Three essays on venture capital and its impact on performance, capital structure, and the exit decision of new ventures

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Dedicated to Adelheid Ufer

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List of abbreviations

2SLS .... *Two Stage Least Squares*

Cboe .... *Chicago Board Options Exchange*

CVC .... *Corporate Venture Capitalist*

FE .... *Fixed effects*

FED .... *Federal Reserve*

FRED .... *Federal Reserve Economic Data*

GDP .... *Gross domestic product*

GVC .... *Government Venture Capital*

IPO .... *Initial Public Offering*

IV .... *Instrumental Variable*

IVC .... *Independent Venture Capitalist*

LLC .... *Limited Liability Company*

M&A .... *Mergers & acquisitions*

NASDAQ .... *National Association of Securities Dealers Automated Quotations System*

NYSE .... *New York Stock Exchange*

PE .... *Private Equity*

S&P .... *Standard & Poor's*

SIC .... *Standard Industrial Classification*

SPX .... Ticker of S&P 500 index

URL .... *Uniform Resource Locator*

US .... *United States*

USD .... *United States Dollar*

USPTO ....*United States Patent and Trademark Office*

VC ....*Venture Capital*

VEIC..*Venture Economics Industry Codes*

VIX..*Volatility Index*

VL.. *Venture Loan*

A. Introduction

1. Motivation and theoretical background

1.1. Relevance of venture capital

Venture capital is a form of private equity that is provided to young, innovative, high-growth companies. Venture capital is often referred to as “smart money” or “money of innovation,” as venture capital funds provide resources beyond financial capital, such as strategic guidance and access to industry-specific networks (Cumming, 2010; Sørensen, 2007). Previous research has shown that venture-capital-backed startups are, on average, significantly more successful in terms of innovativeness, employee growth, and stock market performance upon going public than startups without venture capital funding (Davila, Foster, & Gupta, 2003; Kortum & Lerner, 2001; Megginson & Weiss, 1991). Thus, venture capital plays a crucial role in the entrepreneurial ecosystem that drives job creation, innovation, as well as economic competitiveness, and growth (Hafer, 2013; Megginson, 2004; Rusu & Dornean, 2019). Consequently, venture capital has been promoted by governments and has become a key part of the diversification strategies of institutional investors, large corporations, and wealthy individuals (Burton & Scherschmidt, 2004; Colombo, Cumming, & Vismara, 2016).

1.2. Venture capital as a distinct form of private equity

Venture capital is a form of private equity and differs from private equity in the narrow sense in several respects.[1] One main difference is that while venture capital funds typically

[1] In the remainder of this dissertation, the term private equity refers specifically to private equity in the narrow sense.

target young, unlisted, and innovative companies, private equity funds tend to focus on established entities and often take public companies private. A second difference is that while venture capital funds focus on equity and equity-like investments, private equity funds usually make extensive use of debt. Furthermore, private equity firms typically perform buyouts to acquire majority stakes in their targets, while venture capitalists usually take minority stakes in the companies they invest in.

1.3. The venture capital cycle

Venture capital firms generally follow the so-called "venture capital cycle." As renowned top venture capital researchers Paul A. Gompers and Josh Lerner state, it is necessary to understand the whole venture capital cycle in order to understand the venture capital industry (Gompers & Lerner, 2001). The cycle begins with the fundraising process, during which the venture capital firm seeks capital from investors. This is followed by the screening and selection of potential portfolio companies. Subsequently, the venture capitalist invests in selected startups, entering a phase of monitoring, follow-on investments, and value-adding. Finally, the venture capitalist exits successful deals and returns capital plus a specific share of the returns to the investors. The cycle renews itself with fundraising for the next fund (Gompers & Lerner, 2001; Tykvová, 2017a). It is crucial to have an understanding of the entire venture capital cycle because the various aspects of the cycle are interconnected. For example, the process of exiting venture capital investments has a significant impact on the raising of venture funds and venture capital investing, a consequence that is inherent to their organizational structure (Cumming & MacIntosh, 2003b; Gompers & Lerner, 2001).

1.3.1 Fundraising process

During the venture capital cycle, venture capitalists encounter several challenges, including high uncertainty, asymmetric information distribution, and various agency conflicts (Amit, Brander, & Zott, 1998; Wright & Robbie, 1998). Many of these challenges occur already in the fundraising process when venture capitalists need to overcome asymmetric information disadvantages, especially when it is the first fund they raise and the venture capital firm has no track record.

In order to overcome asymmetric information issues when raising funds for the first time, the fund managers' track record with other venture capital funds, commitments from other recognized investors, and the fund managers' prior professional relationships with investors were found to be of high importance (Barnes & Menzies, 2005; Burton & Scherschmidt, 2004). Moreover, private sources of capital can be easier to access than large public capital providers when raising a venture capital fund for the first time (Burton & Scherschmidt, 2004). After gaining traction in the industry, venture capital firms can build a reputation to signal quality to potential investors. This reputation can stem from surviving for a specific time in the market, having raised and closed several funds, having performed well in the past, or having accumulated a large venture capital firm over time in terms of the number of partners, employees, and/or assets under management (Barnes & Menzies, 2005; Gompers & Lerner, 1998; Groh & Von Liechtenstein, 2011). Moreover, investors tend to invest in venture capital funds that have been trialed and tested, which benefits incumbent venture capitalists but also highlights the large barriers for entrant venture capital firms to raise funds (Barnes & Menzies, 2005).

Venture capital funds are typically organized as limited partnerships or similar organizational structures when operating outside the legal systems of the United States or the

United Kingdom (Sahlman, 1990; Tykvová, 2017a). In such organizational constructs, investors take on the role of Limited Partners and venture capital managers act as General Partners. The General Partner holds complete control over the committed funds and the investment process of the partnership. The Limited Partners are legally constrained from direct involvement in the operation of the fund in order to enjoy limited liability (Jääskeläinen, Maula, & Murray, 2007; Sahlman, 1990).

The typical compensation structure of venture capitalists aligns incentives and reduces moral hazard. Thereby, supporting the matching process of Limited Partners and General Partners and facilitating fundraising for venture capital funds. Besides a management fee of usually 2%-2.5% of committed capital, a carried interest incentivizes the venture capitalists with a typically 20%-25% carried interest on fund profit (Litvak, 2009). Before receiving any return participation, venture capitalists are often contractually required to return the total drawn-down capital to the Limited Partners with a minimum level of agreed interest, known as the "hurdle rate." Once this hurdle has been met, the venture capitalist participates in capital gains up to the agreed carried interest, thereby "catching up" on the distributed profits of the investors (Jääskeläinen et al., 2007; Sahlman, 1990). Hence, the compensation of the venture capitalist is highly dependent on the commercial success of the fund in order to align incentives of the Limited Partners and the General Partners and mitigate moral hazard.

1.3.2 Selection and initial investment process

After securing capital commitments, the venture capital cycle's next stage is the screening and selection process of potential portfolio companies. The process of selecting investment opportunities, in which a venture capitalist functions as an investor, is characterized by similar challenges to those encountered in the matching process between Limited Partners and General Partners. Startups are opaque and difficult to assess due to a very short or missing financial track record (Bollazzi, Risalvato, & Venezia, 2019; Tykvová, 2017a). Moreover, startups are subject to the liabilities of newness and smallness. That is, startups are limited in experience, routine, as well as tangible, intangible, and financial resources and exhibit high failure rates (Aldrich & Auster, 1986; Stinchcombe, 1965). To operate successfully in this context, venture capitalists use a set of screening, contracting, and monitoring schemes to mitigate risk.

Due to a lack of financial history, venture capitalists rationalize an investment hypothesis in the screening process, taking into account the potential market size of the product, strategy, technology, customer adoption, competition, the founder or the founder team, and contract terms (Kaplan & Strömberg, 2001). Signaling and certification are crucial in this context as mechanisms to reduce asymmetric information between entrepreneurs and venture capitalists. Among others, the managerial and entrepreneurial experience, as well as the educational attainment of the founders, accelerator/incubator affiliation, prior business angel investments, and government research grants were shown to be effective quality signals, leading to a significantly increased probability of receiving venture capital in the early stage (Harrison & Mason, 2000; Islam, Fremeth, & Marcus, 2018; Plummer, Allison, & Connelly, 2016; Stuart & Abetti, 1990).

A further tool to manage the risk inherent to the selection process is to invest in syndicates. The process of due diligence is enhanced by incorporating the "second opinion" of fund managers from different venture capital funds with complementary skill sets and industry expertise (Bubna, 2002; Cumming, 2006). Additionally, syndication can help venture capitalists mitigate risk by allowing them to invest smaller amounts of capital in a larger number of startups, thereby diversifying their portfolios (Lockett & Wright, 1999; Manigart et al., 2006). The resulting diversification helps venture capitalists to benefit from the so-called "venture capital power law," which describes the highly skewed distribution of returns among venture-capital-backed companies (Cochrane, 2005; Schwienbacher, 2005). That is, a rather small number of portfolio companies generate the majority of the returns, while the vast majority generate relatively small returns or even losses (Dimov & Shepherd, 2005; Puri & Zarutskie, 2012; Torstila & Laine, 2003). Hence, one of the primary goals of venture capitalists is to invest in a diverse portfolio of startups in order to increase the probability of identifying and investing in highly successful companies, that can significantly impact the fund's performance (Cochrane, 2005).

1.3.3 Monitoring, follow-on investing, and value-added

Stage financing is a fundamental characteristic of venture capital with similar risk-mitigating features as investing in syndicates. Stage financing describes the stepwise disbursement of capital from venture capitalists to startups (Tian, 2011). This approach offers three fundamental advantages in the screening and selection process as well as in the phase of monitoring, follow-on investments, and value-adding.

First, stage financing can help to invest in a large number of companies at the beginning of the fund's lifetime to increase the probability of identifying and selecting highly successful startups. Therefore, the further reduction of the initial investment in the selection process supports the diversification needs of venture capitalists in initial investments (Cochrane, 2005; Tian, 2011).

Second, stage financing allows for the sequential assessment of a startup's progress and the alignment of interests between entrepreneurs and venture capitalists. From the agency perspective, stage financing can mitigate the hold-up problem, in which an entrepreneur threatens to leave a firm or renegotiate after receiving a venture capital investment (Hart & Moore, 1994). In a simple case of splitting one investment into a two-stage investment, the initial investment made by the venture capitalist has decreased in size, and therefore, the investor's subsequent claim is less likely to be negotiated downward during the startup's initial period. The venture can also establish collateral through the entrepreneur's efforts with the initial investment, which can safeguard the venture capitalist's claim from being negotiated downward during the second period (Neher, 1999; Tian, 2011).

Third, stage financing allows venture capitalists to learn additional information about the startup over time. In this context, stage financing generates value by providing the venture capitalist with a real option to discontinue funding the project at each financing round based on what is learned about the startup between rounds (Bergemann & Hege, 1998; Tian, 2011). Hence, stage financing is a fundamental characteristic of venture capital, as it helps to align incentives and to reduce the venture capitalist’s monitoring costs (Tian, 2011).

Incentive alignment and a reduction of monitoring costs can also be facilitated by comprehensive contracts between the venture capitalist and the startup. Venture capital contracts typically allow the individual allocation of cash flow rights, board rights, voting rights, liquidation rights, and other control rights. The allocation of these rights is frequently dependent on observable indicators of both financial and non-financial performance. Generally, board rights, voting rights, and liquidation rights are typically arranged so that venture capitalists gain complete control in the event of poor performance by the startup. Conversely, as the startup's performance improves, the entrepreneur either retains or gains a greater share of control rights, with the venture capitalists retaining their cash flow rights but relinquishing a significant portion of their control and liquidation rights in the event of exceptional performance (Kaplan & Strömberg, 2003; Kaplan & Strömberg, 2004).

An important tool in this context is vesting, which is frequently included in venture capital contracts and can be implemented by according cash flow rights to the entrepreneur that are contingent on either subsequent performance or time remaining in the company. In this way, the entrepreneur's incentives can be aligned and the hold-up problem as well as monitoring costs can be further reduced (Hart & Moore, 1994; Kaplan & Strömberg, 2003; Kaplan & Strömberg, 2004).

Board rights and voting rights are also important in this context and essential for venture capitalists to fulfill their role as active investors, allowing them to effectively monitor and advise their portfolio companies (Van Den Berghe & Levrau, 2002). Hence, it is common for venture capitalists to send multiple officers to sit on boards, and previous research has shown that top-tier venture capitalists obtain a larger share of board seats and that reputable venture capital board members are associated with superior fundraising and investment performance (Hasan et al., 2018; Rosenstein et al., 1993).

Venture capital is a form of equity financing, and venture capital funds in the United States predominantly use convertible preferred stocks to invest in portfolio companies (Cumming, 2005). However, several studies show that venture-capital-backed companies exhibit a relatively diverse capital structure (Cumming, 2005; Ibrahim, 2010; Tykvová, 2017b). Venture capital firms enable their portfolio companies to overcome barriers that typically prevent startups from receiving debt financing in two ways. First, due to their advanced screening and selection skills, being venture-capital-backed can serve as a certification, signaling quality to potential lenders (Hesse, Lutz, & Talmor, 2016; Ibrahim, 2010). Second, the stage financing scheme of venture capitalists can ensure sufficient cash flow for repayment of debt in the absence of positive cash flows or appropriate collateral for venture lenders (Hesse et al., 2016; Ibrahim, 2010). The latter is especially relevant in capital-intensive industries with a high level of intellectual property and a long period between early investments and substantial returns. In such a scenario, the venture capitalist can exhibit a "long horizon of disappointment," i.e., the venture capitalist is unlikely to abandon the startup in the early years. Thus, future funding rounds are expected at a sufficiently high probability to substitute for collateral or positive cash flows from operating activities for debt providers (Hesse et al., 2016).

Venture capitalists can benefit from their portfolio company's use of debt in two ways. First, debt can reduce dilution in a scenario where the portfolio company runs out of cash before reaching a valuation-increasing milestone. Using debt financing to achieve a milestone and enhance the valuation for the subsequent round of funding can decrease dilution for the entrepreneur and existing venture capitalists who are unwilling or unable to participate in the next funding round (Hesse et al., 2016). Second, debt can reduce monitoring costs by incentivizing managerial discipline through the need to make interest payments to lenders rather than using free cash for potentially inefficient purposes such as empire-building or incurring organizational inefficiencies (Ibrahim, 2010). Therefore, venture capitalists impact the capital structure of their portfolio companies not only by equity injections but also due to their certification role and a long horizon of disappointment, mitigating barriers that typically prevent startups from receiving debt.

Aside from these passive incentive-aligning and value-adding mechanisms and practices, venture capitalists are active investors and use their influence to add value to their portfolio companies with specific value-added services or resources (Sapienza, 1992). These value-added services by venture capitalists include but are not limited to strategic development, business development, assistance in marketing and hiring activities, as well as the introduction to operational and financial networks (Cumming, Fleming, & Suchard, 2005; Granz, Lutz, & Henn, 2021; Smith, 2001). The reputation of venture capitalists can also help their portfolio companies as a valuable certification to third parties, including suppliers, investors, investment banks, and other resources that potentially add value to the startup (Krishnan et al., 2011; Nahata, 2008; Smith, 2001). Research has frequently shown that venture-capital-backed companies outperform comparable companies without venture capital, which is attributed to value-added resources (Krishnan et al., 2011; Nahata, 2008). Furthermore, it has been frequently shown that venture-capital-backed startups are, on average, significantly more successful in terms of innovativeness, employee growth, and stock market performance upon going public than startups without venture capital funding, which is also attributed to value-added resources (Davila et al., 2003; Kortum & Lerner, 2001; Megginson & Weiss, 1991).

1.3.4 Exit process

In the exit stage of the venture capital cycle, the venture capitalist has several options for exiting the investment. Since venture capitalists mainly achieve returns through capital gains and not from dividends or interests, the exit phase is of crucial importance for the fund's success (Cumming & MacIntosh, 2003b). Venture capitalists typically prefer IPOs as an exit option, in which the venture capitalists exit the portfolio company by selling their shares to public markets investors, or trade sales, i.e., an acquisition by a strategic acquirer (Bayar & Chemmanur, 2011; Bienz & Leite, 2008; Cumming & MacIntosh, 2003b). In the exit stage of the venture capital cycle, asymmetric information arises between potential new investors, existing venture capitalists, and the startup. Therefore, a key aspect of successfully exiting the portfolio company is to mitigate information asymmetries (Cumming & Johan, 2008b).

In the context of IPOs, information asymmetries between corporate insiders and public investors play a crucial role in the process of exiting a portfolio company (Megginson & Weiss, 1991). Research has shown a certification effect of venture capitalists in IPOs, hence conveying an important quality signal to public investors (Dolvin, 2005; Megginson & Weiss, 1991). Moreover, it was shown that portfolio companies backed by reputable venture capitalists are associated with superior long-run stock market performance upon going public (Krishnan et al., 2011). Hence, venture capitalists perform a valuable certification role in IPOs for public market investors.

Less reputable venture capitalists can signal a portfolio company's quality in IPOs with third-party certification by hiring prestigious investment banks as underwriters and/or reputable auditors (Beatty, 1989; Carter & Manaster, 1990). A further means to signal a portfolio company's long-term viability and quality to public investors in IPOs is implementing a lock-up period. That is, a period of time during which company insiders, e.g., founders, employees, and venture capitalists, are prohibited from selling their shares following the IPO. Earlier studies that were using samples of IPOs in the United States, found that the average lockup period floats around 220 days (Arthurs et al., 2009; Bradley et al., 2001). Moreover, it has been demonstrated in prior studies that a more extended lock-up period can serve as a substitute for certification by reputable venture capitalists in IPOs, and that reputable venture capitalists, in turn, tend to have shorter lock-up periods (Arthurs et al., 2009; Dolvin, 2005).

Trade sales as a venture capital exit option have received significantly less attention than IPOs in the scientific literature (Masulis & Nahata, 2011). Existing research has strongly focused on comparing trade sales to IPOs and other exit channels (Bayar & Chemmanur, 2011; Cumming & MacIntosh, 2003a, b; Giot & Schwienbacher, 2007). Empirical studies provide mixed results on whether the IPO or trade sale is generally the most profitable exit path (Cochrane, 2005; Cumming & MacIntosh, 2003b). In the context of trade sales, the extent of information asymmetry between the acquirer and venture capitalists can depend on the level of overlap between the industries of the portfolio company and the acquirer (Achleitner et al., 2014; Cumming & MacIntosh, 2003b). In contrast to IPOs, existing research yet needs to yield consistent evidence for the certification role of reputable venture capitalists in trade sales. Existing studies mainly used data from trade sales to publicly listed companies and have shown that venture capital backing leads to higher acquisition announcement returns for the acquirer's stock, which can be interpreted as a certification effect (Gompers & Xuan, 2009; Masulis & Nahata, 2011). However, it was shown that the financial ties of the venture capitalist to both the target and the acquirer also led to a lower acquisition premium (in terms of the difference between the acquisition price and the target's book value) paid by acquirers, indicating conflicts of interest in these transactions (Masulis & Nahata, 2011).

Financial sales, i.e., acquisitions by financial buyers, have been ranked behind IPOs and trade sales in the pecking order of venture capital exits, as financial acquirers cannot benefit from synergies as strategic acquirers and, hence, would have a lower valuation for the company (Bayar & Chemmanur, 2011; Bienz & Leite, 2008; Cumming & Johan, 2008a). However, recent reports suggest that acquisitions of venture-capital-backed companies by financial acquirers, more specifically private equity firms, follow a trend to close the gap between trade sales and financial sales within the pecking order of venture capital exits (Davis & Le, 2020; Lloyd & Jackson-Moore, 2019).

A further exit option is a secondary sale, in which an individual venture capital fund can sell its ownership interests, whereas other investors and the founders will retain their investments (Cumming & MacIntosh, 2003a). Hence, in contrast to IPOs and acquisitions, secondary markets operate at the level of individual investors rather than at the level of startups (Ibrahim, 2012). This option is particularly interesting for small seed-stage investors to exit early in order to keep the focus on seed investments and to avoid dilution in later rounds that potentially exceed their investment capacity (Klingler-Vidra, 2016). Thus, a growing secondary market adds liquidity to the venture capital market, which is typically characterized by illiquid long-term investments (Andrieu & Groh, 2021).

A buyback, also referred to as a management buyout, describes an exit in which the founders or the management team repurchase the shares from the venture capitalist. This exit type is generally assumed to be inferior to the aforementioned exit channels due to lower returns (Cumming & MacIntosh, 2003b). Consequently, this exit option is unpopular in developed economies and the aforementioned exit types are generally preferred by venture capitalists (Cumming & MacIntosh, 2003b; Wang & Wang, 2017).

Finally, the write-off, in which the venture capitalist abandons unsuccessful deals, is tried to be avoided but is common in venture capital due to the risk inherent in this asset class (Cumming & MacIntosh, 2003b).

Following the exit of all portfolio companies, venture capitalists liquidate the fund, returning capital to the Limited Partners and distributing returns according to the agreed-upon terms. The venture capital cycle then begins anew with fundraising for the next fund (Gompers & Lerner, 2001).

Beyond that, many of the presented features and aspects of venture capital have been investigated in the context of internationalization, public policy and macroeconomic environments, alternative entrepreneurial financing sources, and the heterogeneity of venture capital investors, e.g., corporate and government venture capitalists (Tykvová, 2017a). Hence, this introduction to venture capital shows the immense body of literature and potential research areas. After this brief overview of venture-capital-related topics, the next section will focus on what is still unexplored within this complex and dynamic field of research and which research gaps will be addressed in this dissertation.

2. Research gaps and objectives

The understanding of the economics of venture capital has been substantially enhanced through academic research in recent decades. However, the venture capital industry is a constantly evolving industry with new business models, technologies, and market cycles, leading to a perpetual need for research. This dissertation aims to contribute to the existing body of knowledge on venture capital by addressing important research gaps in this field, particularly those related to performance, capital structure, and the exit decisions of venture-capital-backed companies.

The past decade has seen a rapid increase in venture capital deal size and valuations, leading to the emergence of new phenomena that potentially act as additional quality signals in the context of venture-capital-backed IPOs. More precisely, terms like “unicorn”, a description of a startup that managed to receive a valuation of one billion US-dollars or more, or “mega-deal”, describing an individual venture capital funding round of 100 million US-dollars or more, have been established in the venture capital industry recently (Brown & Wiles, 2015; Gornall & Strebulaev, 2020; Kerai, 2017). As discussed in Section 1.3, venture capitalists perform a certification role by investing in startups, thereby signaling quality to suppliers, customers, investment banks, and other third parties (Krishnan et al., 2011; Nahata, 2008; Smith, 2001). However, the strength of the certification effect varies, depending on the characteristics of the venture capitalist, e.g., the venture capitalist's reputation (Krishnan et al., 2011). Venture capitalists who invest large sums in portfolio companies could signal their optimism about the startup, potentially strengthening the initial certification effect. Theoretically, a venture capital mega-deal fulfills all requirements necessary for effective quality certification. That is, (i) the certifier has reputational capital at risk, (ii) the certification is not easy to receive, and (iii) the certification must be easily observable to outsiders (Megginson & Weiss, 1991; Myers & Majluf, 1984).

Behavioral finance provides several theoretical concepts that indicate an additional signaling effect of mega-deals. A mega-deal potentially triggers the anchoring effect, which occurs when a specific number, like 100 million US-dollars, is frequently reported and is therefore perceived as important by investors (Slovic & Lichtenstein, 1971). The anchoring effect can fuel herd behavior, whereby investors follow other investors’ decisions rather than their own analyses (Tversky & Kahneman, 1974). Hence, mega-deals could facilitate an irrational over-valuation in follow-on funding rounds and exits.

Based on the free cash flow hypothesis, the large amount of financial slack resulting from a mega-deal could harm the efficiency of the portfolio company. However, large investments could also meet the capital demand needed to efficiently grow the business (Bradley, Shepherd, & Wiklund, 2011; Jensen, 1986; Vanacker, Collewaert, & Paeleman, 2013). A prediction based on the free cash flow hypothesis is difficult since recent studies describe the relationship of free cash flow and performance as an inverted U-shape with a theoretical optimum amount of financial slack that is hard to determine for individual companies with individual capital needs (George, 2005; Tan & Peng, 2003).

Despite the requirement for IPO candidates to disclose extensive information about their past performance and equity story, uncertainty about future performance and stock price development persists, particularly for venture-capital-backed companies that often have a high degree of uncertainty, a short track record, and potentially limited or negative earnings (Dey et al., 2019). Consequently, signaling is especially relevant in the context of exiting via an IPO with asymmetric information distribution among corporate insiders and public investors (Megginson & Weiss, 1991).

Therefore this dissertation aims to analyze the effect of venture capital mega-deals on the IPO performance of venture-capital-backed companies, thereby joining and contributing to the research stream on quality signaling in IPOs (Krishnan et al., 2011; Megginson & Weiss, 1991; Stuart, Hoang, & Hybels, 1999). This field has focused on the certification by reputable third-party affiliations, e.g. venture capitalists, underwriters, and auditors (Carter & Manaster, 1990; Gulati & Higgins, 2003). A mega-deal potentially strengthens the certification from venture capital backing due to the signaled optimism by the informed investor. Theory does not provide clear predictions on whether mega-deal recipients perform superior IPOs compared to venture-capital-backed companies without mega-deal. Moreover, this dissertation recognizes the research gap on the recently emerging phenomena of venture capital mega-deals. Therefore, this dissertation aims to answer the following overarching research question:

RQ1: What are the treatment and signaling effects of venture capital mega-deals on the IPO success and post-IPO performance of venture-capital-backed companies?

Venture capital has a significant impact on the capital structure of startups. Although venture capitalists use equity injections to finance their portfolio companies, several studies have shown that venture-capital-backed companies tend to have a relatively diversified capital structure (Cumming, 2005; Ibrahim, 2010; Tykvová, 2017b). Even though venture debt accounted for roughly 13% of US venture financing in 2017 (Tykvová, 2017b), the use of debt in early-stage startups constitutes a riddle from the perspective of traditional capital theories, like the tradeoff theory by Kraus & Litzenberger (1973) and the pecking order theory by Myers & Majluf (1984). Existing research has found that venture capital backing is a key requirement for startups to be suitable candidates for venture debt (Hesse et al., 2016; Ibrahim, 2010;

Tykvová, 2017b). As discussed in Section 1.3, the advanced screening and selection processes used by venture capital firms can serve as a signal of quality to potential venture lenders (Hesse et al., 2016; Ibrahim, 2010). Furthermore, the stage financing provided by venture capitalists can ensure that sufficient cash flow is available to repay loans, even without positive cash flows or suitable collateral (Hesse et al. 2016; Ibrahim 2010).

The terms venture debt and venture lending are not consistently defined and are broadly used to describe every type of debt employed in startups (Ibrahim, 2010; Tykvová, 2017b). Thus, the definition includes traditional bank debt as well as convertible debt constructs with equity-like characteristics. Hence, one motivation of this dissertation is to account for the heterogeneity of venture debt and to specifically examine venture loans as a distinct form of venture debt. The venture loan is typically designed as an annuity loan featuring a warrant. While the annuity loan has to be repaid with fees and interest, the warrant enables the venture loan provider to participate in the startup's upside potential (Hesse et al., 2016).

Existing research has almost exclusively focused on venture debt in the broad sense, neglecting the heterogeneity of venture debt instruments (Ibrahim, 2010; Levin, 2008; Tykvová, 2017b). In their pioneering study, Hesse et al. (2016) examined venture loans and the business model of venture lending funds. Building on this initial research on venture loans, this dissertation aims to add to the literature by examining venture loans as a distinct form of venture debt and focuses on circumstances that foster the use of venture loans.

From the perspective of relationship lending, venture loans provide interesting research questions due to the interplay of venture capitalists, startups, and venture lenders. The role of the venture capitalists, hence, adds another dimension to the traditional relationship lending model (Elyasiani & Goldberg, 2004). There are significant research gaps on the relationships between the characteristics of the venture capitalist, the startup, and the use of venture loans.

More precisely, little is known about venture loans in the context of heterogeneity among venture capital types, e.g., corporate or government venture capital (Tykvová, 2017b). Additionally, the characteristics of previous venture capital investments could have a signaling effect on venture lenders, similar to the additional signaling effect of mega-deals in IPOs.

Venture loans have not been analyzed in the context of the financing lifecycles of startups and how different capital providers shape the capital structure of startups over time (Bertoni et al., 2019; Harrison, 2018; Park, LiPuma, & Park, 2019). Consistent with the financial growth cycle of small businesses in Berger & Udell (1998), Cotei & Farhat (2017) found that, with increasing maturity, startups accumulate tangible assets and are more likely to be profitable, leading to an increase in debt use. Thus, the maturity of a startup could foster the use of venture loans in venture-capital-backed startups.

In early-stage startups, patents could substitute for tangible assets. Existing research has examined patents as quality signals and potential collateral for venture debt in general, but empirical work has not yet delivered results for venture loans in particular (Hochberg, Serrano, & Ziedonis, 2018; Hsu & Ziedonis, 2008; Zhang, Guo, & Sun, 2019). Driven by these research gaps, this dissertation aims to provide answers to the following overarching research question:

RQ2: What factors drive the probability of a startup receiving a venture loan, and what role do prior investments by venture capitalists play in this context?

Financial sales, i.e., acquisitions of venture-capital-backed companies by private equity firms, were briefly discussed in Section 1.3. Financial sales are considered to be less preferred by venture capitalists and are constantly ranked below IPOs and trade sales when discussing a pecking order of venture capital exits (Bienz & Leite, 2008; Cumming & MacIntosh, 2003b).

The theoretical argument is that given bargaining power is equally distributed, a financial acquirer would always pay less than a strategic acquirer since financial acquirers cannot benefit from traditional synergies and hence have a lower valuation for the company (Bayar & Chemmanur, 2011). Thus, following Akerlof (1978) the market for buyouts of venture-capital-backed companies could constitute a market for lemons or a competition for the best of the rest, since venture capitalists and founders would only seek an exit via a buyout if the company does not meet the criteria for an IPO or trade sale.

However, despite the theoretical validity of this argument, recent reports point towards a convergence of strategic and financial acquisitions in the pecking order of venture capital exits. Davis & Le (2020) present recent data indicating that venture-capital-backed companies are increasingly acquired by private equity firms.

Due to the contradiction between theory and empirical evidence, this dissertation aims to challenge the prevalent theory of the pecking order of venture capital exits. Therefore, the following overarching research question will be examined:

RQ3: Are venture-capital-backed companies acquired by private equity firms of the same quality as those acquired by strategic buyers, and what are the underlying mechanisms of the recent increase in private equity buyouts of venture-capital-backed companies?

3. Overview of the dissertation and additional remarks

After the introduction, this dissertation proceeds with three essays, each of which represents a distinct academic contribution dealing with the research questions derived in the previous section. Essay 1 investigates the effects of venture capital mega-deals on the IPO success and post-IPO performance of venture-capital-backed companies by analyzing the treatment and signaling effect of venture capital financing rounds of 100 million US-dollars or more on IPO proceeds, IPO pre-money-valuation, underpricing, price revision, and the 90-day, 180-day, 1-year, and 2-year valuations. Essay 2 presents the venture loan as a distinct financing form of venture lending and provides analyses of the relations between the company, venture capital, and environmental characteristics and the use of venture loans in venture-capital-backed companies. Essay 3 examines the differences and similarities of strategic and financial buyers in acquisitions of venture-capital-backed companies in recent years by analyzing changes in the impact of the company, investor, and environmental characteristics on the probability of a portfolio company being acquired by a financial buyer compared to a corporate acquirer. Finally, the dissertation concludes by summarizing all three essays and discussing their main findings, contributions, implications, and avenues for future research. Table A-1 summarizes the key aspects of the essays, that is, the title, theoretical perspective, research objectives, contributions, sample characteristics, and applied methods. Table A-2 presents the current status of each essay and gives additional information on conference presentations.

Table A-1: Characteristics of the essays

	Title	Theoretical perspective	Research objectives	Contributions	Sample	Method
Essay 1	Effects of venture capital mega-deals on IPO success and post-IPO performance	Free cash flow hypothesis, signaling theory, and behavioral finance.	Investigation of the effects of venture capital mega-deals on the IPO success and post-IPO performance of venture-capital-backed companies.	1. Extension of the academic literature on quality signaling in IPOs. 2. Showing that the outperformance stems from treatment and signaling effect. 3. Validation of the mega-deal as a quality signal in IPOs.	Secondary data on 364 IPOs in the years from 2010 to 2019 at major US stock exchanges, 69 of which were conducted by mega-deal recipients.	Descriptive analysis, using t-tests for differences in means, instrumental variables (IV) two-stage least squares (2SLS) regression models, and regression discontinuity design.
Essay 2	Why deep pockets make great borrowers: an empirical analysis of venture loans	Tradeoff theory and capital pecking order theory.	Investigation of circumstances, startup and investor characteristics that foster the use of venture loans.	1. Enhancement of the literature on financing lifecycles of startups. 2. First quantitative study on venture loans as a distinct form of venture debt. 3. Contribution to the literature on relationship lending.	Secondary panel data of 27,577 financing rounds of 13,540 startups. 286 financing rounds were identified as venture loans granted to startups.	Descriptive analysis, using t-tests for differences in means, and binary logistic regression models.
Essay 3	Acquisitions of venture-capital-backed companies: a convergence of strategic and financial acquirers?	Principal-agent-theory, industry-relatedness-hypothesis, and venture capital exit pecking order.	Investigation of differences in the quality of startups when exited via trade sale or buyout.	1. Extension of the literature on venture capital exit options and the pecking order of venture capital exits. 2. Contribution to the research gap in investment criteria of private equity firms.	Secondary data on 6,348 acquisitions of US-based venture-capital-backed companies between 2005 and 2021 of which 296 were identified as buyouts.	Descriptive analysis, using t-tests for differences in means, and binary logistic regression models, including sample splitting.

Table A-2: Status of the essays

	Current status	Conferences
Essay 1	Published in the Financial Analysts Journal, Vol. 78, No. 4 (2022), pp. 99-120. VHB-JQ3-Rating: B	• 22nd Annual Interdisciplinary Conference on Entrepreneurship, Innovation and SMEs (G-Forum), Karlsruhe, Germany, 28.09.-02.10.2020. (virtual conference due to the covid-19 pandemic) • 5th Annual Entrepreneurial Finance Conference (ENTFIN), Marseille, France, 25.06.-26.06.2021. (virtual conference due to the covid-19 pandemic) • 2nd Annual Financial Management & Accounting Research Conference (FMARC), Paphos, Cyprus, 19.09.-21.09.2021.
Essay 2	Published in the Journal of Business Economics, Vol. 92, No. 9, pp. 1431-1453. VHB-JQ3-Rating: B	None
Essay 3	Working paper.	• 23rd Annual Interdisciplinary Conference on Entrepreneurship, Innovation and SMEs (G-Forum), Dresden, Germany, 21.09.-23.09.2022.

B. Essay 1 - Effects of venture capital mega-deals on IPO success and post-IPO performance[2]

1. Introduction

Venture capital rounds with a financing volume of 100 million US dollars (USD) or more are defined as “mega-deals” (NVCA, 2020). The number of these mega-deals has grown rapidly in recent years, and they are now an integral part of the venture capital market and have been the subject of recent venture capital reports published by CB-Insights (2021), KPMG (2021), and NVCA (2022b). In the United States, the number of mega-deals grew from 25 in 2010 to 234 in 2019 in deal count and from 3.8 billion USD in 2010 to over 54 billion USD in 2019 in deal volume. We set out to investigate whether these mega-deals are justified by subsequent superior company development, leading to a successful IPO. This is particularly relevant, as venture-capital-backed companies increasingly undertake IPOs prior to generating positive earnings (Dey et al., 2019). Therefore, for stock market investors, quality signals are important when assessing such companies.

Motivated by these factors, we analyze how companies that have received a venture capital mega-deal later perform in an IPO event. We thereby join the ongoing debate on quality signaling in the IPO process (Carter, Dark, & Singh, 1998; Gulati & Higgins, 2003; Megginson & Weiss, 1991; Stuart et al., 1999). Certification by reputable third-party affiliations, e.g. venture capitalists, underwriters, and auditors, have dominated this field, especially in the 1990s

[2] Authors: Lehnertz, N., Plagmann, C., and Lutz, E.
Presented at the 22nd Annual Interdisciplinary Conference on Entrepreneurship, Innovation and SMEs (G-Forum), Karlsruhe, Germany, 28.09.-02.10.2020 (virtual conference), the 5th Annual Entrepreneurial Finance Conference (ENTFIN), Marseille, France, 25.06.-26.06.2021 (virtual conference), and the 2nd Annual Financial Management & Accounting Research Conference (FMARC), Paphos, Cyprus, 19.09.-21.09.2021.
Published in the Financial Analysts Journal, Vol. 78, No. 4 (2022), pp. 99-120.

and 2000s. While most of the venture-capital-related research has focused on the role of venture capitalists in IPOs, Krishnan et al. (2011) went a step further by analyzing the effect of the lead venture capitalist's reputation on IPO performance. They found that IPOs involving venture capitalists with good reputations exhibit, on average, better post-IPO performance, than their counterparts. Moreover, due to the rapid increase in venture capital deal size and valuations, new phenomena have emerged that may act as additional signals in the context of venture-capital-backed IPOs, with unicorn valuations and venture capital mega-deals being the most prominent examples (Brown & Wiles, 2015). While unicorn valuations have been investigated in several recent research studies, there has been a tendency to neglect venture capital mega-deals (Gornall & Strebulaev, 2020; Kerai, 2017). Due to the importance of signaling in venture-capital-backed IPOs and the research gap on venture capital mega-deals, we set out to study their effects on IPO success and post-IPO performance.

To do this, we examine a sample of 364 IPOs between the years 2010 and 2019 at major US stock exchanges, 69 of which were conducted by mega-deal recipients. Due to the non-random nature of mega-deal status, we apply an instrumental variables approach in order to determine causal effects. Furthermore, we make use of the regression discontinuity design to isolate the signaling effect of mega-deals.

We show that mega-deal recipients perform better than their counterparts in IPOs in terms of proceeds, valuation, and price revision at a higher underpricing. In addition, we find that the superior IPO performance of mega-deal companies is sustained over a two-year post-IPO period. In isolating the signaling effect, we find that the mere fact of a company receiving a mega-deal has a significant positive effect on IPO success but that this effect fades out over the two-year post-IPO period.

We contribute to the existing literature in three ways. First, we explore mega-deals and their implications for IPOs as a previously under-researched phenomenon in the venture capital market. Thus, we directly add a new certification mechanism to the literature on venture capital signaling in the context of IPOs (Gulati & Higgins, 2003; Krishnan et al., 2011; Megginson & Weiss, 1991). In doing this, we show that the mega-deal's positive effect on IPO success and post-IPO performance can be partially explained by the isolated signaling effect, i.e., when companies only differ in the sense that one received a mega-deal, and the other did not (Mitchell, 2001; Slovic & Lichtenstein, 1971; Tversky & Kahneman, 1974). Second, our results can also be interpreted in light of behavioral finance. A mega-deal seems to trigger the anchoring effect, which occurs when a specific number (in our case the 100 million USD threshold) is frequently reported and is therefore perceived as important by investors (Slovic & Lichtenstein, 1971). This anchoring effect can, in turn, lead to herd behavior whereby investors follow other investors' decisions rather than their own analysis (Tversky & Kahneman, 1974). Third, we contribute to the academic discussion regarding the correctness of the free cash flow hypothesis, as our findings indicate that the companies examined were able to efficiently use the financial resources resulting from mega-deals to rapidly grow their businesses (Bradley et al., 2011; Jensen, 1986; Vanacker et al., 2013).

Beyond its academic contributions, this study has several practical implications for entrepreneurs, venture capitalists, investors in public equity, and financial analysts. While entrepreneurs have different long-term goals when founding a company, some do envision building a successful publicly listed company. Based on our results, each of these entrepreneurs should strive for large venture capital financing rounds in their company's lifecycle to lay the groundwork for a future IPO. For venture capitalists, our results underscore the importance of having the label of a mega-deal in a financing round. In financing rounds that approach the threshold of 100 million USD, venture capitalists should strive to increase the capital volume above the threshold in order to take advantage of the quality signal. Furthermore, the results suggest that large amounts of capital can be effectively employed to grow the company, which could result in potentially large returns when exiting the company through an IPO. Overall, our results show that a mega-deal is an important milestone on the path to building promising IPO candidates.

What is more, our results are relevant to investors in public equity and to financial analysts. Although IPO candidates must provide detailed information about past performance and their equity story, uncertainty regarding future performance and stock price development remains. This is particularly relevant for venture-capital-backed companies that are characterized by high uncertainty, a short track record, and, oftentimes, limited or even negative earnings. For this context, we provide validation that venture capital mega-deals are an easily observable quality signal that point to a successful future IPO and positive post-IPO performance. Finally, by showing that, on average, mega-deal recipients have superior IPOs and post-IPO performance, we rebut the common argument that mega-deals are “dumb money,” as suggested by IPOs of mega-deal companies that were less successful but highly visible, e.g., Facebook and Uber.

2. Theoretical background

The venture capital market is characterized by asymmetric information, multiple incentive problems, limited regulation, and high growth potential (Fan, 2016; Manigart et al., 2006; Tykvová, 2007). New ventures often have no access to traditional financing sources, such as bank loans, due to their lack of physical assets and the high uncertainty attached to the future success of their business model (Gompers, 1995). Venture capitalists specialize in investing equity in young, innovative companies in high-risk environments (Sonne, 2012). Due to their familiarity with this market, successful venture capitalists enjoy a positive reputation in terms of their selection, monitoring, and management skills within the finance industry (Gulati & Higgins, 2003; Krishnan et al., 2011). As a result, venture capitalists play a certification role, and their investments convey information regarding the quality of young private companies to other potential capital providers (Jain & Kini, 1995; Megginson & Weiss, 1991). Such signals are important when the company goes public due to the asymmetric information issues that arise between corporate insiders and outside investors (Megginson & Weiss, 1991). Quality-revealing signals can be third-party affiliations of the issuer, such as renowned venture capitalists, underwriters, auditors, and attorneys (Brau & Johnson, 2009; Carter et al., 1998; Gulati & Higgins, 2003).

However, quality signals are not limited to third-party affiliations. We aim to examine venture capital mega-deals as quality-revealing signals that extend beyond the mere presence of a third party. Krishnan et al. (2011) showed that the venture capitalist's reputation has a positive effect on post-IPO performance, thereby highlighting the relevance of venture-capital-related signals. Due to the major increase in very large venture capital investments over the last decade, new signals related to investment and valuation size have emerged. Companies that exceed specific thresholds, such as 100 million USD financing rounds or 1 billion USD valuations, are tagged with catchy terms like "mega-deal" or "unicorn." Such tags imply that these thresholds are difficult to breach and that they function as quality signals that extend beyond the mere presence of venture capitalists. The unicorn tag, in particular, has attracted the attention of academic researchers (Brown & Wiles, 2015; Gornall & Strebulaev, 2020; Kerai, 2017). A unicorn is defined as a private company with a reported one billion-dollar valuation

(Gornall & Strebulaev, 2020). This popular term tends to attract positive media coverage, with the existence of elite unicorn "clubs," which companies with unicorn status join, even being described in the press (Lehmann, Schenkenhofer, & Wirsching, 2019). This positive association is then further reinforced by high investor expectations that such companies could potentially become the next Facebook or Google (Gornall & Strebulaev, 2020), as has been confirmed by Kerai (2017), who has reported that the unicorn tag has positive effects on subsequent funding activities.

A venture capital mega-deal can be seen as a precursor to unicorn valuation and has a similar certification mechanism. Theoretically, mega-deals meet the three fundamental criteria for certification, which are generally as follows: (i) the investor must have reputational capital at stake; (ii) acquisition of certification must take time and effort; and (iii) the certification must be observable and verifiable by outsiders (Megginson & Weiss, 1991; Myers & Majluf, 1984). The first criterion is met because mega-deals are investments made by venture capitalists who have reputational capital at stake. Reputational capital is a fundamental asset in the financial industry; it takes time to accumulate (Walter, 2013) and can be heavily compromised when investments fail. In the special case of highly visible mega-deals, this effect is reinforced because a significant amount of capital is at risk. Second, it is generally difficult for young entrepreneurial companies to attract venture capital. Venture capitalists screen up to 5,000 business plans per year while only investing in a few (Nadeau, 2010). Mega-deals, meanwhile, are even rarer, leading to the conclusion that only the most promising ventures can attract a mega-deal. Third, mega-deals are easily observable and verifiable by outside investors, as they are usually made public so as to achieve positive publicity. Based on these arguments, we hypothesize that a mega-deal has a positive effect on the company's IPO success.

Because mega-deals are a relatively new phenomenon, we focus on the latest available data. The phenomenon's recent emergence limits our ability to study the long-term performance of mega-deal-receiving companies; however, along with the immediate effects, we also consider the post-IPO performance of companies within two years of the IPO. The mega-deal's effect might not be persistent in the aftermath of the IPO and could vanish after two years. It could be the case that the mega-deal creates irrational "hype" among investors, as was the case with the "dot-com" tag during the dot-com bubble (Chan, Karceski, & Lakonishok, 2000; Gollotto & Kim, 2003), but there are several factors that suggest positive post-IPO performance. Mega-deals are only granted by specialized venture capitalists who comprehensively assess the startup (Yung, 2009). Thus, the quality of the mega-deal recipient company is certified in two ways. First, a distinction is made between startups that are able to attract investors and those that are struggling to attract investors (Baeyens, Vanacker, & Manigart, 2006). In the special case of mega-deals, the startups succeed in attracting large sums of capital by passing venture capitalists' due diligence. Second, the question of whether venture capitalists enter the company by paying average or multi-million-dollar amounts makes a key difference. This is because it serves as a further assurance of quality if mega-deal companies can justify venture capital investments at exceptional volumes. As previously discussed, the mega-deal tag fulfills the theoretical criteria for certification. Krishnan et al. (2011) found that venture capitalists with good reputations select companies that prove to be capable of superior post-IPO performance. It seems plausible that this would hold for mega-deals as well and that it would constitute a positive impact of the mega-deal on post-IPO performance. Hence, we hypothesize that receipt of a mega-deal positively affects post-IPO performance.

The mega-deal threshold of 100 million USD is not arbitrary and presents an important psychological barrier, according to behavioral finance (Aggarwal & Lucey, 2007; Mitchell, 2001; Urquhart, 2017). This effect is a widespread phenomenon permeating financial market environments and economic decision making (Mitchell, 2001). Based on financial behavior literature, we identified two major explanations for the importance of the threshold: the tendency toward round numbers, e.g. 100 million USD, (which stems from cultural and conventional norms, such as the development of the modern decimal system) (Mitchell, 2001) and the anchoring effect (which is the phenomenon of individuals fixating on a recent number, or on a number that is commonly perceived as being important by informed commentators) (Slovic & Lichtenstein, 1971). This threshold is derived from the NVCA mega-deal definition (2020).

Moreover, practitioners, databases, and most media use the term (CB-Insights, 2021; KPMG, 2021). Both effects are reinforced by the use of heuristic concepts as well as by herd behavior in financial markets (Avery & Zemsky, 1998; Tversky & Kahneman, 1974). Behavioral finance research provides a theoretical framework and empirical evidence for the importance of the signaling effect of a mega-deal in IPOs. Based on these arguments, we hypothesize that the mere fact of a company receiving a venture capital mega-deal, all else being equal, positively influences the IPO success and post-IPO performance.

3. Data and Methodology

3.1. Dataset rationale

We use IPO and venture capital data from Refinitiv Eikon and Datastream as well as additional hand-collected information from IPO prospectuses.[3] The final sample consists of 364

[3] Available: https://eikon.refinitiv.com. This resource requires installation of the database on a standalone computer. The URL is the best available source for information about the database.

IPOs of venture-capital-backed companies, of which 69 raised at least one mega-deal before going public. The sample is restricted to companies based in the United States that went public on NASDAQ or NYSE between 2010 and 2019. We exclude spinoff and carve-out IPOs as well as financial vehicles, closed-end funds, trusts, buyouts, and any IPOs or companies that lacked the necessary fundamental data to conduct the study (Krishnan et al., 2011; Megginson & Weiss, 1991).

Meanwhile, in regard to outliers, we found Uber Technologies, Inc. to be disproportionately far away from the rest of the observed companies. Indeed, in terms of total funding value received in all financing rounds combined prior to the IPO, Uber received more than twice the amount received by the second highest-funded company, Lyft, Inc. Plus, in comparing the size of the largest single venture capital financing round a company has received, Uber outpaced the rest by more than double the second-largest value in the sample and more than triple the value of Snap, Inc. or Facebook, Inc. Thus, to prevent this single case from distorting our results, we decided to remove Uber from the sample.

3.2. IPO success and post-IPO performance

We created two regression specifications: one to measure the effect of a mega-deal on IPO success and the other to measure the effect on post-IPO performance. In the following, we present the variables used in these regressions, starting with the IPO success measures. Table B-1 provides a brief overview of the variables used in the regressions.

Table B-1: Variable definitions

	Definition
Variable of interest	
Mega-deal	A binary variable that takes the value of 1 if an issuer has received a venture capital financing round of 100 million USD or more prior to the IPO, and 0 otherwise.
IPO success measures	
ln(proceeds)	A metric variable that depicts the logarithm of total proceeds in million USD generated during the IPO.
ln(Pre-money valuation)	A metric variable reporting the logarithm of the pre-money valuation in million USD based on Stuart et al. (1999). The pre-money valuation is calculated as follows: $V^* = (p_u q_t - p_u q_i)$, where p_u is the final offer price, q_t is the total number of shares, and q_i is the number of shares sold in the offering.
Price revision	A metric variable representing the difference in percentage between the final offer price and the mid-price of the initial subscription price range.
Underpricing	A metric variable reporting the difference in percentage between the final offer price and the closing price on the first day of trading.
Post-IPO perf. measures	
ln(90-day valuation) *ln(180-day valuation)* *ln(1-year valuation)* *ln(2-year valuation)*	Metric variables that depict the pre-money valuation in million USD after 90, 180, 360, and 720 days. Based on Stuart et al. (1999) and following Gulati & Higgins (2003), we replace p_u with the stock price at 90 days, 180 days, 360 days, and 720 days, respectively. For example, the 90-day valuation formula is as follows: $V_{90}^* = (p_{90} q_t - p_{90} q_i)$.
Control variables	
Lead VC reputation	A metric variable reporting a reputation score calculated from four components, namely, the lead VC's age, the average number of funds managed over the previous five years, the equity invested over the last five years, and the number of startups invested in. We follow the methodology of Lee, Pollock, & Jin (2011) and Plagmann & Lutz (2019) in calculating the index.
Lead underwriter reputation	A metric variable representing the lead underwriter reputation based on the widely used Carter & Manaster (1990) ranking. The data were taken from J.R. Ritter's publicly available IPO database. (site.warrington.ufl.edu/ritter/ipo-data/)
Profitability	A binary variable that equals 1 if the issuer is profitable at the time of the IPO, and 0 otherwise.
Total assets pre-IPO	A metric variable that depicts the company's total assets, taken from the last financial statement before the IPO.
Age at IPO	A metric variable that counts the years between the founding year and the IPO year of the issuer.
Startup hub	A binary variable that takes the value of 1 if the company is located in California, Massachusetts, New York, or Texas, and 0 otherwise. Startup hubs are defined based on the research of Stephens et al. (2019).
Multiple mega-deal	A binary variable that equals 1 if the issuer managed to raise more than one mega-deal prior to the IPO.
IPO market hotness	A metric variable that reports a three-month moving average leading up to the IPO, consisting of the standardized average market price revision, market underpricing, and market volume. The data were taken from J.R. Ritter's publicly available IPO database. (site.warrington.ufl.edu/ritter/ipo-data/)
M/B ratio	A metric variable that reflects the market-to-book ratio of the company after the IPO.
Stock exchange	A binary variable that takes the value of 1 if the issuer went public at NASDAQ, and 0 if the issuer went public at NYSE.
Industry	A metric variable that classifies the companies into different industries according to the lowest SIC level of detail.
IPO year	A metric variable that reports the IPO year for each issuer.
Instrument variables	
Lead VC avg. deal size	A metric variable that represents the average USD volume of the deals in which the lead venture capitalist was involved between 2000 and 2019.
Company avg. deal size	A metric variable that depicts the total amount of venture capital a company has received, divided by the number of individual financing rounds. Additionally, we adjust the variable by subtracting the industry median.
Lead VC distance	A metric variable that equals the geodetic distance in thousands of miles between the company's headquarters and the venture capitalist's headquarters.

Note: This table presents the definitions and measurements of all the variables used in this study.

We posit a set of four dependent variables as measures for IPO success that are all based on Refinitiv Eikon data. IPO proceeds are commonly used as an IPO performance measure in finance-related academic research (Gulati & Higgins, 2003; Wu, Li, & Li, 2013). Proceeds are defined as the number of shares sold in the IPO multiplied by the offering price. The proceeds are a relevant factor of IPO success because they are the fundamental reason for going public (Pagano, Panetta, & Zingales, 1998). Therefore, the first proxy is ln(Proceeds), which is the logarithm of the proceeds or earnings of the IPO.

The second proxy is *ln(Pre-money valuation)*, which is the logarithm of the market value of a company at the time of the IPO. Originally introduced by Stuart et al. (1999), this measure is defined as:

$$V^{*} = (p_u q_t - p_u q_i) \quad (1)$$

where p_u is the final offer price, q_t is the total number of shares, and q_i is the number of shares sold in the offering. By subtracting the dollar amount raised in the offering from the firm's total market capitalization, V^{*} measures the market's assessment of a company's value at the time of the offering. The value of V^{*} is contingent on public investors' estimate of the value of the company's quality, e.g., in terms of reputation, portfolio strategic alliances, and management (Stuart et al., 1999).

As a third measure of IPO success, we use *Price revision*, which is the percentage difference between the final offer price and the mid-price of the initial subscription price range. Consequently, the measure is positive if the final offer price is above the mid-price and negative if the final offer price is below the mid-price. Price revision is less dependent on company size and is a measure of the demand for the company's shares, which can be interpreted as the investment interest of the market (Krishnan et al., 2011).

Our fourth measure is *Underpricing*, which is defined as the difference in percentage between the offer price and the closing price on the first day of trading. While the media generally associates underpricing with a successful IPO, underpricing is in fact a measure of how much money the company has "left on the table" (Loughran & Ritter, 2004). However, IPOs with large underpricing are usually those whose market price is higher than originally anticipated. Consequently, some issuers lose wealth via large underpricing and simultaneously discover they are wealthier than expected (Loughran & Ritter, 2002). The underpricing measure should be considered in connection with the other performance measures because high or low underpricing can be interpreted differently, depending on the IPO's success.

To measure post-IPO performance, we use modified versions of the valuation measure V^*. Following Gulati & Higgins (2003), we replace p_u with the stock price at 90 days, 180 days, one year, and two years after the IPO. For example, the 90-day valuation formula is as follows:

$$V_{90}^* = (p_{90}q_t - p_{90}q_i) \tag{2}$$

This method allows us to capture the market's assessment at four points in time. We can then look at dynamic developments and control for temporary biases in valuations. Additionally, the measure enables a comparison with the IPO success measure V^* and helps to determine whether the stock market performance carries on after the IPO.

3.3. Mega-deal variable

Our variable of interest is the *Mega-deal* variable. It equals 1 if the company has managed to receive at least one single venture capital financing round amounting to 100 million USD or more. To find mega-deals and then allocate them to the companies, we used the data of venture capital transactions from Refinitiv Eikon's Private Equity Screener. After the matching and deal size analysis, 69 of the 364 companies were found to be mega-deal recipients.

3.4. Control variables

We control for several variables found to impact IPO success measures in previous research. The lead venture capitalist's reputation has been shown to impact the IPO performance of portfolio companies and is therefore used as a control variable throughout our regressions (Krishnan et al., 2011). Like Lin & Smith (1998), Hochberg, Ljungqvist, & Lu (2007), and Krishnan et al. (2011), we define a lead venture capitalist as the actor with the largest stake in the portfolio firm as of the IPO date, according to the IPO prospectus. We use data from Refinitiv Eikon's Private Equity Screener to create a reputation score calculated from four components: the age of the lead venture capitalist, the average number of funds managed over the last five years, the equity invested over the last five years, and the number of startups invested in. We follow the methodology of Lee et al. (2011) and Plagmann & Lutz (2019) in calculating the index. In our sample, this measure allocates the highest values to renowned venture capitalists such as Sequoia Capital, Kleiner Perkins, New Enterprise Associates, Accel Partners, and Bessemer Venture Partners, i.e., venture capitalists that are featured among the top venture capitalists in publicly available rankings (CB-Insights, 2021).

Underwriter reputation is a relevant factor of IPO success, as shown in many studies, such as those conducted by Carter et al. (1998) and Higgins & Gulati (2003). *Lead underwriter reputation* covers the lead underwriter's reputation score based on the widely used Carter & Manaster (1990) underwriter reputation ranking. We used the publicly available data from

IPOScoop.com, LLC to identify the lead underwriter, while data on the reputation score was taken from J.R. Ritter's publicly available IPO database.[4]

Profitability is also a predictor of a company's future success and survival in relation to IPO success (Chou, Cheng, & Chien, 2013). Moreover, Bloomberg reported a recent increase in IPOs by unprofitable companies (Dey et al., 2019). Therefore, we include the *Profitability* variable, which takes a value of 1 if the company generates positive net income at the time of the IPO, and 0 otherwise. To generate this variable, we used the companies' earnings data from Refinitiv Eikon.

Company size and maturity, measured as total assets and company age, are further factors that are widely used in IPO performance research (Bach, Judge, & Dean, 2008; Gulati & Higgins, 2003). The variable *Total assets pre-IPO* represents the company's total assets, taken from the last financial statement before the IPO. *Age at IPO* is the company's age at the time of the IPO, calculated as the difference between the IPO year and the founding year. Data were taken from Refinitiv Eikon.

The entrepreneurial ecosystem around a startup influences its development. Startup hubs offer several advantages, such as networks, funding opportunities, and labor talent (Stephens et al., 2019). All these advantages potentially influence performance; therefore, we include the binary variable *Startup hub*, which takes the value of 1 if the company is located in California, Massachusetts, New York, or Texas, and 0 otherwise. Startup hubs were defined based on research by Stephens et al. (2019), and we used data on company locations from Refinitiv Eikon's Private Equity Screener to create this variable.

[4] Available at https://site.warrington.ufl.edu/ritter/ipo-data/

The sample includes 69 companies that raised mega-deals before going public, 19 of which even managed to acquire two or more mega-deals. We control for bias caused by multiple mega-deals in the regressions by including the variable *Multiple mega-deal*, which takes the value of 1 when a company received more than one mega-deal, and 0 otherwise. Data were taken from Refinitiv Eikon's Private Equity Screener.

Market sentiment, meanwhile, plays a crucial role in the timing and pricing of IPOs and is therefore included as *IPO market hotness* (Ljungqvist, Nanda, & Singh, 2006; Neupane, Paudyal, & Thapa, 2014). *IPO market hotness* is a three-month moving average leading up to the IPO, consisting of the standardized average market price revision in percentage, market underpricing in percentage, and market volume used to represent the market sentiment regarding the quality and quantity of IPOs. For this, we collected the publicly available data from Jay R. Ritter's website.[5]

The *Stock exchange* variable equals 1 if the IPO took place on the NASDAQ, and 0 if the IPO took place on the NYSE, in order to control for a possible market bias (Fan, Wong, & Zhang, 2007). Finally, *IPO Year* indicates the year when the company went public, while *Industry* classifies the companies into seven different industries according to the lowest Standard Industrial Classification (SIC) level of detail. *IPO Year* and *Industry* are used to control for differences across years and industries within the sample, with both being taken from Refinitiv Eikon (Krishnan et al., 2011).

To analyze post-IPO performance, we must adjust control variables in several ways, given that many of the IPO success measures can influence post-IPO performance. Following Krishnan et al. (2011), we include *Underpricing*, *Price revision*, *Proceeds*, *Lead VC reputation*,

[5] Available at site.warrington.ufl.edu/ritter/ipo-data

Lead underwriter reputation, *Age at IPO*, and *M/B ratio* as controls in the post-IPO performance regressions. Additionally, we control for the variables *Startup hub*, *Multiple mega-deals*, and *Stock exchange*, and include year and industry fixed effects.

We control for the variables *Underpricing*, *Price Revision*, and *Proceeds* because they are widely used as control variables in post-IPO performance studies to control for differences in firm quality and IPO demand (Hanley, 1993; Loughran & Ritter, 2004; Welch, 1989). *Lead VC reputation*, meanwhile, is included because it was found to influence post-IPO performance by Krishnan et al. (2011), while *Lead underwriter reputation* and *Age at IPO* are also frequently used controls in IPO literature (Barry et al., 1990; Carter et al., 1998). Furthermore, we include *Startup hub*, as it potentially influences performance (Stephens et al., 2019), while the *Multiple mega-deals* variable is used as a control to account for the possibility that multiple mega-deals bias the results throughout the post-IPO performance and *Stock exchange* is included to control for possible market biases between NASDAQ and NYSE (Fan et al., 2007). The only new variable, the *M/B ratio*, reflects the market-to-book ratio of the company after the IPO and is commonly used in stock-market-related literature as a measure of firm growth opportunities (Brav & Gompers, 1997; Krishnan et al., 2011). The market-to-book ratio was taken from Refinitiv Eikon.

3.5. Descriptive statistics

Panel A of Table B-2 displays the yearly IPO frequencies of mega-deal-receiving and non-mega-deal-receiving companies. In total, our sample consists of 69 companies with mega-deals and 295 companies that had not been funded with a mega-deal before going public, with most total venture-capital-backed IPOs taking place in 2014 and most mega-deal-financed portfolio company IPOs taking place in 2018 and 2019. Approximately one-fifth of the venture-capital-backed IPOs were conducted by mega-deal recipients. In more recent years, from 2017 to 2019, the average share was approximately one-third. Thus, the sample data support the argument that mega-deals are becoming an integral part of the venture capital market.

Panel B of Table B-2 compares the characteristics of mega-deal- and non-mega-deal-funded companies. The numbers indicate that companies that received a mega-deal before their IPOs were generally bigger, were managed by underwriters with a better reputation, and were more likely to go public on the NYSE than those that had not received a mega-deal. The sample data on profitability also provide evidence that IPOs of unprofitable companies are broadly accepted by public investors, at least in the context of venture-capital-backed IPOs. Only 11.8 % of IPOs in our sample were conducted by companies that were profitable at the time of the IPO; however, the variable does not indicate whether a company was never profitable until the IPO, as this variable only considers profitability at the time of the IPO. Linking the current situation and the dot-com era, an article by Dey et al. (2019) states that in 2019, IPOs of unprofitable companies with proceeds of at least 100 million USD or more had raised the most cash of any year since at least 2000.

Panel C of Table B-2 presents the descriptive statistics for the IPO success measures. The numbers suggest that mega-deal-receiving companies exhibit, on average, higher IPO proceeds, pre-money valuations, price revision outcomes, and underpricing. Remarkably, the proceeds and valuations of mega-deal recipients are, on average, several times higher than those of their counterparts without mega-deals, indicating that mega-deals could be associated with rapid growth and advantages in follow-on financing events.

Table B-2: Descriptive statistics

Panel A. IPO frequencies by year

Year	Total	*Mega-deal* = 0	*Mega-deal* = 1	*Mega-deal* in %
2010	26	24	2	7.7
2011	27	20	7	25.9
2012	27	22	5	18.5
2013	43	38	5	11.6
2014	75	67	8	10.7
2015	49	43	6	12.2
2016	16	14	2	12.5
2017	22	16	6	27.3
2018	38	24	14	36.8
2019	41	27	14	34.1
Total	364	295	69	100.0

Panel B. VC-backed company characteristics

Variables	*Mega-deal* = 0		*Mega-deal* = 1	
	Mean	S.d.	Mean	S.d.
Lead VC reputation	0.341	0.247	0.377	0.267
Lead underwriter reputation	8.288	1.274	8.819**	0.575
Profitability	0.112	0.316	0.145	0.355
Total assets pre-IPO (m. USD)	93.8	175.3	559.7**	1,014.3
Age at IPO (in years)	8.797	3.898	8.319	4.107
Startup hub	0.759	0.428	0.841	0.369
Multiple mega-deals	0.000	0.000	0.275**	0.450
M/B ratio	3.727	8.314	4.949	7.729
IPO market hotness	0.013	0.763	-0.004	0.777
Stock exchange	0.800	0.401	0.594**	0.495

Panel C. IPO success measures

Variables	*Mega-deal* = 0		*Mega-deal* = 1	
	Mean	S.d.	Mean	S.d.
Proceeds (m. USD)	97.9	77.7	605.4**	1,959.4
Pre-money valuation V^* (m. USD)	450.1	729.2	3,474.5**	9,321.7
Price revision	-0.008	0.146	0.058**	0.138
Underpricing	0.204	0.307	0.337**	0.359

Panel D. Post-IPO performance measures

Variables	*Mega-deal*=0		*Mega-deal*=1	
	Mean	S.d	MeanS.d	
90-day valuation (m. USD)	662.4	1,300.8	3,854.2**	6,774.9
180-day valuation (m. USD)	598.2	1,070.3	3,304.9**	5,552.9
1-year valuation (m. USD)	718.3	1,855.1	3,797.5**	7,473.0
2-year valuation (m. USD)	883.3	2,839.2	6,684.5**	16,080.7

Notes: Panel A of this table reports the number of IPOs from non-mega-deal-receiving companies and mega-deal-receiving companies in each year from our sample of 364 IPOs completed in the 2010–2019 period. Panel B reports means and standard deviations for issue and company characteristics of the non-mega-deal-receiving and mega-deal-receiving companies. Panel C reports means and standard deviations for the IPO success measures of the non-mega-deal-receiving and mega-deal-receiving companies. Panel D reports means and standard deviations for the post-IPO performance measures of the non-mega-deal-receiving and mega-deal-receiving companies. The definitions and measurements of variables can be found in Table B-1. Also reported is the significance of the differences in means between the two samples.

* Significant at the 5% level.

** Significant at the 1% level.

Panel D of Table B-2 reports the descriptive statistics for the post-IPO performance measures. Means of the 90-day, 180-day, one-year, and two-year valuations are several times higher for mega-deal recipients than they are for their counterparts without mega-deals. Notably, after exceeding the 90-day period after the IPO, the average valuations decline by 180 days before rising again in the one- and two-year periods. This holds for both mega-deal recipients and non-mega-deal recipients. In terms of the hype assumption, based on the descriptive evidence, the valuations of mega-deal companies do not seem to collapse after a strong IPO. This can be interpreted as a first indication that irrational hype such as that of the dot-com era does not occur during the IPOs of mega-deal companies. For information on the variables' pairwise correlations please see Appendix 1 and Appendix 2.

3.6. Methodological framework

We adopt an econometric approach, which allows us to study the effect of mega-deals on IPO success and post-IPO performance. Given the non-random nature of mega-deals, we implemented instrumental variables (IV) two-stage least squares (2SLS) regression models based on robust standard errors that allow for the correction of selection bias and endogeneity issues. The most basic form of the regression can be written as follows:

$$y_1 = \beta_1 y_2 + \beta_2 x'_1 + u \tag{3}$$

where y_1 is one of the IPO success or post-IPO performance measures, and y_2 is the endogenous mega-deal variable. The vector x_1 represents the set of exogenous control variables. In the 2SLS regressions, the mega-deal receipt is modeled in the first stage and the IPO success/post-IPO performance in the second stage. The mega-deal receipt can be described as follows:

$$y_2 = \gamma_1 x'_1 + \gamma_2 x'_2 + \varepsilon \tag{4}$$

The second-stage equation in its simplest form is then the following:

$$y_1 = \beta_1 \hat{y}_2 + \beta_2 x'_1 + u \tag{5}$$

It is important to note that the same attributes of a young company that affect the mega-deal status could also explain the IPO success or post-IPO performance. In more technical terms, the error term and the treatment variable in the equation could be correlated in such a way that the estimator might be inconsistent. Instrumental variables are a common solution for this issue as this approach requires instruments that are correlated with the endogenous variable *Mega-deal*. At the same time, the instrument may only affect the dependent IPO success or post-IPO performance variables through the *Mega-deal* variable (Conley, Hansen, & Rossi, 2012).

We therefore conduct IV 2SLS regressions based on Baum, Schaffer, & Stillman (2010) in order to examine the effect of the mega-deal status of young companies on their IPO success measures and post-IPO performance measures.

We identify three instruments that fulfill all strength and validity requirements. The first instrument, *Lead avg. deal size*, represents the average USD volume of the deals in which the lead venture capitalist was involved between 2000 and 2019. The variable is a proxy for the lead venture capitalist's investment behavior. Lead venture capitalists generally involved in larger deals increase the chance of a mega-deal investment in the portfolio company. However, the investment behavior of the lead investor cannot be directly extrapolated to IPO success or post-IPO performance; rather, investment behavior affects IPO success and post-IPO performance through the mega-deal.

The second instrument, *Company avg. deal size*, is the total amount of venture capital a company has received divided by the number of individual financing rounds. Additionally, to account for cash intensity across industries, we adjust the variable by subtracting the industry median. This value reflects the average USD amount gained by a company in each individual financing round and thus the financial resources of the company that are available to foster growth (Vanacker et al., 2013). All data were taken from Refinitiv Eikon. The company's average deal size per financing round positively correlates with the likelihood of receiving a mega-deal. The variable also exhibits a moderate correlation with IPO success and post-IPO performance measures. We argue that the mechanism behind this correlation functions through the mega-deal. Therefore, we assume that a large average deal size signals high quality and financial stability through the mega-deal.

The third instrument, *Lead VC distance*, captures the geodetic distance in thousands of miles between the company's headquarters and the lead venture capitalist's headquarters. Company addresses were collected from Refinitiv Eikon, and geodetic distances were calculated using the data and the Stata package from OpenCage.[6] Geodetic distance between venture capitalists and portfolio companies is an important factor of investment behavior (Sorenson & Stuart, 2001). This is because proximity allows for more sophisticated monitoring and leads to a more transparent information transfer between the investor and investee (Bernstein, Giroud, & Townsend, 2016). Thus, geodetic distance negatively impacts the chance of receiving a mega-deal. While there is no obvious reason for the geodetic distance between venture capitalists and portfolio companies to affect IPO success or post-IPO performance, it should be noted that distance can influence performance measures through the mega-deal.

[6] Available at opencagedata.com

Testing for the strength and validity of these instruments reinforces the presented theoretical relationships. We apply the Sanderson-Windmeijer multivariate F-test of excluded instruments to test the strength of the instruments used (Sanderson & Windmeijer, 2016). The results shown in Tables B-3 and B-4 are significant and demonstrate the strength of the instruments. To determine whether our instruments are valid, we use the Sargan-Hansen over-identification test (Hansen, 1982; Sargan, 1958). The results displayed in Tables B-3 and B-4 are insignificant, thereby confirming the instruments' validity. It should be noted that these tests can only be seen as supplementary to the logical and theoretical arguments given above; they should not be seen as standalone certification for instruments (Wooldridge, 2002).

4. Results and discussion

4.1. The effect of venture capital mega-deals on IPO success

Table B-3 summarizes the results of the IV 2SLS regressions (see Columns 3 to 6). The table reports the first- and second-stage results. Note that the first-stage results are only reported once, as they are identical for every second-stage regression. In the first stage, the instruments *Lead VC avg. deal size*, *Company avg. deal size*, and *Lead VC distance* are significant and display the expected signs.

Looking at the control variables, *Total assets pre-IPO* is significant in all specifications except the third regression (see Table B-3, Column 5). This implies that company size plays a role in the IPO success measures presented; however, it does not affect the *Mega-deal* variable's significance. Controlling for total assets pre-IPO thereby rebuts the argument that mega-deal companies are successful simply because they are big. While the effect on proceeds and pre-money valuation is also positive, it is negative for underpricing. This contradicts the significant positive effect on price revision and underpricing of the mega-deal variable. These results indicate that mega-deal status is not only associated with company growth and size. The lead underwriter's reputation does positively impact all four success measures, thus reinforcing the signaling importance of prestigious underwriters in IPOs. Meanwhile, in terms of multiple mega-deals, we find the coefficient to be positive and significant in the first regression (see Table B-3, Column 3). Notably, multiple mega-deals have no further explanatory power when estimating the effect on price revision and underpricing. While the additional effect on IPO proceeds seems relatively intuitive, multiple mega-deals do not indicate additional demand.

Regarding the main effects, the first regression (see Table B-3, Column 3) analyzes the effect of mega-deal status on the logarithm of the IPO proceeds and shows that mega-deal status has a significant positive effect on the IPO earnings of a young company. On average, the proceeds increase by a factor of 2.5 if the portfolio company received a mega-deal.[7] As IPO proceeds easily reach triple-digit million USD amounts or more, an increase by a factor of 2.5 is significant.

The results from the second regression (see Table B-3, Column 4) show that mega-deals have a significant positive effect on the pre-money valuation, or, in other words, the market's assessment of a young company. On average, the valuation rises by a factor of 3.4 with mega-deal status. Again, just as with IPO proceeds, pre-money valuations for IPOs easily reach triple-digit millions, or even billions, in USD. In this case, the results show an even larger increase for even higher amounts, clearly supporting the first hypothesis.

[7] We use ln-transformed dependent variables when examining effects on proceeds and valuations. Hence, the coefficients in the regression represent the effect of a mega-deal on the ln-transformed variable. To obtain the effect on the actual variable, we need to look at exponentiated regression coefficients: $\exp(0.931)\approx 2.5$.

Table B-3: Mega-deal's effect on IPO success

	First stage	Second stage	Second stage	Second stage	Second stage
Dependent variables	***Mega-deal***	***ln(Proceeds)***	***ln(Pre-money valuation)***	***Price revision***	***Underpricing***
Mega-deal	-	0.931**	1.219**	0.086*	0.192*
	-	(0.211)	(0.373)	(0.040)	(0.097)
Lead VC reputation	0.016	0.094	-0.134	0.025	0.060
	(0.072)	(0.104)	(0.267)	(0.029)	(0.061)
Lead underwriter reputation	0.000	0.194**	0.306**	0.011*	0.030*
	(0.011)	(0.030)	(0.050)	(0.005)	(0.014)
Profitability	0.009	0.005	0.140	-0.016	-0.007
	(0.061)	(0.107)	(0.157)	(0.024)	(0.051)
Total assets pre-IPO	-0.000	0.001**	0.001**	0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age at IPO	-0.000	-0.011	-0.004	-0.001	0.003
	(0.005)	(0.007)	(0.015)	(0.002)	(0.004)
Startup hub	0.003	0.076	0.160	0.025	-0.002
	(0.037)	(0.057)	(0.122)	(0.017)	(0.033)
Multiple mega-deals	0.384**	0.450*	0.479	-0.047	-0.079
	(0.102)	(0.194)	(0.363)	(0.043)	(0.103)
IPO market hotness	0.011	0.050	0.055	0.010	0.028
	(0.033)	(0.044)	(0.092)	(0.013)	(0.027)
Stock exchange (NASDAQ)	-0.116*	-0.108	-0.207	-0.022	0.037
	(0.057)	(0.085)	(0.203)	(0.022)	(0.046)
Lead VC avg. deal size	0.003**	-	-	-	-
	(0.001)	-	-	-	-
Company avg. deal size	0.004**	-	-	-	-
	(0.001)	-	-	-	-
Lead VC distance	-0.013*	-	-	-	-
	(0.005)	-	-	-	-
Constant	0.064	2.782**	2.678**	-0.184**	-0.316*
	(0.123)	(0.296)	(0.578)	(0.064)	(0.141)
Year fixed effects	Incl.	Incl.	Incl.	Incl.	Incl.
Industry fixed effects	Incl.	Incl.	Incl.	Incl.	Incl.
Observations	364	364	364	364	364
F-test of excluded IVs	F(3;336) = 18.07**	-	-	-	-
Over-identification test	-	$\chi^2(2) = 1.896$	$\chi^2(2) = 3.970$	$\chi^2(2) = 2.968$	$\chi^2(2) = 1.162$

Notes: This table presents IV 2SLS regression estimates based on standard errors that are robust to heteroscedasticity. In the first-stage regression, the variable *Mega-deal* is regressed on the instruments *Lead VC avg. deal size*, *Company avg. deal size*, *Lead VC distance*, and a set of control variables. In the second stage, each IPO success measure is regressed on the first-stage estimates for the *Mega-deal* variable and a set of control variables. For the first-stage regression, the Sanderson-Windmeijer multivariate F-test of excluded instruments is reported to confirm the sufficient strength of the instruments. For the second-stage regression, the Sargan-Hansen over-identification test is reported to confirm the validity of instruments. The first stage uses the following regression:

$$Mega\ deal\ dummy = \beta_0 + \beta_1\ Lead\ VC\ avg.deal\ size + \beta_2 Company\ avg.deal\ size + \beta_3 Lead\ VC\ distance$$
$$+\beta_4 Lead\ VC\ reputation + \beta_5 Lead\ underwriter\ reputation\ + \beta_6 Profitability + \beta_7 Total\ assets\ pre\ IPO + \beta_8 Age\ at\ IPO$$
$$+\beta_9 Startup\ hub + \beta_{10} Multiple\ mega - deals + \beta_{11} IPO\ market\ hotness + \beta_{12} Stock\ exchange + \beta_{Year} + \beta_{Industry} + \gamma$$

The second stage uses a regression described as follows:

$$P = \beta_0 + \beta_1\ Mega\ deal\ dummy + \beta_2 Lead\ VC\ reputation + \beta_3 Lead\ underwriter\ reputation + \beta_4 Profitability$$
$$+\beta_5 Total\ assets\ pre\ IPO + \beta_6 \text{Age at IPO} + \beta_7 Startup\ hub + \beta_8 ultiple\ mega - deals + \beta_8 IPOmarket\ hotness$$
$$+ \beta_9 Exchange\ dummy + \beta_{Year} + \beta_{Industry} + \varepsilon$$

where *P* is one of the IPO success measures, *ln(Proceeds)*, *ln(Pre-money valuation)*, *Price revision*, and *Underpricing*.
* Significant at the 5% level.
** Significant at the 1% level.

A possible explanation for these major differences could be the immediate consequences of mega-deals on further follow-on investments before the company finally goes public. Like unicorn valuations, mega-deals could facilitate further high-level venture capital funding rounds, potentially multiplying the effect of a mega-deal on growth and later IPO success (Kerai, 2017).

The third regression (see Table B-3, Column 5) demonstrates a significant positive effect of mega-deal status on *Price revision* at the ≤0.05 level of confidence. On average, a mega-deal increases the offer price revision by 8.6%. As a non-size-related measure, the third regression provides evidence that not only are the IPOs of mega-deal companies larger; they also generate higher demand. This could potentially be due to the easily observable signal of a mega-deal that attracts further non-specialized investors, thus resulting in increased investment interest.

The results of the fourth regression (see Table B-3, Column 6) show that a mega-deal has a significant effect on the fourth IPO success measure, *Underpricing*. A mega-deal increases underpricing, on average, by 19.2%, according to our estimation. Within the context of higher (average) demand prior to the IPO, measured by the price revision, higher (average) underpricing reinforces the hypothesis that mega-deals create additional demand during IPOs.

When the results are combined, mega-deals have a significant positive effect on IPO proceeds, the pre-money valuation, the price revision, and underpricing. By controlling for the total assets of the company, we show that mega-deal companies are not successful simply because they are big. In summary, the results support the hypothesis that mega-deals have a positive effect on IPO success.

4.2. The effects of venture capital mega-deals on post-IPO performance

Table B-4 displays the results of the IV 2SLS regressions (see Table B-4, Columns 3 to 6) with robust standard errors on our post-IPO performance measures. The table shows the first- and second-stage results. Again, the first-stage results are only reported once, as they are identical for every second-stage regression. In the first stage, the instruments *Lead VC avg. deal size*, *Company avg. deal size*, and *Lead VC distance* are significant and display the expected signs.

The first regression analyzes the impact of mega-deal status on the logarithm of the valuation V_{90}^{*} after 90 days (see Table B-4, Column 3). The regression shows that mega-deals still have a positive effect on the valuation of a young company after 90 days. On average, valuations after 90 days are higher by a factor of 3.7 if the portfolio company has received a mega-deal. While mega-deal companies' pre-money valuation increases by a factor of 3.4 compared to their counterparts without mega-deal financing, the value increase during the first 90 days after the IPO is, on average, 3.7 times that of companies without mega-deal financing. This is evidence of stable post-IPO stock market performance and supports the hypothesis that mega-deals' effects permeate the aftermath of the IPO.

The results from the second regression (see Table B-4, Column 4) show that mega-deal recipients outperform their non-mega deal financed counterparts in the same way in the 180-day valuation V_{180}^{*}. On average, the valuation is higher by a factor of 4.4 after 180 days if a mega-deal has been achieved. Therefore, we can state that over a post-IPO period of 180 days, the positive impact is sustained.

Table B-4: Mega-deal's effect on post-IPO performance

	First stage	Second stage	Second stage	Second stage	Second stage
	Mega-deal	***ln(90-day valuation)***	***ln(180-day valuation)***	***ln(1-year valuation)***	***ln(2-year valuation)***
Mega-deal	-	1.302**	1.485**	1.287**	1.248**
	-	(0.422)	(0.400)	(0.390)	(0.461)
Underpricing	0.099	1.042**	1.011**	1.057**	1.286**
	(0.061)	(0.195)	(0.207)	(0.230)	(0.275)
Price revision	-0.028	1.190**	1.141**	1.095*	1.125*
	(0.126)	(0.394)	(0.388)	(0.541)	(0.553)
Proceeds	-0.000	0.000**	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lead VC reputation	0.013	-0.282	-0.232	-0.497	-0.793*
	(0.072)	(0.282)	(0.288)	(0.308)	(0.353)
Lead underwriter reputation	-0.003	0.332**	0.335**	0.401**	0.479**
	(0.011)	(0.054)	(0.057)	(0.064)	(0.079)
Age at IPO	-0.000	0.003	-0.005	0.000	0.009
	(0.005)	(0.017)	(0.017)	(0.020)	(0.023)
Startup hub	0.005	0.069	0.097	0.133	0.100
	(0.037)	(0.131)	(0.135)	(0.154)	(0.173)
Multiple mega-deals	0.398**	0.776*	0.382	0.547	0.886*
	(0.086)	(0.372)	(0.353)	(0.368)	(0.429)
M/B ratio	0.002	0.029*	0.029*	0.033**	0.028*
	(0.002)	(0.012)	(0.011)	(0.011)	(0.012)
Stock exchange (NASDAQ)	-0.122*	-0.185	-0.069	-0.057	-0.151
	(0.059)	(0.223)	(0.231)	(0.237)	(0.239)
Lead VC avg. deal size	0.003**	------	------	------	------
	(0.001)	2.390**	2.337**	1.635*	14.517**
Company avg. deal size	0.004**	(0.620)	(0.650)	(0.681)	(0.778)
	(0.001)	Incl.	Incl.	Incl.	Incl.
Lead VC distance	-0.012*	Incl.	Incl.	Incl.	Incl.
	(0.005)	364	364	364	364
Constant	0.083	-	-	-	-
	(0.113)				
Year fixed effects	Incl.				
Industry fixed effects	Incl.				
Observations	364				
F-test of excluded IVs	F(3;335) = 13.47**				
Over-identification test	-	$\chi^2(2) = 4.446$	$\chi^2(2) = 3.829$	$\chi^2(2) = 2.988$	$\chi^2(2) = 2.045$

Notes: This table presents IV 2SLS regression estimates based on standard errors that are robust to heteroscedasticity. In the first-stage regression, the variable *Mega-deal* is regressed on the instruments *Lead VC avg. deal size*, *Company avg. deal size*, *Lead VC distance*, and a set of control variables. In the second stage, each post-IPO performance measure is regressed on the first-stage estimates for the *Mega-deal* variable and a set of control variables. For the first-stage regression, the Sanderson-Windmeijer multivariate F-test of excluded instruments is reported to confirm the sufficient strength of the instruments. For the second-stage regression, the Sargan-Hansen over-identification test is reported to confirm the validity of instruments. The first stage uses the following regression:

$$Mega - deal = \beta_0 + \beta_1\, Lead\ VC\ avg.deal\ size + \beta_2 Company\ avg.deal\ size + \beta_3 Lead\ VC\ distance$$
$$+\beta_4 \text{Underprcing} + \beta_5 \text{Price revision} + \beta_5 \text{Proceeds} + \beta_6 Lead\ VC\ reputation + \beta_7 Underwriter\ reputation + \beta_9 Age\ at\ IPO$$
$$+\beta_9 \text{Startup hub} + \beta_{10} \text{Multiple mega} - \text{deals} + \beta_{11} \text{M/B ratio} + \beta_{12} Exchange\ dummy + \beta_{Year} + \beta_{Industry} + \gamma$$

The second stage uses a regression described as follows:

$$P = \beta_0 + \beta_1\, Mega - deal + \beta_4 \text{Underprcing} + \beta_5 \text{Price revision} + \beta_5 \text{Proceeds} + \beta_6 Lead\ VC\ reputation + \beta_7 Underwriter\ reputation$$
$$+\beta_9 Age\ at\ IPO + \beta_{10} \text{Startup hub} + \beta_{11} \text{Multiple mega} - \text{deals} + \beta_{12} \text{M/B ratio} + \beta_{13} Exchange\ dummy + \beta_{Year} + \beta_{Industry} + \varepsilon$$

where P is one of the post-IPO performance measures, *ln(90-day valuation)*, *ln(180-day valuation)*, *ln(1-year valuation)*, and *ln(2-year valuation).*

* Significant at the 5% level.

** Significant at the 1% level.

The third regression (see Table B-4, Column 5), for the one-year valuation V_{365}^{*}, again shows that mega-deal status has a significant effect. On average, the valuation after one year is higher by a factor of 3.6 for mega-deal recipients. Based on these results, we conclude that mega-deal recipients outperform their counterparts without mega-deals over the one-year post-IPO period.

Looking at the fourth regression (see Table B-4, Column 6) and the two-year valuation, we still find that mega-deal recipients outperform their counterparts who lack mega-deal financing. The average valuation of companies that received a mega-deal is 3.5 times higher, indicating that resources from mega-deals may be used to create sustainable value.

In summary, mega-deal recipients exhibit stable post-IPO performance, thereby showing that during the IPO, mega-deals are not associated with the irrational hype that characterized the dot-com tag, but persist for at least two years after the IPO.[8]

4.3. Isolating the signaling effect

With our instrumental variables approach, we focus on the treatment effect of mega-deals. As treatment, we define the receipt of large volumes of capital through the mega-deal financing round. We then analyze whether this treatment leads to an efficient use of capital and facilitates superior company development leading to a successful IPO. We separate this treatment effect from the signaling effect which is based only on the label "mega-deal", but not on the receipt of particularly large volumes of capital. Part of the mega-deal's positive effect on IPO success and post-IPO performance could be explained simply by such a label. In order to separately focus on this signaling effect of a mega-deal, we analyze only companies that

[8] To test the robustness of these results to the choice of instruments and the functional form of the instrumental variables approach, we perform propensity score matching and are able to confirm the results. A more detailed explanation by the authors is available upon request.

received their largest financing round near the 100 million USD threshold. This subsample is characterized by homogeneous companies as they all received large volumes of capital, i.e., they were not treated differently. By analyzing similar deals, e.g. a company that received a 99 million USD financing round and a company that received a 101 million USD financing round, we still expect to find a significant increase in the IPO success measures of the company that received a mega-deal due to the distinct label it has obtained with it. This would imply that investors pay attention to the mega-deal as a signal. In that way we are able to isolate the signaling effect of a mega-deal and to analyze psychological components of the mega-deal's impact on IPO success and post-IPO performance separately from the treatment effect that comes from receiving large volumes of capital.

Therefore, we apply a regression discontinuity design based on Nichols (2007b) to examine a sample of companies that received (their largest) financing rounds in the region of 100 million USD prior to the IPO. The rationale for using the regression discontinuity design is that near the threshold, the level of treatment can be assumed as if it were randomly assigned. For this reason, regression discontinuity design is generally considered to have favorable internal validity compared to that of other quasi-experimental methods (Nichols, 2007a). The validity assumption of this method requires the observed subjects to have no control over being below or above the threshold. In the case of venture capital mega-deals, many parties are involved in the process of determining the financing round's volume. Theoretically, entrepreneurs have an incentive to increase the price per share, while investors are incentivized to decrease the price per share. Therefore, we argue that no party has total control of the final outcome. We also find statistical evidence concerning that assumption in an unreported manipulation test using local polynomial density estimation. Tables B-5 and B-6 show the results of the regression discontinuity design for several bandwidths between one and five million USD around the mega-deal threshold. Bold coefficients and standard errors mark optimal bandwidths, which minimize mean squared errors, according to Imbens & Kalyanaraman (2012). These bandwidths are optimal in the sense that they include a sufficient number of observations, while at the same time minimizing the distance to the threshold so as to reduce the influence of confounding effects.

Table B-5: Signaling effect of mega-deals in the IPO success context

Bandwidth	*ln(Proceeds)*	*ln(Pre-money valuation)*	*Price revision*	*Underpricing*
1 m. USD	**1.145****	1.143**	**0.221****	**1.010****
	(0.173)	(0.210)	**(0.009)**	**(0.131)**
2 m. USD	1.153**	1.159**	0.218**	1.023**
	(0.149)	(0.187)	(0.010)	(0.119)
3 m. USD	1.089**	0.976**	0.178**	0.955**
	(0.141)	(0.229)	(0.041)	(0.116)
4 m. USD	1.080**	**0.951****	0.172**	0.945**
	(0.146)	**(0.255)**	(0.048)	(0.123)
5 m. USD	0.072	0.427	0.169**	0.723**
	(0.568)	(0.381)	(0.050)	(0.171)

Note: This table provides estimates of regression discontinuity design based on Nichols (2007b) for several bandwidths between 1 and 5 million USD around the 100 million USD mega-deal threshold for all IPO success measures. Bold coefficients and standard errors mark optimal bandwidths, which minimize mean squared errors, according to Imbens & Kalyanaraman (2012).
* Significant at the 5% level.
** Significant at the 1% level.

Table B-6: Signaling effect of mega-deals in the post-IPO performance context

	ln(90-day valuation)	*ln(180-day valuation)*	*ln(1-year valuation)*	*Ln(2-year valuation)*
1 m. USD	2.607**	2.516**	1.372**	-0.625
	(0.322)	(0.211)	(0.335)	(0.563)
2 m. USD	2.653**	2.595**	1.440**	-0.470
	(0.310)	(0.300)	(0.355)	(0.669)
3 m. USD	2.432**	2.335**	1.116**	-0.731
	(0.320)	(0.317)	(0.393)	(0.612)
4 m. USD	**2.402****	**2.299****	1.072*	**-0.767**
	(0.347)	**(0.356)**	(0.440)	**(0.635)**
5 m. USD	1.288	1.281	**1.427****	1.405
	(0.695)	(0.657)	**(0.494)**	(1.352)

Note: This table reports estimates of regression discontinuity design based on Nichols (2007b) for several bandwidths between 1 and 5 million USD around the 100 million USD mega-deal threshold for all post-IPO performance measures. Bold coefficients and standard errors mark optimal bandwidths, which minimize mean squared errors, according to Imbens & Kalyanaraman (2012).
* Significant at the 5% level.
** Significant at the 1% level.

The estimated effect of a mega-deal on all IPO success measures is positive and significant. Estimates of the isolated signaling effect of a mega-deal on post-IPO performance show that in the 90- to 360-day post-IPO period, the effect decreases with each period until it becomes insignificant after two years. The results indicate that the pure signaling effect of the mega-deal is present during the IPO and in the post-IPO period; however, the isolated signal's effect decreases each month until it fades out after two years in the public market. The results of the regression discontinuity design confirm the hypothesis that the mere fact of a company receiving a mega-deal, all else being equal, positively influences IPO success.

The results regarding post-IPO performance, however, lead to a different conclusion. More specifically, the results from the regression discontinuity design indicate that the isolated signaling effect of the mega-deal fades over time after being highly impactful in the beginning, which could be the result of psychological factors. According to the anchoring effect, individuals fixate on a number that is frequently mentioned by informed commentators and therefore commonly perceived as being important (Slovic & Lichtenstein, 1971). The mega-deal financing volume threshold of 100 million USD, frequently reported by venture capital associations, financial data providers, or consultancies (e.g., NVCA (2020), CB-Insights (2021), or KPMG (2021)), could represent such a number. Moreover, the anchoring effect could potentially be reinforced by herd behavior in financial markets whereby investors follow seemingly better-informed investors, rather than their own analysis (Tversky & Kahneman, 1974). These psychological factors are likely to fade over time because investors have access to the ongoing reporting published by the listed company as well as timely data on the stock price development.

5. Limitations and future research

This study is based on a US sample of venture-capital-backed IPOs. The US venture capital market is the most mature market globally, with companies being more likely to have easier access to mega-deals in the United States than in other countries in Asia or Europe. Our results might therefore not be directly applicable to economic environments with less favorable venture capital markets. Receiving a mega-deal in less mature venture capital markets could be a stronger quality signal for investors than in the United States because companies there might have to perform better than their US counterparts to close such a high-volume financing round. It would therefore be interesting to compare the performance of mega-deal-receiving companies in different countries and to analyze the effect of mega-deals on IPO success and post-IPO performance in less mature venture capital markets.

Our results provide evidence that IPOs of mega-deal companies are not only larger but also generate higher demand during IPOs (see Table B-3, Column 5). This could be due to further demand from stronger retail investor participation (Bushee, Cedergren, & Michels, 2020; Dorn, 2009). The easily observable signal of a mega-deal possibly attracts further non-specialized investors, resulting in increased demand; however, we do not have the necessary data to validate this assumption and therefore refer it to future research.

In addition, research and development expenses, along with patents of portfolio companies, could serve as interesting additional control variables, as the positive impact of innovation on IPO success and primary market performance has been shown multiple times (Eberhart, Maxwell, & Siddique, 2004; Kaplan, Sensoy, & Strömberg, 2009; Useche, 2014). More sophisticated data would be helpful when investigating relations between mega-deals and unicorn valuations in the context of IPO performance. Furthermore, we assess the lead venture capitalist but face limitations regarding syndicate properties. It is not unlikely, however, that the reputations of syndicate members, aside from the lead venture capitalist, constitute signals to the market. Therefore, it would be desirable for future research on related topics to include data on the VC syndicate composition. Finally, while we do not find effect-moderating relationships in our data, we do believe that the context of our findings is relevant and should be exploited in future research.

6. Conclusion

We used data from 364 US IPOs to analyze relationships between venture capital mega-deals and IPO success and post-IPO performance. Our first key finding is that young companies receiving a venture capital mega-deal of 100 million USD or more perform significantly better during IPOs. On average, they receive significantly higher proceeds and higher pre-money valuations; at the same time, they also exhibit better price revision outcomes at higher underpricing, indicating larger investment interest from the public market. Regarding the size-related measures (proceeds, pre-money valuation), the results are relatively intuitive: a mega-deal is likely to help a young company grow rapidly and to facilitate beneficial follow-on financing in the venture capital market (Kerai, 2017). Results regarding the offer price revision and underpricing are less intuitive, though. On average, companies that received a mega-deal exhibit higher price revisions and higher underpricing than companies that had not received a mega-deal before their IPO. This finding supports our hypothesis that, on average, mega-deals do not simply lead to bigger IPOs; indeed, they also create stronger demand among investors during IPOs.

Our second key finding is that a mega-deal can signal firm quality for the two-year post-IPO period. Unlike the dot-com tag, which led to many irrational, hype-driven valuations in the late 1990s, mega-deal recipients' post-IPO performance remains robust for at least two years after the IPO. A third key finding is that the isolated signaling effect of a mega-deal has a significant impact on IPO success. The signaling effect also significantly influences post-IPO performance in the short term but fades over the observed post-IPO period until it vanishes after two years.

We conclude that a venture capital mega-deal can be used as a valid signal of firm quality and help reduce asymmetric information between corporate insiders and outside investors during the IPO. In other words, for venture capital mega-deals, more really is more; it is not simply "dumb money." Thus, we offer an additional validated signal to IPO investors in an investment environment characterized by asymmetric information and thereby add to the academic literature on venture capital signaling in IPOs (Gulati & Higgins, 2003; Krishnan et al., 2011; Megginson & Weiss, 1991). Contrary to the free cash flow hypothesis, most companies with a mega-deal seem to be able to use the financial slack to grow their business rapidly (Davila et al., 2003; Vanacker et al., 2013; Zhang, 2007). At the same time, the mega-deal status seems to help these companies attract remunerative follow-on investments, which can easily multiply the growth effect of the mega-deal (Kerai, 2017).

Though the mega-deal threshold seems arbitrary, concepts of behavioral finance provide theoretical frameworks to explain the importance of such thresholds and the consequences when surpassing it. The positive effect of mega-deals on IPO performance can be partially explained by the anchoring effect, which occurs when a specific number, in our case the 100 million USD threshold of mega-deals, is frequently reported and therefore considered important (Slovic & Lichtenstein, 1971).This anchoring effect can lead to herd behavior whereby investors follow other investors' decisions instead of trusting their own judgements (Tversky & Kahneman, 1974). Thus, we add to the stream of behavioral finance literature by providing evidence that these concepts are applicable in the context of venture capital mega-deals and IPO performance (Mitchell, 2001; Slovic & Lichtenstein, 1971; Tversky & Kahneman, 1974)

This paper is among the first to provide insights into the recent trend of mega-deals in venture capital markets. We hope to see our results assessed and extended in future research to better understand the phenomenon of mega-deals. To do this, qualitative research could delve deeper into the mechanisms underlying the treatment and signaling effects of mega-deals, which would enable us to better understand how large volumes of venture capital funding are used to build successful publicly listed companies.

C. Essay 2 - Why deep pockets make great borrowers: an empirical analysis of venture loans[9]

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 (2017b) 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 billion 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

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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.[10] 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 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

[10] 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.

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, 2017b). 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 & 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 & Litzenberger (1973) and pecking order theory by Myers & 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 & Fischer, 2016; Hesse & 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 (2017b) 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 & Fischer, 2016; Ibrahim, 2010; Tykvová, 2017b). 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 million 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 & 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 & 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 & 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 & Udell (1998), Cotei & 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 & 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 & 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 & 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 six to twelve 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 (2017b) 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 provides 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 & 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 & Fischer, 2016; Ibrahim, 2010; Tykvová, 2017b).

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 C-1 presents the structure of the unbalanced panel data and Table C-2 provides brief definitions of the variables.

Table C-1: Structure of unbalanced panel data

Obs. rounds per company	Total	*Non-VL*	*VL*
1	6,977	6,953	24
1,2	6,100	6,071	29
1,2,3	4,764	4,722	42
1,2,3,4	3,488	3,454	34
1,2,3,4,5	2,525	2,501	24
1,2,3,4,5,6	1,542	1,519	23
1,2,3,4,5,6,7	1,029	1,013	16
1,2,3,4,5,6,7,8	1,152	1,122	30
Total	27,577	27,355	222

Note: This table presents observed financing rounds according to the length of a company's financing history.

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

3.3. Independent variable

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 Section 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

$Round\ number_{i;t}$ 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.

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 (2017b) 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.

Table C-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: $\ln\left(\frac{\sum_{k=1}^{t} Capital\ amount_{i;k} / Investors_{i;k}}{Round\ number_t}\right)$, 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.
$FED\ prime\ ratei;t$	Represents the yearly average of the bank prime loan rate on a yearly basis according to the FRED database.
$Ln(VC\ AUM)_{i;t}$	The logarithm of the yearly aggregated assets under management in billion 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: This table 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.

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, 2017b). 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 billion US-dollars in the venture capital market in the US according to NVCA data. Tykvová (2017b) 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 C-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 C-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 C-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 & Lerner, 2016). Retterath & 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.

Table C-3: Descriptive statistics

Panel A. Investment years

	Unrestricted sample			Panel data sample		
Year	Total	*Equity*	*VL*	Total	*Equity*	*VL*
2009	3,616	3,611	5	658	658	0
2010	4,125	4,046	79	1,119	1,111	8
2011	4,499	4,337	162	1,656	1,632	24
2012	4,469	4,332	136	1,869	1,841	28
2013	4,877	4,725	151	2,209	2,170	39
2014	5,235	5,100	135	2,534	2,505	29
2015	5,288	5,195	95	2,757	2,729	28
2016	4,641	4,600	43	2,454	2,434	20
2017	4,570	4,533	37	2,611	2,598	13
2018	4,702	4,690	11	2,990	2,984	6
2019	5,017	4,989	27	3,284	3,273	11
2020	4,913	4,887	26	3,436	3,420	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	6,563	6,506	57
3	7,442	7,332	110	3,513	3,467	46
4	5,451	5,359	92	1,925	1,900	25
5	3,940	3,848	92	1,053	1,033	20
6	2,918	2,835	83	548	537	11
7	2,312	2,239	73	291	286	5
8	1,746	1,691	55	144	138	6
9	1,301	1,246	55	-	-	-
≥10	3,757	3,581	176	-	-	-
Total	55,952	55,045	907	27,577	27,355	222

Panel C: Mean variables

Variable	Unrestricted sample Equity N=55,045	VL N=907	Panel data sample 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***
$Ln(Avg.capital\ per\ investor)_{i;t}$	-	-	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 this table 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 C-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.

Panel C of Table C-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.

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:

$$\begin{aligned} Venture\ loan\ dummy_{i;t} \\ &= \beta_0 + \beta_1 Number\ of\ patents_{i;t} + \beta_2 Round\ number_{it} + \beta_3 Biotechnology_i \\ &+ \beta_4 Medical\ health\ life\ science_i + \beta_5 Semiconductor_i \\ &+ \beta_6 Ln(Avg.capital\ per\ investor)_{i;t-1} + \beta_7 IVC\ dummy_{i;t} + \beta_8 CVC\ dummy_{i;t} \\ &+ \beta_9 GVC\ dummy_{i;t} + \beta_{10} Ln(Capital\ amount)_{i;t} + \beta_{11} Number\ of\ investors_{i;t} \\ &+ \beta_{12} Avg.capital\ growth_{i;t-1} + \beta_{13} Avg.months\ between\ rounds_{i;t-1} \\ &+ \beta_{14} Leverage\ ratio_{i;t-1} + \beta_{15} Startup\ hub\ dummy_i + \beta_{16} FED\ prime\ rate_{i;t} \\ &+ \beta_{17} Ln(VC\ AUM)_{i;t} + \beta_{18} VIX_{i;t} + \beta_{19} GDP\ growth\ rate_{i;t} + \varepsilon \end{aligned} \tag{6}$$

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 C-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.

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

	Model 1	
	Coefficients	**Odds ratios**
Independent variables		
$\boldsymbol{Number\ of\ patents_{i;t}}$	**-0.012**	**0.988**
	(0.023)	**(0.023)**
$\boldsymbol{Round\ number_{i;t}}$	**0.194*****	**1.214*****
	(0.068)	**(0.082)**
$\boldsymbol{Biotechnology_{i}}$	**0.241**	**1.273**
	(0.295)	**(0.376)**
$\boldsymbol{Medical/health/life\ science_{i}}$	**0.877*****	**2.404*****
	(0.240)	**(0.578)**
$\boldsymbol{Semiconductor_{i}}$	**-0.201**	**0.818**
	(0.571)	**(0.467)**
$\boldsymbol{Ln(Avg.capital\ per\ investor)_{i;t-1}}$	**0.064*****	**1.067*****
	(0.017)	**(0.018)**
$\boldsymbol{IVC\ dummy_{i;t}}$	**0.879*****	**2.409*****
	(0.205)	**(0.494)**
$\boldsymbol{CVC\ dummy_{i;t}}$	**0.714****	**2.042****
	(0.357)	**(0.728)**
$\boldsymbol{GVC\ dummy_{i;t}}$	**-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)
Observations	27,577	
Number of CompanyID	13,540	
χ^2	191.83***	

Note: This table presents logistic regression estimates and odds ratios based on robust standard errors using the panel data sample. Variable definitions can be found in Table C-2. *, **, and *** denote coefficient estimates significantly different from 0 at the 10%, 5%, and 1% levels respectively. Robust standard errors are in parentheses.

The coefficient of the variable $Round\ number_{i;t}$ 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 $Ln(Avg.\,capital\ per\ investor)_{i;t-1}$ 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 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 C-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.

5. Robustness checks and limitations

We performed the logistic regression from Section 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 C-5.

Due to the inaccuracy of the data sample concerning the relatively large number of venture loans in the first financing rounds discussed in Section 3.3, we re-ran the regression of Table C-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 Section 4, the significant result for the corporate venture capital indicator vanishes when applying these robustness checks.

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

Table C-5: Results of logistic regression using an unrestricted sample

	Model 2 $\boldsymbol{Venture\ loan\ dummy_{i;t}}$	
	Coefficients	**Odds ratios**
Independent variables		
$\boldsymbol{Number\ of\ patents_{i;t}}$	**0.000**	**1.000**
	(0.000)	**(0.000)**
$\boldsymbol{Round\ number_{i;t}}$	**0.123*****	**1.130*****
	(0.006)	**(0.007)**
$\boldsymbol{Biotechnology_{i}}$	**0.608*****	**1.836*****
	(0.095)	**(0.174)**
$\boldsymbol{Medical/health/life\ science_{i}}$	**0.788*****	**2.200*****
	(0.088)	**(0.193)**
$\boldsymbol{Semiconductor_{i}}$	**0.033**	**1.033**
	(0.177)	**(0.183)**
$\boldsymbol{IVC\ dummy_{i;t}}$	**0.650*****	**1.916*****
	(0.091)	**(0.174)**
$\boldsymbol{CVC\ dummy_{i;t}}$	**0.418*****	**1.519*****
	(0.131)	**(0.200)**
$\boldsymbol{GVC\ dummy_{i;t}}$	**-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: This table presents logistic regression estimates and odds ratios based on robust standard errors using the unrestricted sample. Variable definitions can be found in Table C-2. *, **, and *** denote coefficient estimates significantly different from 0 at the 10%, 5%, and 1% levels respectively. Robust standard errors are in parentheses.

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 & Fischer, 2016; Ibrahim, 2010; Tykvová, 2017b).

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 & 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, 2017b). 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 & 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.

D. Essay 3 - Acquisitions of venture-capital-backed companies: a convergence of financial and strategic acquirers?[11]

1. Introduction

Acquisitions are the most frequently used venture capital exit channel in the United States. For 2021, the NVCA (2022a) reported 1,357 venture capital exits via mergers & acquisitions (M&A). Consequently, acquisitions as a venture capital exit channel have been a topic in many research articles (Cumming & MacIntosh, 2003b; Giot & Schwienbacher, 2007; Isaksson, 1998). However, these studies mainly focused on strategic acquisitions or did not further distinguish between strategic and financial acquirers (Achleitner et al., 2014; Cumming & Johan, 2008b; Isaksson, 1998). Despite the underrepresentation of financial acquisitions in the scientific literature, Davis & Le (2020) showed an increasing trend of private equity firms acquiring venture-capital-backed companies, peaking in 2019 by taking a share of nearly one-fifth of total venture capital exits in the United States. Hence, acquisitions by financial acquirers, specifically private equity firms, have become a more important exit channel for venture capitalists in recent years. The commonly perceived pecking order of venture capital exits ranks financial acquisitions behind initial public offerings and strategic acquisitions (Bienz & Leite, 2008; Cumming & Johan, 2008b). Bayar & Chemmanur (2011) state that, given equally distributed bargaining power, a financial acquirer would always pay less than a strategic acquirer since financial acquirers cannot benefit from traditional synergies and, hence, have a

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lower valuation for the company. Thus, an IPO or a trade sale to a strategic acquirer would be preferred over a financial acquisition. However, private equity firms have adjusted their value creation levers in recent years, which could explain the increased ability of private equity firms to compete and partially outbid strategic acquirers. For example, the industry specialization of private equity firms can help to optimize investment activities when identifying, selecting, and developing portfolio companies and has been shown to have a positive impact on the operating profitability of portfolio companies (Ahlers et al., 2016; Cressy, Munari, & Malipiero, 2007; Rigamonti et al., 2016). Steady improvements in private equity firms' value creation strategies and the rise of acquisitions of venture-capital-backed companies by private equity firms in recent years point toward a potential convergence of strategic and financial acquirers, contradicting the currently perceived pecking order of venture capital exits in the scientific literature (Bayar & Chemmanur, 2011; Bienz & Leite, 2008; Cumming & Johan, 2008b).

Motivated to re-evaluate the pecking order of venture capital exits and the cause of the recent increase in financial acquisitions, I analyze up to 6,348 acquisitions of venture-capital-backed companies in the United States between 2005 and 2021. The sample includes 6,052 acquisitions by corporate buyers, assumed strategic acquirers, and 296 acquisitions by private equity firms, representing financial acquirers. Data on portfolio companies, venture capitalists, and acquirers were taken from Refinitiv Eikon and supplemented by data from the United States Patent and Trademark Office, the United States Bureau of Economic Analysis, the Chicago Board Options Exchange, and Jay R. Ritter's IPO database. Using multivariate logistic regression, I analyze (i) whether private equity firms acquire companies of a similar quality as corporate acquirers do, approximated by the total amount of venture capital received and by the reputation of the target's venture capital investors; (ii) whether private equity firms engage in opportunity seeking, e.g., targeting companies backed by more mature venture capital funds that potentially face liquidity pressure and are thus in an unfavorable bargaining position; and (iii) whether private equity firms use industry-specialization by comparing the portfolio industry focus to the targets primary industry. Finally, I apply sample splitting by dividing the sample into two periods from 2005 to 2014 and 2015 to 2021 in order to analyze whether private equity firms have changed their investment behavior over time when acquiring venture-capital-backed companies.

Results on the quality of targets are mixed in the main sample, as private equity acquisitions are related to companies that receive larger amounts of venture capital but are backed by venture capitalists with a lower reputation. The analysis of the opportunistic behavior of private equity firms provides evidence that financial acquisitions are indeed related to companies being backed by more mature venture capital funds. Moreover, private equity firms are positively related to companies that match their portfolio industry focus. The results of the sample splitting in two periods from 2005 to 2014 and 2015 to 2021 point to a trend from opportunity-seeking toward competing for higher-quality companies. While private equity acquisitions are negatively related to venture capital reputation and positively related to the venture capital fund age in the years from 2005 to 2014, private equity acquisitions between 2015 and 2021 are positively related to companies with larger amounts of venture capital funding and companies that match their industry focus. Hence, this study provides empirical evidence for a trend toward a convergence of financial and strategic buyers in acquisitions of venture-capital-backed companies.

This paper contributes to the literature in three main ways. First, this study extends the literature on venture capital exit options and the pecking order of venture capital exits by providing one of the first detailed empirical comparisons of financial and strategic acquisitions (Bienz & Leite, 2008; Cumming & Johan, 2008b; Cumming & MacIntosh, 2003b). The results point toward a contradiction of the commonly perceived pecking order of venture capital exits by indicating that financial and strategic acquirers converge in acquisitions of venture-capital-backed companies and, thus, have become equally attractive as venture capital exit options. Second, this study follows a recent trend in the entrepreneurial finance literature by tackling the research gap on alternative but recently emerging venture capital exit channels, e.g., going public via a special purpose acquisition company (SPAC) or secondary sales (Andrieu & Groh, 2021; Kolb & Tykvova, 2016; Nadauld et al., 2019). This study provides first empirically driven explanations of the recent increase in venture capital exits via financial acquisitions and emphasizes important economics that venture capitalists and entrepreneurs should consider in their exit choice. Third, this paper recognizes the research gap in the investment criteria of private equity firms and provides empirical evidence on investment criteria and a change in the investment strategy over time when acquiring venture-capital-backed companies (Gompers, Kaplan, & Mukharlyamov, 2016; Wilson, Amini, & Wright, 2022).

This paper proceeds as follows. After a brief introduction, I present the theoretical background and develop several testable hypotheses. I then describe the data and methodology, followed by a presentation and discussion of the results. Finally, I detail my conclusions and avenues for future research.

2. Theoretical background and hypothesis building

2.1. Portfolio company quality and the probability of a private equity acquisition

Prior research has chiefly focused on IPOs and trade sales to strategic acquirers as return-maximizing exits for venture capitalists (Tykvová, 2017b). Earlier studies on acquisitions as a venture capital exit option have mostly neglected or excluded financial acquirers (Achleitner et al., 2014; Cumming & Johan, 2008b; Isaksson, 1998). In one of the scarce studies dealing with financial acquisitions, Bayar & Chemmanur (2011) argue that, given that the bargaining power of both types of acquirers is equal, financial acquirers will always pay less than strategic acquirers since incremental synergy is higher under strategic acquirers. Hence, one would expect return-maximizing venture capitalists to exit a company via a financial acquisition only if they can not exit the company via an IPO or a trade sale to a strategic acquirer. This would create a market for lemons, as described by Akerlof (1978).

In deals in which one financial investor acquirers a portfolio company of another financial investor, the potential for further operational value creation is typically assumed to be limited since the value creation measures with the most significant impact usually have been improved by the first financial investor already (Cumming & MacIntosh, 2003b). However, Sousa (2010) and Wang (2012) suggest that different skill sets of financial sponsors allow for different value-creation strategies. In the case of financial acquisitions of venture-capital-backed companies, venture capitalists and private equity firms differ significantly in their skill sets. Maas et al. (2020) showed that venture capitalists mainly focus on product innovation, while private equity firms rely on process innovation and optimization. Hence, private equity firms could use this expertise in later-stage ventures when the company's focus starts shifting from growth to profitability to enhance the company's value.

In summary, prior research and theory do not indicate a specific direction of the portfolio company's quality on the probability of being acquired by a private equity firm. It could be a market for lemons, but it could also be that private equity firms can efficiently enhance the value of a company after acquiring it. In order to operationalize the quality of a portfolio company and to formulate testable hypotheses, I use the total amount of venture capital received and the reputation of the venture capitalists as proxies for portfolio company quality. Prior research has shown a significant relationship between better-funded companies and successful exits and used the total venture capital amount a portfolio company has received as an approximation for the company's quality (Krishnan et al., 2011; Nahata, 2008). As a second quality proxy, I employ the reputation of the venture capitalists invested in the company. Sorenson & Stuart (2001) and Krishnan et al. (2011) showed that more reputable venture capitalists are related to both selecting better companies and superior company development after the initial investment. Hence, I will use the total venture capital amount received and the reputation of the venture capitalists of a portfolio company to approximate its quality. Hence, I state the non-directional hypotheses:

$H1_a$: *The total venture capital amount a company has received is related to the probability of a private equity acquisition.*

$H1_b$: *The reputation of the invested venture capitalist is related to the probability of a private equity acquisition.*

2.2. Investment opportunities and the probability of a private equity acquisition

Achleitner & Figge (2014) and Lutz, Figge, & Achleitner (2014) discuss situations in which the buyer's bargaining power is enhanced, e.g., when the selling investor faces liquidity pressure. This could allow the acquirer to negotiate a discount to enhance value creation potential. Another reason could be that the company development advances slower than expected, and the venture capitalist could not realize benefits from implementing operational improvements in time, leaving the potential for the buying private equity firm.

Corporate acquirers typically focus on strategic considerations and do not rely as much on opportunity-seeking as private equity firms (Lantz, Sahut, & Teulon, 2011). Hence, private equity firms have the greater incentive to pursue such an approach to potentially execute a *buy low, sell high* strategy and maximize fund returns. Therefore, I state the following hypothesis:

$H2_a$: *The average venture capital syndicate's fund age is positively related to the probability of an acquisition by a private equity firm.*

Regardless of the bargaining skills of the selling venture capitalist, market conditions can impact acquisition negotiations. Cold IPO sentiment periods temporarily remove an IPO from the toolbox of exit options for the venture capitalist and usually correlate with poor M&A conditions. Whereas hot stock market sentiment leads to increased multiples in the M&A market, lowering value creation potential for private equity firms (Fung, Jo, & Tsai, 2009; Shleifer & Vishny, 2003). In such market conditions, private equity firms could exceptionally profit from opportunities to acquire undervalued firms or avoid investments in a high-multiple environment. Hence, I state the following two hypotheses:

$H2_b$: *A cold IPO sentiment is positively related to the probability of an acquisition by a private equity firm.*

$H2_c$: *A hot IPO sentiment is negatively related to the probability of an acquisition by a private equity firm.*

2.3. Industry fit and the probability of a private equity acquisition

An explanation of why private equity firms pay lower premiums in acquisitions compared to strategic acquirers is that they would not equally benefit from synergies and thus have a lower valuation for the target (Bayar & Chemmanur, 2011). However, in their analyst note, Davis & Le (2020) highlight that private equity firms adapted their strategies in order to benefit from industry-specialization. Hence, private equity firms can benefit from *synergetic* acquisitions in a similar way as strategic buyers. These buyout firms frequently acquire venture-capital-backed companies operating in industries with stable cash flows and high recurring revenues. By specializing in specific industries, private equity firms accumulate industry expertise and in-depth knowledge about certain industries (Cressy et al., 2007). This potentially reduces information asymmetries when assessing targets, leading to superior selection skills of industry-specialized private equity firms (Cressy et al., 2007; Le Nadant, Perdreau, & Bruining, 2018). Moreover, industry-specialized private equity firms are able to accumulate in-depth knowledge and exceptional networks within certain industries (Ahlers et al., 2016; Cressy et al., 2007; Rigamonti et al., 2016). Hence, they are able to provide substantial managerial and operative support which decreases post-deal uncertainty about the success of the target (Cressy et al., 2007; Rigamonti et al., 2016). Consequently, industry-specialization has been shown to increase the operating profitability of portfolio companies by 8.5% and to increase the probability of successful exits, e.g. via IPO or trade sale (Cressy et al., 2007; Rigamonti et al., 2016). Hence, private equity firms could benefit from industry-specialization in a similar way as strategic acquirers benefit from synergies and exhibit equal valuations when competing with corporate buyers for venture-capital-backed companies.

Industry-relatedness is also important for corporate acquirers, as Mazza & Shuwaikh (2022) show that industry-relatedness leads to corporate-venture-capital-backed companies being more likely to be acquired than exited via IPO. However, in contrast to a synergy-driven strategy, corporate acquirers can also have incentives to diversify via lateral acquisitions in order to enter new markets (Achleitner et al., 2014). Hence, private equity firms could be more focused on the industry fit than corporate acquirers, leading to the following hypothesis:

H3: *The industry fit is positively related to the probability of an acquisition by a private equity firm.*

2.4. A trend toward convergence?

Earlier studies and recent reports diverge in their assessments of financial acquisitions as venture capital exits, suggesting that there has been a change in the private equity approach in recent years toward strategies that create returns beyond financial engineering and cost-cutting (Bayar & Chemmanur, 2011; Davis & Le, 2020; Lloyd & Jackson-Moore, 2019). While Bayar & Chemmanur (2011) argue that financial investors are not able to benefit from traditional synergies, recent analyst notes and reports suggest that pure financial engineering will not generate competitive returns anymore and that private equity firms have adapted their value-enhancing strategies (Davis & Le, 2020; Lloyd & Jackson-Moore, 2019). In their analyst note, Davis & Le (2020) discuss that private equity firms have adapted their *playbook* to act more like strategic acquirers, specializing in specific industries, and can thus more frequently outbid corporate acquirers when competing for targets in recent years. In order to test whether the investment behavior of private equity firms has changed over the observed period, I hypothesize:

*H*4: *The influence of the industry fit on the probability of an acquisition by a private equity firm has increased in recent years.*

3. Data and methodology

3.1. The rationale of the dataset

I tested the hypotheses using venture capital and private equity data from Refinitiv Eikon, data on patents from the United States Patent and Trademark Office, as well as data on IPO sentiment from Jay R. Ritter's IPO database, GDP growth from the United States Bureau of Economic Analysis, and historical data on stock market volatility from the Chicago Board Options Exchange. The sample contains information on 6,348 acquisitions of US-based venture-capital-backed companies between 2005 and 2021, of which 296 were identified as acquisitions by private equity firms. If an acquirer could not be identified as a private equity firm or corporate buyer, the acquisition was excluded to facilitate a comparison between private equity and corporate acquisitions. Furthermore, I excluded observations that exhibit illogical values, e.g., investment dates being after the exit dates and companies being older than 20 years at the time of the acquisition. The rationale of the employment and the definitions of variables will be explained in the following. Table D-1 provides short descriptions for all used variables.

3.2. Dependent variable

The dependent variable *PE acquisition* is a binary variable that takes the value 1 if the acquirer is a private equity firm and 0 if the acquirer is a corporate buyer. Private equity acquisitions were identified using the acquirers' business description, which must contain the words “private equity firm” or “private equity fund” and must not include the words “venture capital,” “venture,” or “startup.” This method ensures that only *true* acquisitions are included in the sample, i.e., buying a majority stake in the company. If an acquirer exhibits the Standard Industrial Classification (SIC) code for investors or investment offices and is not identified as a private equity firm, I excluded the acquisition in order to facilitate a comparison of private equity and corporate acquisitions.

3.3. Independent variables

In order to test $H1_a$, I used the variable *ln(Total VC funding)*, which is the logarithm of the total venture capital amount in million US-dollars a portfolio company has received until the acquisition. Guo, Lou, & Pérez-Castrillo (2015), Nahata (2008) as well as Wang & Sim (2001) implemented the total venture capital amount received in their empirical models and found that successful exits, e.g., IPOs, are positively related to the total amount of venture capital a company has received. Thus, I include the variable as a proxy for portfolio company quality.

Table D-1: Variable definitions

Variables	Definition
Independent variable	
PE acquisition	A binary variable that takes the value 1 if the acquirer is a private equity firm and 0 if not. Private equity acquisitions were identified using the acquirer's business description, which must contain the words "private equity firm" or "private equity fund" and must not include the words "venture capital," "venture," or "startup."
H1	
Ln(Total VC funding)	A metric variable reporting the logarithm of the total venture capital amount in million US-dollar a portfolio company received until the acquisition.
VC reputation	A metric variable that depicts the reputation score of the most reputable venture capital firm invested at the time of the exit. The reputation score was calculated from the following components: (i) the venture capitalists' age, (ii) the average number of funds managed over the previous five years, (iii) the equity amount invested over the last five years, (iv) the number of portfolio companies over the last five years, and (v) IPOs conducted over the last five years. I follow the methodology of Lee et al. (2011) and Plagmann & Lutz (2019) in computing the score.
H2	
VC syndicate avg. fund age	A metric variable reporting the average fund age of all venture capital firms that invested in the company at the time of the exit.
Cold IPO sentiment	A binary variable that takes the value 1 if the acquisition took place in a month that was among the bottom quartile of all months within the respective sample period in terms of average IPO underpricing, gross volume, net volume, and price revision. The data were taken from J.R. Ritter's publicly available IPO database.
Hot IPO sentiment	A binary variable indicating whether the acquisition took place in a month that was among the top quartile of all months within the respective sample period in terms of average IPO underpricing, gross volume, net volume, and price revision. The data were taken from J.R. Ritter's publicly available IPO database.
H3	
Industy match	A binary variable that indicates whether the acquiree operates in the same industry as the acquirer. For private equity acquisitions, the target's 4-digit Standard Industrial Classification (SIC) code was compared to the private equity firm's investment focus. The investment focus of the private equity firm was determined by analyzing the most frequent 4-digit SIC code within the firm's portfolio of companies. For corporate acquisitions, I compared the 4-digit SIC codes of the acquirer and the target.
Controls	
Company age	A metric variable that approximates the age of a portfolio company at the time of the exit. The company age at the time of the exit was approximated by the time between the first venture capital investment and the exit date. The variable was constructed in this way since the information about the company's founding date is missing in many cases.
B2B business	A binary variable that takes the value 1 if the portfolio company's primary clients are businesses and 0 otherwise.
Patent claims	A metric variable that gives the target's total number of patent claims at the time of the acquisition, according to data from the United States Patent and Trademark Office.
Startup hub	A binary variable that takes the value 1 if the company is located in California, Massachusetts, New York, or Texas and 0 otherwise. Startup hubs were defined following Stephens et al. (2019) and Tykvová (2017b).
Syndicate size	A metric variable that displays the total number of venture capital firms that have invested in the company at the time of the acquisition.
GDP growth	A metric variable displaying the quarterly GDP growth rate in the quarter the acquisition took place. Data were taken from the US Bureau of Economic Analysis.
Volatility index	A metric variable that depicts the daily closing values of the Cboe VIX Index. The Cboe VIX index measures the three-day expected volatility of the S&P 500 index and is expressed in percentage terms as an annualized one standard deviation move of returns in the S&P 500 index using SPX option prices. Higher values mean more expected uncertainty in the marketplace and vice versa. Data were taken from the Chicago Board Options Exchange website.
Acquisition year	A metric variable representing the year in which the acquisition took place.
Industry group	A categorical variable that classifies companies into major industry groups according to the Venture Economics Industry Codes (VEICs). Major industry groups are: Biotechnology, Communications and media, Computer-related, Medical, health, and life sciences, Non-high-technology, Semiconductors, and others.

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

The variable *VC reputation* was deployed to test $H1_b$. It depicts the reputation score of the most reputable venture capital firm invested in the company. The reputation score was calculated from the venture capitalists' age, the average number of funds managed over the previous five years, the equity amount invested over the last five years, the number of portfolio companies over the last five years, and IPOs conducted over the last five years. I followed the methodology of Lee et al. (2011) and Plagmann & Lutz (2019) in computing the score. The resulting score can also be interpreted as a measure of the experience and success of venture capitalists, and venture capitalists' reputation has been shown to be positively related to portfolio companies' quality (Krishnan et al., 2011; Nahata, 2008; Sorenson & Stuart, 2001). I chose the most reputable venture capitalist in favor of the lead venture capitalist since top-tier venture capitalists, regardless of being the lead investor or not, were shown to positively impact the performance and success of portfolio companies (Nahata, 2008). Hence, the variable yields an appropriate proxy for the quality of the company.

Testing $H2_a$, I created the variable *VC syndicate avg. fund age* which reports the average fund age of all invested venture capital firms. Masulis & Nahata (2011) found that companies that are backed by venture capital funds who are closer to liquidation yield significantly lower takeover premiums. This is consistent with venture capitalists that are closer to liquidation exerting substantial pressure on target management to accept lower sale prices so as to ensure a profitable exit in a timely manner. Private equity firms could explicitly seek such opportunities to enhance their bargaining position, executing a *buy low, sell high* strategy (Achleitner & Figge, 2014; Lutz et al., 2014).

To test $H2_b$ and $H2_c$, I created the variables *Cold IPO sentiment* and *Hot IPO sentiment*. *Cold IPO sentiment* indicates that the acquisition took place in a month in the bottom quartile of all months within the respective sample period in terms of average underpricing, gross volume, net volume, and price revision. *Hot IPO sentiment* indicates that the acquisition took place in a month that was among the top quartile of all months within the respective sample period in terms of average underpricing, gross volume, net volume, and price revision. The data were taken from J.R. Ritter's publicly available IPO database.

Testing $H3$ and $H4$, I used the variable *Industry match*, which takes the value 1 if the target operates in the same industry as the acquirer, indicating whether an acquisition is synergetic or not. Thereby, I follow Achleitner et al. (2014), who refer to synergetic acquisitions if the acquirer and target operate in the same industry, according to the 4-digit SIC code. For private equity acquisitions, the target's 4-digit SIC code was compared to the private equity firm's investment focus. The private equity firm's investment focus was determined by analyzing the most frequent 4-digit SIC code within the firm's portfolio of companies. I analyzed the portfolios using data on private equity investments from Refinitiv Eikon. For corporate acquisitions, I compared the 4-digit SIC codes of the acquirer and the target.

3.4. Control variables

Several studies on venture capital exit choice controlled for startup maturity (Giot & Schwienbacher, 2007; Krishnan et al., 2011; Wang & Sim, 2001). Thus, I control for company maturity by including the variable *Company age*, which approximates the age of a portfolio company at the time of the acquisition. The company age at the time of the exit was approximated by the time between the first venture capital investment and the exit date. The variable was constructed in this way because the information about the founding date was missing in many cases.

I controlled for the companies' target customers by including the binary variable *B2B business*, which takes the value 1 if the company supplies businesses and 0 if it supplies consumers or the government.

In order to control for knowledge intensity, I included the variable *Patent claims*, which gives the target's total number of patent claims at the time of the acquisition. I chose patent claims in favor of the number of patents since the number of claims indicates the patents' rights and the potential value of patents (Obrimah, 2016; Sun, Zhao, & Sun, 2020). In this way, the variable also reflects the degree of innovation and knowledge intensity that comes with a company's patents.

In their study, Lutz et al. (2013) found that the location of startups and their proximity to venture capitalists impacts the probability of receiving venture capital. Beyond that, startup hubs offer several advantages, such as networks and labor talent (Stephens et al., 2019). These advantages potentially have an impact on the exit choice. Hence, I include the binary variable *Startup hub*, which takes the value 1 if the company is located in California, Massachusetts, New York, or Texas and 0 otherwise. Startup hubs were defined following Stephens et al. (2019) and Tykvová (2017b).

Nguyen & Vu (2021) found companies backed by larger venture capital syndicates to generate higher acquisition premiums. Hence, I controlled for the syndicate size at the time of the acquisition by including the variable *Syndicate size*.

I controlled for the economic sentiment by including the variable *GDP growth* and *Volatility Index*. The variable *GDP growth* gives the quarterly GDP growth rate at the time of the acquisition. The variable *Volatility index* is a measure of uncertainty in public capital markets and represents the S&P 500 Volatility index from the Chicago Board Option Exchange. In the media, the index is sometimes described as *a fear gauge*. Hence, a high value of the index indicates a period of solid uncertainty. Finally, I included year and industry-fixed effects in the model to control for year-specific events and industry-specific characteristics. I used the major industry group classification according to Venture Economics Industry Codes (VEICs) to control for industry-specific characteristics. While the VEIC scheme was developed for venture-specific industries, the SIC system includes public administration, agriculture, forestry, fishing, or mining at the least granular level of classification. Only a few of the ventures within the sample operate in these industry categories, leading to omitted observations when applying logistic regression analyses. Hence, the VEIC is a more appropriate scheme and is therefore applied when controlling for industry-specific effects within the econometric analyses.

3.5. Descriptive statistics

Table D-2 displays several descriptive statistics. Panel A of Table D-2 provides the yearly acquisition frequency of venture-capital-backed companies within the sample. In total, the sample consists of 6,348 acquisitions, of which 296 were acquisitions by private equity firms. Most of the private equity acquisitions took place in 2017 and 2018, with almost every tenth acquisition being undertaken by a private equity firm.

Panel B of Table D-2 presents the most frequent industries in which private equity acquisitions occurred within the sample. Both corporate and private equity firms acquired the most venture-capital-backed companies operating in computer-related industries. Taking a view on the next granular classification, of the 169 private equity acquisitions within computer-related industries, 123 (>72%) operate in computer and software services. Software offers scalability and high margins in the early stages, leading to appropriate cash flows for a buyout strategy (Davis & Le, 2020).

Panel C of Table D-2 shows the number of observations, means, and standard deviations for all variables divided into private equity acquisitions and corporate acquisitions. Significant differences in means occur among 9 of the 14 variables. Concerning portfolio company quality, companies that were acquired by private equity firms are backed by venture capitalists who are, on average, less reputable. This gives a first descriptive indication that private equity acquisitions are related to companies of lower quality. There is no significant difference in means of the venture capital amount received between companies being acquired by corporations and private equity firms.

Regarding the average fund age at the time of the acquisition, targets of private equity firms are, on average, backed by older funds. The funds are on average older than 10 years which exceeds the typical lifetime of a venture capital fund, indicating potential liquidity pressure (Gompers, 1996; Masulis & Nahata, 2011). This could potentially enhance a private equity firm's bargaining position in acquisition negotiations and open up opportunities for low-multiple acquisitions. A significant difference in means for the variable *Hot IPO sentiment* provides the first descriptive evidence that private equity firms might avoid M&A environments of high multiples, indicating less potential for value enhancing by a *buy low, sell high* strategy.

Inspecting the mean of the *Industry match* variable, private equity acquisitions exhibit, on average, a higher value than corporate acquisitions. Thus, within the sample, private equity firms have acquired venture-capital-backed companies that, on average, fit their industry focus more often than corporations have acquired companies that fit their core operating industry. This provides a first indication that private equity firms potentially benefit from synergies, too. For information on the variables' correlations, please see Appendix 3.

Table D-2: Descriptive statistics

Panel A. PE acquisitions per year

Year	Total acquisitions	*PE acquisitions*	*Share of PE acquisitions*
2005	391	13	3.3%
2006	448	19	4.2%
2007	434	16	3.7%
2008	347	17	4.9%
2009	322	10	3.1%
2010	490	20	4.1%
2011	463	11	2.4%
2012	428	26	6.1%
2013	359	10	2.8%
2014	443	18	4.1%
2015	343	17	5.0%
2016	291	12	4.1%
2017	318	29	9.1%
2018	327	29	8.9%
2019	293	21	7.2%
2020	252	13	5.2%
2021	399	15	3.8%
Total	6,348	296	4.7%

Panel B: PE acquisitions per industry

	Total acquisitions	*PE acquisitions*	*Share of PE acquisitions*
Biotechnology	312	4	1.3%
Communication and media	629	13	2.1%
Computer-related	4,006	169	4.2%
Medical, health, life sciences	546	39	7.1%
Non-high-technology	541	64	11.8%
Semiconductors and others	314	7	2.2%
Total	6,348	296	4.7%

Panel C: Means and standard deviations

	PE acquisitions			*Corporate acquisitions*		
Variable	*N*	*Mean*	*Sd*	*N*	*Mean*	*Sd*
H1						
Ln(Total VC funding)	296	2.792	1.425	6,052	2.689	1.480
VC reputation	232	0.266***	0.200	5,602	0.333	0.239
H2						
Avg. syndicate fund age	239	10.676***	3.677	4,881	8.060	3.617
Cold IPO Market	296	0.098	0.298	6,052	0.099	0.299
Hot IPO Market	296	0.010**	0.100	6,052	0.032	0.175
H3						
Industry match	296	0.372**	0.484	6,052	0.312	0.464
Controls						
Company age	296	8.642***	3.961	6,052	6.029	3.718
B2B business	296	0.584	0.494	6,052	0.538	0.499
High-tech industry	296	0.784***	0.412	6,052	0.921	0.269
Patent claims	296	31.686**	127.683	6,052	65.658	272.229
Startup hub	296	0.466***	0.500	6,052	0.641	0.480
Syndicate size	296	3.919***	3.071	6,052	4.699	3.288
GDP growth	296	0.019	0.051	6,052	0.021	0.049
Volatility index	296	18.506	8.449	6,052	19.310	8.789

Note: Panel A of this table reports the number of total acquisitions and private equity acquisitions in the panel data sample year-wise. Panel B reports the allocation of total acquisitions and private equity acquisitions among industries based on major industry groups according to the Venture Economics Industry Codes (VEICs). Industries are sorted from most to least private equity acquisitions per industry. Panel C provides means and standard deviations for all used variables. The variables are defined in Table D-1. Also reported are the significance levels of the differences in means. N denotes the number of observations analyzed. *, **, and *** denote a significant difference in the means at the 10%, 5%, and 1% levels, respectively.

3.6. Methodology

For the statistical analysis, I applied multivariate logistic regression with robust standard errors. 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 (Judge, 1982; Menard, 2010). To test the hypotheses, I used the following basic model:

$$Prob(y = 1) = F(\beta_0 + \beta_1 x_{1,i} + \dots + \beta_k x_{k,i}) \tag{7}$$

where $F(z) = \frac{e^z}{(1+e^z)}$ is the cumulative logistic distribution. The independent binary variable *PE acquisition* is represented by y, and the independent and control variables 1 to k for all observations i are denoted by $x_{1,i}$to $x_{k,i}$. The probability of a private equity acquisition $Prob(y = 1)$ represents the likelihood of the dependent variable being equal to 1. The parameter estimates are denoted by β_j.

4. Results and discussion

4.1. Portfolio company quality, opportunity-seeking, and synergies

Table D-3 presents the results of multivariate logistic regressions with robust standard errors on the probability of a private equity acquisition compared to a corporate acquisition. The variables *VC reputation* and *Avg. syndicate fund age* provide information for only 3,959 and 3,648 observations, respectively. Hence, I present regressions without these variables (Model 1), including these variables separately (Models 2 & 3), and including both variables within the regressions (Model 4) (Tykvová, 2017b). In order to induce robustness, results will only be considered significant when holding for all presented models.

Regarding $H1_a$, it is observable that in all four models a larger amount of total venture capital received significantly increases the probability of an acquisition by a private equity firm compared to a corporate acquisition. While differences in means are insignificant, the results of the multivariate logistic regression indicate that private equity acquisitions are related to higher-quality companies. In contrast, the variable *VC reputation* shows significantly negative coefficients, indicating that private equity acquisitions are related to lower-quality companies. Thus, the two quality proxies provide contrary results. An explanation for the negative impact of *VC reputation* could be due to a stronger reliance on such quality signals by corporate acquirers. Despite having in-house M&A arms, corporate acquirers rely more on assistance from investment banks and consultants than private equity firms. Hence, this result could be driven by investment preferences and a reliance on quality signals rather than company quality aspects.

The coefficients of the variable *Avg. syndicate fund age* are significantly positive, indicating that private equity acquisitions are related to companies that are backed by more mature venture capital funds, supporting $H2_a$. This result provides evidence that private equity firms might seek opportunities in which the bargaining position of the seller is harmed by liquidity pressure. The coefficients of the variable *Cold IPO sentiment* are not significant in all four presented models. The effect of a *Hot IPO sentiment* is significantly negative in the Models 1 & 3, but the effect does not persist in models that include *VC reputation.* Thus, hypotheses $H2_b$ and $H2_c$ cannot be confirmed.

Table D-3: Logistic regression with robust standard errors – PE vs. strategic acquisitions

Variables	(1)	(2)	(3)	(4)
H1				
Ln(Total VC funding)	0.185***	0.305***	0.160**	0.296***
	(0.060)	(0.074)	(0.071)	(0.089)
VC reputation	--	-1.318***	--	-1.262***
		(0.372)		(0.413)
H2	-		0.095***	
Avg. syndicate fund age	-	-	(0.026)	0.104***
	0.055	-	0.081	(0.028)
Cold IPO sentiment	(0.236)	0.118	(0.248)	0.180
	-1.290**	(0.261)	-1.321*	(0.270)
Hot IPO sentiment	(0.652)	-1.020	(0.794)	-0.909
		(0.649)		(0.790)
H3	0.450***		0.440***	
IndustryMatch2	(0.130)	0.587***	(0.144)	0.612***
		(0.144)		(0.157)
Controls	0.180***		0.098***	
Company age	(0.015)	0.179***	(0.027)	0.086***
	0.198	(0.018)	0.148	(0.029)
B2B business	(0.135)	0.318**	(0.149)	0.260
	-0.002***	(0.158)	-0.002**	(0.170)
Patent claims	(0.001)	-0.002**	(0.001)	-0.001*
	-0.447***	(0.001)	-0.338**	(0.001)
Startup hub	(0.130)	-0.328**	(0.144)	-0.280*
	-0.186***	(0.148)	-0.147***	(0.160)
Syndicate size	(0.038)	-0.170***	(0.039)	-0.129***
	-0.645	(0.041)	-1.175	(0.042)
GDP growth	(1.641)	-1.112	(1.550)	-1.449
	-0.006	(1.880)	-0.005	(1.796)
Volatility index	(0.012)	0.001	(0.013)	0.004
		(0.013)		(0.014)
Observations	6,348	5,834	5,120	4,842
Year FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	Yes
Pseudo R^2	0.142	0.139	0.137	0.134
Wald Chi2	316.9	268.5	260.1	220.3

Note: This Table presents multivariate logistic regression estimates based on robust standard errors. Variable definitions can be found in Table D-1. *, **, and *** denote coefficient estimates significantly different from 0 at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in parentheses.

The coefficients of the *Industry match* variable are significantly positive in every model presented in Table D-3. Hence, *H*3 is confirmed by the results. It seems that private equity firms focus on industries in order to potentially benefit from synergies, e.g., accumulating in-depth industry knowledge or building strong networks within certain industries which leads to superior target selection and lower post-deal uncertainty of the target's success (Cressy et al., 2007; Rigamonti et al., 2016). Corporate acquirers, however, can also have strategic goals in lateral acquisitions to diversify or to enter new markets when investing in venture-capital-backed companies, which seems to reduce the reliance on synergetic acquisitions.

In summary, the results on portfolio company quality are mixed. On the one hand, private equity acquisitions are related to companies that receive more venture capital funding but are backed by less reputable venture capitalists. However, the negative relation with *VC reputation* could be driven by a stronger reliance of corporate acquirers on quality signals such as venture capital reputation. Moreover, the analysis shows a relationship between private equity acquisitions and companies being backed by more mature venture capital funds, which potentially face liquidity pressure. There is no robust evidence for private equity firms to more or less seek opportunities in M&A environments of low or high multiples, approximated by the IPO sentiment. Finally, there is empirical support for the hypothesis that private equity firms target venture-capital-backed companies that fit their portfolio's industry focus, potentially benefiting from industry-specialization in a similar way as corporate acquirers profit from synergies. That would rebut the explanation presented by Bayar & Chemmanur (2011), that financial acquirers always pay less compared to strategic acquirers since financial acquirers have a lower valuation due to not benefiting from synergies.

4.2. Changes in the behavior of private equity firms over time

Table D-4 and Table D-5 present multivariate logistic regression results with robust standard errors for the sample period from 2005 to 2014 and 2015 to 2021, respectively. The Industry match variable remains insignificant in the early period while being positively significant in the recent period. Thus, the results support Hypothesis $H4$, which supposes the influence of the industry fit on the probability of a private equity acquisition has increased in recent years. In other words, private equity firms have adjusted their investment strategy and behavior toward industry specialization in recent years.

Figure 1 illustrates the predictive margins of the *Industry match* variable when interacting with the time variable *Acquisition year* in Model 4 using a 95% confidence interval. Model 4 was adjusted by adding the interaction term and including the year variable as a continuous variable instead of using it for year-fixed effects. For the underlying regression, please see Appendix 4. Figure D-1 shows the rise in importance of industry fit for the probability of being acquired by a private equity firm over the observed period from 2005 until 2021. Thus, the interaction confirms the robustness of the results from sample splitting.

The remaining variables in Table D-4 and Table D-5 show the change in the investment patterns that come with an industry-specialization. Table D-4 presents that in the sample period from 2005 to 2014, private equity firms are related to companies backed by less reputable venture capitalists, while coefficients of *Ln(Total VC funding)* remain insignificant. The results presented in Table D-5 for the period between 2015 and 2021 are inverted. While the total venture capital funding is significantly positive, the relation to a lower venture capital reputation does not remain robust in recent years.

Table D-4: Logistic regressions – PE vs. corporate acquisitions (2005-2014)

Variables	(1)	(2)	(3)	(4)
H1				
Ln(Total VC funding)	0.086	0.147	0.091	0.168
	(0.079)	(0.102)	(0.089)	(0.114)
VC reputation		-1.802***		-1.794***
		(0.508)		(0.540)
H2				
Avg. syndicate fund age			0.151***	0.173***
			(0.035)	(0.037)
Cold IPO sentiment	0.518	0.541	0.462	0.477
	(0.340)	(0.383)	(0.351)	(0.392)
Hot IPO sentiment	0.392	0.290	-0.040	0.058
	(0.479)	(0.526)	(0.594)	(0.599)
H3				
Industry match	0.133	0.319	0.192	0.405*
	(0.183)	(0.205)	(0.194)	(0.214)
Controls				
Company age	0.191***	0.185***	0.068*	0.055
	(0.023)	(0.026)	(0.036)	(0.038)
B2B business	0.176	0.470**	0.064	0.414*
	(0.184)	(0.229)	(0.196)	(0.234)
Patent claims	-0.004***	-0.005**	-0.004**	-0.004**
	(0.002)	(0.002)	(0.002)	(0.002)
Startup hub	-0.457**	-0.363*	-0.466**	-0.453**
	(0.179)	(0.207)	(0.192)	(0.213)
Syndicate size	-0.140***	-0.085	-0.113**	-0.072
	(0.051)	(0.052)	(0.054)	(0.055)
GDP growth	1.821	1.648	0.332	-0.304
	(4.107)	(4.472)	(4.313)	(4.592)
Volatility index	-0.005	0.012	0.000	0.014
	(0.017)	(0.018)	(0.017)	(0.019)
Observations	4,125	3,799	3,511	3,319
Year FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	Yes
Pseudo R^2	0.139	0.138	0.146	0.155
Wald Chi2	194.2	156.2	171.2	149.9

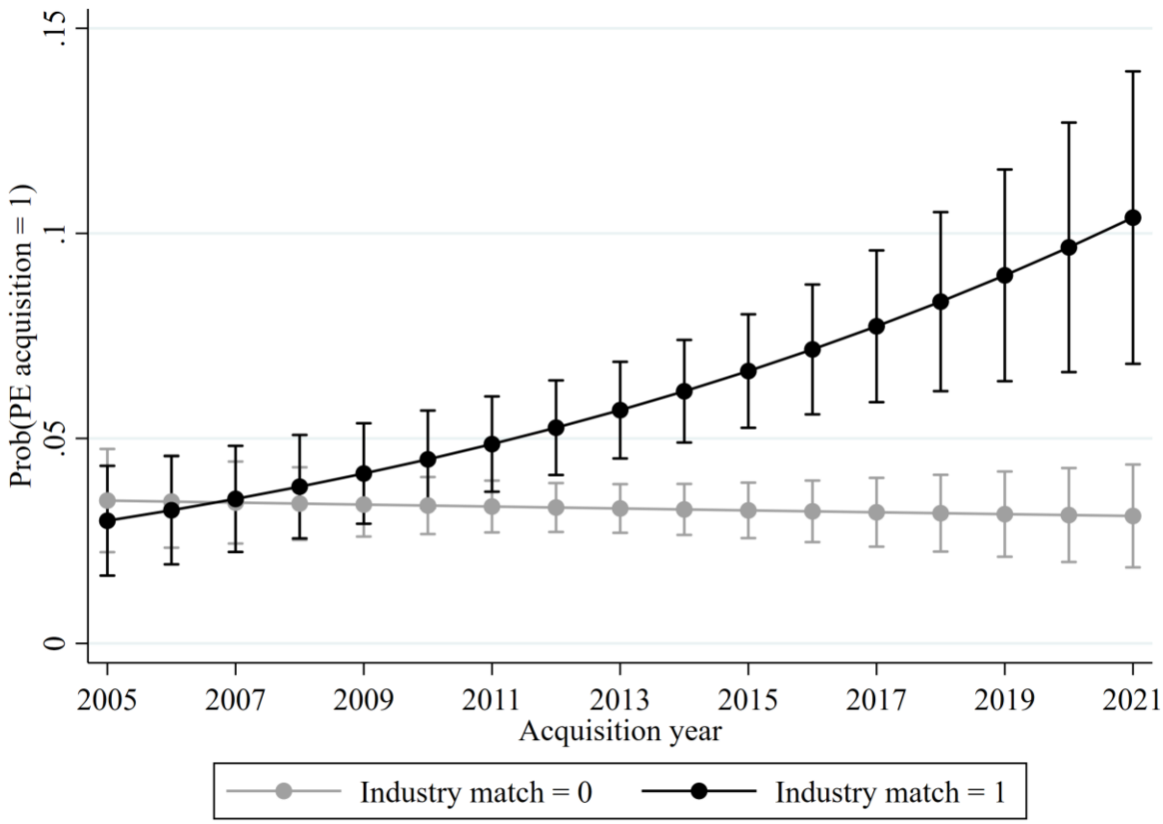
Note: This table presents multivariate logistic regression estimates based on robust standard errors. Variable definitions can be found in Table D-1. *, **, and *** denote coefficient estimates are significantly different from 0 at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in parentheses.

Table D-5: Logistic regressions – PE vs. corporate acquisitions (2015-2021)

Variables	(1)	(2)	(3)	(4)
H1				
Ln(Total VC funding)	0.294***	0.490***	0.258**	0.500***
	(0.089)	(0.100)	(0.116)	(0.130)
VC reputation	--	-0.904*	--	-0.786
		(0.520)		(0.585)
H2	-		0.032	
Avg. syndicate fund age	-	-	(0.038)	0.031
	-0.034	-	0.242	(0.042)
Cold IPO sentiment	(0.373)	0.076	(0.394)	0.363
	-1.449*	(0.405)	-0.993	(0.422)
Hot IPO sentiment	(0.829)	-1.232	(0.850)	-0.637
		(0.846)		(0.856)
H3	0.829***		0.794***	
Industry match	(0.198)	0.890***	(0.227)	0.917***
		(0.215)		(0.246)
Controls	0.174***		0.140***	
Company age	(0.021)	0.180***	(0.041)	0.134***
	0.231	(0.024)	0.276	(0.045)
B2B business	(0.202)	0.142	(0.234)	0.049
	-0.002**	(0.225)	-0.001	(0.251)
Patent claims	(0.001)	-0.001	(0.001)	-0.001
	-0.394**	(0.001)	-0.121	(0.001)
Startup hub	(0.191)	-0.251	(0.225)	0.009
	-0.240***	(0.214)	-0.186***	(0.254)
Syndicate size	(0.054)	-0.268***	(0.055)	-0.201***
	-0.128	(0.060)	-1.143	(0.059)
GDP growth	(1.783)	-0.580	(1.737)	-1.565
	-0.002	(2.062)	-0.008	(2.070)
Volatility index	(0.019)	-0.013	(0.022)	-0.010
		(0.023)		(0.023)
Observations	2,223	2,035	1,609	1,523
Year FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
Pseudo R^2	0.156	0.161	0.141	0.143
Wald Chi2	144.3	129.5	96.93	89.43

Note: This table presents multivariate logistic regression estimates based on robust standard errors. Variable definitions can be found in Table D-1. *, **, and *** denote coefficient estimates are significantly different from 0 at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in parentheses.

Figure D-1: Predictive margins of the industry match variable on the probability of a private equity acquisition



Note: This figure illustrates predictive margins of the *Industry match* variable using a 95% confidence interval. Predictive margins were calculated on the basis of Model 4, including the interaction of the Industry match variable and the Exit year variable without year-fixed effects. Variable definitions can be found in Table D-1. For the underlying regression please see Appendix 4.

When comparing the results of the *Avg. syndicate fund age* variable, coefficients are significantly positive in the early period while remaining insignificant in the recent period. Thus, the results indicate that private equity firms are now able to compete with corporate acquirers for high-quality companies and partially outbid corporate buyers. These results confirm a trend toward a convergence of financial and strategic buyers in acquisitions of venture-capital-backed companies.

5. Limitations and future research

This paper provides evidence that the investment behavior of private equity firms has changed over time from opportunity-seeking toward industry specialization. Further qualitative research could focus on the actual drivers of this change. The private equity market and its environment have changed significantly over the last decade. The zero-interest policy of the Federal Reserve led to favorable debt conditions for private equity firms and caused a massive cash inflow into private equity funds. In order to invest large committed sums, private equity firms needed to expand their investment focus (Ahlers et al., 2016). Especially software businesses offer scalability and high margins (Davis & Le, 2020). However, the orientation toward venture-capital-backed targets and the specialization in target industries could also be driven by the booming technology and e-commerce business in recent years. Qualitative research could shed more light on the actual motives for private equity firms changing their investment and value-enhancing strategies.

Investigating the industry fit of private equity acquisitions, this study focuses on horizontal acquisitions, i.e., when the acquirer and the target operate in the same industry. Hence, the study neglects vertical acquisitions that also provide potential synergies (Achleitner et al., 2014).

Finally, this paper mainly focuses on the investors' perspective on acquisitions of venture-capital-backed companies. Founders also play a crucial role in the decision-making process (Andrieu & Groh, 2021; Bayar & Chemmanur, 2011). While the acquisition marks an exit for venture capital investors, it constitutes another major capital injection for the company on its growth path. Hence, future research could emphasize the founder's role in the decision-making process.

6. Conclusion

In this paper, I used data from 6,348 acquisitions of venture-capital-backed companies in the United States between 2005 and 2021 to analyze relationships between the company, investor, and market characteristics and the exit via an acquisition by either a strategic or financial buyer. The study provides two key findings. First, the results point toward increased competition for corporate acquirers from private equity firms in recent years. The results suggest that the increased competition stems from a change in the investment strategy and behavior of private equity firms when acquiring venture-capital-backed companies. The results of the sample split indicate a shift from opportunity-seeking to industry specialization. In the period from 2005 to 2013, private equity acquisitions were related to companies backed by significantly more mature venture capital funds that potentially faced liquidity pressure which harms the seller's bargaining position. In this way, private equity firms were able to benefit from discounts to enhance value creation potential. In the period from 2014 to 2021, this relation remains insignificant, while private equity acquisitions are significantly related to companies that match their portfolio industry focus. Industry-specialization of private equity firms can help to optimize investment activities when identifying, selecting, and developing portfolio companies and has been shown to have a positive impact on the operating profitability of portfolio companies (Ahlers et al., 2016; Cressy et al., 2007; Rigamonti et al., 2016). Therefore, industry specialization could be a key driver for private equity buyouts to close the gap between financial sales and trade sales in the pecking order of venture capital exits (Cumming & MacIntosh, 2003b).

This study contributes to the literature in three main ways. First, this paper extends the literature on venture capital exit options by providing one of the first detailed empirical comparisons of financial and strategic acquisitions. The entrepreneurial finance literature is increasingly interested in recently emerging venture capital exit channels like financial acquisitions. Other examples include going public via a special purpose acquisition company (SPAC) or secondary sales (Andrieu & Groh, 2021; Kolb & Tykvova, 2016; Nadauld et al., 2019). By showing relations that point toward a convergence of financial and strategic acquirers, this study offers an empirically driven explanation of the recent rise in venture capital exits via financial acquisitions (Davis & Le, 2020). Second, by adapting the investment rationale, private equity firms benefit from industry specialization, which rebuts the argument that financial acquirers, given that both types of acquirers have the same bargaining power, always pay lower acquisition prices due to a lack of synergies and are therefore avoided by venture capitalists or seen as the exit of last resort (Akerlof, 1978; Bayar & Chemmanur, 2011). By showing that financial acquisitions can be as attractive as strategic acquisitions for venture capitalists, this study adds to the literature on the pecking order of venture capital exits (Bienz & Leite, 2008; Cumming & Johan, 2008b; Cumming & MacIntosh, 2003b). Third, this study recognizes the research gap in the investment criteria of private equity firms and provides empirical evidence of a change in the investment strategy of private equity firms over time from opportunity-seeking to industry-specialization when acquiring venture-capital-backed companies (Block et al., 2019; Gompers et al., 2016; Wilson et al., 2022).

In conclusion, this study contributes novel empirical evidence for a shift in the investment strategy of private equity firms from opportunity seekers to industry-specialists in acquisitions of venture-capital-backed companies. As such, this study enriches the literature on recently emerging alternative exit routes for venture capitalists as well as investment criteria and value-enhancing strategies of private equity firms. Regarding future research, I see great potential for qualitative research to broaden the understanding of private equity firm's rationale behind adapting investment strategies.

E. Conclusion

1. Summary of the main findings and contributions

Throughout the essays, valuable insights have been uncovered that contribute to the field of venture capital. The following paragraphs highlight the key findings and demonstrate the impact of this dissertation.

First, by examining venture capital mega-deals of 100 million US-dollars or more in a single transaction, this dissertation contributes to the body of literature on venture capital by investigating a recently emerging form of quality signaling in venture-capital-backed companies that has not been empirically studied in academic research before. The findings indicate that the examined companies were able to efficiently use the financial resources resulting from venture capital mega-deals to rapidly grow their businesses and perform superior IPOs compared to venture-capital-backed companies without mega-deals. The dissertation thus adds to the academic discussion about the free cash flow hypothesis in the context of large venture capital deals and their implications on a company's exit performance (Bradley et al., 2011; Jensen, 1986; Vanacker et al., 2013).

Using IPO success as a performance measurement, the findings indicate that venture capital mega-deals are a valid quality signal that goes beyond the certification of being venture-capital-backed. Thus, the dissertation extends the literature on quality signaling in IPOs by examining and validating a new certification mechanism in IPOs (Gulati & Higgins, 2003; Krishnan et al., 2011; Megginson & Weiss, 1991).

When applying the regression discontinuity design, the signaling effect of mega-deals was isolated. It was shown that the out-performance in IPOs is partially caused by a signaling effect of mega-deals that is highly impactful on the IPO success and fades in post-IPO performance until becoming insignificant after two years post-IPO. This finding can be interpreted in light of behavioral finance by applying the concepts of the anchoring effect and herd behavior in financial markets (Mitchell, 2001; Slovic & Lichtenstein, 1971; Tversky & Kahneman, 1974). As mega-deals are frequently reported they are perceived as important by investors, and the threshold of 100 million US-dollars would constitute an anchor that biases the valuation of investors (Slovic & Lichtenstein, 1971). The anchoring effect can, in turn, lead to herd behavior, whereby investors follow other investors' decisions rather than their own analyses (Tversky & Kahneman, 1974).

Second, this dissertation adds to the scientific literature on venture capital and entrepreneurial finance by finding relations between earlier venture capital funding rounds and subsequent venture loans provided by venture lenders. The dissertation provides empirical evidence that sufficient financial commitment from existing venture capitalists is associated with a higher probability of obtaining venture loans by satisfying venture lenders' needs for downside protection. Thus, the dissertation contributes to the literature on the financing lifecycles of startups and the interplay of venture capitalists and venture lenders (Berger & Udell, 1998).

Moreover, the dissertation expands the literature on venture debt by addressing the heterogeneity of venture debt and focusing on venture loans as a distinct form of debt financing for innovative startups (Hesse et al., 2016; Ibrahim, 2010; Tykvová, 2017b). This dissertation is among the first to delve deeper into one type of venture debt and to examine venture loans in a comprehensive quantitative study. In showing the relevance of startup maturity, the startup industry, and the types of venture capital investors involved in the startup, this dissertation gives initial indications on how venture lenders might select startups.

Furthermore, findings demonstrate that performance-orientated venture capitalists are particularly associated with venture loans, which could indicate a close-knit relationship between startups, venture capitalists, and venture lenders. Accordingly, this dissertation adds a further dimension to the classic model of relationship lending in which banks and companies have a tight relationship (Elyasiani & Goldberg, 2004). In addition to this bilateral relationship, the results show the relevance of involved venture capitalists and, hence, a relationship triangle in venture finance (Hesse et al., 2016).

Third, the dissertation extends the literature on venture capital exit options and the pecking order of venture capital exits by providing one of the first detailed empirical comparisons of financial and strategic acquisitions of venture-capital-backed companies (Bayar & Chemmanur, 2011; Bienz & Leite, 2008; Cumming & Johan, 2008b). The findings suggest that private equity firms adapted their investment rationale toward an industry-specialization approach. Therefore, the dissertation adds to the literature stream of private equity investment criteria by providing empirical evidence for a change in the investment strategy of private equity firms over time from opportunity-seeking to industry-specialization when acquiring venture-capital-backed companies (Block et al., 2019; Gompers et al., 2016; Wilson et al., 2022).

The findings rebut the argument that financial acquirers, given that both types of acquirers have the same bargaining power, always pay lower acquisition prices due to a lack of synergies and are therefore avoided by venture capitalists or seen as the exit of last resort (Akerlof, 1978; Bayar & Chemmanur, 2011). Thus, the dissertation contributes new insights into the pecking order of venture capital exits (Bienz & Leite, 2008; Cumming & Johan, 2008b; Cumming & MacIntosh, 2003b).

Overall, this dissertation provides novel findings and relevant contributions to the literature on venture capital and related research streams by showing that (i) venture capital mega-deals are an effective quality signal in IPOs, (ii) venture loans significantly depend on the financial commitment of existing venture capitalists, and (iii) buyouts are about to close the gap to trade sales in the pecking order of venture capital exits and are becoming an equally attractive exit route for venture capitalists.

2. Implications for practitioners

This dissertation examines relevant topics in venture capital in order to offer implications for practitioners and market participants in the venture capital industry and beyond. After starting with the implications for founders, this section will continue to elaborate on the implications for venture capitalists, followed by those for private equity and public investors.

Founders are the foundation of entrepreneurial finance, and visionary and innovative founders give researchers in the field of venture capital a basis for examining associated financing needs and sources that help founders efficiently put their visions and innovations into practice. While founders have different long-term goals when founding a company, some do envision building a successful publicly listed company. Based on this dissertation’s results, these entrepreneurs should strive for large venture capital financing rounds in their company’s lifecycle to lay the groundwork for a successful future IPO.

Venture loans can be helpful for entrepreneurs in milestone-driven industries, for example, the medical, health, and life science industries. The valuation function of a startup in these industries is a step function with significant increases in the company’s valuation after reaching specific milestones, e.g., when a new product passes clinical trials necessary for regulatory approval. In a scenario where the startup runs out of liquidity before reaching such a milestone, a venture loan can be employed to extend the cash runway in order to reach the value-enhancing milestone before conducting the next equity funding round. Entrepreneurs who are unwilling or unable to invest prorate in the next equity funding round can benefit from reduced dilution by employing a venture loan in such a scenario.

Finally, this dissertation offers implications for the exit decisions of founders when facing the choice between a buyout and a trade sale as exit options. The results show that especially software startups are attractive targets for private equity firms since subscription-based business models and moderate costs offer great potential for buyout strategies. Thus, founders in this field should be aware of their bargaining power when negotiating with strategic and financial acquirers.

Venture capital investors are the central focus of this dissertation, and the findings provide several implications for venture capital investors and complementary financing sources. Venture capital mega-deals of 100 million US-dollars or more in a single funding round have been shown to be associated with superior IPO success and post-IPO performance. In the presented study, founders proved able to efficiently employ the financial resources to rapidly grow the company, which ultimately leads to outperformance in IPO and post-IPO performance. Beyond the treatment effect, it was found that venture capitalists can additionally benefit from the signaling effect of mega-deals since the analysis reveals that the positive signaling effect of mega-deals explains a part of the outperformance at the IPO. Therefore, venture capitalists can benefit from mega-deals in several ways when investing in an IPO candidate.

Suppose a portfolio company is rather attractive for strategic and financial acquirers. In that case, the results indicate that private equity firms can increasingly compete for high-quality portfolio companies against strategic acquirers. Consequently, the buyout is becoming an attractive exit route for venture capitalists.

Like entrepreneurs who are unwilling to or unable to invest in subsequent funding rounds, venture loans can offer an opportunity to mitigate dilution in specific scenarios. The presented results indicate an important relationship between the large prior investments of a venture capitalist and the probability of receiving a venture loan. Large prior investments can signal financial commitment, satisfying the need for the downside protection of venture lenders and helping to facilitate a venture loan agreement. Moreover, it was shown that independent venture capitalists are more associated with venture loans than corporate or government venture capitalists. This association could be due to the beneficial effect of venture loans on the internal rate of return, thereby enhancing performance measures that are of higher importance to venture capitalists who pursue mainly financial returns rather than strategic or welfare goals.

Private equity investors can play an essential role in a startup's transition from an entrepreneurial company to an established corporation. The results of this dissertation show that the efforts of private equity firms to extend their value-enhancing strategies by focusing on industry specialization and competing for venture-capital-backed companies against strategic acquirers lead to a convergence of financial and trade sales in the pecking order of venture capital exits. For private equity firms that still focus on opportunity-seeking, in terms of seeking targets backed by inexperienced venture capitalists or venture capitalists who face liquidity pressure, the results implicate that a shift in strategy is needed to keep up with the increased competition within the private equity industry.

Public investors are important for startups to successfully perform the transition from an entrepreneurial company to an established corporation via an IPO. The findings on venture capital mega-deals have direct implications for public investors and financial analysts. IPO candidates must provide detailed information about their past performance and equity story. However, uncertainty regarding future performance and stock price development remains. This circumstance is particularly relevant for venture-capital-backed companies that are characterized by high uncertainty, a short track record, and, oftentimes, limited or even negative earnings (Dey et al., 2019). In this context, the dissertation provides validation that venture capital mega-deals are an easily observable quality signal that points to a successful future IPO and positive post-IPO performance.

3. Avenues for future research

This dissertation seeks to advance the knowledge base within the scholarly domain of venture capital. However, it also raises several questions that merit further investigation in future studies.

Venture capital mega-deals are a recently emerging phenomenon; hence, the scientific literature on this topic is still in its infancy and offers a wide range of topics for future research. In the direct context of the present study, the findings provide empirical evidence that the IPOs of mega-deal companies are characterized by larger deal sizes and heightened investor demand. This phenomenon may be partly attributed to the presence of stronger retail investor participation (Bushee et al., 2020; Dorn, 2009). The conspicuous nature of mega-deal IPOs may serve to attract a wider range of non-specialized investors, leading to increased demand. Additionally, further investigation on the role of syndicate composition, unicorn status, as well as research and development expenses in the context of mega-deal IPOs could enhance the understanding of underlying relationships in such IPOs and offer a fruitful avenue for future research (Eberhart et al., 2004; Gornall & Strebulaev, 2020; Kaplan et al., 2009).

In a broader sense, a potential signaling effect resulting from large venture capital investments could be examined in the context of follow-on funding rounds or other exit channels, e.g., trade sales or buyouts. Kerai (2017) provided the first evidence that the unicorn tag helps venture-capital-backed companies in gaining legitimacy and access to follow-on investments. Consequently, an examination of the signaling effects of substantial venture capital investments in alternative settings warrants further investigation in future research.

Although the literature on venture debt has grown in recent years, it is still not extensive. Future investigations may examine the heterogeneity of venture debt instruments, the conditions that facilitate their utilization, and their impact on company performance (Tykvová, 2017b). In a broader context, venture lending funds and their interplay with capital providers in establishing funding sources, similar to research on venture capital funds and their investors, would be valuable additions to this stream of literature (Veena Iyer, 2020).

According to a recent news article by Köhler (2022), venture lenders recently saw an increasing demand for venture debt as the venture capital market cooled down in 2022. Despite soaring interest rates, later-stage companies seem to be interested in venture debt to avoid down rounds which potentially dilute the stake of existing venture capitalists and founders. These developments motivate the exploration of the sensitivity of startup demand for venture debt and venture lender supply to macroeconomic conditions in future research.

The dissertation presents a change in private equity firms' investment strategies that drive the convergence of buyouts and trade sales in the pecking order of venture capital exits (Bienz & Leite, 2008; Cumming & MacIntosh, 2003b). Further qualitative research could focus on the actual drivers of this change. Potential drivers could be the zero-interest policy of Western central banks which created a favorable environment for private equity, resulting in an influx of capital and potentially increased competition in the private equity industry. Further qualitative investigation may provide greater insights into the underlying motivations behind the shifting investment and value-enhancing strategies of private equity firms.

Finally, the study neglected the entrepreneur's perspective on acquisitions of venture-capital-backed companies. Founders play a crucial role in the exit decision-making process (Andrieu & Groh, 2021; Bayar & Chemmanur, 2011). The acquisition of a company by private equity firms represents a significant exit opportunity for venture capital investors but also constitutes a substantial injection of capital as the company continues to grow. Thus, future studies may focus on exploring the decision-making, considering the role of the company's founders in this process.

To conclude, this dissertation provides novel findings and contributions on important topics in venture capital research that have relevant implications for practitioners within the venture capital industry and beyond. I hope to see the present studies and results challenged, assessed, and extended in future research.

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Appendix

Appendix 1: Pairwise correlation matrix of the IPO success framework

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
IPO success measures																			
(1) ln(Proceeds)	1.000																		
(2) ln(Pre-money valuation)	0.768	1.000																	
(3) Price revision	0.408	0.398	1.000																
(4) Underpricing	0.296	0.324	0.420	1.000															
Variable of interest																			
(5) Mega-deal	0.532	0.414	0.179	0.162	1.000														
Control variables																			
(6) Lead VC reputation	0.128	0.080	0.128	0.096	0.056	1.000													
(7) Lead underwriter reputation	0.480	0.447	0.222	0.174	0.175	0.071	1.000												
(8) Profitability	0.078	0.129	0.030	0.030	0.040	0.046	-0.002	1.000											
(9) Total assets pre-IPO	0.622	0.483	0.125	0.002	0.365	0.062	0.119	0.186	1.000										
(10) Age at IPO	-0.085	-0.022	-0.009	0.078	-0.048	-0.016	-0.078	0.196	0.016	1.000									
(11) Start-up hub	0.193	0.167	0.132	0.057	0.076	0.090	0.237	-0.129	0.072	-0.039	1.000								
(12) Multiple mega-deals	0.588	0.443	0.112	0.042	0.485	0.081	0.121	-0.009	0.502	-0.086	0.067	1.000							
(13) IPO market hotness	-0.009	-0.008	0.020	0.073	-0.009	-0.093	-0.082	-0.070	-0.017	-0.017	-0.026	0.009	1.000						
(14) Stock exchange	-0.275	-0.299	-0.210	-0.161	-0.189	-0.146	-0.261	-0.154	-0.075	-0.152	-0.025	-0.100	0.010	1.000					
(15) Industry	0.111	0.122	0.120	0.129	0.107	0.032	0.052	-0.092	0.053	-0.109	0.113	0.054	0.007	-0.054	1.000				
(16) IPO year	0.138	0.066	-0.002	0.011	0.177	-0.225	0.007	-0.261	0.064	-0.024	0.115	0.140	0.287	0.120	0.192	1.000			
Instrumental variables																			
(17) Lead VC avg. deal size	0.209	0.199	0.104	0.107	0.204	0.006	0.093	0.047	0.103	0.023	0.054	0.087	0.063	-0.064	-0.042	0.109	1.000		
(18) Company avg. deal size	0.587	0.426	0.123	0.052	0.564	-0.009	0.187	0.000	0.501	-0.124	0.087	0.528	-0.039	-0.003	0.086	0.263	0.232	1.000	
(19) Lead VC distance	-0.055	-0.078	-0.114	-0.023	-0.089	-0.156	-0.012	-0.016	-0.045	0.069	-0.041	-0.056	0.073	0.142	-0.013	0.066	0.164	0.049	1.000

Note: This table reports pairwise correlations of all variables used in all regressions in the IPO success framework.

Appendix 2: Pairwise correlation matrix of the post-IPO performance framework

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Post-IPO performance measures																				
(1) ln(90-day valuation)	1.000																			
(2) ln(180-day valuation)	0.973	1.000																		
(3) ln(360-day valuation)	0.927	0.950	1.000																	
(4) ln(720-day valuation)	0.861	0.875	0.920	1.000																
Variable of interest																				
(5) Mega-deal	0.375	0.368	0.326	0.352	1.000															
Control variables																				
(6) Underpricing	0.426	0.424	0.392	0.388	0.162	1.000														
(7) Price revision	0.403	0.392	0.359	0.361	0.179	0.420	1.000													
(8) Proceeds	0.304	0.297	0.282	0.276	0.228	0.008	0.074	1.000												
(9) Lead VC reputation	0.070	0.075	0.037	0.007	0.056	0.096	0.128	0.083	1.000											
(10) Lead underwriter reputation	0.455	0.462	0.475	0.484	0.175	0.174	0.222	0.080	0.071	1.000										
(11) Age at IPO	0.006	-0.013	0.007	0.027	-0.048	0.078	-0.009	-0.020	-0.016	-0.078	1.000									
(12) Start-up hub	0.142	0.153	0.158	0.143	0.076	0.057	0.132	0.062	0.090	0.237	-0.039	1.000								
(13) Multiple mega-deals	0.404	0.370	0.345	0.360	0.485	0.042	0.112	0.403	0.081	0.121	-0.086	0.067	1.000							
(14) M/B ratio	0.207	0.209	0.211	0.180	0.058	0.051	0.047	0.021	-0.039	0.010	0.057	-0.037	-0.009	1.000						
(15) Stock exchange	-0.290	-0.269	-0.249	-0.270	-0.189	-0.161	-0.210	-0.028	-0.146	-0.261	-0.152	-0.025	-0.100	0.072	1.000					
(16) Industry	0.113	0.125	0.135	0.122	0.107	0.129	0.120	0.049	0.032	0.052	-0.109	0.113	0.054	0.094	-0.054	1.000				
(17) IPO year	0.052	0.051	0.079	0.121	0.177	0.011	-0.002	-0.004	-0.225	0.007	-0.024	0.115	0.140	0.010	0.120	0.192	1.000			
Instrumental variables																				
(18) Lead VC avg. deal size	0.205	0.216	0.197	0.191	0.204	0.107	0.104	0.056	0.006	0.093	0.023	0.054	0.087	0.052	-0.064	-0.042	0.109	1.000		
(19) Company avg. deal size	0.383	0.386	0.355	0.359	0.564	0.052	0.123	0.335	-0.009	0.187	-0.124	0.087	0.528	0.027	-0.003	0.086	0.263	0.232	1.000	
(20) Lead VC distance	-0.060	-0.058	-0.076	-0.038	-0.089	-0.023	-0.114	-0.045	-0.156	-0.012	0.069	-0.041	-0.056	-0.105	0.142	-0.013	0.066	0.164	0.049	1.000

Note: This table reports pairwise correlations of all variables used in the regressions of the post-IPO performance framework.

Appendix 3: Pairwise correlation matrix

Variables		*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*	*(13)*	*(14)*
(1)	*PE acquisition*	1.000	0.028	-0.053	0.140	0.014	-0.022	0.045	0.128	0.029	-0.020	-0.053	-0.031	-0.021	-0.004
(2)	*Ln(Total VC funding)*	0.028	1.000	0.423	0.241	0.015	0.061	0.031	0.436	0.089	0.181	0.122	0.594	0.033	-0.001
(3)	*Most reputated VC*	-0.053	0.423	1.000	0.038	0.023	-0.012	0.022	0.126	0.042	0.092	0.198	0.387	-0.005	0.012
(4)	*Avg. syndicate fund age*	0.140	0.241	0.038	1.000	0.016	-0.033	-0.019	0.766	0.113	0.132	-0.062	0.188	0.004	0.000
(5)	*Cold IPO Market*	0.014	0.015	0.023	0.016	1.000	-0.058	0.011	0.013	0.013	-0.003	0.005	0.004	-0.200	0.252
(6)	*Hot IPO Market*	-0.022	0.061	-0.012	-0.033	-0.058	1.000	0.008	-0.017	-0.021	0.023	-0.006	0.028	0.182	0.028
(7)	*Industry match*	0.045	0.031	0.022	-0.019	0.011	0.008	1.000	-0.008	0.051	0.016	0.004	0.020	-0.011	-0.004
(8)	*Company age*	0.128	0.436	0.126	0.766	0.013	-0.017	-0.008	1.000	0.160	0.174	-0.051	0.389	0.014	-0.003
(9)	*B2B businees*	0.029	0.089	0.042	0.113	0.013	-0.021	0.051	0.160	1.000	0.035	0.001	0.093	-0.003	-0.005
(10)	*Patent claims*	-0.020	0.181	0.092	0.132	-0.003	0.023	0.016	0.174	0.035	1.000	0.033	0.169	-0.006	0.001
(11)	*Startup hub*	-0.053	0.122	0.198	-0.062	0.005	-0.006	0.004	-0.051	0.001	0.033	1.000	0.104	0.011	0.020
(12)	*Syndicate size*	-0.031	0.594	0.387	0.188	0.004	0.028	0.020	0.389	0.093	0.169	0.104	1.000	0.037	0.004
(13)	*GDP growth*	-0.021	0.033	-0.005	0.004	-0.200	0.182	-0.011	0.014	-0.003	-0.006	0.011	0.037	1.000	-0.084
(14)	*Volatility index*	-0.004	-0.001	0.012	0.000	0.252	0.028	-0.004	-0.003	-0.005	0.001	0.020	0.004	-0.084	1.000

Appendix 4: Logistic regression including an interaction of *Industry match* and time

Variables	(4a)
Ln(Total VC funding)	0.280***
	(0.088)
VC reputation	-1.118***
	(0.402)
Avg. syndicate fund age	0.103***
	(0.027)
Hot IPO sentiment	-1.160
	(0.745)
Cold IPO sentiment	0.252
	(0.246)
Industry match	-195.552***
	(65.996)
Acquisition year	-0.013
	(0.024)
Industry match x Acquisition year	0.097***
	(0.033)
Company age	0.087***
	(0.029)
B2B business	0.253
	(0.169)
Patent claims	-0.001*
	(0.001)
Startup hub	-0.287*
	(0.159)
Syndicate size	-0.126***
	(0.041)
GDP growth	-2.075
	(1.545)
Volatility index	0.001
	(0.009)
Observations	4,842
Year FE	yes
Industry FE	yes
Pseudo R^2	0.126
Wald Chi2	213.2

Note: This table presents multivariate logistic regression estimates based on robust standard errors. Variable definitions can be found in Table 1. *, **, and *** denote coefficient estimates significantly different from 0 at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in parentheses.

Eidesstattliche Versicherung

Ich, Nico Lehnertz, versichere an Eides statt, dass die vorliegende Dissertation von mir selbstständig und ohne unzulässige fremde Hilfe unter Beachtung der „Grundsätze zur Sicherung guter wissenschaftlicher Praxis an der Heinrich-Heine-Universität Düsseldorf" erstellt worden ist.

Düsseldorf, 13.01.2023