startup demonstrates maturity and commitment (Plummer et al., 2016). In that spirit, we argue that VD can function as a signal of quality, as well. However, the signaling effect of VD and VC can be differentiated: The involvement of VC investors has been found to signal positive future prospects and the general quality of a startup (de Rassenfosse & Fischer, 2016). On the other hand, we argue that VC involvement can only provide a limited signaling effect in terms of maturity and stability. VC investors rely on a small portion of their portfolio companies to be highly profitable (Zider, 1998). This makes VC-funded companies on average highly promising but also highly volatile in their development. In contrast, the involvement of VD investors does not necessarily signal exorbitant future growth prospects but it can serve as a signal of the quality and the safety of a startup to outsiders since VD investors only invest in companies where the risk-adjusted return works for them (Ibrahim, 2010). Therefore, we argue that the fact that a VD investor was willing to invest in a startup provides a lot more value since it signals more maturity, higher stability, and fewer potential defaults.

In the past, the active involvement and monitoring activities of VCs have been seen as one of the value-adding activities of VCs (Barry et al., 1990). As VD investors are much less involved in the startup, these positive value-adding effects are likely to be missing.

However, it needs to be considered that the market for entrepreneurial finance has changed significantly over the past decades and entrepreneurs do not profit as much from the direct value-adding practices of VCs anymore. Entrepreneurs are far more educated in comparison to the early 2000s in the phases where they require large amounts of funding from VC or VD investors (Lerner & Nanda, 2020). With the rise of educational programs for entrepreneurs (von Graevenitz et al., 2010; Kuratko, 2005), the emergence of incubators (Aernoudt, 2004) and accelerators (González-Uribe & Leatherbee, 2018; Hochberg, 2016), the professionalization of business angels (Mason et al., 2016), and other entrepreneurial enhancing programs, entrepreneurs are provided with substantial knowledge about building a successful startup from the beginning. This change is also influencing the VC market and is reflected in a declining emphasis on the governance by VCs and the emergence of more "founder-friendly" terms in the VC industry (Lerner & Nanda, 2020). VD investors go one step further and let the entrepreneurs all the freedom they need, in exchange for (intangible) securities. Looking at these arguments, the question of whether VD-supported startups develop better than VC-supported startups is not easy to answer. We find arguments in both directions. Therefore, we ask the question if the positive influence of VD on a startup's development outcome with the absence of "political cost" of VD compared to VC and the stronger signaling effect does dominate the negative influences?

Data and sample selection

Data and variables

The main source of data used in this study is the database Crunchbase. Crunchbase describes itself as the leading destination for company insights from early-stage startups to the Fortune 1000. Crunchbase collects its data using crowdsourcing and news aggregation and provides detailed information on startups, funding rounds, and investors. Therefore, Crunchbase provides funding round level data on each financing event including the announcement date, investors, funding amount, and stage of financing (Series A, B, C, etc.). Additionally, other startup information is available such as the founding date of the startup, industry categories, the number of founders, headquarter location, and exit outcomes (IPO and trade sale).

Although Crunchbase also provides an investor classification and type of financing for each funding round, we found that the quality of this data in the context of VD is not satisfying. To overcome this issue, we first exported an overview of all investors listed on Crunchbase with at least 10 financing rounds classified as "Debt Financing". This resulted in 86 investors after the first step. Second, for those 86 investors, we manually screened their website and looked at their deals in Crunchbase, Preqin, and Pitchbook to verify whether those investors can be classified as VD investors. This resulted in our final sample of 64 investors that we classified as VD investors.

Next, we used all 338,188 funding rounds and only kept funding rounds from 2009 and forward (34,747 deleted) since VD became more mature after the financial crisis. For similar reasons, we only focus on the US market because VD is the most mature in this market. Hence, we dropped funding rounds from other countries (157,137 deleted). Thereafter, we classified all funding rounds with the participation of one or more of the identified 64 VD investors as VD funding rounds and deleted all other funding rounds with no VD participation. Since we are comparing rounds with VD participation to VC funding rounds we also kept also all other VC funding rounds of startups with VD participation and startups with no VD participation. Additionally, we deleted observations with missing crucial variables (16,572) and bankruptcy as the next event (1,516). Our final sample contains 41,568 different startups. 1,431 of these startups are VD-backed and 40,137 experienced no VD funding round. As the fundament of our analysis, the sample contains a total of 83,532 funding rounds where 2,950 funding rounds have VD participation and the remaining 79,066 are solely VC funding rounds. Table 1 gives an overview of our final data sample including the type of event following the respective funding rounds. For our model, we clustered the type of next event to construct our dependent variable which will be discussed in the following section.

Table 1: Data Sample

Type of next event	VD-backed	Non-VD-backed	N
Follow-up funding	1,724	44,370	46,094
IPO	74	882	956
Trade sale	331	4,961	5,292
Not event ("nothing")	821	28,853	29,674
N	2,950	79,066	83,532

Dependent variable:

Success: Our dependent variable for the analysis is *Success*. The variable is coded as a dummy variable where the funding rounds with no next event has occurred are coded as 0. The other types of events, follow-up funding, IPO, and trade sale are clustered in 1. This allows us to differentiate between favorable startup development outcomes and no outcomes.

Independent variable:

VD-backed: This dummy variable is coded as 1 at the point of time where a startup got VD funding for the first time. The variable is coded as 0 for all rounds previously to a VD funding or for all funding rounds of startups that never received VD funding.

Control variables*:*

We integrated several control variables that can affect both the startup's development outcome and the unique selection of VD investors. *Patents* are used because startups can use patents to signal their quality to outside investors (Long, 2002) which could improve their development outcomes and patents are incremental features of VD (de Rassenfosse & Fischer, 2016). The patents are captured as a dummy variable which is coded 1 when a startup has granted patents.[1]

Since the presence of VC investors can influence a startup's development (Brander et al., 2002) and VCs are an important selection criterion for VDs (Ibrahim, 2010), we included *VCinv, VCBest, Syndication* as variables. *VCinv* is a dummy variable that is coded 1 if a startup received funding from a VC. *VCBest* is a dummy variable that captures whether one of those VC funds was one of the largest VC funds according to FundComb's list[2] and *Syndication* captures the number of investors that are involved in the funding round.

Next, we have a set of variables that can also influence a startup's development outcome and also can play a role in VD investors selection: The cumulative dollar inflow received by the startup before year t (*prior funding),* the logarithmic age of a startup at the time of funding, the *Stage* of a startup coded as an ordinal variable with the stages 'Seed', 'Series A', …, 'Series J'[3], and the # *Funding Rounds*, a startup had before year t.

[1] We extracted the INPADOC-patent family from the database PATSTAT and matched the patents to the companies in our dataset with damerau levenshtein distance meassures..
[2] https://fundcomb.com/lists/largest/startup-capital accessed 17.01.2021
[3] VD funding rounds do not necessarily get assigned a stage by Crunchbase if there is no VC participation. For those cases, the stage of the VD funding rounds is assigned to the stage of the previous VC round.

Additionally, we also included controls for the VD market with *VD deal value* that captures the logarithmic aggregated deal value of the VD market lagged by one year.[4]

Last, we used some standard control variables: *Year*, *Industry*[5], and *State*[6] as indicator variables, and *# Founders* to control for the number of founders, and *Gender* to control for the gender heterogeneity of the founding team.

Summary statistics and univariate analysis

The summary statistics of the startups on the firm level are illustrated in

[4] The data for *VD deal value* was extracted from the database Preqin.

[5] Crunchbase offers 46 industry categories that we clustered into 19 categories. The industry dummies contain advertising, artificial intelligence, biotechnology, consumer goods, consumer services, data and analytics, education, energy, engineering, financial services, hardware, healthcare, information technology, media, professional services, real estate, software, transportation, and 'other'.

[6] The variable contains the states with the most VD investors: California, Illinois, Massachusetts, New York, Texas, and 'other states'.

Table 2. Of the 41,568 firms in our sample, 1,431 (3.44%) are VD-backed. The average VD-backed startup was founded in the year 2007 and received its first VD round around 6 years later. Additionally, VD-funded startups more often have patents present and do more funding rounds in general. The industry and state distribution of VD and only VC-funded companies are similar and do not show substantial differences. However, the IPO, trade sale, and success rate of VD-funded startups are clearly higher.

Table 2: Descriptive statistics (observation unit: firm-level)

	VD-backed	Only VC-backed
Average year startup founded	2007.4	2011.5
Average year of first investment	2013.0	2014.7
Startup age in years (at first investment)	5.96	3.45
Proportion of startups with at least one patent	0.39	0.23
Rounds of investment		
≤2	0.37	0.76
3-4	0.30	0.17
>4	0.33	0.07
Industries (multiple classifications possible)		
Advertising	0.15	0.09
Artificial Intelligence	0.06	0.06
Biotechnology	0.11	0.10
Consumer Goods	0.23	0.31
Consumer Services	0.16	0.18
Data and Analytics	0.16	0.14
Education	0.04	0.04
Energy	0.04	0.03
Engineering	0.22	0.22
Financial Services	0.13	0.10
Hardware	0.17	0.15
Health Care	0.23	0.22
Information Technology	0.25	0.19
Media	0.14	0.17
Professional Services	0.37	0.32
Real Estate	0.04	0.04
Software	0.50	0.42
Transportation	0.04	0.05
Other	0.07	0.09
State		
California	0.42	0.38
Illinois	0.03	0.03
Massachusetts	0.06	0.06
New York	0.13	0.13
Texas	0.04	0.05
Other	0.31	0.35
# Founders	2.07	1.92
IPO	0.06	0.02
Trade sale	0.26	0.14
Success (IPO, trade sale, or subsequent funding)	0.88	0.58
Observations (N)	1,431	40,137

Methodology and results

To test the impact of VD participation on the startup development outcomes, we follow Dutta & Folta (2016) and Croce et al. (2013). First of all, we apply a probit regression model. With the inclusion of all our control variables, we should be able to already control various selection aspects of VD investors. Even though a general probit model is not able to completely control for selection effects it allows us to get a baseline analysis for our following steps. In the next step, we use a two-step Heckman approach with the following counterfactual analysis to disentangle selection from treatment effects.

Baseline probit estimation

For our baseline model we apply the following general probit estimation to assess the startup development outcome of VD and non-VD-backed startups:

$$Y_{i,t}^{*} = \beta\left(VD - backed_{i,t}\right) + \gamma' X_{i,t} + \mu_t\left(Year(t)\right) + \varepsilon_{i,t}$$
$$Y_{i,t} = 1(Y_{i,t}^{*} > 0)$$

where i indexes the startups and t indexes time. $Y_{i,t}^{*}$ is the dummy dependent variable (success), $VD - backed_{i,t}$ is equal to 1 if startup i is VD-backed in year t, and 0 otherwise. In vector X the following control variables are included: the logarithmic amount of patents filed by the startup i before year t, the logarithmic amount of cumulative funding that startup i received before year t (prior funding), the logarithmic startup age, the startup stage, the number of funding rounds startup i received before year t, the number of investors involved in the funding round at year t (syndication), the dummy variable if a VC was involved in startup i before year t, the dummy variable if one of the largest VCs was involved in startup i before year t, location dummies, number of founders, the logarithmic aggregated deal value of the

VD market lagged by one year (VD deal value), the gender heterogeneity of the founding team of startup i, and industry dummies. Year(t) captures year fixed effects.

Table 3: Baseline analysis: Probit regression

Dependent variable	Success
	(1)
VD-backed	0.11***
Patents	0.06***
Prior Funding	0.00
Age	-0.06***
Stage	0.06***
# Funding rounds	-0.03***
Syndication	0.06***
VCinv	0.16***
VCBest	0.15***
# Founders	0.17***
VD Deal Value	-0.36***
Gender	-0.14***
Year	Yes
State	Yes
Industry	Yes
Observations (N)	82,016
χ^2	8680.65***

Note: This table reports the regression results of the probit baseline estimation. The dependent variable is the dummy variable of positive startup development outcomes. The variable is equal to one if a positive event (IPO, trade sale, subsequent funding) follows the funding round and equal to zero if nothing followed (yet). The main independent variable is the dummy variable VDTreatment equal to one for the years a startup is VD-backed.
*** Significance at 1% level
** Significance at 5% level
* Significance at 10% level

Table 3 illustrates our baseline probit regression with the successful startup development outcomes as the dependent variable. The coefficient of the VD-backed dummy is positive and significant, suggesting that there is a positive effect from the VD's treatment on the startup development outcome. This effect becomes visible even though we control for both prior VC involvement (*VCinv*) and prior involvement of one of the largest VC investors (*VCBest*). We see that both of those terms are positive and significant, as well. This suggests that prior VC involvement also has a positive impact on a startup's development and that the largest VCs can foster those outcomes even better.

However, one of the concerns with this baseline estimation is that the positive effect of VD investors could be attributed to their ability to choose better startups in contrast to VC investors. Even though we already controlled for a number of VD-specific selection criteria (patents, prior funding, age, stage, syndication, VC involvement), it remains unclear if our selection criteria variables capture all aspects of VD-specific selection criteria or whether there are still unobserved selection effects that could influence the results of our analysis. To address this issue, we control in the next step for selection to isolate whether the positive effect of VD investors on the positive startup development outcome can be ultimately attributed to the treatment effect of VD investors or to unobserved selection effects.

Switching regression estimation

Therefore, we apply an endogenous switching regression approach. This allows us to control specifically for selection effects and isolate? the VD treatment effect. The analysis focuses on how a startup that received VD would have developed without this investment. This helps us to answer the two questions: 1) what would the startup development that received VD funding have been had it not received VD funding, and 2) what would the startup development have been if it had not received VD funding (but received VC-funding)?

We adopt a typical Heckman (1977, 1979) two-step sample selection approach that sorts the startups over two different funding options (VD-backed and VC-backed). In the first stage, the estimates of the VD selection equation are used to compute the inverse Mill's ratio (*IMR(VD)*).

$VD_{i,t}^{*} = \gamma' w_{i,t} + \varepsilon_{i,t}; VD_{i,t} = 1\ if\ VD_{i,t}^{*} > 0;\ VD_{i,t} = 0\ if\ VD_{i,t}^{*} \leq 0$

$VD_{i,t}^{*}$ is the dummy dependent variable that captures whether a VD investor chose to invest in startup i at time t. If a startup receives VD funding $VD_{i,t}$equals "1" and "0" otherwise. The vector w includes variables that could affect VD selection: The logarithmic amount of patents filed by the startup i before year t, the logarithmic amount of cumulative funding that startup i received before year t, the logarithmic startup age, the startup stage, the number of funding rounds startup i received before year t (prior funding), the number of investors involved in the funding round at year t (syndication), the dummy variable if a VC was involved in startup i before year t, the dummy variable (VCBest) if one of the largest VCs from the FundComp's list was involved in startup i before year t, location dummies, number of founders, the time dummy (yrlate) capturing if the funding round happened during the last observed three years (dummy = 1 for the years 2018, 2019, 2020), the gender heterogeneity of the founding team of startup i, industry dummies, and VD market characteristics captured via the logarithmic aggregated deal value of the VD market lagged by one year.

Then the inverse Mill's ratio is used as a control variable in a within-group regression of the subset of firms that received VD funding and those that received only VC funding. The idea behind this is to control for the unobserved heterogeneity that affects the selection equation and the startup development outcome equation.[7]

VD-backed startups: $Success_{i,t}^{*} = \beta_1' X_{i,t} + \beta_{\lambda 1}[\phi(\gamma' w_{i,t})/\Phi(\gamma' w_{i,t})] + \epsilon_{1i,t}$

$Success_{i,t} = 1(Success_{i,t}^{*} > 0)$ (3)

[7] Startups that received both VD and VC funding are treated as VD-funded for the years after VD investment.

$$\text{VC-backed startups: } Success^*_{i,t} = \beta'_2 X_{i,t} + \beta_{\lambda 2}[-\phi(\gamma' w_{i,t})/(1-\Phi(\gamma' w_{i,t}))] + \epsilon_{2i,t} \quad (4)$$
$$Success_{i,t} = 1(Success^*_{i,t} > 0)$$

The inverse mills ratio ($\lambda = [\phi[.]/\Phi[.]]$) captures the unobservable VD-selection factor and the vector X includes the control variables. As noted by Certo et al. (2016), it is essential to include an exclusion restriction variable for the two-step Heckman regression that should have a significant impact on the selection in the first step but no impact on the treatment in the second step. This variable should then be excluded from the second step. As an exclusion restriction variable, we use *VD deal value* since the aggregated deal value of VD should affect the probability of a startup receiving additional VD funding, but should have no impact on the actual treatment effect of VD.

Lastly, we use the model estimates from the second step of the regression for a hypothetical (counterfactual) analysis to assess the superiority of one investor type over another. We compute the hypothetical probability of a startup experiencing a positive startup development outcome for VD-backed (VC-backed) startups if it had not received VD (VC) funding and instead received VC (VD) funding. We obtain the probability of positive startup development outcomes by including the funding round level attributes of the VD-backed subsample into the second-step regression for VC-backed startups and vice versa. To analyze the difference of the VD treatment effect (VC treatment effect), we measure the difference between the actual and hypothetical probability of a positive startup development outcome of VD-backed (VC-backed) startups.

Table 4 reports the results of the switching regression. Column 1 illustrates the probit regression of the first step that examines the drivers of VD funding. Columns 2 and 3 report the results for the second-step sub-sample regression with the included inverse Mills ratio that was obtained from the first-step regression.

Table 4: Switching regression: Stages 1 and 2

	First Stage	Second Stage	
Dependent variable	VD year dummy	Success	
		VD-backed	VC-backed
	(1)	(2)	(3)
IMR		5.98***	4.92***
Patents	0.03	0.19***	0.18***
Prior Funding	0.01***	0.08***	0.06***
Age	0.43***	2.16***	1.88***
Stage	0.04***	0.22***	0.27***
# Funding rounds	0.02	0.16***	0.09***
Syndication	0.05***	0.26***	0.27***
VCinv	-0.16***	-0.67***	-0.49***
VCBest	0.10**	0.67***	0.56***
# Founders	0.01	0.12***	0.20***
VD Deal Value	0.20***		
Gender	-0.17	-1.08***	-0.93***
yrlate	-0.22***	-2.16***	-1.81***
State	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Observations (N)	81,996	2,950	79,066
χ^2 / R^2	209.52***	0.17	0.13

Note: Stage 1 dependent variable (VD year dummy) is a dummy variable that equals one for the year a startup received its first VD investment, and zero otherwise. It is set to missing in the following years after VD funding. The dependent variable in stage 2 is the positive development outcome variable (*Success*). Stage 2 includes the inverse Mills ratio obtained from stage 1.
*** Significance at 1% level
** Significance at 5% level
* Significance at 10% level

After the first step, we see that the determinants of receiving VD funding are for the most part in line with prior research. Surprisingly, the number of patents is not statistically significant in our model which is in contrast to the findings of de Rassenfosse & Fischer (2016) who found that intellectual property plays a crucial part for VD investors. However, in practice also intangible assets that cannot get patented are used by VD investors as securities. It needs to be considered, that we are not able to observe these types of securities in our dataset.

Interestingly, we find that *VCinv* has a negative and significant impact on the VD investor's choice to select a startup into their portfolio in the first stage. However, the involvement of one of the largest VCs (*VCBest*) from the FundComp's list has a positive impact on the selection. These findings suggest that the VD investors do highly emphasize the quality of the involved VC for their decision to invest in a startup or not.

In the second stage, we see that the inverse Mill's ratios for both VD-backed and VC-backed startups are positive and significant. However, the coefficient of the inverse Mill's ratio of VD-backed startups is higher than for VC-backed startups. This indicates that both VD and VC investors have additional unobservable selection criteria that are not captured by our control variables that explain the positive development of their portfolio companies. In other words, both VD and VC investors select startups that have more promising startup development outcomes due to further unobserved character traits of these startups. However, with a coefficient value of the inverse Mill's ratio (IMR) of 5.98 for the VD investors and 4.92 for the VC investors, the VD investors seem to have a slightly superior unobserved selection process in identifying promising startups.

Table 5: Switching regression: counterfactual analysis

	Actual value of VD-backed startup	Predicted value of VD-backed startup if they had received VC instead of VD (counterfactual)	Difference between (1) and (2)	Actual value of VC-backed startup	Predicted value of VC-backed startup if they had received VD instead of VC (counterfactual)	Difference between (4) and (5)
	(1)	(2)	(3)	(4)	(5)	(6)
Success	0.72	0.51	0.21***	0.64	0.70	-0.06***

*** Significance at 1% level
** Significance at 5% level
* Significance at 10% level

In the third step, we did a counterfactual analysis (Table 5) to analyze whether there remains a treatment effect of VD investors on their portfolio companies after controlling for unobserved selection. We find that the probability of success of VD-backed startups is higher if they received actual VD funding compared to hypothetical VC funding. Additionally, for VC-backed startups, the success probability is higher if they received VD funding instead. Both times the differences between the real and hypothetical probabilities of success are statistically significant. This indicates that VD investors do not only select more promising startups but additionally positively influence their portfolio companies with their treatment.

Parametric hazard rate analysis

Finally, we apply a parametric hazard analysis for the separate events to further investigate the differences of time-to-exit for VD-backed and VC-backed startups. Therefore, we employ a parametric accelerated time-to-exit model with a log-normal distribution. Since our dataset is limited to 2020, startups that have not experienced an exit up to that point are right-censored and might exit after our sample period. We include all our prior control variables.

Table 6 reports the results of our hazard analysis with an accelerated time-to-exit parametric hazard model. Negative (positive) coefficients indicate that the time between the funding and the respective event decreases (increases). The main focus lies on the variable VD-backed which equals "1" for the years a startup is VD-backed, and "0" otherwise. In columns (1), (2), and (3) the variable VD-backed is negative and significant which indicates that VD-backed startups need less time to reach successful events. Especially trade sales are heavily influenced by the backing of VD investors. However, for IPOs we do not find statistically significant evidence of an influence of the involvement of VD investors.

Table 6: Proportional hazard analysis

Dependent variable	Log of time to exit			
	(1)	(2)	(3)	(4)
Hazard type	Success	Subsequent funding	Trade sale	IPO
VD-backed	-0.10***	-0.07***	-0.29***	0.16
Patents	-0.05***	-0.05***	-0.02	-0.14***
Prior Funding	-0.00***	-0.00***	0.01*	-0.10***
Age	0.11***	0.14***	-0.20***	-0.31***
Stage	-0.06***	-0.05***	-0.12***	-0.27***
# Funding Rounds	-0.03***	-0.04***	0.02	0.04
Syndication	-0.05***	-0.05***	-0.05***	-0.10***
VCinv	-0.26***	-0.26***	-0.36***	0.88***
VCBest	-0.08***	-0.04**	-0.37***	-0.56**
# Founders	-0.15***	-0.15***	-0.10***	-0.18***
Gender	0.12***	0.09**	0.43***	0.66*
VD Deal Value	0.15***	0.16***	0.01	0.22
State	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes

Note: The hazard types are defined as follows: Succes (dummy = 1 for IPO, trade sale, or subsequent funding), subsequent funding (dummy = 1 for subsequent funding), trade sale (dummy = 1 for trade sale), and IPO (dummy = 1 for IPO). Negative (positive) coefficients indicate that the variable decreases (increases) the time a startup takes to exit.
*** Significance at 1% level
** Significance at 5% level
* Significance at 10% level

Discussion and Conclusion

With our study, we contribute to the scarce VD literature and bring some light to this complex product. Since the VD market continues to grow more important for entrepreneurs and investors it is important to understand the empirical influence of VD on startup development outcomes.

To address this relevant field, we examined a large dataset limited to the US and after the financial crisis concerning the positive events that follow after single funding rounds. Following Dutta & Folta (2016) and Croce et al. (2013), we first conducted a baseline probit regression and further advanced the analysis with a switching regression model to disentangle selection and treatment effects. Finally, we complemented the analysis with a proportional hazard model to investigate the event separately.

Our study aimed to disentangle the selection and treatment effects of VD on a startup's development after their funding by VD investors.

We found both: VD investors do select more promising startups as their portfolio firms and also have an additional treatment effect on their portfolio firms. Consequently, the startups that got VD funding have better development outcomes since a VD investor was involved. Further, the time until a startup experience subsequent funding rounds and an exit via trade sale decrease with VD involvement which further supports the value-adding practices of VD investors.

From a theoretical point of view, the treatment effect could go in both directions. On the one hand, VD investors can have a positive influence on their portfolio companies by providing a signal to other outside investors. In addition, VD investors do not get as actively involved in the daily business of their portfolio companies compared to VCs, which provides entrepreneurs with more freedom in their decisions and to focus on their value-maximizing practices. On the other hand, the active involvement of VCs and monitoring activities are the cornerstone of the past success of VC investors and their portfolio companies (Sapienza, 1992). Therefore, the more relaxed/reserved approach of VDs could also harm their portfolio companies due to the lack of discipline. However, our results highlight a positive treatment effect of VD on their portfolio companies. This raises the question if VD could have been successful during earlier times, as well? And are VCs able to provide that much value to their portfolio companies anymore? The recent paper of Lerner & Nanda (2020) can act as a starting point that outlines the change in the entrepreneurial finance industry and the changing role of VCs. As they illustrated, VCs started to do more "founder-friendly" contracts to get better deals where their traditional value-added services are less pronounced. Also, the rise of entrepreneurial orientation and sophistication supports those developments since entrepreneurs are more supported by early pre-seed programs and entrepreneurial education in the recent decade. Therefore, the traditional value-adding practices of VCs might become less important, and other types of entrepreneurial finance can bring additional value. Consequently, we expect to see more VD-funded startups in the future since VD seems to supplement this development very well with more entrepreneurial freedom in daily business activities. However, we would argue that VD can still not be the only focus for entrepreneurs to get funded by. VD investors have strong selection criteria with a strong focus on an involved VC investor and other already involved parties. As our results show, it is less important that a VC is involved, of great importance is the quality of the involved VC. This leaves startups with the need to further stand out of the crowd to be able to attract the best sources of capital for the early stage in order to have superior opportunities to access VD funding. This effect can push the best startups even more in favorable developments and reach new performance heights and potentially a faster run through the startup stages.

With our study, we provide several contributions to the existing literature. First, we are contributing to the growing VD literature (e.g., Ibrahim, 2010; Fischer & Ringler, 2014; de Rassenfosse & Fischer, 2016; Tykvová, 2017; Hochberg et al., 2018) by investigating which influence VD funding has on a startup's development. We show that VD-funded companies develop better than non-VD-funded companies. Second, we are contributing to the literature disentangling selection from treatment effects of financing options for startups (e.g., Aerts et al., 2007; Bertoni et al., 2011; Lee & Zhang, 2011; Croce et al., 2013; González-Uribe & Leatherbee, 2018; Bonini et al., 2019). Our study contributes to this research stream by examining VD as an alternative funding option for startups and shows that a better startup development can be contributed to both the selection and the treatment of VD investors. Third, we contribute to the broader research stream dealing with capital structure and the signaling effects of debt funding (Ross, 1977; Flannery, 1986; Harris & Raviv, 1990). We find empirical evidence that is consistent with the debt literature in a VD setting and show that high-quality startups are preferred by debt investors, in our case VD.

We have several limitations in our study. First, the specification of VD players still remains a challenge. First, due to limitations in our dataset, we needed to classify VD investors manually according to the information provided on their website and their deals we found in various databases. Second, some investors are not just active in VD but also provide other types of funding such as VC or traditional bank loan financing without the traditional VD structure. In these cases, we are not able to differentiate whether such an investor acts as a VD investor or as another type of debt provider in a funding round since the detailed financing tools are not recorded in the database.

Overall, VD is still a very under-researched field that has various avenues open for future research. Building upon our research, there is room to further dive into the selection and treatment debate of VD on startup development. We are currently observing that data quality regarding VD gets better over the years. This will allow a deeper analysis of the effects of VD on startup development and startup performance in the future.

Additionally, we included as many selection variables as possible to account for the unique set of selection criteria of VD investors (e.g., Hardymond et al., 2004; Fischer & Ringler, 2014; de Rassenfosse & Fischer, 2016; Hesse & Lutz, 2016; Hochberg et al., 2018) in our study. However, we still find unobservable selection effects from VD investors that are connected with better startup development outcomes. Therefore further examination of unique selection criteria of VD investors is possible and should be pursued.

References

Aernoudt, R. (2004). Incubators: tool for entrepreneurship?. *Small business economics*, *23*(2), 127-135.

Aerts, K., Matthyssens, P., & Vandenbempt, K. (2007). Critical role and screening practices of European business incubators. *Technovation*, *27*(5), 254-267.

Alemany, L., & Marti, J. (2005). Unbiased estimation of economic impact of venture capital backed firms. In *EFA 2005 Moscow Meetings Paper*.

Audretsch, D. B., & Lehmann, E. E. (2004). Financing high-tech growth: the role of banks and venture capitalists. *Schmalenbach Business Review*, *56*(4), 340-357.

Barry, C. B., Muscarella, C. J., Peavy Iii, J. W., & Vetsuypens, M. R. (1990). The role of venture capital in the creation of public companies: Evidence from the going-public process. *Journal of Financial economics*, *27*(2), 447-471.

Bertoni, F., Colombo, M. G., & Grilli, L. (2011). Venture capital financing and the growth of high-tech start-ups: Disentangling treatment from selection effects. *Research policy*, *40*(7), 1028-1043.

Brander, J. A., Amit, R., & Antweiler, W. (2002). Venture-capital syndication: Improved venture selection vs. the value-added hypothesis. *Journal of Economics & Management Strategy*, *11*(3), 423-452.

Berger, A. N., & Udell, G. F. (1998). The economics of small business finance: The roles of private equity and debt markets in the financial growth cycle. *Journal of banking & finance*, *22*(6-8), 613-673.

Bertoni, F., Colombo, M. G., & Grilli, L. (2011). Venture capital financing and the growth of high-tech start-ups: Disentangling treatment from selection effects. *Research Policy*, *40*(7), 1028-1043.

Bonini, S., Capizzi, V., & Zocchi, P. (2019). The performance of angel-backed companies. *Journal of Banking & Finance*, *100*, 328-345.

Campello, M. (2006). Debt financing: Does it boost or hurt firm performance in product markets?. *Journal of Financial Economics*, *82*(1), 135-172.

Cassar, G. (2004). The financing of business start-ups. *Journal of business venturing*, *19*(2), 261-283.

Croce, A., Martí, J., & Murtinu, S. (2013). The impact of venture capital on the productivity growth of European entrepreneurial firms: 'Screening' or 'value added' effect?. *Journal of Business Venturing*, *28*(4), 489-510.

Chua, J. H., Chrisman, J. J., Kellermanns, F., & Wu, Z. (2011). Family involvement and new venture debt financing. *Journal of business venturing*, *26*(4), 472-488.

De Rassenfosse, G., & Fischer, T. (2016). Venture debt financing: Determinants of the lending decision. *Strategic Entrepreneurship Journal*, *10*(3), 235-256.

Diamond, D. W. (1989). Reputation acquisition in debt markets. *Journal of political Economy*, *97*(4), 828-862.

Dutta, S., & Folta, T. B. (2016). A comparison of the effect of angels and venture capitalists on innovation and value creation. *Journal of business venturing*, *31*(1), 39-54.

Engel, D., & Keilbach, M. (2007). Firm-level implications of early stage venture capital investment—An empirical investigation. *Journal of Empirical Finance*, *14*(2), 150-167.

Fischer, T., & Ringler, P. (2014). What patents are used as collateral?—An empirical analysis of patent reassignment data. *Journal of Business Venturing*, *29*(5), 633-650.

Flannery, M. J. (1986). Asymmetric information and risky debt maturity choice. *The Journal of Finance*, *41*(1), 19-37.

Gompers, P. A. (1995). Optimal investment, monitoring, and the staging of venture capital. *The journal of finance*, *50*(5), 1461-1489.

González-Uribe, J., & Leatherbee, M. (2018). The effects of business accelerators on venture performance: Evidence from start-up chile. *The Review of Financial Studies*, *31*(4), 1566-1603.

Gorman, M., & Sahlman, W. A. (1989). What do venture capitalists do?. *Journal of business venturing*, *4*(4), 231-248.

Hardymon, G., Leamon, A., & Lerner, J. (2004). Gold Hill venture lending.

Harris, M., & Raviv, A. (1990). Capital structure and the informational role of debt. *The Journal of Finance*, *45*(2), 321-349.

Heckman, J. J. (1977). Dummy endogenous variables in a simultaneous equation system (No. w0177). National Bureau of Economic Research.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica: Journal of the econometric society*, 153-161.

Hesse, M., & Lutz, E. (2016). Patent Activity of Start-Ups and the Structuring of Venture Lending Contracts. *Journal of Modern Accounting and Auditing*, *12*(8), 410-428.

Hochberg, Y. V. (2016). Accelerating entrepreneurs and ecosystems: The seed accelerator model. *Innovation Policy and the Economy*, *16*(1), 25-51.

Hochberg, Y. V., Serrano, C. J., & Ziedonis, R. H. (2018). Patent collateral, investor commitment, and the market for venture lending. *Journal of Financial Economics*, *130*(1), 74-94.Ibrahim, D. M. (2010). Debt as venture capital. *U. Ill. L. Rev.*, 1169.

Ibrahim, D. M. (2010). Debt as venture capital. *U. Ill. L. Rev.*, 1169.

Jain, B. A., & Kini, O. (1995). Venture capitalist participation and the post-issue operating performance of IPO firms. *Managerial and decision economics*, *16*(6), 593-606.

Janney, J. J., & Folta, T. B. (2006). Moderating effects of investor experience on the signaling value of private equity placements. *Journal of Business Venturing*, *21*(1), 27-44.

Lee, J. J., & Zhang, W. (2011, January). Financial capital and startup survival. In *Academy of Management Proceedings* (Vol. 2011, No. 1, pp. 1-6). Briarcliff Manor, NY 10510: Academy of Management.

Lerner, J., & Nanda, R. (2020). Venture Capital's Role in Financing Innovation: What We Know and How Much We Still Need to Learn. *Journal of Economic Perspectives*, *34*(3), 237-61.

Long, C. (2002). Patent signals. *The University of Chicago Law Review*, 625-679.

Mason, C., Botelho, T., & Harrison, R. (2016). The transformation of the business angel market: empirical evidence and research implications. *Venture Capital*, *18*(4), 321-344.

Plummer, L. A., Allison, T. H., & Connelly, B. L. (2016). Better together? Signaling interactions in new venture pursuit of initial external capital. *Academy of Management Journal*, *59*(5), 1585-1604.

Puri, M., & Zarutskie, R. (2012). On the life cycle dynamics of venture-capital-and non-venture-capital-financed firms. *The Journal of Finance*, *67*(6), 2247-2293.

Ross, S. A. (1977). The determination of financial structure: the incentive-signalling approach. *The bell journal of economics*, 23-40.

Sapienza, H. J. (1992). When do venture capitalists add value?. *Journal of business venturing*, *7*(1), 9-27.

Sapienza, H. J., Manigart, S., & Vermeir, W. (1996). Venture capitalist governance and value added in four countries. *Journal of Business Venturing*, *11*(6), 439-469.

Tykvová, T. (2017). When and Why Do Venture-Capital-Backed Companies Obtain Venture Lending?. *Journal of Financial & Quantitative Analysis*, *52*.

Veena Iyer, S. (2020). Venture debt: a catalyst for Indian entrepreneurship. *Venture Capital*, *22*(3), 215-238.

Zider, B. (1998). How venture capital works. *Harvard business review*, *76*(6), 131-139.