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ORIGINAL PAPER

Why deep pockets make great borrowers: an empirical analysis of venture loans

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Abstract

Startups typically have no positive cash flow, little collateral to offer, and high bankruptcy rates. As a result, they seem to be poor loan candidates. However, venture loans as hybrid form financing that include a loan and a warrant are used in practice. We focus on this distinct form of venture debt and identify characteristics of startups and their financing history that are related to their probability of receiving a venture loan. We use an unbalanced panel data sample of 13,540 companies that have conducted 27,577 financing rounds. Our key finding is that venture loans are associated with strongly committed existing investors, which stimulates the requirements of venture lenders and is signaled through large invested capital amounts per investor in previous rounds. Furthermore, we find that venture loans are associated with rather mature startups and offer empirical indication that the medical, health, and life science industry with clear milestones provides good conditions for venture loans.

Keywords Venture lending · Venture debt · Venture loan · Venture capital

JEL Classification C23 · G24 · G32 · M13 · M21

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1 Introduction

Innovative startups usually have limited access to debt. They do not have positive cash flows (yet), have limited collateral assets, and are characterized by uncertainty regarding the success of their business model and high bankruptcy rates. However, Tykvová (2017) shows that debt instruments are indeed relevant and even make up 15.9% of all financing rounds in her sample. Her study is based on venture debt in a broad sense, including all debt and debt-linked financial instruments, such as straight debt, convertible bonds, and venture loans, which can also be denominated as venture debt in a narrow sense. The latter are typically provided by specialized institutional venture loan funds and include a classical loan part as well as a warrant (Hesse et al. 2016).

Despite its relatively small market share of 1.6% of all venture capital transactions in our sample, venture loans add up to a volume of 3.1 bn. US-dollars within the sample period. This financing instrument leads to distinct dynamics in the financing lifecycle of startups. In contrast to straight debt, venture loans are also provided to startups with negative earnings and only limited collateral and are hence already relevant in earlier stages. The involvement of a venture capitalist acts as a substitute collateral for the venture lending fund. This makes the venture capital financing history of a startup particularly relevant for venture lenders. The venture capitalists are expected to provide value to the startup, and they are also seen as a potential source for future financing (Hesse et al. 2016). In contrast to convertible bonds, venture loans are not loans to own and are not provided by current or future equity investors. Rather than focusing on the upside potential, the business model of venture lenders is built upon managing downside risks through relationships with venture capitalists. In such, venture loans can be seen as hybrid form of financing in between straight debt and convertible bonds.

Our aim is to investigate the specific context of venture loans and shed light on conditions that are related to its use in startups. We follow a multi-level approach and investigate conditions related to the startup and investors. Thereby, we take into account the multifaceted, complementary relationships between venture lenders, startups, and venture capitalists.

We use a panel data sample of 27,577 financing rounds based on Refinitiv Eikon's Private Equity Screener.[1] Our key findings are that venture loans are significantly more frequently associated with the maturity of the startup, milestone-driven industries, performance-oriented investor types, and with startups with financially strongly committed investors.

Our paper contributes to the literature in three main ways. First, we extend the literature on financing lifecycles of startups. Entrepreneurial finance literature is increasingly interested in understanding complementary relationships between different capital providers (Bertoni et al. 2019; Harrison 2018; Park et al. 2019). We

[1] Available at: https://eikon.refinitiv.com. This resource is only available on standalone computers where the database is installed. The URL is the best available for information about the database. Refinitiv is the successor of Thomson Reuters's financial data services, which were renamed in 2018.

add to this literature stream by showing relations between earlier financing rounds by venture capitalists and subsequent venture loans provided by venture lenders. In particular, we provide empirical evidence that a sufficient financial commitment of existing equity investors fosters venture loans by satisfying venture lenders' needs for downside protection. We are able to show that, in particular, performance-orientated venture capitalists are associated with venture loans due to their performance-enhancing characteristics. Second, we extend the literature on venture debt by focusing on venture loans as a distinct form of debt financing for innovative startups. So far, the quantitative, empirical literature generally has not made that distinction (Tykvová 2017). In fact, we are among the first to examine venture loans in a comprehensive quantitative study. Third, we extend the literature on relationship lending by showing patterns in the financing stages of startups regarding the use of equity and venture loans. In particular, we highlight the relevance of the involvement of a venture capitalist for the likelihood to obtain a venture loan. Thereby, we find evidence for the relationship dimension of involved institutional equity investors and venture lenders. In venture debt, relationship lending includes a triangle of the startup, the venture lender, and the venture capitalist.

The paper proceeds as follows. After a brief introduction, we present the theoretical background and develop five hypotheses. We then describe our data and methodology, followed by a presentation and discussion of the results. Finally, we detail our conclusions and avenues for future research.

2 Theoretical background and hypothesis building

2.1 The venture loan as a distinct form of venture debt

New ventures are subject to the liabilities of newness and smallness, meaning their bankruptcy rates are significantly higher and their access to resources is strongly limited compared to those of established firms (Aldrich and Auster 1986; Stinchcombe 1965). Consequently, financing these new ventures is risky and characterized by asymmetric information, multiple incentive problems, and limited regulation (Manigart et al. 2006). In other words, most startups appear to be the opposite of attractive borrowers. Yet venture debt exists, and scholars have struggled explaining the usage of venture debt using traditional financing theories.

Ibrahim (2010) describes lending to new ventures as a puzzle. Using traditional capital structure theories, like the tradeoff theory by Kraus and Litzenberger (1973) and pecking order theory by Myers and Majluf (1984), Ibrahim (2010) deduces that traditional theories provide a rationale for venture debt after the first round of venture capital financing. Consistent with that, further research finds that venture capital backing substitutes for positive free cash flows in the context of startups and that intellectual property plays a crucial role by substituting tangible assets as collateral, making venture debt attractive to lenders (De Rassenfosse and Fischer 2016; Hesse and Lutz 2016; Hochberg et al. 2018; Ibrahim 2010).

The literature also provides venture debt rationales for startups and existing investors. Hesse et al. (2016) and Ibrahim (2010) explain that venture debt helps avoid dilution for venture capitalists and entrepreneurs. From the venture capitalist's perspective, Tykvová (2017) finds that early-stage venture capitalists prefer venture debt if their portfolio companies have low upside potential and if they cannot benefit from the value that a late-stage venture capitalist adds or if uncertainty is low. She also provides empirical evidence that venture debt is associated with weaker exits.

The majority of research on venture debt does not further differentiate between different types of debt and defines every financing round that includes debt as venture debt (De Rassenfosse and Fischer 2016; Ibrahim 2010; Tykvová 2017). The definition of venture debt can vary widely, from straight debt that is clearly different from equity to convertible debt constructs that offer equity-like characteristics (Cumming 2005). Hesse et al. (2016) are among the first to explicitly distinguish venture loans from bridge loans, traditional bank loans, convertible debt, and all other forms of debt that fall into the broad definition of venture debt.

To account for the heterogeneity of venture debt, we focus on venture loans as defined by Hesse et al. (2016). Accordingly, a venture loan is composed of two major components: a loan and warrants. Being a hybrid financing instrument, a venture loan offers many specific economic mechanisms worth examining. The loan is typically structured as an amortizing loan with equal monthly payments and always has to be paid back along with fees and interest. According to Hesse et al. (2016), the term of the loan usually ranges from 30 to 36 months, and the average loan amount in our sample is 3.4 m. US-dollars. The warrant, also known as the *equity kicker*, makes up about 15% of the original loan volume and allows the venture lender to participate in a successful exit in the future.

With these specific characteristics, venture loans can be seen as a hybrid form of financing. The warrant allows the venture lender to participate in return of successful exits. In contrast to straight debt, a venture loan hence provides upside potential. However, a venture loan is not a "loan to own" and has to be differentiated from convertible notes that are often provided by existing or future equity investors. The business model of venture lenders is not focused on the upside potential, as is the case for equity investors. Instead, venture lenders' profit is largely built upon the interest rates and fees they receive and a distinct lending model that reduces downside risk. The aim of our paper is to provide insights on factors related to a higher probability that a startup receives a venture loan.

2.2 Collateral and the probability to receive a venture loan

Intellectual property of new ventures is often suggested as a substitute for missing tangible assets as potential loan collateral (Hesse et al. 2016; Hochberg et al. 2018; Ibrahim 2010). De Rassenfosse and Fischer (2016) analyze the lending decision process of debt providers in a discrete choice experiment and find that the provision of patents is as important as the provision of tangible assets as collaterals for venture debt. In his interview-based study, Ibrahim (2010) provides statements of debt providers that also confirm the frequent use of intellectual property as a substitute of tangible assets as downside protection.

The results of De Rassenfosse and Fischer (2016) indicate that the warrant part of the venture loan is not only a "nice to have" extra profit but highly valued among venture lenders. Studies by Hsu and Ziedonis (2008) and Zhang et al. (2019) have focused on patents as quality signal in entrepreneurial finance. Both find that patents have a positive impact on the amount of funding received.

Since patents satisfy the requirements of venture lenders concerning downside protection, we believe that startups that can provide sufficient intellectual property as collateral and as quality certification are suitable candidates for venture loans. Thus, we state the first hypothesis:

> $H1_a$: The number of patents a startup holds is positively related to its probability to obtain a venture loan.

Tangible assets and/or constant cash flows are relevant components to ensure downside protection in traditional debt. Since startups are not limited to intellectual property and usually grow at a significant pace, startups quickly accumulate intellectual or tangible assets through the startup lifecycle by deploying the funds they receive to foster growth. Consistent with the financial growth cycle of small businesses in Berger and Udell (1998), Cotei and Farhat (2017) find that, with increasing maturity, startups accumulate tangible assets and are more likely to be profitable, leading to an increasing in debt use.

The financial growth cycle of startups usually starts with one's own capital injections and support from family and friends, followed by participation from business angles (Berger and Udell 1998). Climbing up the financial ladder requires time, and there is broad evidence that invested venture capitalists are a fundamental requirement of venture lenders (De Rassenfosse and Fischer 2016; Hesse et al. 2016; Ibrahim 2010). Hence, startups in intermediate or later stages of the lifecycle are more likely to exhibit at least one existing venture capital investor or a track record of venture capital rounds. With respect to the upside potential due to the warrant, the startup's exit channel becomes graspable with rising maturity, leading to easing estimation on the exit outcomes for the venture lender.

Thus, we expect that more mature startups are more likely to receive a venture loan and offer the following hypothesize:

> $H1_b$: The maturity of a startup is positively related to its probability to receive a venture loan.

2.3 Industry characteristics and the probability to receive a venture loan

Prior research has provided consistent evidence that the medical, health, and life science industries are a preferred environment of venture debt providers. An interviewee of Ibrahim (2010) estimates that about 40% of startups within the life science sector use venture debt. Due to the clearly observable and verifiable milestones, venture loans are especially attractive for borrowers and existing venture capitalists. De Rassenfosse and Fischer (2016), Hesse et al. (2016), and Ibrahim (2010) stress that the extension of the cash runway is one of the major rationales for startups and existing venture capitalists to deploy venture loans. If a startup is at risk of running out of financial resources before reaching the next milestone, a venture loan can help extend the cash runway for another 6–12 months (Ibrahim 2010). The startup can deploy the loan to reach the milestone before conducting the next equity financing round. In that way, entrepreneurs and existing venture capitalists achieve a substantial reduction of dilution, depending on the valuation increase coming with the milestone. Thus, a prevalence of venture loans in milestone-driven industries would be caused by a large demand of entrepreneurs and investors in these fields rather than by the venture lenders requirements on borrowers. Consistent with previous studies, Tykvová (2017) shows descriptive statistics that most venture debt rounds in her sample occur in the healthcare industry. She uses industries as fixed effects and does not put further attention on industry for her further analyses.

Besides clearly defined milestones, knowledge-intensive industries might attract venture lenders since they provide startups with sufficient intangible assets. In fact, according to the latest intellectual property report of USPTO (2013), the healthcare, biotechnology, and semiconductor industries are among the top five industries in producing products for which patents were considered an effective mechanism for appropriating the returns to innovation. Hesse et al. (2016) explain that the phenomenon of a long horizon of disappointment occurs in these industries and provide an example. Due to the years of previous research in industries like the drug discovery sector, which is additionally very cash intensive, venture capitalists' extended patience with their investees causes this phenomenon. Thus, the venture lender can provide loans even in relatively early stages since the investors' patience will at least cover the loan period. In that way, the venture lender's downside protection becomes independent of the exit scenario.

To test whether milestone- and patent-driven industries provide either demand of venture loans or satisfy the downside protection requirements of venture lenders, we state the following three hypotheses:

> $H2_a$: Startups operating in the medical, health, and life science industries have a higher probability to receive a venture loan.
> $H2_b$: Startups operating in the biotechnology industry have a higher probability to receive a venture loan.
> $H2_c$: Startups operating in the semiconductor industry have a higher probability to receive a venture loan.

2.4 Financial commitment of involved investors and the probability to receive a venture loan

The presence of a venture capitalist as a shareholder in a startup is a key requirement to being granted a venture loan. Venture capitalists are important in two ways. First, since entrepreneurial finance is usually characterized by informational opacity, specialized venture capitalists provide a first quality certification and simplify the due diligence process of the venture lender significantly (De Rassenfosse and Fischer 2016).

Second, due to staged financing, future venture capital injections can substitute for positive cash flows and therefore reduce downside risk for the venture lender

(Gompers 1995). In addition, venture lenders prefer strongly financially committed venture capitalists with a large stake at risk (Hesse et al. 2016; Ibrahim 2010). The rationale is that strongly committed venture capitalists are more likely preventing a potential default of the startup in periods of negative external shocks and thus ultimately more likely to prevent the loan default. Furthermore, committed venture capitalists signal deep pockets through their large investments, adding to the expectation that they will be more willing to prevent a default, as they are able to supply the startup with the necessary financial resources in tough times. Beyond the strong downside protection effects of committed venture capitalists, their large investments reinforce the first quality certification and thus also enhance the expected gains from the warrant for the venture lender.

We therefore hypothesize:

$H3$: The average capital amount invested per existing venture capitalist is positively related to the probability to receive a venture loan.

2.5 Venture capital types and the probability to receive a venture loan

The expansion of the cash runway by using a venture loan can reduce dilution of existing investors' shares. Reducing dilution is directly linked to the performance measurements of venture capital funds. Hence, venture loans can be used to improve the performance of venture capitalists. Venture capitalists can use venture loans to improve the internal rate of return by stretching equity rounds. The internal rate of return only considers capital that is already drawn. Extending the cash runway—and thereby extending the time to draw further capital from the limited partners—can improve the venture capital fund's internal rate of return (Ibrahim 2010).

Venture capitalists can be roughly categorized as independent or corporate- and government-affiliated venture capitalists. Independent venture capitalists are, with exceptions, usually performance oriented or classified as purely financial investors (Hellmann 2002). Corporate venture capitalists usually pursue strategic objectives by investing in startups that work on complementing or substituting products or services (Chesbrough 2002; Sykes 1990). Governmental venture capitalists are usually set up to foster the development of a private venture capital market and to close the financing gap of young startups (Colombo et al. 2016). Due to the performance enhancing features of the venture loan, independent venture capitalists may demand venture loans more frequently than corporate or governmental venture capitalists. Since venture capitalists differ in their primary objectives and because of the performance enhancing effect of venture loans, we hypothesize:

$H4_a$: The involvement of independent venture capitalists is positively related to the startup's probability to receive a venture loan.
$H4_b$: The involvement of corporate venture capitalists is positively related to the startup's probability to receive a venture loan.
$H4_c$: The involvement of government venture capitalists is positively related to the startup's probability to receive a venture loan.

3 Data and methodology

3.1 Rationale of the dataset

We tested our hypotheses using venture capital data from Refinitiv Eikon's Private Equity Screener. Our sample is restricted to US companies that conducted a venture capital financing round between 2009 and 2020, leading to a sample size of 55,045 financing rounds, of which 907 were identified as venture loans. These financing rounds took place in 21,835 entrepreneurial companies, of which 636 received at least one venture loan. Compared to other studies that examine debt in general in new venture financing, venture loans make up approximately 10% of all debt financing rounds in the venture capital market (De Rassenfosse and Fischer 2016; Ibrahim 2010; Tykvová 2017).

To analyze the data with a multi-level approach, we converted the data into a panel data structure. Since panel data contain information on the intertemporal dynamics and the individuality of the companies, the panel data structure provides two main advantages. First, panel data allows for consideration of the inter-individual differences to reduce the collinearity between current and lag variables (Hsiao 2007). Second, the panel data structure enables us to examine the previous financing rounds as lagged variables. In that way, we can account for the characteristics of all previous financing rounds. The panel data is structured in the dimensions portfolio company i and round number t.

In advance, we had to apply two restrictions to build the panel dataset. First, we excluded all financing rounds that are neither venture loans nor equity rounds. This specifically affected rounds involving convertible debt, bridge loans, and mezzanine financing. This restriction guarantees a clear comparison of venture capital equity rounds to venture loans. Second, we tracked portfolio companies for a maximum of eight consecutive financing rounds. Taking into account that many entrepreneurial companies fail or exit before conducting eight financing rounds, we also considered companies with fewer than eight consecutive financing rounds under the condition that their financing history is without gaps. By doing so, we also avoided a survival bias in contrast to only considering startups with a full lifecycle up to an exit.

Applying this conversion resulted in an unbalanced panel data sample of 13,540 entrepreneurial companies, of which 222 were granted a venture loan. The sample consists of 27,577 financing rounds allocated among these companies, of which 286 were identified as venture loans (Table 1).

3.2 Dependent variable

We used the dependent variable *Venture loan dummy*$_{i;t}$, which is a dummy variable that takes the value 1 if financing round t of portfolio company i is a venture loan and 0 otherwise. In order to identify venture loans according to the definition of Hesse et al. (2016), we used the investment security type used in the respective

Table 1 Structure of unbalanced panel data

Obs. rounds per company	Total	Non-VL	VL
1	6977	6953	24
1,2	6100	6071	29
1,2,3	4764	4722	42
1,2,3,4	3488	3454	34
1,2,3,4,5	2525	2501	24
1,2,3,4,5,6	1542	1519	23
1,2,3,4,5,6,7	1029	1013	16
1,2,3,4,5,6,7,8	1152	1122	30
Total	27,577	27,355	222

Note: Table 1 presents observed financing rounds according to the length of a company's financing history

financing round and consider combinations of (senior/subordinated) straight debt and warrants as venture loans (Table 2).

3.3 Independent variables

To test $H1_a$, we used the variable $Number\ of\ patents_{i;t}$ as the best available proxy for intangible assets. The variable gives the number of granted patents of company i at the time of financing round t. We collected and merged the data from the United States Patent and Trademark Office (USPTO).

Concerning $H1_b$, we would like to test the direct relation of tangible assets and profitability to venture loan probability but unfortunately do not have access to balance sheet data of the examined portfolio companies. As derived in Sect. 2.2, tangible assets and profitability are closely related to the startup's age. As investment dates are significantly better maintained in the database than founding dates, we decided to use the variable $Roundnumber_{i;t}$ as the best available proxy for the maturity of the startup in order to test $H1_b$.

For testing $H2_a$, we applied the dummy variable $Medical/health/life\ science_i$, which indicates whether company i belongs to the medical, health, and/or life science industry or not. In the same way, we tested $H2_b$ using the variable $Biotechnology_i$ and applied the variable $Semiconductor_i$ to test $H2_c$. As a reference category, we used all other categories, which mainly consist of non-high technology sectors. The industry classification is based on the VentureXperts Primary Industry Major Group Classification.

Testing $H3$, we used the variable $Ln(Avg.\ capital\ per\ investor)_{i;t}$ as a proxy for the investors' commitment and depth of the investors' pockets. The variable represents the logarithm of the average capital amount per investor and per financing round of company i at financing round t. Venture capital financing rounds usually increase with every further round, since the resources provided in previous rounds are deployed to foster growth (Gompers and Lerner 2004), suggesting that venture loans are associated with larger venture capital financing rounds. To account for the possibility that venture loans are associated with a larger capital amount per investor

Table 2 Variable definitions

Variables	Definition
$Venture\ loan\ dummy_{i;t}$	A dummy variable that takes the value 1 if the financing round t of portfolio company i is identified to be a venture loan and 0 otherwise. To identify venture loans according to the definition by Hesse et al. (2016), we looked at the investment security type used in the respective financing round and considered combinations of (senior/subordinated) straight debt and warrants as venture loans
$Number\ of\ patents_{i;t}$	Represents the number of total granted patents of a portfolio company i until the financing round t according to USPTO data
$Round\ number_{i;t}$	The round number indicates the current financing round number and ranges from one to eight
$IVC\ dummy_{i;t}$ $CVC\ dummy_{i;t}$ $GVC\ dummy_{i;t}$	The variable IVC dummy takes the value 1 if an independent VC was involved in the respective financing round and 0 otherwise. The same applies to the variables CVC dummy, GVC dummy, and Other type dummy if a corporate VC, a government VC, or another investor type is involved in a given round. For example, in the case of a syndicated financing round that involved an independent and a governmental VC, the IVC dummy and GVC dummy would both take the value 1. Please note that, since these dummy variables do not perfectly predict outcomes, no reference group is needed
$Ln(Avg.\ capital\ per\ investor)_{i;t}$	The logarithm of the average capital amount invested per investor of portfolio company i divided by the current financing round number t. More formal: $\ln\left(\frac{\sum_{k=1}^{t} Capital\ amount_{i;k}/Investors_{i;k}}{Roundnumber_t}\right)$, where k represents round numbers from 1 to a maximum of 8 and t the current financing round
$Biotechnology_i$ $Medical/health/life\ science_i$ $Semiconductors/other\ elect._i$ $Non\ high\ techn.\&\ others_i$	The variable Biotechnology takes the value 1 if the company operates in the biotechnology industry and 0 otherwise. The same applies to the other industry variables. As a reference category, we chose Non high Technology and others, since this represents the base case with most companies belonging to this industry. In order to categorize industries, we used the VentureXpert primary industry major group classification
$Ln(Capital\ amount)_{i;t}$	The logarithm of the capital amount gained by portfolio company i in the financing round t
$Number\ of\ investors_{i;t}$	Number of investors participating in financing round t of portfolio company i
$Avg.\ capital\ growth_{i;t}$	The capital growth of portfolio company i until the finacing round t divided by the round number t. More formal: $\frac{\frac{Capital\ amount_t - capital\ amount_{t-1}}{capital\ amount_{t-1}}}{Round\ number_{t-1}}$
$Avg.\ months\ between\ rounds_{i;t}$	Indicates the average number of months between financing rounds of a portfolio company i until the current financing round t. More formal: $\frac{\sum_{k=1}^{t} Investment\ date_{i;k} - Investment\ date_{i;k-1}}{Round\ number_{i;t-1}}$, where k represents round numbers from 1 to a maximum of 8 and t the current financing round
$Leverage\ ratio_{i;t}$	The leverage ratio represents the total debt divided by total capital until the current financing round t of a portfolio company i. More formal: $\frac{\sum_{k=1}^{t} Debt\ amount_{i;t}}{\sum_{k=1}^{t} Capital\ amount_{i;t}}$, where k represents round numbers from 1 to a maximum of 8 and t the current financing round
$Startup\ hub\ dummy_i$	A dummy variable that takes the value 1 if the company is located in California, Massachusetts, New York, or Texas and 0 otherwise
$FED\ prime\ rate_{i;t}$	Represents the yearly average of the bank prime loan rate on a yearly basis according to the FRED database

Table 2 (continued)

Variables	Definition
$Ln(VC\,AUM)_{i;t}$	The logarithm of the yearly aggregated assets under management in bn. US-dollars in the venture capital market in the US according to NVCA data
$VIX_{i;t}$	The yearly average of the volatility index VIX based on the S&P 500 index volatility according to macrotrends data
$GDP\,growth\,rate_{i;t}$	The yearly growth rate of the gross domestic product of the US according to macrotrends data

Note: Table 2 presents information on the variables' definitions, creation processes, and sources. Data was taken from Thomson Reuters Eikon's Private Equity Screener if no other source is given in the description

because they occur in later stages, we further divided by the respective round number. This gave us the average capital amount per investor and per financing round. In that way, we were also able to include the complete financing history.

We used the dummy variables $IVC\,dummy_{i;t}$, $CVC\,dummy_{i;t}$, and $GVC\,dummy_{i;t}$,which indicate if an independent, corporate, or government venture capitalist was involved in financing round t of portfolio company i. It is possible that all three variables take the value 1 if an independent, a corporate, and a government venture capitalist were syndicating in financing round t. Therefore, these variables did not need a reference group since they do not perfectly predict the outcome variable.

3.4 Control variables

Tykvová (2017) finds that venture lending rounds are significantly smaller in terms of amount invested compared to equity financing rounds. To control for the amounts invested in the respective financing rounds, we used the variable $Ln(Capital\,amount)_{i;t}$, which represents the logarithm of the capital amount invested in financing round t of company i.

We also controlled for syndicate size using the variable $Number\,of\,investors_{i;t}$, which is the number of investors involved in financing round t of company i.

We included $Avg.\,capital\,growth_{i;t}$ and $Avg.\,months\,between\,rounds_{i;t}$ as performance proxies in our model. $Avg.\,capital\,growth_{i;t}$ measures the average capital growth rate per financing round from round 1 for company i until financing round t, and $Avg.months\,between\,rounds_{i;t}$ measures the average time between financing rounds in months from round 1 to round t of company i. Furthermore, we included the variable $Leverage\,ratio_{i;t}$, which is debt in round t divided by total capital in round t for company i.

Finally, we controlled for several environment-specific variables. Since venture-capital-backed companies are the target groups of venture lenders and existing research finds evidence for venture lending being associated with startup hub proximity, we implemented the variable $Startup\,hub\,dummy_i$, which indicates whether the portfolio company is located in one of the startup hubs California, Massachusetts, New York, or Texas (Stephens et al. 2019; Tykvová 2017). We believe that venture loans are sensitive to the overall interest level and thus controlled for $FED\,prime\,rate_{i;t}$, which represents the yearly average of the bank prime loan rate according to the FRED database. Further, we controlled for $Ln(VC\,AUM)_{i;t}$, which is the logarithm of the aggregated assets under management in bn. US-dollars in the venture capital market in the US according to NVCA data. Tykvová (2017) finds that the usage of venture debt depends on the level of uncertainty in the market. Hence, we controlled for $VIX_{i;t}$, which is the yearly average of the volatility index VIX based on the S&P 500 index volatility according to macrotrends data. As another control for uncertainty, we implemented the control $GDP\,growth\,rate_{i;t}$, which is the yearly growth rate of the gross domestic product of the US according to macrotrends data.

3.5 Descriptive statistics

Table 3 presents several descriptive statistics of the unrestricted sample and our panel data sample. In the following, we will put more emphasis on the descriptive statistics of the unrestricted sample, since the panel data sample is subject to several restrictions. Moreover, we will use the unrestricted data to show the representativeness of the panel data sample.

Panel A of Table 3 displays the yearly frequencies of venture loans and equity financing rounds with most venture loans granted in 2011 in the unrestricted sample. Since the panel data sample only considers companies that received their first investment in 2009, these numbers differ from the unrestricted sample. In terms of total numbers, the unrestricted sample provides a better understanding of the *true* dissemination of venture loans.

Panel B of Table 3 presents the frequency of venture loans in a given round number, showing that, in both samples, venture loans occur most often in the second and third financing rounds. It is notable that 52 venture loans took place in a company's first round of financing, which is difficult to explain. We suspect that large databases like Refinitiv, which have a high reputation in academic literature, are subject to biases and data errors (Kaplan and Lerner 2016). Retterath and Braun (2020) examine eight databases suitable for venture capital research and find that larger financing rounds are more likely to be reported than small financing rounds. In our case, it could be that there were smaller financing rounds before Refinitiv started tracking a company. Later on, we addressed this inconsistency of the dataset by re-running our analysis and excluding the first as well as first and second rounds respectively.

Panel C of Table 3 displays the means of all independent variables. By comparing the unrestricted sample and the panel data sample, the main advantage of the panel data sample becomes visible. All variables that do not exhibit a value in the restricted sample are only possible to include in our analysis due to the panel data structure. The table indicates that venture loans in both samples occur on average in later rounds, provide less capital, and are conducted by smaller syndicates or a single lender, particularly in the medical, health, and life science industries.

Table 3 Descriptive statistics

Panel A. Investment years

	Unrestricted sample			Panel data sample		
Year	Total	Equity	VL	Total	Equity	VL
2009	3616	3611	5	658	658	0
2010	4125	4046	79	1119	1111	8
2011	4499	4337	162	1656	1632	24
2012	4469	4332	136	1869	1841	28
2013	4877	4725	151	2209	2170	39
2014	5235	5100	135	2534	2505	29
2015	5288	5195	95	2757	2729	28
2016	4641	4600	43	2454	2434	20
2017	4570	4533	37	2611	2598	13
2018	4702	4690	11	2990	2984	6
2019	5017	4989	27	3284	3273	11
2020	4913	4887	26	3436	3420	16
Total	55,952	55,045	907	27,577	27,355	222

Panel B. Round numbers

	Unrestricted sample			Panel data sample		
Round	Total	Equity	VL	Total	Equity	VL
1	16,470	16,410	60	13,540	13,488	52
2	10,615	10,504	111	6563	6506	57
3	7442	7332	110	3513	3467	46
4	5451	5359	92	1925	1900	25
5	3940	3848	92	1053	1033	20
6	2918	2835	83	548	537	11
7	2312	2239	73	291	286	5
8	1746	1691	55	144	138	6
9	1301	1246	55	–	–	–
≥ 10	3757	3581	176	–	–	–
Total	55,952	55,045	907	27,577	27,355	222

Panel C. Mean variables

Variable	Unrestricted sample		Panel data sample	
	Equity $N=55{,}045$	VL $N=907$	Equity $N=27{,}355$	VL $N=222$
$Number\ of\ patents_{i;t}$	2.073	3.789**	0.827	0.734
$Round\ number_{i;t}$	3.697	6.141***	2.047	2.941***
$Biotechnology_i$	0.115	0.179***	0.096	0.108
$Medical/health/life\ science_i$	0.109	0.241***	0.076	0.185***
$Semiconductor_i$	0.036	0.041	0.023	0.018
$Non\ high\ technology\&\ others_i$	0.741	0.539	0.806	0.689***

Table 3 (continued)

Panel C. Mean variables

Variable	Unrestricted sample		Panel data sample	
	Equity $N=55{,}045$	VL $N=907$	Equity $N=27{,}355$	VL $N=222$
$Ln(Avg.\, capital\, per\, investor)_{i;t}$	–	–	14.290	14.129
$IVC\, dummy_{i;t}$	0.743	0.803***	0.754	0.698*
$CVC\, dummy_{i;t}$	0.134	0.085***	0.145	0.059***
$GVC\, dummy_{i;t}$	0.054	0.024***	0.041	0.023
$Ln(Capital\, amount)_{i;t}$	15.051	14.261***	15.142	14.095***
$Number\, of\, investors_{i;t}$	2.715	1.765***	2.853	1.311***
$Avg.\, capital\, growth_{i;t}$	–	–	2.248	4.003
$Months\, between\, rounds_{i;t}$	–	–	7.114	10.532***
$Leverage\, ratio_{i;t}$	–	–	0.002	0.313***
$Startup\, hub\, dummy_{i}$	0.623	0.546***	0.647	0.545***
$FED\, prime\, rate_{i;t}$	0.037	0.034***	3.814	3.491***
$Ln(VC\, AUM)_{i;t}$	5.768	5.640***	5.837	5.717***
$VIX_{i;t}$	28.906	27.657***	27.890	26.895*
$GDP\, growth\, rate_{i;t}$	0.015	0.020***	0.015	0.018**

Note: Panel A of Table 3 reports the number of venture loan rounds and non-venture loan rounds for the unrestricted and the panel data sample year wise. Panel B reports the allocation of venture loan rounds and non-venture loan rounds among round number. Panel C provides means on all used variables. The variables are defined in Table 2. Also reported is the significance of the differences in means between the two samples. *N* denotes the number of observations analyzed

*, **, and *** denote a significant difference in the means at the 10%, 5%, and 1% levels respectively

We observe that the mean of number of patents is strongly reduced in the panel data sample for venture loan rounds. We address this particularity by providing a regression analysis on the unrestricted sample to check whether the results are biased. Furthermore, we note that $Ln(Avg.\, capital\, per\, investor)_{i;t}$ is on average lower for venture loan rounds. However, this value might be biased due to the fact that venture loan provides far less capital than equity rounds. Later in the model, we thus used the lagged variable $Ln(Avg.\, capital\, per\, investor)_{i;t-1}$.

3.6 Methodology

For the econometrical analysis of the panel data, we applied logistic regression with robust standard errors clustered by portfolio company. We chose logistic regression to identify significant predictors of venture loan occurrence. It is a typical method used to analyze predictors of a binary dependent variable by modeling the probability that the dependent variable is different from 0 (Menard 2010). To test hypotheses, we estimated the following model:

$$
\begin{aligned}
&\textit{Venture loan dummy}_{i;t} \\
&\quad = \beta_0 + \beta_1 \textit{Number of patents}_{i;t} + \beta_2 \textit{Round number}_{i;t} + \beta_3 \textit{Biotechnology}_i + \beta_4 \textit{Medical health life science}_i \\
&\quad + \beta_5 \textit{Semiconductor}_i + \beta_6 \textit{Ln(Avg. capital per investor)}_{i;t-1} + \beta_7 \textit{IVC dummy}_{i;t} + \beta_8 \textit{CVC dummy}_{i;t} \\
&\quad + \beta_9 \textit{GVC dummy}_{i;t} + \beta_{10} \textit{Ln(Capital amount)}_{i;t} + \beta_{11} \textit{Number of investors}_{i;t} + \beta_{12} \textit{Avg. capital growth}_{i;t-1} \\
&\quad + \beta_{13} \textit{Avg. months between rounds}_{i;t-1} + \beta_{14} \textit{Leverage ratio}_{i;t-1} + \beta_{15} \textit{Startup hub dummy}_i \\
&\quad + \beta_{16} \textit{FED prime rate}_{i;t} + \beta_{17} \textit{Ln(VC AUM)}_{i;t} + \beta_{18} \textit{VIX}_{i;t} + \beta_{19} \textit{GDP growth rate}_{i;t} + \varepsilon
\end{aligned}
\tag{1}
$$

where i denotes the respective company and t the respective financing round. We also calculated the odds ratios to simplify interpretation of the results.

4 Results and discussion

Table 4 presents the results of the logistic regression with robust standard errors for testing our hypotheses. The table includes coefficient estimates and odds ratios.

Analyzing the results concerning $H1_a$, we must reject the hypotheses that patents are positively related to a startup's probability of receiving a venture loan. Our results indicate that patents are less important for venture lenders to reduce downside risk than other aspects, such as the involvement of a venture capitalist. While patents do provide collateral, it is difficult for venture lenders to liquidate them. Patents are often specific to a startup and are difficult to valuate quantitatively, and it is time-consuming to find a potential buyer and negotiate the terms. However, we observe a strong decrease in the mean of the patent variable after the transformation to panel data. Future research is needed to further explore and reinforce the role of patents for venture lenders.

The coefficient of the variable $\textit{Round number}_{i;t}$ is positive and significant at the < 0.01 level of confidence. Since we used the variable as a proxy for the startup age, the result supports $H1_b$ that the maturity of the startup increases the probability to obtain a venture loan. Odds ratios tell us that, on average, the probability for receiving a venture loan increases by 21.4%. It seems that venture loans are particularly appropriate for financing startups in later stages of the financial lifecycle.

Regarding the hypotheses $H2_a$, $H2_b$, and $H2_c$, we have to reject $H2_b$, and $H2_c$, since the indicators for biotechnology and semiconductor industry remain insignificant. The indicator variable for medical, health, and life science industries exhibits a positive coefficient, being significant at the < 0.01 level of confidence. On average, startups within the medical, health, and life science industries increase the probability of obtaining a venture loan by a factor of 2.4. The results provide empirical evidence that clearly observable and verifiable milestones in the medical, health, and life sciences industry are relevant for the probability to receive a venture loan, whereas the potentially high financing needs within the other two high-tech industries do not seem to be a driving force for venture loan granting.

We find that our proxy for investor commitment $\textit{Ln(Avg. capital per investor)}_{i;t-1}$ is significant and has a positive coefficient. Hence, the result supports hypothesis $H3$ that the startup's probability of receiving a venture loan increases when existing venture capitalists have a large capital amount at risk. Since investor commitment

Table 4 Effects of capital gained and investor base on venture loan probability

	Model 1	
	Coefficients	Odds ratios
Independent variables		
Number of patents$_{i;t}$	**− 0.012**	**0.988**
	(0.023)	**(0.023)**
Round number$_{i;t}$	**0.194*** **	**1.214*** **
	(0.068)	**(0.082)**
Biotechnology$_{i}$	**0.241**	**1.273**
	(0.295)	**(0.376)**
Medical/health/life science$_{i}$	**0.877*** **	**2.404*** **
	(0.240)	**(0.578)**
Semiconductor$_{i}$	**− 0.201**	**0.818**
	(0.571)	**(0.467)**
Ln(Avg. capital per investor)$_{i;t-1}$	**0.064*** **	**1.067*** **
	(0.017)	**(0.018)**
IVC dummy$_{i;t}$	**0.879*** **	**2.409*** **
	(0.205)	**(0.494)**
CVC dummy$_{i;t}$	**0.714** **	**2.042** **
	(0.357)	**(0.728)**
GVC dummy$_{i;t}$	**− 0.423**	**0.655**
	(0.519)	**(0.340)**
Controls		
Ln(Capital amount)$_{i;t}$	− 0.210***	0.811***
	(0.043)	(0.035)
Number of investors$_{i;t}$	− 1.078***	0.340***
	(0.156)	(0.053)
Avg.capital growth$_{i;t-1}$	0.000	1.000
	(0.000)	(0.000)
Months between rounds$_{i;t-1}$	1.288**	3.624**
	(0.619)	(2.243)
Leverage ratio$_{i;t-1}$	0.020*	1.020*
	(0.011)	(0.011)
Startup hub dummy$_{i}$	− 0.028	0.972
	(0.184)	(0.179)
FED prime rate$_{i;t}$	− 0.655***	0.519***
	(0.223)	(0.116)
Ln(VC AUM)$_{i;t}$	− 0.378	0.685
	(0.549)	(0.376)
VIX$_{i;t}$	− 0.025	0.975
	(0.017)	(0.016)
GDP growth rate$_{i;t}$	− 3.022	0.049
	(8.476)	(0.413)
Constant	2.170	8.759
	(2.900)	(25.399)

Table 4 (continued)

	Model 1	
	Coefficients	Odds ratios
Observations	27,577	
Number of CompanyID	13,540	
χ^2	191.83***	

Note: Table 4 presents logistic regression estimates and odds ratios based on robust standard errors using the panel data sample. Variable definitions can be found in Table 2

*, **, and *** denote coefficient estimates significantly different from 0 at the 10%, 5%, and 1% levels respectively. Robust standard errors are in parentheses

satisfies the venture lender's downside protection and upside potential requirements, this result seems to be driven by the supply side of venture loans.

Table 4 also provides a significant and positive estimate for the indicators of independent venture capital funds. Hence, the results provide support for $H4$ that performance-oriented independent venture capitalists seem to use venture loans to push the internal rate of return. The indicator for corporate venture capitalist's participation is significant and positive as well. Thus, we have to reject $H4_b$. Other than the result for independent venture capitalists, the corporate venture capitalists' coefficient will not remain significant when running robustness checks. We cannot find support for $H4_c$, since the coefficient of the government venture capital indicator is not significant. Nevertheless, from the perspective of the venture lender, financially oriented investors seem to provide potentially more downside protection and upside potential, leading to a positive relation between the involvement of an independent venture capitalist to the probability of venture loan occurrence.

Concerning the controls, our results show that venture loan recipients exhibit a significantly longer average time between financing rounds. This could be due to venture capitalists and startups using venture loans effectively to stretch the time between equity financing in order to reduce dilution and enhance performance. We also observe a positive and significant coefficient for the leverage ratio, providing evidence that venture loans often occur twice within the life of a startup. Taking a look at the environment-specific controls, the results show that venture loans are significantly less associated with startups within a startup hub and that venture loan demand and supply are negatively related to the FED prime rate. The prime rate steadily increased between 2016 and 2020, which fits the picture of decreasing venture loan numbers from 2016 onward.

In summary, we find indications that venture lenders prefer older startups with potentially more tangible assets and/or positive cash flows, with strongly financially committed investors persuading primarily financial goals. On the demand side, we find indications that independent venture capital funds demand venture loans to push the internal rate of return and make use of the extended runway, especially in the milestone-orientated medical, health, and life science industries.

Table 5 Results of logistic regression from Sect. 4 using an unrestricted sample

	Model 2 *Venture loan dummy*$_{i;t}$	
	Coefficients	Odds ratios
Independent variables		
Number of patents$_{i;t}$	**0.000**	**1.000**
	(0.000)	**(0.000)**
Round number$_{i;t}$	**0.123*** **	**1.130*** **
	(0.006)	**(0.007)**
Biotechnology$_{i}$	**0.608*** **	**1.836*** **
	(0.095)	**(0.174)**
Medical/health/life science$_{i}$	**0.788*** **	**2.200*** **
	(0.088)	**(0.193)**
Semiconductor$_{i}$	**0.033**	**1.033**
	(0.177)	**(0.183)**
IVC dummy$_{i;t}$	**0.650*** **	**1.916*** **
	(0.091)	**(0.174)**
CVC dummy$_{i;t}$	**0.418*** **	**1.519*** **
	(0.131)	**(0.200)**
GVC dummy$_{i;t}$	**− 0.726*** **	**0.484*** **
	(0.231)	**(0.112)**
Controls		
Ln(Capital amount)$_{i;t}$	− 0.114***	0.892***
	(0.016)	(0.014)
Number of investors$_{i;t}$	− 0.372***	0.689***
	(0.033)	(0.023)
Startup hub dummy$_{i}$	− 0.118*	0.888*
	(0.072)	(0.064)
FED prime rate$_{i;t}$	− 0.870***	0.419***
	(0.135)	(0.057)
Ln(VC AUM)$_{i;t}$	− 0.685**	0.504**
	(0.331)	(0.167)
VIX$_{i;t}$	− 0.020***	0.980***
	(0.007)	(0.007)
GDP growth rate$_{i;t}$	0.133***	1.142***
	(0.032)	(0.037)
Constant	4.380**	79.900**
	(1.705)	(136.236)
Observations	55,952	
Number of CompanyID	21,835	
χ^2	804.39***	

Note: Table 5 presents logistic regression estimates and odds ratios based on robust standard errors using the unrestricted sample. Variable definitions can be found in Table 2

*, **, and *** denote coefficient estimates significantly different from 0 at the 10%, 5%, and 1% levels respectively. Robust standard errors are in parentheses

5 Robustness checks and limitations

We performed the logistic regression from Sect. 4 without the variables, which require panel data, using the unrestricted sample. We received similar results, providing robustness for the panel data sample's results and representativeness. We are only concerned about the strong decrease in the mean of patents for venture loan rounds. Therefore, the patent-related results should be treated with caution. The results of the logistic regression are reported in Table 5.

Due to the inaccuracy of the data sample concerning the relatively large number of venture loans in the first financing rounds discussed in Sect. 3.3, we re-ran the regression of Table 4 without the first and then without the first and second rounds. The main findings remain unchanged in this unreported regression, which suggests robust results. As mentioned in Sect. 4, the significant result for the corporate venture capital indicator vanishes when applying these robustness checks.

We also performed the regression of Sect. 4 with year-fixed effects instead of the macroeconomic variables. Again, the main findings prove robust in these unreported robustness checks.

A limitation of the study is a possible endogeneity bias due to omitted variables in the model. A potential omitted variable is the startup's quality, which is difficult to measure for practitioners and researchers. The variable $Ln(Avg.\,capital\,per\,investor)_{i;t}$ could be especially affected by an omitted variable bias. Due to venture loans occurring more frequently in later rounds compared to the equity rounds, the variable could be biased upwards due to the fact that the startup is of higher quality and survives longer, thus obtaining a venture loan since it signals little risk. We tried to address this issue in three ways. First, when building the panel data, we included startups with up to eight consecutive financing rounds but also included startups with fewer than eight financing rounds, which should reduce survival bias. Second, as to the best of what our dataset provides, we included two performance proxies using the variables $Avg.\,months\,between\,rounds_{i;t}$ and $Avg.\,capital\,growth_{i;t}$ to capture at least a little part of the company quality. Third, we used the average amount per investor per round instead of the average capital per investor, which would accumulate over time, leading to an overestimation of any effect.

6 Conclusion

In this paper, we examined how characteristics of startups and their financial history are related to the probability to receive a venture loan. We explicitly focused on venture loans as a distinct form of financing that is different from straight debt and convertible debt (De Rassenfosse and Fischer 2016; Ibrahim 2010; Tykvová 2017).

We collected data from 55,045 financing rounds and converted the data into an unbalanced panel data structure comprising 27,577 financing rounds in order to examine under which circumstances venture loans occur.

The paper provides four key findings. First, venture loans are associated with older startups, which potentially have more tangible assets and/or positive cash flows to offer as collateral. Moreover, this relation could be explained due to the exit being within sight in later stages, increasing the upside potential of the warrant. Second, we find that venture loan usage is more popular in industries that exhibit a clearly observable and verifiable milestone, like the medical, health, and life science industries. Third, according to our results, startups with strongly financially committed venture capitalists attract venture lenders because they satisfy the lenders' requirements on downside protection and upside potential. One mechanism seems to be the enhanced signaling on the startup's quality, which drives upside expectations and signals deep pockets and commitment to use their financial resources in times of negative external shocks, thereby, satisfying the venture lenders' need for downside protection. Fourth, the results indicate that performance-orientated investors, like independent venture capitalists, use the performance-measure-enhancing effects of venture loans rather than corporate or government venture capitalists with primary non-financial objectives. In summary, we show indications for important mechanisms, incentives, and relations among the lenders, the investors, and startups that relate to venture loan supply and demand.

Our paper contributes to the literature in three main ways. First, we contribute to the literature on financing lifecycles of startups (Berger and Udell 1998). In recent years, entrepreneurial finance literature has identified complementarities between different capital providers. For example, the impact of corporate and foreign investors in venture capital syndicates (Park et al. 2019) or the interplay of public–private venture capital funds (Harrison 2018). We add to this literature by focusing on venture loans as a form of venture debt and showing relations with prior equity rounds provided by venture capitalists. In particular, we investigated the sequence and interconnectedness of financing rounds and financing instruments by showing relations between earlier financing rounds by venture capitalists and subsequent venture loans provided by venture lenders. We provide empirical evidence that sufficient financial commitment of existing equity investors is associated with a higher probability of obtaining venture loans by satisfying venture lenders' needs for downside protection.

Second, we add to the literature on venture debt by focusing on venture loans as a distinct form of debt financing for innovative startups. So far, the quantitative, empirical literature generally has not made such a distinction (Tykvová 2017). The debt instruments used in startups are heterogeneous and range from straight debt to convertible notes. We are among the first to delve deeper into one type of venture debt and to examine venture loans in a comprehensive quantitative study. We define venture loans as a hybrid form of financing and show characteristics of startups and their investors that are associated with a higher likelihood of obtaining a venture loan. In showing the relevance of the maturity, the industry, and the type of investor involved in a startup, we give initial indications on how venture lenders might select startups.

Third, we contribute to the literature on relationship lending. In finance literature, the closely knit relationship between debt providers and companies has long been stressed (Elyasiani and Goldberg 2004). By building up a long-term relationship to a so-called house bank, companies are able to gain access to traditional bank debt. With our study, we add another dimension to this relationship lending. In addition to the above bilateral relationship, we show the relevance of involved venture capitalists and, hence, a relationship triangle. We are able to show that performance-orientated venture capitalists are particularly associated with venture loans, which could be an indication for a close-knit relationship between startup, venture lender, and equity investor.

Concluding, we contribute novel empirical evidence on relations between venture lenders, venture capitalists, and startups. We see great potential for future research on venture debt and venture loans in particular. The importance of patents for venture lenders or the heterogeneity of different venture debt vehicles might be two promising avenues for future research. In addition, we want to encourage future research to focus on the relationship triangle and depict formal and informal ways of cooperation between venture lenders and venture capitalists. We would like to understand how stable these relationships are and how venture loans are initiated for startups. Furthermore, performance implications of venture loans would be interesting to analyze in future studies. We do not yet know whether venture loans have an impact on the growth and success of startups.

Author contributions Conceptualization: NL, CP, and EL; validation: NL; formal analysis: NL; investigation: NL; data curation: NL; methodology: NL, CP, and EL; writing—original draft: NL; writing—review and editing: CP, and EL; supervision: CP, and EL; project administration: CP and EL.

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Code availability We used Stata SE 15 to conduct our analyses. Stata code is available upon request.

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

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