Information Asymmetries and Signals in Markets for Venture Capital: Relevance for the Selection Behavior and Performance of Early-stage Investors

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List of Abbreviations

AG	Aktiengesellschaft
AME	Average marginal effect
EPO	European Patent Office
EU	European Union
FE	Fixed effects
GDP	Gross domestic product
GmbH	Gesellschaft mit beschränkter Haftung
HR	Hazard ratio
IIA	Assumption of the independence of irrelevant alternatives
IPC	International Patent Classification
IPO	Initial public offering
Max	Maximum
Min	Minimum
NACE	Nomenclature Statistique des Activités Économiques dans la Communauté Européenne
NAICS	North American Industry Classification System
OECD	Organization for Economic Co-operation and Development
OLS	Ordinary least squares
PATSTAT	Patent Statistical Database
SARL	Société à Responsabilité Limitée
SAS	Société par Actions Simplifiée
SD	Standard deviation
UK	United Kingdom
U.S.	United States of America
USPTO	United States Patent and Trademark Office
WIPO	World Intellectual Property Organization
VC	Venture Capital

General Introduction

Analyzing the relationship between early-stage investors and young innovative firms is a central research topic in the entrepreneurial finance literature. Venture capital (VC) has been shown to be an important source of financing for entrepreneurial firms to develop and commercialize their inventions and drive technological, industrial and societal change (e.g., Timmons and Bygrave 1986, Kaplan and Lerner 2010, Samila and Sorenson 2011). Financing young innovative firms requires early-stage investors to have a mindset of experimentation and willingness to fail (e.g., Nanda and Rhodes-Kropf 2013), as these firms lack financial resources, managerial experience and complementary assets. Additionally, they face a considerable uncertainty due to the nature of their inventive activity (e.g., Souder and Moenaert 1992, Fleming 2001, Freel 2005, Jalonen 2012). Not surprisingly, the majority of returns for early-stage investors comes from a minority of their investments (Sahlman 2010).

Despite this uncertainty, early-stage investors take on the risk of financing young firms by building a portfolio of promising start-ups, hoping that at least some of them turn out to be blockbusters (Chan 1983, Sahlman 1990). In doing so, early-stage investors have been shown to effectively deal with agency problems in markets with imperfectly distributed information, which occur in situations where economic agents that engage in a transaction do not have access to the same information set, i.e., one party has private information (Akerlof 1970, Spence 1973, Stiglitz 1975).

Prior to entering the investment relationship, founders of a young firm are better informed about the quality of their start-up than a potential investor. This might lead to an adverse selection when entrepreneurs exploit their information advantage and overstate the quality of their firm (e.g., Kaplan and Strömberg 2004). To overcome problems of adverse selection and select high-quality firms, investors can rely on observable information, so-called signals, that are costly to obtain and correlated with quality, so that only high-quality firms have an incentive to invest in the signal (Spence 1973, 2002, Stiglitz 2000). During the investment relationship, VC investors actively monitor their portfolio firms to prevent moral hazard, e.g., founders taking (unobservable) actions out of self-interest that are not aligned with the objectives of the investor (Sahlman 1990, Amit et al. 1998, Kaplan and Strömberg 2004, Denis 2004). They also provide management expertise in addition to financial resources in order to support young firms in overcoming their funding gap, growing and outperforming their competitors

(Gorman and Sahlman 1989, Sapienza 1992, Lerner 1994, Hellmann and Puri 2002, Baum and Silverman 2004).

In summary, the superior performance of VC-backed firms compared to non-VC-backed firms might be related to the fact that early-stage investors are able to identify high quality firms (selection), or the fact that early-stage investors support them with value-enhancing resources (treatment). However, the exact nature of this relationship is still an open research question due to unobserved heterogeneity that might determine the selection behavior of early-stage investors and the empirical challenge of disentangling selection from treatment (e.g., Bertoni et al. 2011, Croce et al. 2013). While previous entrepreneurial finance studies have shown the importance of distinct signals and additional information for the selection behavior of early-stage investors, recent work has noted complementary or substitutional effects between multiple signals and additional (positive or negative) information in interaction (Pollock et al. 2010, Conti et al. 2013a, Haeussler et al. 2014, Stern et al. 2014, Plummer et al. 2016, Colombo et al. 2019b). This emphasizes the complexity of the cognitive processes that determine the selection behavior and decision-making quality of early-stage investors. Moreover, external contingencies such as recession periods, eventually have an impact on the selection behavior of early-stage investors and the subsequent treatment effect of VC financing on young innovative firms, as early-stage investors face severe liquidity constraints during economic downturns (e.g., Block et al. 2010, Nanda and Rhodes-Kropf 2013, Conti et al. 2019).

This thesis therefore develops a new theoretical and advanced empirical understanding of the investment relationship between early-stage investors and young entrepreneurial firms by studying the relevance of signals, additional (positive or negative) information and external contingencies (i.e., recession periods) for the selection behavior and decision-making quality of early-stage investors, as well as the subsequent treatment effect of VC financing on firm innovation. In the following, I shortly summarize the theoretical contribution, empirical approach and most important findings of each of the three essays, which form the chapters of my thesis.

Chapter 1 – The Dark Side of Signals: Patents Protecting Radical Inventions and Venture Capital Investments

The first essay of my thesis is joint work with Massimo Colombo, Massimiliano Guerini and Karin Hoisl. The objective of this essay is to examine how ambiguous signals, i.e., signals that convey positive and negative information at the same time, affect the selection behavior of reputable compared to less reputable VC investors. While the signaling value of patents to prospective investors is well understood (Lanjouw and Schankerman 2001, Long 2002, Farre-Mensa et al. 2020), this study focuses on the signaling effect of patents that protect radical inventions, i.e., inventions that are based on knowledge components that had previously not been combined (Schumpeter 1934, Fleming 2001, Dahlin and Behrens 2005). On the one hand, patents protecting radical inventions can be considered a strong signal of quality, since radical inventions have shown to be developed by high-performing firms and offer tremendous earning potential in case the underlying invention outperforms existing technologies (e.g., Ahuja and Lampert 2001, Eggers and Kaul 2018). On the other hand, radical inventions require high investment sums for their potential to be realized and are characterized by a high risk of failure, as firms developing these inventions face considerable technical, market and legal uncertainty (e.g., Dewar and Dutton 1986, Fleming 2001, Harhoff et al. 2003). Thus, patents protecting a radical invention also contain negative information.

Based on signaling theory and entrepreneurial finance literature, we theoretically model the sorting process between Venture Capital (VC) investors and young firms (Sørensen 2007, Conti et al. 2013b). Young firms generally prefer more reputable VC investors, as they offer more financial and non-financial resources than less reputable investors (Hsu 2004, Sørensen 2007, Nahata 2008). In turn, highly reputable investors are attracted by young firms with a patent protecting a radical invention. We argue that they are better able to deal with the higher uncertainty of radical inventions, as their reputation makes it easier for them to form syndicates, which ultimately leads to better decision-making and allows for risk-sharing among partners (Bygrave 1987, Lerner 1994, Wright and Lockett 2003).

Using a sample of 759 young life science firms and 555 independent VC investors, we implement a matching model and assess all realized standalone and syndicated investment ties against unrealized investment ties that could have formed but did not. We show that a first-round investment tie between a highly reputable investor and a firm is more likely to occur when the firm has at least one patent protecting a radical invention compared to a firm with no patents or patents that only protect incremental inventions, while no significant correlation is found for less reputable investors. Moreover, this relationship is entirely attributable to the formation of syndicated investment ties. Finally, we observe that this relationship disappears for follow-on investment ties, as more information about the firm and its patents is revealed over time, thereby decreasing information asymmetry (e.g., Haeussler et al. 2014).

We can derive that negative information accompanying a signal of quality matters for the selection behavior of VC investors, as investors react to this signal according to their ability to deal with this negative information.

Chapter 2 – The Selection Ability of Crowdinvestors and the Value of Campaign Information

The second essay is a single-author paper and focuses on the selection behavior and quality of early-stage investors on crowdinvesting platforms. Crowdinvesting platforms are an alternative financing channel for young firms that allows private investors without (visible) early-stage investment experience to participate in a market with high information asymmetries (e.g., Ahlers et al. 2015, Bruton et al. 2015, Vulkan et al. 2016, Hornuf and Schwienbacher 2017). Recent literature has dealt with signals on crowdinvesting platforms and suggests that crowdinvestors rely on the investment decisions of peer investors who contributed earlier to the funding campaign and are visible on the platform (Ahlers et al. 2015, Vismara 2018). These information cascades from early to late investors might be detrimental if late investors do not evaluate the signals that young firms send, but only mimic the investment decisions of (potentially uninformed) early investors (e.g., Herzenstein et al. 2011, Zhang and Liu 2012). Therefore, this essay investigates whether additional information, generated through the funding decisions of investors that contributed earlier to the funding campaign, benefits the decision-making quality of crowdinvestors who invest later.

Based on literature on observational learning (Banerjee 1992, Bikhchandani et al.1992), I argue that positive campaign information, e.g., if the campaign already reached a high funding level, is valuable to uninformed investors, if these investors delay their investment decisions until informed investors have invested and then additionally join the campaign at higher funding levels. Moreover, I argue that the value of additional campaign information is contingent on the strength of the observable firm signals. Firms with a strong signal of quality attract more uninformed investors, as decision-makers typically focus on stronger signals and discard potentially conflicting information in complex decision-making situations (Drover et al. 2018).

To empirically examine the value of campaign information for the decision-making quality of crowdinvestors, I use a sample of 52,024 investments from 18,690 investors on the largest German crowdinvesting platform. I estimate the hazard of an individual investment to result in a failure or exit and analyze whether investments made at high campaign funding levels (i.e., positive campaign information) turn out to be more successful than investments at lower funding levels. Moreover, I examine whether this relationship differs between investments in firms with a high pre-money valuation (i.e., strong signal) compared to investments in less valuable firms (i.e., weaker signal). The results show that investments at high funding levels turn out to be more successful than investments at lower funding levels. However, this relationship is confined to investments in firms with a lower pre-money valuation.

This essay adds to the recent discussion on complementary effects of additional information and signals by showing that positive campaign information generated through earlier funding decisions benefits the decision-making quality of early-stage investors in case the firm sends a weaker signal of quality. Moreover, the fact that crowdinvestors are not entitled to any voting or monitoring rights to issue management instructions allows to directly investigate the selection ability of crowdinvestors in the absence of any treatment effect. That is, the performance of crowdinvestors solely depends on their ability to select companies of high quality that turn out to be successful investments over time.

Chapter 3 – Selection or Treatment: Venture Capital Investments During Recessions and the Innovation Output of Young Life-science Firms

The third chapter of my thesis is, again, coauthored with Massimo Colombo, Massimiliano Guerini and Karin Hoisl. The first objective of this study is to investigate the selection behavior of VC investors under consideration of resource constraints induced by recession periods. Recent literature suggests that economic shocks introduce a new type of uncertainty that affects both VC investors and their portfolio firms (e.g., Gompers et al. 2021). There is empirical evidence that VC investors adapt their selection behavior during economic downturns by funding less innovative firms (Nanda and Rhodes-Kropf 2013) or decreasing the number of first-round investment deals (Block et al. 2010). Second, we are interested in whether a potential shift of the selection behavior of VC investors during economic recessions propagates into a differential treatment effect of VC financing on firm innovation, as VC investors have been shown to stimulate the innovative activities of their portfolio firms (Kortum and Lerner 2000, Bertoni et al. 2010, Bertoni and Tykvová 2015). A better understanding of the potential heterogeneity in selection and treatment by economic situation is highly relevant, as a decline in innovation—either due to the selection of less-innovative firms or a decreased treatment effect of VC financing on firm innovation—might have severe effects on the overall economic development (e.g., Timmons and Bygrave 1986, Samila and Sorenson 2011).

To empirically investigate the selection and treatment effect of VC financing, we use a sample of 372 VC-backed firms and 625 non-VC-backed firms operating in the life sciences. In our analysis of the determinants of the transition of young life science firms into VC financing, we do not find VC investors to change their investment behavior during periods of recession, as firms with a higher patent stock have a higher likelihood of receiving a first round of VC, regardless of the economic situation. Considering the treatment effect of VC investments on firm innovation, we only observe a significant difference of the patenting activity of VC-backed firms in the short-term, i.e., firms that received their first financing round during a recession compared to a period of non-recession show a smaller increase of the patent stock in the first two years after VC receipt. However, this difference vanishes in the long-term. Interestingly, the magnitude of the treatment effect is economically quite small when correcting for selection, which is consistent with recent survey evidence suggesting that VC investors view deal selection as being more important than their post-investment activities (Gompers et al. 2020).

We can conclude that VC investors stick to their established decision-making processes even under severe economic constraints. Moreover, although we can only speculate about why firms have a smaller short-term innovation output when they receive VC financing during a recession compared to a period of non-recession, the fact that they are able to catch up thereafter is reassuring from an economic and societal perspective.

1 The Dark Side of Signals: Patents Protecting Radical Inventions and Venture Capital Investments

1.1 Introduction

Signals are observable costly actions whose cost is higher for lower-quality agents (Spence 1973, 2002). Firms can use signals to make their high quality visible to uninformed third parties, thus overcoming the adverse selection problems resulting from information asymmetries (Akerlof 1970). As young innovative firms lack a track record and have uncertain prospects, it is very difficult for potential resource providers (e.g., investors) to assess these firms' quality. Therefore, signals play a key role in facilitating these firms' access to external resources, especially external financing (Carpenter and Petersen 2002, Hall and Lerner 2010).

Patents are an important signal of the unobserved quality of young innovative firms, as patents are more costly to obtain for low-quality firms than for high-quality firms (Lanjouw and Schankerman 2001, Long 2002, Farre-Mensa et al. 2020). As a result, patents can help these latter firms mobilize external resources by providing access to venture capital (VC) financing (see Hall 2019 for a review). Previous studies highlight that beyond their signaling function, patents reveal valuable information (e.g., the data emerging during patent examination) concerning the technical value or the strength of protection of the underlying inventions and their market prospects, which would otherwise be difficult for prospective investors to grasp (Heeley et al. 2007, Haeussler et al. 2014, Hegde et al. 2020). This information affects the strength of the signal conveyed by patents and makes signaling firms more or less attractive to prospective investors.[1] Patents protecting *radical inventions*, i.e., inventions that are based on knowledge components that had previously not been combined (Schumpeter 1934, Fleming

[1] Spence (1973) makes an important distinction between the observable, inalterable attributes of an individual (or firm), such as gender and race, and the alterable attributes that the individual (or firm) can manipulate by bearing some costs. He reserves the term "signal" for these manipulable and costly attributes, while he calls the inalterable attributes "indices". As a corollary, while indices may convey fully negative information, signals cannot, as individuals (and firms) have no incentive to bear a cost to communicate negative information. In the management literature, the distinction between signals and indices has often gone lost. Indeed, scholars have considered "rhetoric signals" (Steigenberger and Wilhelm 2018), whose cost is independent of the quality of the sender, and "negative signals" (Drover et al. 2018), which convey completely negative information. We adhere to Spence's approach in that we consider costly signals. However, in line with the management literature, we allow that in addition to the primary positive information about the quality of the signaling agent, signals convey negative secondary information.

2001, Dahlin and Behrens 2005), are a case in point. These patents send additional information to prospective investors. The quality signal of patents protecting radical inventions is stronger than that of patents protecting incremental inventions, since strong performers in a technology area have been shown to be more likely than weak performers to develop radical inventions (Dewar and Dutton 1986, Henderson 1993). However, the stronger signal is accompanied by negative information about the greater uncertainty and longer-term payoff of radical inventions (Eggers and Kaul 2018). The dark side of a signal has so far gone almost unnoticed in the signaling literature (for a partial exception, see again Haeussler et al. 2014 and Hegde et al. 2020). What has to our knowledge not been considered at all is a signal with additional information that *simultaneously* increases (= strong signal) and decreases (= dark side) the attractiveness of a firm—in our case, a patent protecting a radical invention.

The aim of this paper is to investigate how the receivers of signals react to strong signals with a dark side. To fill this gap in the literature, we investigate how patents protecting radical inventions are related to the investment behavior of VC investors. In particular, we examine how depending on the characteristics of signal receivers and their ability to deal effectively with the negative aspects of the underlying radical inventions, these complex signals make signaling firms more or less attractive.

Answering this research question is important since radical invention is instrumental in promoting technological and social change (Nelson and Winter 1982, Tushman and Anderson 1986). Radical inventions are more likely to originate from new entrants than from established firms (Schumpeter 1934). Although young firms have greater incentives to invest in radical inventions than do incumbent firms (Arrow 1962) and are not held back by inertia (Hannan and Freeman 1984, Hill and Rothaermel 2003, Lavie 2006), they often lack the financial resources needed for these inventions. As a result, external resource mobilization is indispensable.

We rely on signaling theory and the entrepreneurial finance literature and model as a sorting process, the match between a VC investor and a young firm (Sørensen 2007, Conti et al. 2013b). In addition to financial resources, VC investors provide management support and access to their network of prospective suppliers, customers, and collaboration partners (Hellmann and Puri 2002, Hochberg et al. 2007). In situations in which they had multiple offers, young firms were shown to regard more reputable VC investors as the most attractive investors because of the greater non-financial value these investors add to portfolio firms (Hsu 2004, Nahata 2008). In turn, highly reputable VC investors are attracted by the strength of the quality signal conveyed by firms that file patent applications for radical inventions. In addition, their high reputation makes it easier for these investors to form syndicates, allowing them to share the risk and obtain a second opinion on the focal venture (Bygrave 1987, Lerner 1994, Wright and Lockett 2003). Conversely, low reputation VC investors need to "grandstand" to be able to raise more capital from prospective investors (Gompers 1996, Nanda et al. 2020) and thus, are discouraged by the high risk and long-term payoff inherent in investing in young firms with radical patents.

Over time, as more information is revealed, the information asymmetry between young firms and prospective VC investors is reduced, which decreases the information value of the signals these firms send (Hsu and Ziedonis 2008, Hoenig and Henkel 2015). Accordingly, as more information about firms with and without patents protecting radical inventions is revealed over time, the effect of the additional (both positive and negative) information radical patents convey to prospective investors also decreases over time, i.e., the effects are stronger in the first financing round and weaker in the follow-on rounds. Based on these arguments, we predict that in the first VC round, firms with patents protecting radical inventions are more likely to form ties with more reputable VC investors and that these ties are more likely to be syndicated. Conversely, we expect these relations to weaken or even vanish in follow-on rounds.

To test these predictions, we use data from the VICO 4.0 dataset, which was created with the support of the VICO and RISIS projects and funded by the European Commission under the FP6, FP7 and H2020 programs. This dataset provides comprehensive geographical, industry, and accounting information on firms located in 27 European countries, the UK and Israel, which received their first VC investment between January 1998 and March 2015. These firms represent a positive selection in terms of quality, ensuring that extreme quality differentials among young firms do not bias our results. We focus our analysis on firms active in the life sciences, since this branch of science is characterized by a high patent propensity, high capital requirements, and vivid startup activity (Cohen and Walsh 2002, Nasto 2008). The information on patent filings was extracted from the PATSTAT database of the European Patent Office (EPO). PATSTAT contains bibliographic patent data from more than 100 patent offices worldwide. The identified VC investors' worldwide investment histories covering 1980 to 2015 were extracted from the VICO and Thomson Reuters EIKON databases. This latter database contains over 30 years of historical information on VC investors and investee firms worldwide. After dropping observations with missing information, our final sample consists of 759 young firms and 555 VC investors. A total of 342 of these firms had at least one (pending) patent application with the EPO before receiving their first round of VC funding, and 62 have at least one (pending) patent application protecting a radical invention.

In the econometric analysis, we use a matching model. We first model the probability that a focal firm has a realized investment tie with a focal VC investor in a first or a follow-on investment round, and second, that this tie corresponds to either a standalone or a syndicated investment tie. We investigate how these probabilities vary depending on the characteristics of the firms (i.e., whether they have developed and patented at least one radical invention) and of the VC investors (their reputation). To do so, we assess the 1,792 realized firm-VC investor ties against unrealized firm-VC investor ties that could have formed.

A logit regression comparing the alternative outcomes "unrealized tie" and "realized tie" for first-round investments provides evidence that when a firm has at least one patent application protecting a radical invention, this is associated with an 89 (90) percent increase in the probability of forming a first-round investment tie with a highly reputable VC investor compared to a firm with no patents (only patents protecting incremental inventions). We do not detect a significant relationship with respect to the probability of forming a first-round investment tie with a less reputable investor. Second, a multinomial logit comparing the alternative outcomes "unrealized tie", "standalone tie" and "syndicated tie" for first-round investments provides evidence that the above-mentioned increase in the probability of forming an investment tie with a reputable VC investor if a firm filed at least one patent protecting a radical invention is confined to syndicated ties. Indeed, we detected a 150 (143) percent increase in the probability of a syndicated first-round investment tie with a highly reputable VC investor compared to firms with no patents (only patents protecting incremental inventions). Last, we find that the abovementioned relations hold true for first-round investments and vanish in follow-on rounds. We conduct several robustness checks based on different specifications of the matching model and different definitions of the VC reputation variable. These estimates confirm our results. We also rule out the most obvious alternative explanations of our results.

Our paper offers a novel contribution to the signaling literature in that we analyze signals that simultaneously convey good and bad additional information, and we show that this opposing information matters for the investment decisions of VC investors. Additionally, we contribute to the entrepreneurial finance literature. First, we show that sorting mechanisms that match VC investors and young firms change over time. Second, we add to this literature by considering the effects of syndication, a key characteristic of VC investments.

1.2 Conceptual background and hypotheses

1.2.1 Signals and young firms' access to external financing

Signaling theory is concerned with overcoming the negative effects of information asymmetries, which may prevent value-creating transactions from being realized (Spence 1973, 2002, Stiglitz 2002). Information asymmetry occurs in situations where the two parties of a transaction do not have access to the same information set (i.e., one party has private information). Specifically, one party cannot observe the quality of the product or service of the other party, that is part of the transaction or cannot observe the behavior and underlying intentions of the other party (Akerlof 1970, Stiglitz 2000, Elitzur and Gavious 2003).

Signals are observable costly actions that are positively correlated with quality and convey information about intentions (Spence 1973, 2002). Signals are effective, i.e., credible, when they are costly to obtain and when the costs are lower for high-quality firms than for low-quality firms. This makes signaling a positive return strategy only for high-quality firms. Under these conditions, sending a signal leads to a separating equilibrium, revealing the true unobserved quality of firms (see Connelly et al. 2011 and Bergh et al. 2014 for a review).

Mobilizing external resources, especially external financing, is fundamental for young firms but is very challenging, as it is impeded by information asymmetries (Hall and Lerner 2010). Young firms have a limited or non-existent track record, and their technologies and market prospects are surrounded by great uncertainty. Moreover, because of knowledge misappropriation concerns, entrepreneurs are reluctant to make their private information public. Therefore, it is very challenging for external investors, including VC investors, to disentangle high-quality from low-quality young firms.

To overcome these information asymmetries and attract external investors, high-quality young firms can resort to signals. Previous studies have shown that young firms signal their quality through the composition of their management team (Higgins and Gulati 2006, Pollock and Gulati 2007) and board of directors (Certo 2003) or through their affiliation with prominent organizations (Stuart et al. 1999). Scholars have also convincingly argued that patents qualify as a credible signal for young firms (Long 2002). Filing a patent application has both direct and indirect costs for young firms. In addition to the non-negligible direct cost of the application, patents have a substantial opportunity cost because of the time entrepreneurs need to spend in communications with patent attorneys. These indirect costs are smaller for firms having higher-quality inventions (Hsu and Ziedonis 2013). Accordingly, several previous studies highlight that patents help young firms obtain VC, especially in the early stage, when information asymmetries are more severe (Cao and Hsu 2011, Conti et al. 2013a, Conti et al. 2013b, Hsu and Ziedonis 2013, Haeussler et al. 2014, Hoenen et al. 2014. See Hoenig and Henkel 2015 for divergent results).

Recent works in management notice that young firms tend to send multiple signals (Pollock et al. 2010, Ozmel et al. 2013, Drover et al. 2018, Colombo et al. 2019b), whose strength can vary (Plummer et al. 2016, Vanacker et al. 2020). Multiple signals have positive additive effects when they convey information relating to complementary domains, such as the entrepreneurs' status and their reputation (Stern et al. 2014) or the science domain and the business and finance domains (Colombo et al. 2019b). Overlapping (strong) signals pertaining to two similar domains, such as the IPO firms' affiliation with several prestigious VC investors and their affiliation with underwriters (Pollock et al. 2010), are redundant and have limited additional information value. However, even an overlapping and redundant signal may bring value when it reinforces another signal that would be perceived by uninformed parties as weak when received in isolation. For example, Plummer et al. (2016) show that an endorsement by a prominent accelerator reinforces the signals conveyed by the managerial experience of entrepreneurs and by the presence of at least one product introduced to the market. Similarly, Audretsch et al. (2012)

find that firms convey a stronger quality signal when their technology is protected not only through a patent but also through a functioning prototype.

In fact, even when young firms send a single signal, the signal may subsequently convey additional information, which reinforces its strength. Patent applications are a case in point. During the subsequent patent examination process, additional information is revealed about the strength of the patent protection and the market prospects of the underlying invention (Hegde et al. 2020). Accordingly, Haeussler et al. (2014) show that patenting firms are more attractive to prospective VC investors and that the time to the first VC round is reduced if more of the firms' patents are opposed by a third party or are cited by large inventive companies. They also show that "bad news" during the patent examination process, such as delays in the publication of the search report by the patent office and a less favorable evaluation by patent examiners of the novelty of patents (i.e., high share of X and Y references in the search report), increases the time to the first VC round.

However, an important aspect that has gone unnoticed in this stream of literature is that sometimes the same characteristic that makes a signal strong also conveys "bad news" – at least to some of the signal receivers. In the next section, we will argue that the patents protecting a radical invention convey a stronger signal of quality than patents protecting incremental inventions, but at the same time, the patents protecting a radical invention have a dark side because of the more uncertain and longer-term returns associated with these inventions. Therefore, whether radical patents make patenting firms more or less attractive to VC investors is questionable and depends on the specific investor characteristics that allow them to neutralize these patents' dark side.

1.2.2 Patents protecting radical inventions: A strong signal with a dark side

Although they are rare events, radical inventions, i.e., inventions based on knowledge components that have not been combined before (Schumpeter 1934, Fleming 2001, Dahlin and Behrens 2005, Rizzo et al. 2020), have attracted considerable interest in the innovation literature, because radical inventions have the potential to influence future technical developments (Schoenmakers and Duysters 2010) and to result in a significant advance in the performance of a technology (Eggers and Kaul 2018). Consequently, firms invest in radical inventions in the hope of outperforming existing technologies

(Dewar and Dutton 1986). Schumpeter (1934) even claimed that radical technological change can render established technologies obsolete and start new technology life cycles.

Radical inventions have been shown to come from high-performing firms more likely than from low-performing firms (Eggers and Kaul 2018). In this context, the term high performing refers to firms that dispose of large and high-quality knowledge pools and are able to combine existing with distant knowledge and to firms that have already outperformed their competitors in the past and employ highly capable engineers who form strong teams (Ahuja and Lampert 2001, Nerkar 2003, Subramaniam and Youndt 2005, Helfat and Winter 2011). Moreover, patents protecting radical inventions are by definition more likely to be granted since radical inventions, i.e., novel knowledge combinations, are more likely to fulfill the requirements of patentability (novelty, inventive step, and usefulness) (Arts and Veugelers 2015). Additionally, these patents are, on average, characterized by a higher scope of protection, since they are often based on inventions resulting from basic rather than applied research (Rizzo et al. 2020).

However, radical inventions also induce considerable costs and have long-term uncertain returns. First, they are accompanied by considerable technical, legal and market uncertainty, and firms have to be able and willing to deal with this uncertainty. Technical uncertainty is high since radical inventions are based on novel combinations of knowledge components, i.e., a requirement to leave safe and comfortable paths (Ettlie et al. 1984, Dewar and Dutton 1986). The more often the same knowledge components are combined, the more inventors learn about successful and unsuccessful knowledge combinations and their application in different contexts. Relying on known knowledge combinations, therefore, is more likely to result in useful inventions (Hargadon 2003, Arts and Veugelers 2015). Novel combinations of knowledge components, on the contrary, can lead to breakthrough inventions, but at the same time, these novel combinations have a high probability of failing completely. In other words, the variance of success is much higher for combinations of so far uncombined knowledge components than for known knowledge combinations (Fleming 2001). At the same time, patents protecting radical technologies may render existing technology and existing competitive advantages obsolete (Dewar and Dutton 1986, Schumpeter 1934), which may induce competitors to file oppositions to challenge the validity of these potentially threatening patents (Harhoff et al. 2003). Oppositions, in turn, increase the legal uncertainty of patents protecting radical inventions. Should a patent be declared invalid in an opposition case, the technology lapses into the public domain, which renders the value of the technology for the firm and for investors to be (almost) zero. Last, market uncertainty surrounding patents that protect radical inventions is high, since firms must move into "unknown territory" and convince potential customers of the advantages of the new technology or of the resulting product or service (O'Connor and McDermott 2004: 11).

Second, radical inventions require massive investments, as firms need to transform their technological and market-related capabilities (Lavie 2006) and acquire new ones (Anderson and Tushman 1990, Hargadon and Sutton 1997). In addition, as mentioned above, radical inventions are often the outcome of basic rather than applied research. Consequently, the development of these inventions is resource intensive, and the time between making the invention and generating revenues can be several years (Rosenberg 1974, Adams 1990, O'Connor and McDermott 2004, Rizzo et al. 2020). Last but not least, the time until the market launch is a function of the investment made by the firm (Reinganum 1983).

1.2.3 Hypotheses

In the previous section, we have argued that patents protecting radical inventions reveal valuable information that reinforces the strength of the conveyed signal. This information includes the fact that the underlying inventions are typically developed by high-performing firms, have the potential to change technologies and markets, have enormous earnings potential, and will be protected by patents characterized as having on average a higher value. However, at the same time, the inventions underlying these patents are tied to high costs and considerable technological, legal and market uncertainty and have long-term returns. Hence, these patents also convey negative information.

As patents protecting radical inventions send a stronger quality signal than patents protecting incremental inventions (and no patents, of course), one may presume that in early investment rounds, where information asymmetry is particularly high, young firms having those patents are especially attractive to VC investors. Given the sorting process underlying the formation of a VC investor-young firm tie (Sørensen 2007, Conti et al. 2013b), i.e., a process in which young firms prefer more reputable VC investors because of the greater non-financial value these investors add (Hsu 2004, Sørensen 2007, Nahata 2008) and highly reputable VC investors, in turn, prefer high-quality young firms, we expect reputable VC investors and young firms having patents protecting a radical invention to be more likely to match. However, what is special about radical inventions is that the additional information these patents convey is at the same time good and bad, i.e., the strong signal has a dark side. The attractiveness of young firms that send strong signals with a dark side to VC investors depends on the characteristics of the signal receivers and their ability to deal effectively with the challenges of radical inventions. As previously mentioned, highly reputable VC investors are attracted by the strength of the signal conveyed by these firms.

Additionally, the dark side of the signal is more or less troublesome depending on the ability of VC investors to deal with high uncertainty. VC investors can deal with the dark side of the signal by syndicating their investment. Syndication refers to the inclusion of two or more investors in the same investment round (Bygrave 1987, Lerner 1994), and syndication allows for risk sharing among partners (Wright and Lockett 2003, Nanda and Rhodes-Kropf 2017). The syndication partners also provide a second opinion, which may lead to better informed decision making (Lerner 1994, Brander et al. 2002). Moreover, the pooled resources of all syndicated partners facilitate providing young firms with the resources required to successfully exploit their business ideas (Brander et al. 2002, Dimov and Milanov 2010, Bayar et al. 2019). It is generally easier for reputable VC investors to form syndicates than for their low-reputation peers since reputable VC investors are more attractive syndication partners (Lerner 1994, Plagmann and Lutz 2019). Consequently, we hypothesize the following:

Hypothesis 1: *In first-round VC investments, young firms with patents protecting radical inventions are more likely than firms without such patents (i.e., firm without patents or patents protecting incremental inventions) to form investment ties with reputable VC investors.*

Hypothesis 2: *In first-round VC investments, the investment ties between reputable VC investors and young firms with patents protecting radical inventions are more likely to be syndicated than are the investment ties between reputable VC investors and ventures without such patents.*

During the first financing round, information asymmetry between VC investors and young firms is particularly high, since young firms lack a meaningful track record. Over time, more information is revealed about firms, their technologies, and patents (Hsu and Ziedonis 2008, Hoenig and Henkel 2015), decreasing the information asymmetry between young firms and prospective VC investors. The uncertainty is also reduced as more information is revealed. Young firms may be able to produce additional valuable information, i.e., multiple signals (Pollock et al. 2010, Ozmel et al. 2013, Audretsch et al. 2012). Information provided by the patent system, for example, the outcome of the examination process, the expiration of the opposition period, or the payment of renewal fees to keep the patent in force (Harhoff et al. 1999, Harhoff et al. 2003, Haeussler et al. 2014, Harhoff 2016), decrease legal uncertainty. Accordingly, the value of the additional information that patents protecting radical inventions convey to prospective VC investors decreases. In summary, we expect that patents protecting radical inventions are particularly strong signals in the first financing rounds, but over time, they lose (part of) their information advantage over patents protecting incremental inventions. Additionally, the dark side of these patents becomes less threatening over time, which makes syndication seem less necessary or even less attractive, as the sharing of the (lower) risk is accompanied by a sharing of the (more certain) returns. Consequently, we expect the above proposed relationships to weaken or even vanish in follow-on rounds. These arguments lead to our last two hypotheses:

Hypothesis 3: *The positive association between patents protecting radical inventions and the likelihood of the formation of an investment tie with a reputable VC investor is weaker in follow-on round VC investments than in first-round VC investments.*

Hypothesis 4: *The positive association between patents protecting radical inventions and the formation of a syndicated investment tie rather than a stand-alone investment tie with a reputable VC investor is weaker in follow-on round VC investments than in first-round VC investments.*

1.3 Data and method

1.3.1 Data source and sample

To test our hypotheses, we focus on young VC-backed firms active in the life sciences. The latter offers an ideal testbed for our study. In this science-oriented industry, commercial applications have a direct link with basic research, and radical inventions are an important source of competitive advantage for young firms (de Vet and Scott 1992, Azoulay et al. 2011, Kolympiris et al. 2014). In addition, this branch of science is characterized by a high patent propensity, high capital requirement, and vivid startup activity (Cohen and Walsh 2002). For VC investors, however, assessing the market potential of life science inventions, especially the more radical ones, is a difficult task, as much time elapses between their creation and their potential commercialization (e.g., Junkunc 2007). In addition, life science firms are reluctant to diffuse information about their inventions because of the risk of misappropriation of the associated knowledge (Deeds et al. 1997, Janney and Folta 2003). Hence, young life science firms that develop radical inventions are an attractive but very risky target for VC investors.

To answer our research question, i.e., to analyze signals that convey good and bad additional information at the same time and to examine how this opposing information matters for the investment decisions of VC investors, we combine several data sources. First, we use the VICO 4.0 dataset to identify young firms that are active in the life sciences and that received VC. The dataset was created as part of the VICO and RISIS projects, funded by the European Commission, and it contains information on VC investments made in firms in EU-27 countries, the UK and Israel over the period 1998-2015, as contained in the commercial databases Zephyr, Crunchbase and Thomson ONE.[2] The dataset includes information on VC-backed firms (e.g., name, location, industry, founding date), VC investors (e.g., name, governance, location, age), and investment deals (e.g., date, round number). In total, we were able to identify 1,423 VC-backed life science firms. We excluded firms that were older than 10 years when receiving their first round of VC, as we are interested in young firms. We also restricted our investment period to the years 2003-2015, as we need a 5-year window before the date of a focal investment to construct our measures of the VC investors’ reputation. Last, we excluded firms backed by captive VC investors (e.g., corporate or governmental VC investors) only, as their investment behavior differs substantially from that of independent VC investors. For instance, investment decisions are also driven by non-financial objectives (Bertoni et al. 2015). Applying these criteria results in a sample of 759 young

[2] The RISIS project resulted in a dataset containing 68,698 VC investments made by 8,761 investors in 24,238 firms. See http://risis.eu for more details.

life science firms.[3] For these firms, we observe 1,368 investment rounds between 2003 and 2015 involving 593 different independent VC investors.

Second, we collected patent information for the 759 identified firms from PATSTAT. Since our sample firms are located in Europe and patent filings from national patent offices cannot be compared due to country-specific examination and grant procedures[4], we only extracted patent applications filed with the EPO. We traced the firms' patent histories by matching the firm names reported in VICO with the applicant names listed in PATSTAT.[5] The matching resulted in 484 firms, which filed 3,999 patent applications with the EPO between 1991 and 2015, belonging to 3,332 patent families. We added bibliographic and procedural information on the respective patents (technology classes, failure events (i.e., revocation, refusal, withdrawals), grant events, forward citations). Patent information allows us to identify radical inventions and describe the firms' patent portfolios at the time of each VC investment round. If a patent family contained a patent that had been withdrawn, refused, revoked, or that had expired (no payment of the annual renewal fee), we considered these inventions invalid and excluded the associated patent family from the dataset.[6] In total, our dataset contains 420 companies that applied for patents to protect their invention(s) at the time of their respective financing round(s) and are either still in the granting process (pending) or have already been granted patents. For the first financing round, we observe 342 firms that filed at least one patent for their invention(s).

Third, to determine the reputation of the 593 identified VC investors, we needed information about their investment histories. As VICO only contains information on VC investments made in

[3] We classify the life science firms based on NACE codes. A total of 39 percent of the firms in our sample are active in biotechnology (72.11), 19 percent in medical instruments (26.6, 32.5), 18 percent in pharmaceuticals (21), and the remaining 25 percent in life-science related retail and service activities (46.46, 47.73, 47.74, 86, 87, 96.09).

[4] For instance, some countries allow deferred patent examination, while others do not (Harhoff 2016).

[5] To date, there are several different approaches to link patent data and the assigned applicant names to firm or inventor names (see Raffo and Lhuullery 2009 for a review). After removing special characters (non-printable characters, blanks, accents, punctuation), legal suffixes (e.g., GmbH, SAS, SARL, AG) and regional indicators (e.g., Europe, UK, Deutschland), we implemented a string match approach that compared to fuzzy matching techniques, limited the number of false positives. After performing the first match, we further cleaned the sample of non-matched firm names by removing generic terms in the life sciences (e.g., pharmaceuticals, medical, diagnostics), and we re-ran the matching, which reduced the number of false negatives at the cost of losing some precision.

[6] Robustness checks, in which we only excluded the invalid patents from our analysis and kept the patent family unless not all patent applications of the family can be considered as invalid, led to robust results. The detailed analyses are available from the authors upon request.

European firms, by using Thomson Reuters EIKON, we collected information on investments made outside of Europe. By combining these two data sources, i.e., VICO and EIKON, we obtained information on the number of worldwide investments made by the focal VC investor between 1980 and 2015, its industry focus[7], and its performance (i.e., exits through IPO). After excluding investors with missing information, we observed the investments of 555 distinct independent VC investors.

Our final sample contains 759 firms and 555 independent VC investors. Our analysis is conducted at the level of the firm-investor dyad. We control for characteristics of the firm, investor, and dyad-specific variables (e.g., distance between the location of the investor and the firm) at the time of the respective investment round.[8]

1.3.2 Description of variables

Dependent variable

Realized Investment Tie is a dummy variable that equals 0 for unrealized investment ties and 1 for realized investment ties. *Dealtype* is a categorical variable that equals 0 for unrealized investment ties, 1 for standalone realized investment ties, and 2 for syndicated realized investment ties.

Independent variables

DRadical Patent is a dummy variable that equals 1 for firms that own at least one patent family containing a patent protecting radical inventions at the time of a given VC round. Note that the patents do not have to be granted at the time of the respective financing round to be included in our analysis.[9] To identify radical inventions, we follow the approach of Verhoeven et al. (2016), who define an invention as novel in recombination (i.e., radical) if the combination of its components and principles applied are different from those embodied in all previous inventions. We use the International Patent

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[7] To be consistent in the identification of life science companies, we converted the NAICS classifications from EIKON into NACE classifications (4-digit) by using a concordance table from Eurostat (https://ec.europa.eu/eurostat).

[8] For 639 firms (84.2 percent), we observe at least one realized investment tie to one of 555 VC investors during the period 2003-2015. For the remaining 120 firms in our sample for which we do not observe a realized investment tie, we know that the firm is financed by an independent VC investor at a specific date, but the investor is unknown in VICO (e.g., name, location). These firms stay part of the sample and are used as counterfactual in our matching approach. Our results are robust when excluding these firms from our sample.

[9] As a robustness check, we distinguish between patents with pending and granted status, since one could argue that granted patents send a stronger signal than pending patent applications. However, our results are mainly driven by pending radical inventions. The regressions are available from the authors upon request.

Classification (IPC) codes as a proxy for the knowledge components underlying an invention. An invention (i.e., all documents of a DOCDB patent family) is considered radical if it contains at least one pair of IPC classes (main group level—seven-digit) that had not been combined in previous patent applications.[10] A total of 217 out of the 3,332 identified patent families owned by sample firms (6.51 percent) are classified as patent families with patents protecting radical inventions. 62 firms (8.2 percent) filed at least one patent protecting a radical invention at the time of their first financing round. This number increases up to 89 firms (11.7 percent) if we also consider follow-on financing rounds.

DReputable Investor measures the VC investors' reputation at a particular investment round. Taking inspiration from previous studies (e.g., Nahata 2008), we measure reputation as the ratio between the number of firms taken public by a VC investor in the 5 years prior to the focal investment and the total number of firms taken public by all VC investors in our sample in the same 5-year window. As this variable is highly skewed (skewness = 4.76), we create a dummy variable *DReputable Investor*, which equals 1 for the top 25 percent of the most successful VC investors. The variable is updated monthly in our observation period between 2003 and 2015.[11]

Control variables

Firm-level variables. Besides our key independent variable, i.e., firms with patents protecting radical inventions at the time of the investment (*DRadical Patent* = 1), we also distinguish between firms with at least one patent that protects an incremental but no radical invention (*DIncremental Patent* = 1), and firms without patents (*DPatent* = 0). We also control for the technological impact of a firm's patent portfolio by counting the number of citations that the patents in their portfolio received from subsequent patents up to the time of the respective investment. The citation variable is built at the patent family level.[12] We use a logarithmic transformation of the number of citations (*Forward Citations*

[10] For the identification of radical inventions, we rely on all 17,706,389 patent applications (8,823,589 patent families) filed at the EPO, the US Patent and Trademark Office (USPTO), and the WIPO between 1980 and 2019.
[11] In robustness checks, we document that our findings do not depend on the (admittedly arbitrary) choice of this threshold and use alternative measures of the investors' reputation.
[12] We built alternative measures of a firm's inventive performance: the number of distinct patent families a firm has filed (*Number Patented Inventions*) or the number of patent families with at least one granted patent (*Number of Granted Patents*). These measures are highly correlated with the citation measure we use in our analysis (corr>0.76). Our results remain robust when using these alternative measures of inventive performance.

(ln+1)), as the distribution of citations is highly skewed (skewness = 13.15).[13] We further control for firm age, operationalized as the number of years since the foundation of the firm at the time of each investment round (*Firm Age*). We control for the home country (*Firm Country*) and industry of operation (three-digit NACE classification, *Industry (NACE)*) by adding country and industry dummies. Last, in follow-on investment rounds, we control for the number of months elapsed since the last funding round (*Months Since Last Funding),* the total number of investors that invested in the focal firm in prior investment rounds (*Number of Prior Investors*), and whether the firm has received an investment from a reputable investor in previous financing rounds, i.e., whether the syndicate that invested in the focal firm includes reputable investors other than the focal investor (*DPrior Reputable Investor*).

Investor-level variables. We control for the VC investors' experience in the life sciences. Dimov and Milanov (2010) show that VC investors tend to syndicate when the industry of the target firm is novel to them, as the investors lack knowledge of market developments in the underlying industry. The variable *Industry Experience (ln+1)* is the logarithm of a VC investor's number of investments in life science firms in the five years prior to the focal investment (skewness = 4.38).

Investment-level factors. We control for the geographical distance between a firm and a VC investor (*Distance (ln+1)*). We further include the dummy variable *DSame Country*, which equals 1 if the firm and the VC investor are from the same country and equals zero otherwise. Geographic distance and national borders have been shown to constitute serious barriers to the realization of VC ties (Chen et al. 2010, Colombo et al. 2019a). In addition, we create a dummy variable that equals 1 for first-round investments and 0 for follow-on round investments (*DFirst Round*). This variable is used to split the sample into early and later investment rounds. In follow-on investment rounds, we also control for the fact that the focal investor previously invested in the focal firm by including the dummy variable *DPrior Investment*. Finally, we control for unobserved heterogeneity over time with time-period fixed effects.

[13] Since our companies are still very young (4 years on average), we cannot use the usual time windows of three or five years after publication of the patent application for the citation variables. The time windows require at least 4.5 to 6.5 years after filing. We, therefore, count all citations received by a patent family of a firm. To avoid biased results, we control for the age of the firm. Robustness checks that also control for the average age of a firm's patent portfolio yield consistent results. Due to the high correlation of the age of the firm and the age of the patent portfolio (corr=0.52), in our main regressions, we only control for the age of the firm.

1.3.3 Empirical strategy

The formation of an investment tie between a firm and a VC investor is the result of a matching process in which firms seeking financing are screened by VC investors seeking investment opportunities. To model this matching process, we estimate factual-counterfactual logit models at the dyad level and compare the formation of *realized* VC investment dyads (i.e., the factual) relative to *unrealized* investment dyads that could have formed but did not (i.e., the counterfactual). For a similar approach in the context of VC investments, see e.g., Dushnitsky and Shaver 2009, Colombo and Shafi 2016). For a tie to be considered potential but unrealized in a given year, at least one realized investment tie had to be observed for the firm and the VC investor in that year. The 759 firms and the 555 independent VC investors in our sample formed 148,204 potential firm-investor dyads that could have resulted in a realized investment tie. A total of 1,792 ties were realized. A total of 429 of these ties were standalone ties, and 1,363 were syndicated ties. A total of 770 of the realized ties were first-round VC investment ties between 578 distinct firms and 426 distinct investors. A total of 1,022 of the realized ties represented follow-on round VC investments between 275 firms and 328 distinct investors.

In addition, to alleviate problems possibly arising from the small proportion of realized ties compared to unrealized ties in the dataset, we replicated our analysis while using a case-control approach (e.g., Sorenson and Stuart 2008, Zhelyazkov and Tatarynowicz 2021). In particular, for each realized tie between firm *i* and VC investor *j*, we randomly drew 10 or 5 ties out of the set of unrealized ties of firm *i*. Lastly, we also run conditional logit models that control for unobserved time invariant firm- and investor-specific characteristics through fixed effects. The results of these additional estimates, that confirm our main results, are illustrated in the robustness check section.

To test our hypotheses, by applying a logistic regression, we first analyze the conditional probabilities that VC investor *j* matches firm *i* in a *realized investment* tie. Hypothesis 1 predicts that in first-round VC investments, young firms with patents protecting radical inventions are more likely to form investment ties with reputable VC investors than are firms without such patents, i.e., firms with patents protecting incremental inventions (counterfactual 1 (C1)) or firms without patents (counterfactual 2 (C2)).[14] In our empirical specification, this requires the marginal effect of *DRadical Patent* on the formation of a first-round investment tie to be significantly greater for reputable investors (*DReputable Investor* = 1) than for less reputable investors (*DReputable Investor* = 0), when comparing firms with patents protecting a radical invention to either firms with patents protecting incremental inventions (= C1) or firms without patents (= C2). According to Hypothesis 3, we also expect the difference in the marginal effect of *DRadical Patent* between highly reputable and less reputable VC investors to be smaller in magnitude for the follow-on rounds.

Second, by applying a multinomial logistic regression, we analyze the conditional probabilities that VC investor *j* matches with firm *i* in a *standalone tie* or in a *syndicated tie*. Hypothesis 2 predicts that in the first round of VC investments, the investment ties between reputable VC investors and young firms with patents protecting radical inventions are more likely than the investment ties with ventures without such patents, i.e., firms with patents protecting incremental inventions (= C1) or firms without patents (= C2), to be syndicated. In our empirical specification, this requires the marginal effect of *DRadical Patent* on the formation of a first-round *syndicated tie* with a reputable investor to be significantly greater than that on the formation of a first-round *standalone tie,* when comparing firms with patents protecting a radical invention to either firms with patents protecting incremental inventions (= C1) or firms without patents (= C2). According to Hypothesis 4, we expect this difference to be smaller in magnitude in follow-on rounds.

In our main estimates, we cluster the standard errors by investor to address the problem of non-independence, as each firm and VC investor repeatedly enters the analysis. As a robustness check, we cluster standard errors by firm. The statistical significance of the marginal effects of *DRadical Patent* are in line with our main results and are available from the authors upon request.

In the following, we report our results. Afterwards, we provide robustness checks to test the validity of our measures and report a number of additional estimations showing that our results are

[14] We distinguish between firms without patents and companies with patents protecting incremental inventions, as we know from the literature that "no patent" usually discourages VC investors. Our sample contains only firms that have received VC financing. This means that companies without a patent must have other advantages to be attractive to a VC investor. These other advantages are not part of our analysis, but we want to prevent them from biasing our comparison between firms with patents protecting radical versus incremental inventions.

unlikely to be driven by unobserved heterogeneity or by the presence of an inflated number of unrealized ties. We also rule out the presumably most obvious alternative explanations of our results. In particular, we show that our results are not driven by the higher investment sums and complementary resources that firms with patents protecting radical inventions require. However, since we cannot rule out all possible sources for endogeneity, we will interpret our results as correlations.

1.4 Results

Table 1.1 reports the descriptive statistics and bivariate correlations of our variables for all 148,204 potential investment ties. In 61% of firm-investor ties (realized and unrealized), the firm has a patent. In 13.9% of all firm-investor ties, the firm has a patent protecting a radical invention. A reputable VC investor is involved in 27.3% of all firm-investor ties. We conducted several tests of multicollinearity. The pairwise correlations are generally low, with a few exceptions where the pairwise correlations amount to approximately 0.6 (e.g., the correlation between *Industry Experience* and *DReputable Investor*). However, the variance inflation factors are low, making us confident that multicollinearity is not a concern in our analysis.

The results of the econometric estimates are illustrated in Table 1.2. In Models 1-4, we only use first-round investment ties, while Models 5-8 use follow-on investment ties as sample specification. Models 1, 2, 5 and 6 are logistic regressions estimating the likelihood of investment tie formation. The reported coefficients represent the changes due to a one-unit increase in the covariates, in the log-odds of forming a tie to not forming any tie. Models 3, 4, 7 and 8 are multinomial logistic regressions that distinguish between standalone and syndicated investment ties. In Table 1.3, we report the average marginal effects (AME) of *DRadical Patent* on the likelihood of the formation of a first-round and follow-on VC investment tie. We also distinguish stand-alone and syndicated ties.

Table 1.1 Descriptive statistics and bivariate correlations (n = 148,204)

	Variable	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	DPatent	0.610		0	1	**1**													
2	DIncremental Patent	0.471		0	1	0.755	**1**												
3	DRadical Patent	0.139		0	1	0.321	-0.379	**1**											
4	DReputable Investor	0.273		0	1	0.008	0.005	0.003	**1**										
5	Number Forward Citations	12.871	73.361	0	1366	0.501	0.173	0.456	0.002	**1**									
6	Company Age	4.014	3.218	0	16	0.274	0.145	0.177	-0.010	0.454	**1**								
7	Number of Prior Investors	1.390	2.164	0	14	0.264	0.164	0.135	0.000	0.348	0.376	**1**							
8	DPrior Reputable Investor	0.211		0	1	0.199	0.116	0.114	-0.002	0.226	0.246	0.612	**1**						
9	Months Since Last Funding	8.620	15.292	0	122	0.166	0.082	0.115	-0.011	0.289	0.442	0.424	0.319	**1**					
10	Industry Experience	12.227	25.434	0	262	0.009	0.008	0.002	0.618	0.001	-0.009	0.004	0.001	-0.009	**1**				
11	DPrior Investment	0.006		0	1	0.028	0.016	0.017	0.031	0.037	0.033	0.100	0.022	0.042	0.054	**1**			
12	DFirst Round	0.505		0	1	-0.252	-0.141	-0.151	-0.001	-0.292	-0.391	-0.649	-0.522	-0.570	-0.005	-0.077	**1**		
13	Distance	2266.284	2627.721	0	17324	0.040	0.016	0.034	-0.013	0.036	0.026	-0.005	-0.032	-0.013	0.013	-0.088	0.011	**1**	
14	DSame Country	0.126		0	1	-0.017	-0.010	-0.011	0.011	-0.019	-0.014	-0.008	0.004	0.004	-0.005	0.109	-0.000	-0.626	**1**

Note: While we report descriptive statistics for the original specifications of our measures, the bivariate correlations are calculated by using a logarithmic transformation for some variables (*Forward Citations (ln+1)*, *Industry Experience (ln+1)*, *Distance (ln+1)*). The dummy variable *DFirst Investment Roun*d is used to split the sample in our main analysis and is an explanatory variable in a full model specification taking into account all potential investment ties of a firm over time.

Table 1.2 (Multinomial) logistic regressions by investment round

	Model 1	Model 2	Model 3		Model 4		Model 5	Model 6	Model 7		Model 8	
Sample specification	First Round	First Round	First Round		First Round		Follow-up Round	Follow-up Round	Follow-up Round		Follow-up Round	
Outcome reference: Unrealized Tie vs.	Realized Tie	Realized Tie	Standalone Tie	Syndicated Tie	Standalone Tie	Syndicated Tie	Realized Tie	Realized Tie	Standalone Tie	Syndicated Tie	Standalone Tie	Syndicated Tie
DPatent	-0.052		-0.367	0.075			0.218		0.223	0.205		
	(0.106)		(0.224)	(0.112)			(0.174)		(0.308)	(0.181)		
DIncremental Patent		-0.057			-0.366	0.068		0.237			0.228	0.228
		(0.107)			(0.232)	(0.112)		(0.176)			(0.316)	(0.183)
DRadical Patent		0.132			-0.449	0.318*		0.167			0.174	0.149
		(0.176)			(0.353)	(0.193)		(0.218)			(0.482)	(0.220)
DReputable Investor	-0.130	-0.132	-0.076	-0.154	-0.076	-0.159	0.209	0.208	0.063	0.198	0.069	0.194
	(0.155)	(0.155)	(0.256)	(0.186)	(0.256)	(0.187)	(0.248)	(0.248)	(0.364)	(0.282)	(0.363)	(0.283)
DPatent X DReputable Investor	0.212		0.270	0.202			-0.125		0.114	-0.122		
	(0.164)		(0.299)	(0.202)			(0.258)		(0.388)	(0.279)		
DIncremental Patent X		0.099			0.308	0.026		-0.187			0.098	-0.200
DReputable Investor		(0.172)			(0.316)	(0.200)		(0.255)			(0.397)	(0.277)
DRadical Patent X		0.577**			-0.019	0.677**		0.043			0.130	0.087
DReptuable Investor		(0.279)			(0.629)	(0.331)		(0.331)			(0.539)	(0.352)
Forward Citations (ln+1)	0.120***	0.091**	-0.069	0.168***	-0.056	0.128***	0.085**	0.085**	-0.053	0.108***	-0.047	0.108**
	(0.038)	(0.040)	(0.098)	(0.039)	(0.097)	(0.042)	(0.040)	(0.043)	(0.083)	(0.041)	(0.093)	(0.043)
Firm Age	-0.002	-0.001	0.036	-0.016	0.036	-0.013	-0.023	-0.023	0.073**	-0.044**	0.073**	-0.045**
	(0.018)	(0.018)	(0.030)	(0.020)	(0.030)	(0.020)	(0.019)	(0.019)	(0.035)	(0.021)	(0.035)	(0.021)
Industry Experience (ln+1)	-0.049	-0.050	-0.052	-0.048	-0.052	-0.048	-0.054	-0.054	0.195*	-0.104*	0.195*	-0.103*
	(0.038)	(0.038)	(0.076)	(0.046)	(0.076)	(0.046)	(0.056)	(0.056)	(0.112)	(0.061)	(0.112)	(0.061)
Distance (ln+1)	-0.258***	-0.259***	-0.296***	-0.242***	-0.296***	-0.244***	-0.088*	-0.088*	-0.145*	-0.077	-0.145*	-0.077
	(0.031)	(0.031)	(0.046)	(0.036)	(0.046)	(0.036)	(0.050)	(0.050)	(0.076)	(0.051)	(0.076)	(0.051)
DSame Country	2.857***	2.858***	3.296***	2.720***	3.296***	2.721***	1.547***	1.549***	1.509***	1.549***	1.504***	1.552***
	(0.149)	(0.149)	(0.266)	(0.174)	(0.266)	(0.173)	(0.197)	(0.197)	(0.349)	(0.207)	(0.349)	(0.207)
Number of Prior Investors							-0.043*	-0.043*	-0.301***	-0.007	-0.302***	-0.007
							(0.025)	(0.025)	(0.095)	(0.024)	(0.095)	(0.024)
DPrior Reputable Investor							-0.740***	-0.742***	-0.899***	-0.710***	-0.900***	-0.713***
							(0.165)	(0.165)	(0.295)	(0.165)	(0.296)	(0.165)
Months Since Last Funding							0.005*	0.005*	-0.002	0.007***	-0.002	0.007***
							(0.003)	(0.003)	(0.007)	(0.003)	(0.007)	(0.003)
DPrior Investment							6.133***	6.133***	6.657***	6.053***	6.660***	6.054***
							(0.158)	(0.157)	(0.312)	(0.155)	(0.313)	(0.154)
Firm Country FE	Yes	Yes	Yes		Yes		Yes	Yes	Yes		Yes	
Industry (NACE) FE	Yes	Yes	Yes		Yes		Yes	Yes	Yes		Yes	
Time Period Fixed FE	Yes	Yes	Yes		Yes		Yes	Yes	Yes		Yes	
Firm X Investor Dyads	74,883	74,883	74,883		74,883		73,321	73,321	73,321		73,321	
Log Likelihood	-3,269.930	-3,265.413	-3,678.844		-3,671.698		-2,557.504	-2,557.072	-2,988.279		-2,987.584	

Note: Standard errors in parentheses are clustered by investor. The coefficients represent the changes in the log-odds. The reference outcome comprises unrealized investment ties. Models 1, 2, 5 and 6 show the results of a logistic regression, while Models 3, 4, 7 and 8 show the results of a multinomial logistic regression.
* p < 0.1, ** p < 0.05, *** p < 0.01

Models 1, 3, 5 and 7 only contain the control variables and the dummy variable *DPatent* to distinguish between firms with at least one patent application (radical or incremental) and firms without any patent application at the time of the financing round. Moreover, we add the variable *DReputable Investor* and its interaction term with *DPatent* to test whether having at least one patent is related to the signaling equilibrium in terms of attracting reputable VC investors. We first report the results for first-round VC investment ties in Models 1 and 3 (Table 1.2).

The dummy capturing whether a firm filed a patent (*DPatent*) is not significantly related to tie formation in a first investment round, regardless of whether the VC investor is reputable or not, as the interaction term between *DPatent* and *DReputable Investor* is not significant. Moreover, the results show that the patents' technological value measured by *Forward Citations (ln+1)* is positively and significantly related to the likelihood of tie formation in a first investment round (Model 1: $p = 0.002$). The positive effect of *Forward Citations(ln+1)* is entirely attributable to syndicated ties (Model 3: $p = 0.000$). Model 3 also shows that the distance between the focal VC investor and the focal firm (*Distance (ln+1)*) is negatively related to the formation of both a standalone ($p = 0.000$) and a syndicated tie ($p=0.000$), while being located in the same country (*DSame Country*) has a positive effect ($p = 0.000$ for both stand-alone and syndicated ties).

In Models 2 and 4, we replace the variable *DPatent* by the two dummy variables *DRadical Patent*, indicating firms with patents protecting radical inventions and *DIncremental Patent*, indicating firms with patents protecting only incremental inventions. Moreover, we add the interaction terms of these two variables with *DReputable Investor*. To test Hypotheses 1 and 2, we consider the values of the average marginal effects (AME) of *DRadical Patent* for these two model specifications, which are shown in Table 1.3.

Table 1.3 Average marginal effects of patents protecting radical inventions

		Model 2	Model 4	Model 6	Model 8
Sample Specification		First Round	First Round	Follow-on Round	Follow-on Round
Average Marginal effect of DRadical Patent on	*Counterfactual*				
(1) P(Realized Tie | DReputable Investor = 0; DIncremental Patent = 0)	*No Patent*	0.001 (0.002)		0.001 (0.001)	
(2) P(Realized Tie | DReputable Investor = 1; DIncremental Patent = 0)		0.008** (0.004)		0.002 (0.002)	
(2) - (1)		0.007* (0.004)		0.000 (0.002)	
(3) P(Realized Tie | DReputable Investor = 0; DIncremental Patent = 1)	*Incremental Patent*	0.001 (0.002)		0.001 (0.002)	
(4) P(Realized Tie | DReputable Investor = 1; DIncremental Patent = 1)		0.009** (0.004)		0.002 (0.002)	
(4) - (3)		0.007* (0.004)		0.000 (0.003)	
(5) P(Standalone Tie | DReputable Investor = 0; DIncremental Patent = 0)	*No Patent*		-0.001 (0.001)		0.000 (0.001)
(6) P(Standalone Tie | DReputable Investor = 1; DIncremental Patent = 0)			-0.001 (0.001)		0.000 (0.001)
(7) P(Syndicated Tie | DReputable Investor = 0; DIncremental Patent = 0)			0.003 (0.002)		0.001 (0.001)
(8) P(Syndicated Tie | DReputable Investor = 1; Dincremental Patent = 0)			0.009** (0.004)		0.001 (0.001)
(8) - (6)			0.011*** (0.004)		0.001 (0.002)
(9) P(Standalone Tie | DReputable Investor = 0; DIncremental Patent = 1)	*Incremental Patent*		-0.001* (0.001)		0.000 (0.001)
(10) P(Standalone Tie | DReputable Investor = 1; DIncremental Patent = 1)			-0.001 (0.001)		0.001 (0.001)
(11) P(Syndicated Tie | DReputable Investor = 0; DIncremental Patent = 1)			0.003 (0.002)		0.001 (0.002)
(12) P(Syndicated Tie | DReputable Investor = 1; Dincremental Patent = 1)			0.010** (0.005)		0.001 (0.002)
(12) - (10)			0.011** (0.004)		0.001 (0.003)
Firm X Investor Dyads		74,883	74,883	73,321	73,321

Note: Standard errors in parentheses are clustered by investor. The average marginal effects are calculated using the delta method, leaving all variables except for the variables of interest at their observed value. Models 2 and 4 only consider potential first round investment ties, while Models 6 and 8 only consider potential follow-up investment ties. Models 2 and 6 report the marginal effects of *DRadical Patent* on the probability of a realized investment tie. Models 4 and 8 report the marginal effects of *DRadical Patent* on the probabilities of a standalone and syndicated tie with varying investor reputations.

* p < 0.1, ** p < 0.05, *** p < 0.01

For model specification 2 (Table 1.2), the AMEs of *DRadical Patent* on the probabilities of forming a first-round investment tie with a reputable VC investor (i.e., when *DReputable Investor* equals 1) are positive and statistically significant for both categories of our counterfactual of firms without a radical invention, i.e., firms without patents (= C2) (*DIncremental Patent* equals 0: AME = 0.008, p = 0.018) and firms with patents protecting only incremental inventions (= C1) (*DIncremental Patent* equals 1: AME = 0.009, p = 0.034). We find that when a firm has at least one patent application protecting a radical invention, this is associated with an 89 (90) percent increase[15] in the probability of forming a first-round investment tie with a reputable VC investor compared to a firm with no patents (= C2) (patents protecting only incremental inventions (= C1)). For non-reputable investors, the AMEs of *DRadical Patent* on the probabilities of forming a first-round investment tie are not significant. Our results, hence, support Hypothesis 1.

Based on the estimates of Model 4 (Table 1.2), the AMEs of *DRadical Patent* on the probabilities of forming a syndicated tie with a reputable VC investor are positive and highly significant for both categories of our counterfactual (firms without any patent (= C2): AME = 0.009, p = 0.01; firms with patents protecting only incremental inventions (= C1): AME = 0.01, p = 0.029). Hence, if a firm filed at least one patent protecting a radical invention this is associated with a 150 (143) percent increase in the probability of a syndicated first-round investment tie with a highly reputable VC investor compared to firms with no patents (= C2) (with patents protecting only incremental inventions (= C1)). Conversely, the AMEs of *DRadical Patent* on the probabilities of forming a standalone first-round investment tie with a reputable investor are not significant. Accordingly, the differences between the AMEs of *DRadical Patent* on the probabilities of forming a syndicated first-round investment tie with a reputable VC investor and the corresponding AMEs relating to a stand-alone tie are positive and significant for both categories of our counterfactual (firms without patents (= C2): difference = 0.011, p = 0.008; firms with patents protecting incremental inventions (= C1): difference = 0.011, p = 0.021). Our results, hence, also support Hypothesis 2.

[15] These associations are calculated based on the estimated probabilities of forming a first-round investment tie with a reputable investor for firms without any patent (P = 0.009) and for firms with patents protecting only incremental inventions (P = 0.01).

To test Hypotheses 3 and 4, we consider the econometric specifications that only consider follow-on investment ties (Table 1.2), and again, we calculate the AME of *DRadical Patent* on the likelihood of the formation of any realized investment tie (Model 6) or of the formation of a standalone investment tie and a syndicated investment tie for reputable and non-reputable VC investors (Model 8). The results are shown in Table 1.3. The AME of *DRadical Patent* on the likelihood of a tie formation in a follow-on investment round is not significant, irrespective of the reputation of the VC investors, the type of tie (stand-alone or syndicated), and the counterfactual (firms without patents (= C2) or firms with patents protecting incremental inventions (= C1)). Thus, the positive effect of having patents protecting radical inventions on the probability of forming a (syndicated) first-round investment tie with reputable investors vanishes in follow-on rounds, as predicted by Hypotheses 3 and 4.

With regard to the effects of our control variables in follow-on VC investment rounds, the fact that an investor was part of a previous investment round (*DPriorInvestment* equals 1) is significantly positively related to the likelihood that the same investor invests in a follow-on investment round (e.g., Model 5: $\beta = 6.13$; $p = 0.000$), while the number of previous VC investors (*Number of Prior Investors*) or the fact that a reputable VC investor already invested in the firm *(DPrior Reputable Investor* equals 1) is significantly negatively related to the likelihood of tie formation in a follow-on round. Consistent with first-round investment ties, the dummy capturing whether a firm filed a patent (*DPatent*) is not significantly related to the likelihood of tie formation in follow-on investment rounds.

As an additional test, we run a multinomial logistic regression based on the full sample of observations without splitting the sample into first- and follow-on round VC investment ties. Instead, we use a triple interaction between *DRadical Patent*, *DReputable Investor*, and the dummy variable *DFirst Round* distinguishing first and follow-on round VC investments ties.[16] Consistent with the results reported above, we find positive and significant AMEs of *DRadical Patent* on the probabilities of forming a syndicated first-round investment tie with a reputable VC investor for both counterfactuals (firms with no patents (= C2): AME = 0.01, p = 0.006; firms with patents protecting incremental

[16] We also add the triple interaction between *DIncremental Patent*, *DReputable Investor* and *DFirst Round* and drop the variable *Months Since Last Funding*, since this variable is not specified for first-round investment ties. The results, which are consistent with the results reported above, are available from the authors upon request.

inventions (= C1): AME = 0.011, p = 0.02). Moreover, the differences between the AMEs of *DRadical Patent* on the probabilities of forming a syndicated first-round investment tie and a stand-alone first-round investment tie with a reputable VC investor are significantly larger than the corresponding differences for a follow-on round investment tie. The differences-in-differences are equal to 0.01 (p = 0.022) when using firms without patents as the counterfactual (= C2), and 0.01 (p = 0.046) when using firms with patents protecting only incremental patents as the counterfactual (= C1).[17]

Overall, our results provide support for our hypotheses that there is a positive and significant association between young firms with patent applications protecting radical inventions and financing from reputable VC investors (Hypothesis 1) and that these investors are more likely to syndicate their investment when investing in firms with patents protecting radical inventions than when investing in firms with either no patents (= C2) or patents that protect only incremental inventions (= C1) (Hypothesis 2). Moreover, these associations are confined to first-round investment deals and vanish in follow-on rounds (Hypotheses 3 and 4).

1.4.1 Robustness checks

To assess the robustness of our results, we run several additional analyses. First, we use different definitions for firm-investor dyads that are at risk of realizing an investment tie. In our main estimates, we used all possible dyads between firms that were financed in a given year and all VC investors that were active in that year. By this definition, realized ties are rare events, accounting for only 1.21 percent of the total observations. This might lead to an underestimation of the likelihood of these events when using logistic regressions (King and Zeng 2001). Hence, as a robustness check, we apply the case-control approach used in previous studies (e.g., Sorenson and Stuart 2008, Zhelyazkov and Tatarynowicz 2021) and for each realized tie between firm *i* and VC investor *j*, we randomly select 10 or 5 ties within the set of unrealized ties of firm *i*. The results of 1,000 simulations of Models 4 and 8 obtained by using random sampling without replacement are shown in Table 1.4.

[17] In this specification, the AME of *DRadical Patent* on the probability of forming a stand-alone first-round investment tie with a reputable VC investor is negative, even if of small economic magnitude (i.e., AME = -0.0016), and (weakly) significant (p-value = 0.092) when we use firms with patents protecting incremental inventions as the counterfactual. These findings provide even stronger support to our hypothesis about the inclination of reputable VC investors to syndicate their first-round investments in firms with patents protecting radical inventions rather than investing on a stand-alone basis.

Table 1.4 Simulation: Random draw of unrealized investment ties per investment deal

		Model 4							Model 8						
Sample specification		First Round							Follow-on Round						
Average Marginal effect of DRadical Patent on:	*Counterfactual*	Rep.	Unreal. Ties	Realized Ties	Mean AME	Mean SD	Mean p-value	# p-value >= 0.1	Rep.	Unreal. Ties	Realized Ties	Mean AME	Mean SD	Mean p-value	# p-value >= 0.1
P(Standalone Tie | DReputable Investor = 0; DIncremental Patent = 0)	*No Patent*	1,000	5,780	770	-0.014	0.002	0.13	616	1,000	5,930	1,022	0.000	0.001	0.946	1,000
		1,000	2,890	770	-0.025	0.003	0.121	576	1,000	2,965	1,022	0.001	0.001	0.939	1,000
P(Standalone Tie | DReputable Investor = 1; DIncremental Patent = 0)		1,000	5,780	770	-0.021	0.003	0.087	336	1,000	5,930	1,022	-0.001	0.001	0.864	1,000
		1,000	2,890	770	-0.041	0.005	0.054	109	1,000	2,965	1,022	-0.002	0.002	0.838	1,000
P(Syndicated Tie | DReputable Investor = 0; DIncremental Patent = 0)		1,000	5,780	770	0.023	0.006	0.151	635	1,000	5,930	1,022	-0.007	0.003	0.577	1,000
		1,000	2,890	770	0.039	0.01	0.145	588	1,000	2,965	1,022	-0.012	0.005	0.556	1,000
P(Syndicated Tie | DReputable Investor = 1; DIncremental Patent = 0)		1,000	5,780	770	0.072	0.012	0.031	28	1,000	5,930	1,022	-0.004	0.006	0.764	1,000
		1,000	2,890	770	0.109	0.021	0.043	81	1,000	2,965	1,022	-0.01	0.012	0.7	999
P(Standalone Tie | DReputable Investor = 0; DIncremental Patent = 1)	*Incremental Patent*	1,000	5,780	770	-0.01	0.001	0.09	346	1,000	5,930	1,022	0.000	0.001	0.946	1,000
		1,000	2,890	770	-0.019	0.002	0.083	301	1,000	2,965	1,022	0.001	0.002	0.94	1,000
P(Standalone Tie | DReputable Investor = 1; DIncremental Patent = 1)		1,000	5,780	770	-0.02	0.002	0.063	167	1,000	5,930	1,022	-0.001	0.001	0.856	1,000
		1,000	2,890	770	-0.039	0.003	0.035	31	1,000	2,965	1,022	-0.003	0.003	0.826	1000
P(Syndicated Tie | DReputable Investor = 0; DIncremental Patent = 1)		1,000	5,780	770	0.023	0.007	0.185	752	1,000	5,930	1,022	-0.007	0.003	0.563	1,000
		1,000	2,890	770	0.038	0.011	0.184	720	1,000	2,965	1,022	-0.012	0.005	0.545	1,000
P(Syndicated Tie | DReputable Investor = 1; DIncremental Patent = 1)		1,000	5,780	770	0.075	0.014	0.049	80	1,000	5,930	1,022	-0.003	0.006	0.762	1,000
		1,000	2,890	770	0.112	0.024	0.059	149	1,000	2,965	1,022	-0.009	0.011	0.698	999

Note: This table presents descriptive results from 1000 simulations of Model 4 and Model 8, where we take into account only 10 or 5 unrealized ties per investment deal of a firm instead of all potential, but unrealized ties to independent VC investors that have been active in the year of the investment. For each of the 1000 repetitions, we randomly draw 10 or 5 unrealized ties of a specific firm per investment round without replacement. In addition, we dropped all firms where we only observe unrealized ties. For these firms, we know that they have been financed by an independent VC investor in a given year, but we do not observe all relevant information of the investor that actually invested in that firm. To sum up, we observe 770 realized first round investment ties for 578 distinct firms. In addition, we observe 1,022 realized follow-on investment ties for 275 distinct firms in 593 distinct investment deals. For each of the 578 first round deals and 593 follow-on round deals, we randomly assign to each funded firm either 10 or 5 independent VC investors, that have been active in that year. We report mean values and standard deviations of the average marginal effects of *DRadical Patent* on the probabilities of either a standalone tie or a syndicated tie with varying investor reputation. In addition, we report the average p-values and the frequencies of p-values that are equal or larger than 10 percent.

Our main result, i.e., that in first-round VC investment ties the AME of *DRadical Patent* on the probability of forming an investment tie is positive and significant when VC investors are reputable and investments are syndicated is confirmed. In the estimates with a random control of 10 unrealized ties for each realized tie, the mean AMEs of *DRadical Patent* are equal to 7.2 percent (mean p-value equal to 0.031) and 7.5 percent (mean p-value equal to 0.049) when we use as counterfactual firms with no patents and firms with patents protecting only incremental inventions, respectively. With 5 unrealized ties for each realized tie, the results are even stronger. Again, this positive association vanishes in follow-on rounds. Moreover, for first-round VC investments, we observe negative and significant AMEs of *DRadical Patent* on the probability of forming a standalone investment tie if the VC investors are reputable. These findings once more confirm our theoretical argument that in first-round VC investments, reputable VC investors prefer syndication over investing alone when selecting firms with patents protecting radical inventions.

Second, our results do not depend on the arbitrary choice of the 75th percentile as a cutoff point to distinguish between reputable and non-reputable VC investors. In Models A1 and A2 in Table A1.1 in the Appendix, we show the outcomes of a multinomial logit model that uses a continuous measure for investor reputation (*Investor Reputation*), and we then calculate the AME of *DRadical Patent* at the 50th, 70th and 90th percentiles of this variable.[18] In first-round VC investments, both the magnitude and the statistical significance of the AMEs of *DRadical Patent* on the likelihood of a syndicated investment tie increase as the reputation of VC investors increases. In addition, the AMEs of *DRadical Patent* on the likelihood of a standalone tie becomes significantly negative as investor reputation increases, which is consistent with the results from the simulations reported above. Moreover, we do not find any significant association between *DRadical Patent*, *DReputable Investor* and the type of investment deal in the follow-on rounds. Furthermore, we build an alternative reputation measure considering a 3-year instead of a 5-year period prior to the focal investment (Models A3 and A4). We also measure VC investor reputation as the share of investments made by each investor in the 5 years prior to the focal

[18] As mentioned earlier, the underlying distribution of investor reputation is highly skewed. The 50th percentile equals the 1st percentile. Thus, we focus on cutoff points equal to or greater than the median.

investment relative to all the investments made by all VC investors in our sample during the same period (Models A5 and A6; see Pollock et al. 2015). The results are shown in Table A1.2 in the Appendix and, again, support our previous results.

Finally, our results might be driven by unobserved characteristics of firms or investors. For example, higher-quality firms may be more likely to both produce radical inventions and attract more reputable VC investors. To address these concerns, we run conditional binary logit models that control for latent firm or VC investor characteristics through fixed effects after checking that the assumption of the independence of irrelevant alternatives (IIA) holds.[19] As the maximization of a conditional log-likelihood does not produce an estimation of fixed effects (i.e., unobserved heterogeneity regarding the firm or investor), the computation of marginal effects is not adequate (Greene and Zhang 2019). Thus, we can only investigate changes in log-odds. The results are shown in Table A1.3 in the Appendix. Regardless of whether we condition on firm or VC investor, the interaction between *DRadical Patent* and *DReputable Investor* increases the log-odds of forming a syndicated first-round investment tie to not forming any tie. Hence, when controlling for unobserved heterogeneity at the firm or investor level, our results are in line with our main estimates.

1.4.2 Additional analyses

As discussed in our theory section, radical inventions require high investment sums and complementary assets to finance the uncertain development process until commercialization. Consequently, syndication might be aimed not only at sharing the risk between investors but also at pooling (allegedly complementary) resources (including financial resources) to optimally support investee firms in the post-financing stage (Brander et al. 2002, Bayar et al. 2019). To disentangle risk sharing and resource

[19] Begg and Gray (1984) show that under the IIA assumption, consistent (albeit inefficient) estimates can be obtained by estimating separate logit models instead of a single multinomial model. This assumption requires the estimates to be robust against the inclusion or exclusion of outcome categories (Hausman and McFadden 1984). We therefore compare the estimated coefficients of *DRadical Patent*, *DIncremental Patent* and *DReputable Investor* and their interaction terms from a multinomial logit model with the same coefficients obtained from two separate logistic regressions excluding either standalone or syndicated ties. Applying the suest-based Hausman test does not show any systematic differences between the coefficients. Thus, the IIA assumption holds. In these models, variables that do not vary across observations (i.e., time-invariant firm-specific variables when conditioning on firms and time-invariant investor-specific variables when conditioning on investors) are dropped from the estimates. The dummy *DReputable Investor* is not dropped as VC investors' reputation varies over time.

pooling for first-round VC investments, we conduct two additional analyses at the investment round level (Table A1.4).

First, we investigate whether the total amount of financing that a firm receives in a first-round VC investment (*Investment Sum Deal (ln)*) that is syndicated (*DSyndicated Round* = 1) is higher when the firm has patents protecting radical inventions (i.e., when *DRadical Patent* = 1). Model A15 in Table A1.4 does not show any evidence in support of this claim. Syndicated deals are associated with higher investment amounts independently of whether firms have patents protecting radical or incremental inventions, or do not have any patents. The interaction term between *DSyndicated Round* and *DRadical Patent* is not statistically significant. Second, we restrict our sample to syndicated investment rounds and investigate whether firms with patents protecting radical inventions tend to be funded by more heterogeneous syndicates (e.g., a combination of independent VC, corporate VC, and/or governmental VC). The idea underlying this test is that heterogeneous syndicates pool more complementary resources. The results from a logistic regression, where the dependent variable *DMixed Syndicate* equals 1 if there is more than one type of investor, do not provide support for this explanation (Model A16).

Another possible alternative explanation of our results is related to the geographic distribution of firms and VC inventors. Firms seeking to develop their radical inventions may be heavily reliant on external funding and therefore intentionally locate in VC hubs with a high density of VC investors (such as London and Paris) to increase the likelihood of funding (De Prijcker et al. 2019). Highly reputable VC investors tend to locate in these VC hubs.[20] To reduce competition and the associated risk of overpaying, these reputable VC investors may decide to collude by syndicating their investments. Hence, the colocation of reputable VC investors and firms with patents protecting radical inventions in VC hubs may explain our results. However, our results show (Table A1.5, Panel A) that the share of VC investments in firms with patents protecting radical inventions is lower in the VC hubs of London and Paris than outside these VC hubs (9.44 percent compared to 15.84 percent; Wilcoxon-Mann-Whitney

[20] For example, out of the 25 VC investors with the highest reputation (measured at the end of 2014) included in our sample, 7 are located in the London or Paris metropolitan areas, the two largest VC hubs in Europe.

test: z = 2.219; p = 0.027). In panel B, we include the 10 largest VC hubs in Europe in terms of the number of VC investments (source: VICO database) and obtain similar results.[21]

1.5 Discussion

The purpose of this study was to examine signals that convey positive and negative information at the same time and to investigate how these signals are related to the investment behavior of VC investors. Accordingly, in our study of patents protecting radical inventions, we empirically analyzed how VC investors with different reputations react to signals that in addition to positive information, simultaneously carry negative information.

We offer a novel contribution to the signaling literature in that we analyze signals that convey good and bad additional information at the same time. The existing literature recognizes that signals may be of different strengths (e.g., Vanacker et al. 2020) and that firms may send multiple signals that may complement, reinforce, or substitute each other (e.g., Pollock et al. 2010, Stern et al. 2014, Ozmel et al. 2016, Colombo et al. 2019b). Some scholars have advanced the argument that multiple signals may overburden receivers characterized by bounded rationality, especially when the signals convey contradictory information (Drover et al. 2018). Hence, signal receivers may react differently to a given signal depending on their information processing capabilities. Even if one assumes that signal receivers are not boundedly rational, we show that depending on the receivers' specific characteristics (in our case, the reputation of VC investors), they react differently to the positive and negative information conveyed by a strong signal with a dark side (in our case, patent applications filing a patent for a radical invention). An important yet so far not discussed aspect of the signal we describe is that the same characteristic that makes a signal strong can also convey "bad news". In other words, it is no longer possible to disregard a signal—which is possible in the case of multiple signals (e.g., a firm owns a patent, but the prototype does not work)—or to disregard a certain characteristic of the signal—which

[21] As additional robustness check, we also perform our main analysis by eliminating from our sample the firms located in VC hubs. We still find a significant effect of having patents protecting radical inventions, on the formation of a syndicated first-round investment tie with a reputable VC investor. The results from these regressions are available from the authors upon request.

is possible if more information about the signal is revealed over time (e.g., a granted patent that is opposed by a third party).

We also contribute to the entrepreneurial finance literature. First, we show that sorting mechanisms that match VC investors and young firms change over time, mainly because a decrease in information asymmetry over time changes the informational value of a signal to VC investors (Hsu and Ziedonis 2008, Hoenig and Henkel 2015). The extant literature has provided extensive evidence of the existence of a sorting mechanism (Sørensen 2007, Conti et al. 2013b). However, the dynamics of VC investment decisions have not been investigated. Our results indicate that because of the information on the firms' quality conveyed by their patents, firms with patents protecting radical inventions match with more reputable VC investors but that this effect progressively vanishes when more information about the firms' quality and prospects become available. We further add to this literature by considering the effects of syndication, a key characteristic of VC investments (Bygrave 1987, Lerner 1994, Wright and Lockett 2003). We highlight that the opportunity to syndicate and share investment risks influences the behavior of VC investors in response to the (complex) signals conveyed by firms. Indeed, under conditions of information asymmetry, we observe positive matching between firms with patent applications protecting radical inventions, a strong signal with a dark side, and more reputable VC investors, but only if investments are syndicated.

Our study also has interesting managerial implications for entrepreneurs. Highly innovative ideas resulting in radical inventions may be punished by VC investors, since non-reputable investors and, in particular, investors without syndication partners may not want to take on the risk involved in such an investment. However, young companies are heavily reliant on external financing. Due to the high risk and long-term returns associated with radical inventions, equity financing is usually the only available source of finance. Hence, to increase their chances of obtaining external financing, the creators of radical inventions have to understand the impact of the signal they send and the target group of potentially interested investors.

Finally, our study has implications for policy makers, as well. Radical inventions are of particular interest since they are the "driving forces of technological, industrial and societal change" (Schoenmakers and Duysters 2010: 1052), and they have the potential to enhance private and social welfare (Trajtenberg 1990, Harhoff et al. 1999, Ahuja and Lampert 2001). If the signals sent by patents on radical inventions are not effective, the result could be an underinvestment problem in radical invention. This situation is more likely if firms are located far from VC hubs, where reputable VC investors tend to be concentrated. Accordingly, policy measures aimed at making reputable VC investors more inclined to invest at long distances (Bertoni et al. 2019) may help solve this problem. Otherwise, potentially break-through inventions may never be developed or brought to market, i.e., turned into innovations.

With respect to the limitations of our study, we did our best to check that (time invariant) unobserved heterogeneity did not drive our results and to rule out seemingly most obvious alternative explanations for our findings. These robustness checks combined with our strong theoretical foundation make us confident that our results are reliable and that our interpretation of the results is correct. However, we recognize that endogeneity might arise from time-varying unobserved heterogeneity. For instance, we cannot rule out that when screening companies with radical inventions, some time-varying unobserved characteristics of investors (e.g., overconfidence of investment managers) might explain the differences between reputable and non-reputable investors. Therefore, caution is required in interpreting our results as indicating causal links. Future research that considers more fine-grained information and adopts different methodologies (e.g., real experiments) is needed to further alleviate causality concerns. Furthermore, although our results are robust to different matching strategies and counterfactuals, we acknowledge that we do not observe which young innovative companies had been evaluated and screened by which VC investors. We therefore welcome studies that have more detailed data on funded and unfunded companies that approached the same VC investor. We also recognize that our study is (for the reasons explained in our paper) restricted to one industry. This may limit the generalizability of our results. Although we are confident that our results hold in other environments, future research should examine the dark side of signals in other industries and possibly also in contexts other than entrepreneurship.

Of course, one could argue that it is optimal for young firms with patents protecting a radical invention if reputable VC investors match with them. In other words, where is the dark side of the signal? However, the reality is not so simple. The fact that firms with patents protecting radical inventions are more likely to be matched with reputable VC investors than with non-reputable ones does not mean that there is no additional risk associated with these investments. This is also confirmed by our findings that reputable investors, rather than investing alone, decide to syndicate, i.e., share risk and consult other experts – even if it means sharing possible returns. Assessing whether this investment strategy is profitable for reputable VC investors (and beneficial for invested firms) would be an interesting extension of our research. Additionally, future research should look at the characteristics of the syndication partners to get a better understanding of what these other VC investors add to the syndicate. Another promising avenue of research is to examine other signals that may have a dark side (e.g., high human capital but overconfident entrepreneurs). Extending our knowledge of the dark side of signals can have an important impact on our understanding of signals and help further develop one of the most respected and most highly cited theories in economics and management research.

2 The Selection Ability of Crowdinvestors and the Value of Campaign Information

2.1 Introduction

Crowdinvesting[22], i.e., the possibility for firms to raise money from a large, undefined group of individuals (the crowd) via an open call on an internet-based platform, has recently gained popularity as an alternative form of entrepreneurial finance (Agrawal et al. 2015, Ahlers et al. 2015, Vismara 2016, 2018). However, researchers, practitioners and policymakers are concerned about private individuals without (visible) early-stage investment experience being exposed to the risks of investing in a young firm (Hornuf and Schwienbacher 2017). Even though some crowdinvestors may have the expertise to evaluate the quality of firms that ask the crowd for funding, most of them are likely to be amateur investors.

When professional investors face information asymmetries caused by the fact that young firms lack a track record or that most of their assets are intangible, i.e., are hard to evaluate (Denis 2004), they rely on signals. Signals are costly to obtain and correlate with the quality of the firm so that only high-quality firms have an incentive to invest in them (Akerlof 1970, Spence 1973, Stiglitz 2000). Thus, signals allow investors to distinguish high-quality from low-quality firms (see Connelly et al. 2011 and Bergh et al. 2014 for a review of the existing literature). Furthermore, professional investors profit from information that is revealed about the firm over time and that may complement the initial signal, e.g., additional information generated through the examination process at the patent office that affects the initial signal of a patent (Haeussler et al. 2014).

It is unclear, though, whether non-professional, private investors can profit from or use signals and additional information in the same way as professional investors. Actually, the investment decisions of investors on crowdinvesting platforms are still a black box. Although the information provided through a pitch deck on the platform are similar to those available to professional investors, recent literature provides evidence of a herding behavior, i.e., crowdinvestors rely on their observation of peer-investors that contributed earlier to the funding campaign (Colombo 2015, Vismara 2018). If uninformed investors simply mimic the investment decisions of (potentially also amateur) peers without

[22] Crowdsourcing is also referred to as equity crowdfunding.

being able to interpret the signals that young firms send, incorrect information about the quality of the firm might be amplified over time, and a herding response could overrule relevant private information (e.g., Herzenstein et al. 2011, Zhang and Liu 2012). Thus, a better understanding of the informational value of the funding decisions of early investors, in the following referred to as “information generated by the funding campaign”, is important. To fill this gap, this paper takes a closer look at the investment decisions of crowdinvestors and investigates whether additional campaign information benefits the quality of decision-making by crowdinvestors.

Based on signaling theory, we argue that the value of campaign information, such as the reached percentage of the funding goal at the time of the investment (in the following referred to as the “funding level”) depends on the decision-making quality of the investors that generate the campaign information. The decision quality is expected to be high when informed investors make early investment decisions and uncertain or uninformed investors wait until the campaign information produced by the informed investors becomes available before they additionally join the funding campaign upon receiving positive campaign information. This argument is in line with the literature on observational learning, which requires the decision-making of individuals to be sequential, allowing uninformed individuals to delay their decision and imitate the actions of individuals who appear to have more information (Banerjee 1992, Bikhchandani et al.1992). Therefore, we predict a positive relationship between investments made at higher funding levels and the investor’s decision quality. Second, we argue that the value which campaign information adds to the decision quality of the crowd depends on the strength of the signals the firm initially sends to the crowd[23]. Recent theoretical work on signaling theory suggests that uninformed investors who are confronted with multiple signals of different informational content focus on more observable, stronger signals and might ignore other signals that contain conflicting information (Drover et al., 2018). In our context, a high pre-money valuation issued by the platform owner represents a strong signal of quality that might induce uninformed investors to discard relevant negative information and invest in a firm. As a result, when the pre-money valuation is high, the information content of campaign information generated by the investment decisions of these more uninformed

[23] Recent theoretical and empirical work on signaling theory suggests that the signals young companies send to resource providers differ in their strength, based on the extent to which the signal is correlated with unobservable quality (Connelly et al. 2011, Vanacker et al. 2020).

individuals is, on average, of lower value compared to a firm with a lower pre-money valuation. In the latter case, uninformed individuals wait for additional campaign information to be revealed. We therefore predict the positive relationship between investments made at higher funding levels and the decision quality to be stronger for firms with a lower pre-money valuation compared to firms with a high pre-money valuation.

To test these predictions, we collected a unique dataset containing investment-level information on all crowdinvestors on Companisto, the leading crowdinvesting platform in Germany. In total, the dataset contains information about 18,690 investors and 52,024 investments in 74 distinct funding campaigns from June 2012 to April 2018. In our econometric analysis, we use the performance of a focal investment to measure the decision quality of a crowdinvestor.[24] A profit-participating loan generates (1) a negative return in case of firm bankruptcy, or (2) a positive return in case of (2a) an exit participation when the crowd agrees to an offer of a third party, or (2b) a profit participation when the loan is still ongoing. To account for the fact that the status of 20,285 investments (39%) in 30 campaigns (40.5%) was still pending at the time the data were analyzed (December 2020), we use survival time techniques and simultaneously estimate the hazard of an investment to result in a failure or exit by applying unordered competing risk regressions (Fine and Gray 1999). We investigate how the hazard rates of these two competing events vary depending on the funding level reached at the time of the investment and the pre-money valuation of the company at the time of the funding campaign.

Our results provide limited support of our hypothesis that additional campaign information is positively associated with the decision quality of crowdinvestors. We find that investments made after 75 percent of the campaign's funding goal is reached have a 27 percent lower likelihood to fail and a 77 percent higher likelihood to exit, hence are of higher quality than investments made before 75 percent of the campaigns funding goal is reached. However, this positive association between investments made at high funding levels and performance is limited to investments in funding campaigns of less valuable

[24] Compared to professional venture capital investors, crowdinvestors are not entitled to any voting rights or rights to issue instructions regarding the management of the operational activities of the company. Therefore, crowdinvesting is often described as a quasi-equity market because investors do not receive any equity in return for their investments but profit-participating loans (Hornuf and Schwienbacher 2018). Consequently, the performance of crowdinvestors solely depends on their ability to select companies of high quality that turn out to be successful investments over time.

firms. For the 25 percent most valuable firms in our sample, investments at funding levels above 75 percent are more likely to be still pending, thereby possibly generating ongoing positive returns for the investor in case of positive firm returns (= profit-participation right), while investments at lower funding levels are associated with a higher likelihood of exit and failure. As we are not able to economically distinguish positive returns from pending investments compared to investments that successfully exited, the informational benefit of positive campaign information for investors contributing to the funding campaigns of highly valuable firms, i.e., firms with a strong signal, remains unclear.

Our paper offers an important contribution to the entrepreneurial finance literature that deals with signals and information cascades between investors on crowdinvesting platforms. While existing studies quantify the return on investments from equity-crowdfunded firms (Signori and Vismara 2018), this paper adds to the literature by exploiting heterogeneity among investors at the level of their investment and investigates how this relates to their ability to select firms that turn out to be either successful or fail. In particular, we show that positive campaign information benefits the decision quality of crowdinvestors in case the firm sends weaker signals. Thereby, we add to the recent discussion on the complementary effects of firm signals and the value of additional information that is revealed over time (e.g., Haeussler et al. 2014, Colombo et al. 2019b). By focusing on the signaling dynamics between investors on crowdinvesting campaigns, we also contribute to the entrepreneurial finance literature that deals with information cascades among investors on crowdinvesting platforms (Vismara 2018).

This study additionally provides interesting implications for policymakers who are aware of the economic potential of equity crowdfunding for young firms by lowering the barriers to external financing, yet are concerned about private investors being exposed to the high information asymmetries and associated risks in equity markets. Despite weaker regulatory constraints for platforms owners and firms that choose this funding channel compared to other traditional sources of early-stage financing, this study highlights that non-professional investors profit from additional information generated during the funding campaign when the firm is of lower value, and help them to distinguish low- from high-quality firms. Moreover, this study provides implications for platform owners, who should be aware of their role as a financial intermediary between the crowd and the platform. Their pre-money valuation of the firm significantly affects the contribution patterns of the crowd, even though no significant direct correlation with the decision quality of an investor is found in this study. Platform owners should motivate crowdinvestors to not solely rely on the issued pre-money valuation as a signal of quality, but facilitate information exchange between crowdinvestors on their platform and emphasize the importance of other signals that justify the valuation of the firm, such as the characteristics of the founder team or the presented business plan.

2.2 Conceptual background

2.2.1 Information asymmetry and signals in crowdinvesting markets

Nowadays, entrepreneurs who lack financial resources to fund their business can raise money via an open call on internet-based crowdinvesting platforms. The financial contributions of the investors are pooled to close the venture's funding gap in return for equity-like participation rights (e.g., Hornuf and Schwienbacher 2018). Young firms typically choose this funding mechanism as their last resort, in the event that they lack internal funds and additional debt capacity (Walthoff-Borm et al. 2018). Not surprisingly, the failure rate of equity crowdfunded firms compared to firms who raised other sources of capital is significantly higher and investor returns are very skewed because only a minority of crowdfunded ventures turn out to be successful over time (see Vanacker et al. 2019 for a review).[25]

When evaluating the quality of potential investment targets on crowdinvesting platforms, investors face considerable information asymmetries, as most firms that ask for equity financing lack a track record, are not yet profitable, and most of their assets are intangible (Denis 2004), i.e., the information required for the decision-making is largely private instead of public (Akerlof 1970, Stiglitz 2000). In case entrepreneurs are better informed about the quality of their firm than a potential investor and exploit their information advantage, for instance, by overstating the quality of their firm, this can lead to adverse selection (Shane and Stuart 2002, Kaplan and Strömberg 2004). To overcome problems of adverse selection, investors can interpret observable attributes, so-called signals, that are costly to obtain and are correlated with quality, so that only high-quality firms have an incentive to invest in the

[25] For example, Walthoff-Borm et al. (2018) examine the failure rate of equity crowdfunded companies using a sample of UK companies that raised financing on the platforms Crowdcube and Seedrs between 2012 and 2015, and a matched sample of comparable UK non-equity crowdfunded companies that raised other sources of capital. They show that the failure rate of equity crowdfunded companies is 15 percent, while the failure rate in the control group of matched firms that raised debt financing is only 6 percent.

signal (Spence 1973, 2002, Stiglitz 2000). Signals result in a separating equilibrium, allowing uninformed investors to distinguish high-quality firms from low-quality ones (for reviews and examples see Connelly et al. 2011, Bergh et al. 2014).

On crowdinvesting platforms, the platform owner acts as a financial intermediary between the crowd and the firm that asks for funding and, hence, plays an important role in communicating signals of quality. When firms choose crowdinvesting as a funding mode, they apply to the platform of their choice. The platform owner then screens the firms, pre-selects the most promising ones and issues a pre-money valuation of these firms for the crowd. Moreover, the platform owner and the firm agree on the amount of "quasi"-equity offered to the crowd and associated funding goal of the campaign, which set the base for the calculation of the participation rights of individual crowdinvestors. Retained equity is a signal of entrepreneurial intentions that strongly correlates with the probability of success in an initial or follow-on offer in stock markets (Leland and Pyle 1977). Consistent with corporate finance literature, a larger percentage of equity offered to the crowd reduces the firm's likelihood to reach its funding goal (Ahlers et al. 2015, Vismara 2016). When the firm finally launches its funding campaign, the investors are presented with a so-called pitch deck[26], i.e., presentation slides presenting the problem, the solution, and the business idea behind it. The information provided on the platform are comparable to those available to a professional venture capital investor when assessing the quality of a young venture (Ahlers et al. 2015, Ralcheva and Roosenboom 2016).

Although crowdinvestors have access to observable signals of quality, there have been considerable concerns from policymakers about private non-accredited investors without early-stage investment experience participating in a market characterized by high information asymmetries and a high risk of failure (Hornuf and Schwienbacher 2017). Even though part of the crowdinvestors may be able to infer the quality of firms based on signals, others are likely to be amateur investors that lack the ability to distinguish between high- and low-quality firms. The evaluation of signals with different informational content requires expertise that crowdinvestors might lack, which ultimately lead investors to abstain from forming their own judgement about the quality of the young venture (Drover et al. 2018).

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[26] See https://www.companisto.com/de/academy/investieren-bei-companisto/die-sprache-des-crowdinvesting, accessed on March 6, 2021.

Moreover, crowdinvestors have lower incentives to form their own expectation about the quality of the firm, as the expected profit from their investment may not cover the high costs of performing a thorough due diligence (Signori and Vismara 2018).

In case observable signals are insufficient for investors to evaluate the quality of the firm, either because the signals are not strong enough or the investor lacks the ability to evaluate signals, additional information that becomes available over time may play an important role. This additional information can be used to decrease uncertainty, since the investors can use the information to update their expectations and form tighter estimates on the firm's quality (e.g., Eil and Rao 2011, Chambers and Healy 2012, Haeussler et al. 2014). In the context of crowdinvesting, investors might rely on their observation of peer investors that already contributed to the funding campaign (Burtch et al. 2013, Zhang and Liu 2012). Potential investors can actively monitor the progress of the funding campaign, such as to what extent the funding goal of a campaign has already been reached. Moreover, potential investors can observe the number of contributions to a funding campaign, the exact financial amount of the individual contributions, as well as information on the other investors (e.g., previous investments, place of domicile, profession).

Recent research on the selection behavior of crowdinvestors suggests that investors rely on information generated during the funding campaign, as the number and characteristics of early contributions are fundamental in increasing the chances of the firm to attract additional investors and, ultimately, reach its funding goal (Colombo 2015, Vismara 2018). This provides evidence of a herding behavior, which is a well-studied phenomenon in the context of financial markets and occurs if investment decisions across individual decision-makers are correlated (see Devenow and Welch 1996 for a review).

2.2.2 The value of campaign information

On crowdinvesting platforms, investors can build a precise estimate of the firm's quality based on observable signals available before the start of the funding campaign. Informed investors have fewer incentives to wait and observe the actions of others, a phenomenon which is known as "skin in the game" and has already been shown in similar contexts of finance such as initial public offerings (Rock 1986).

If informed investors consider the firm as an attractive investment, they invest a sufficiently large amount of money to cover for the high costs of evaluating the quality of the firm. On the contrary, investors with higher uncertainty towards the quality of the firm wait for positive campaign information to be revealed in order to inform themselves about the quality of the firm. This strategy implies that the later investors assume that the earlier investors made the right decisions, i.e., are informed investors, and is consistent with the decision-making of professional investors who inform themselves through sharing their opinions on investment deals. Once a firm has attracted a highly reputable or experienced investor, other investors are motivated to join the investment syndicate (e.g., Lerner 1994, Tykvova 2007).

Empirical evidence shows that crowdinvestors rely on their observation of peers and tend to avoid campaigns with small funding contributions, suggesting a reverse herding in case the contributions of early investors do not contain sufficiently positive information (Zaggl and Block 2019). On the contrary, funding campaigns characterized by early investors contributing high amounts of money build a herding momentum, i.e., a higher number of additional investors join the funding campaign upon positive campaign information, and ultimately reach higher funding levels (Colombo 2015, Vismara 2018). Thus, it can be assumed that the funding level of a campaign correlates with the firm's quality if uninformed investors delay their investment decision until informed investors have invested and then additionally join the funding campaign upon receiving positive campaign information. In line with that argument, we expect the performance of investments made at high funding levels, i.e., after 75 percent of the campaign's funding goal is reached, to be better than the performance of investments made prior to that funding threshold, as uncertain investors can base their funding decision on more information.[27] This leads to our first hypothesis:

Hypothesis 1: *Investments made at higher funding levels are positively associated with the investor's decision-making quality.*

So far, we have argued that campaign information can be valuable for uninformed investors if they delay their investment decision and wait for informed investors to generate campaign information.

[27] We also run an econometric specification with a continuous measurement of the funding level when testing the robustness of our results.

However, recent theoretical work on signaling theory suggests that decision makers who are confronted with multiple signals and cannot realize a satisfactory level of judgmental confidence typically resort to faster heuristic cognitive processes (Drover et al. 2018). Accordingly, individual decision-makers typically focus on more observable, stronger signals and discard the remaining signals and other information which might even be negative. On crowdinvesting platforms, a high pre-money valuation of the firm issued by the platform owner is a strong signal of quality, as it is prominently placed on the webpage that summarizes current investment opportunities for crowdinvestors and represents an objective evaluation of the firm's value. We therefore argue that the funding campaigns of firms with a high pre-money valuation attract a higher number of uninformed investors that are not able to interpret the firm's quality based on the information provided through the pitch-deck, but build enough confidence to invest in the firm based on its pre-money valuation without having to rely on additional campaign information. Consequently, the additional campaign information, i.e., a high funding level, generated through the investment decisions of these early investors in firms with high pre-money valuation (i.e., strong signal) is of lower value compared to campaign information in firms with a lower pre-money valuation (i.e., less strong signal) where uninformed investors are more likely to wait and observe the funding campaign until sufficiently positive campaign information is revealed.

In line with this reasoning, Zhang and Liu (2012) empirically show that the inferences drawn by individuals on crowd-lending platforms from prior investments into a focal campaign depend on observable characteristics of the individual that asks for money. Funding campaigns of individuals with a high credit rating (strong signal) have a lower herding momentum, i.e., the number of additional investors that join the funding campaign upon positive campaign information, than funding campaigns with unfavorable credit ratings, as uninformed investors built enough judgmental confidence to fund the individual without having to rely on positive campaign information. In case of funding campaigns with unfavorable credit rating (weaker signal), uninformed investors infer from positive campaign information that the individual is worth funding despite its unfavorable characteristics, because other investors are willing to financially support the individual and additionally join the funding campaign at higher funding levels. Ultimately, these investors benefit from their observation of peers, since their loans have a lower default rate.

We therefore expect the value that positive campaign information, i.e., campaigns that reach a high funding level (above 75 percent), generates in terms of helping uninformed investors to distinguish high- from low-quality firms to be higher for firms with a lower pre-money valuation compared to firms with a high pre-money valuation, i.e., the 25 percent most valuable firms in our sample. This leads to our next hypothesis:

Hypothesis 2: *The positive association between investments made at higher funding levels and the investor's decision-making quality is stronger for investments in firms with a lower pre-money valuation compared to investments in firms with a high pre-money valuation.*

2.3 Data and method

2.3.1 Data source and sample description

To empirically investigate whether campaign information benefits the decision quality of crowdinvestors, we collected data on all investments made on Companisto from June 7, 2012 to April 9, 2018. With a market share of 30.6% in 2017, Companisto was the leading crowdinvesting platform in Germany and collected 62,805 investments with a total amount of 44,936,036 EUR in 87 funding campaigns until the date of this study's data collection.

In Germany, crowdinvesting offers are not issued as shares or debt securities, which are the most common forms in the U.S. and UK, but through subordinated profit-participation loans (Hornuf and Schwienbacher 2018). The investor grants a profit-participating loan to the firm after the funding campaign ended successfully by reaching a funding threshold, which is usually well below the funding goal of the firm.[28] The subordinated profit-participating loan grants the investor participation in the firm's profit and a bonus in case of an exit. As the crowd does not hold any equity that can be converted into tradeable shares on the stock-market, crowdinvestors are restricted to the exit opportunity of selling their loans to a third party, typically a venture capitalist, or the issuing firm itself in case the firm wants to buy out the crowd. Otherwise, loans or virtual shares of firms listed on crowdinvesting platforms are difficult to trade between individual crowdinvestors, since there is no accredited secondary market for

[28] On Companisto, the funding threshold for most campaigns is 100,000 EUR. Investors contributing to campaigns that are not successfully funded get their money reimbursed and do not enter a loan agreement.

profit-participating loans (Signori and Vismara 2018). An exit offer has to be validated by the crowd in a legally binding manner. To facilitate an exit, the crowd enters a pooling agreement with the platform who represents the crowd in the event of interest from a third party and facilitates negotiations (Hornuf and Schwienbacher 2018). In case of an exit or profit participation, the investor's return depends on the share of his investment in relation to the total amount of "quasi"-equity offered to the crowd. On Companisto, the loans are granted for an indefinite period of time, but have a minimum term of 5 to 8 years. Once the minimum term has ended, both the investor and the issuing firm may terminate the loan. It is important to note that the rights to participate in the firm's profit as well as a potential exit persist in case the firm terminates the loan agreement, while these rights expire in case the crowdinvestor terminates the loan. Moreover, the crowdinvestor also has a final contractual claim for repayment of the subordinated profit participating loan amount on payment of a final revenue-independent fixed interest rate (Kloehn et al. 2016).

For each funding campaign on Companisto, we gathered all publicly observable information. Out of the 87 observed funding campaigns from 80 firms, we excluded 4 campaigns that did not reach their funding threshold, and 9 campaigns that offered venture loans[29], resulting in a final dataset with information on 74 funding campaigns of 68 firms. We also gathered legal information by collecting data on the incorporation date of the firms as well as the status of their loans and added the respective dates of the exit of the crowd or the insolvency of the firm.

Table A2.1 in the Appendix provides summary statistics of the firms we use in the analysis at the time of their crowdinvesting campaigns and shows the differences between the 25 percent most valuable firms compared to all other firms. On average, the firms have a pre-money valuation of 3,860,000 EUR at the date of their funding campaign and target to raise 392,500 EUR from the crowd. The funding campaigns attract on average 738.3 investors and have a duration of approximately 3 months (91.28 days). Firms seem to successfully reach their funding goal (mean = 99.36 percent), and 22 percent of the funding campaigns even overreached their funding goal. When considering the post-campaign

[29] Venture loans guarantee annual payments of a fixed interest of around 8% over a predefined period. These are not part of this study, as they are comparable to contracts offered on crowd-lending platforms and cannot be sold to a third party.

outcomes of the crowdfunded firms, the loans of 8 funding campaigns (11%) from 6 firms were successfully sold to third parties, the loans of 36 funding campaigns (49%) from 33 firms defaulted, and the loans of 30 funding campaigns (39%) from 29 firms were still pending as of December 2020. Interestingly, we do not observe significant differences of the exit or failure rates when comparing the 25 percent most valuable firms with the ones characterized by a lower pre-money valuation. Nonetheless, the funding campaigns of the 25 percent most valuable campaigns attract significantly more investors (1036.19 investors vs. 620.26 investors; Wilcoxon-Mann-Whitney test: $p = 0.000$) and reach significantly higher funding levels (130.61 percent of the funding goal vs. 86.96 percent of the funding goal; Wilcoxon-Mann-Whitney test: $p = 0.000$). Thus, the platform's objective evaluation of the firm's quality at the time of the funding campaign might be perceived as a signal of quality by the crowd, as more investors contribute to the campaigns of highly valuable firms.

For the selected campaigns, we gathered all available investment-level data available on the platform, such as the investor's name, his or her location and the date as well as the amount of his or her investment. The availability of a unique identifier for each investor in the source code of Companisto's online platform allows us to observe an investor's selection behavior over time.[30] For investors that invested in more than one funding campaign of a firm (3.4%) we only kept the first investment into that firm, as follow-on investments of one investor are likely to be correlated. Our results stay robust to the inclusion of follow-on investments. In total, the final dataset consists of 18,690 investors with 52,024 investments in 74 campaigns from June 2012 to April 2018.

2.3.2 Description of the variables

Dependent variables

In order to measure the decision-making quality, we investigate the performance of a focal investment. We consider that investments can generate (1) a negative return in case the issuing firm goes bankrupt and the issued loans default (*Failure*), or (2) a positive return in case of (2a) an exit participation when the crowd agrees to an offer of a third party (*Exit*), or (2b) a profit participation when the loan is still

[30] For each unique investor identifier, we checked the consistency of the name over time and dropped ambiguous investors.

ongoing (*Pending*). While investments that exit definitely generate a positive return for the investor, pending investments yield ongoing positive returns in case the firm has a positive cash-flow, but will eventually default in case of an insolvency of the issuing firm. It might even be the case that the aggregated crowd is satisfied with the ongoing profit participation and denies a potential exit offer, as the exit participation right persists even if the subordinated loan agreement is terminated by the issuing firm. Thus, the total return of pending investments cannot yet be exactly determined, but the pending status of the loan is nevertheless an important factor to consider in our empirical specification. In our sample, 39 percent of the investments still have a pending status as of December 2020, while 11.2 percent of the investments successfully exited and 49.8 percent of the investments failed (see Table 2.2 for the descriptive statistics at the level of the investment).

Independent variables

The *Funding Level, t-1* measures the share of the firm's funding goal that has been reached the day before the focal investment. For our main analysis, we build the dummy variable *Funding Level, t-1: [75%, .)* which equals 1 for investments made after 75 percent of the funding goal is reached and 0 for investments made prior to this funding level. 26.2 percent of the investments are made after 75 percent of the funding goal is reached.

The *Firm Value* represents the pre-money valuation of the firm and is estimated by the platform previously to the start of the funding campaign. As this variable is highly skewed (skewness = 4.71), we create the dummy variable *Firm Value > p75*, which equals 1 for the 25 percent most valuable firms at the time of their funding campaign and 0 for less valuable firms.[31]

Control variables

We created control variables at the level of the investment, the investor, the firm, and the firm-investor dyad. The variable *Investment Sum* measures the amount of money an investor contributes to the focal funding campaign. Due to the skewness of this variable (mean = 548.53 EUR, skewness = 19.71), we separate investments at the 25th, 50th, 75th and 90th percentile and define dummy variables for

[31] The variable *Pre-Money Valuation* is highly correlated with the age of the company (*Company Age*) at the time of the funding campaign (corr = 0.73). Thus, we do not use this variable in our main analysis, but use this variable in our robustness checks as younger companies are typically surrounded by higher information asymmetries.

each of the categories (reference category: *Investment Sum: [p0, p25)*). The assignment is updated every year in our observation period. Moreover, we control for the timing of the contribution to the funding campaign and create three mutually exclusive dummy variables for investments made in the first month of the campaign (*Campaign Month 1*, reference category), second month (*Campaign Month 2*) and thereafter (> *Campaign Month 2*). At the level of the investor, we control for the total amount of money he or she invested on Companisto including the focal investment at the time of the contribution (*Total Amount Invested (ln)*). This variable is also updated when investments of the investor exit or fail. Consistent with the variable *Investment Sum*, this variable is highly skewed (skewness = 6.49) and we therefore use its logarithmic transformation. Moreover, we control for the number of firms in the investment portfolio of the investor over time (*Number of Firms*) and distinguish between investors with only one active investment, two to five active investments and more than five active investments.[32] At the level of the firm, we control for the *Firm Share Offered (%)* to the crowd, as well as the *Funding Goal (1000 EUR).* We also control for the *Distance (ln+1)* between the firm and the investor, as the tendency to invest locally is a well-known behavioral bias that is also relevant on crowdinvesting platforms (Hornuf and Schmitt 2016). Lastly, we control for unobserved heterogeneity across offerings on Companisto over time with *Campaign Year* fixed effects.

Table 2.1 shows that the bivariate correlations between our variables are generally low with a few exceptions. Not surprisingly, investments made within the first month of the campaign negatively correlate with the variable that identifies investments at high funding levels (corr = -0.494) while investments made after the second campaign month positively correlate with investments at high funding levels (corr = 0.486). Moreover, the lowest and highest categories of the variable *Investment Sum* are highly correlated with the total amount the investor invested in different firms on Companisto over time (corr = -0.508 and 0.457).[33]

[32] 57 percent of the investors in our sample only invested in one company. The measurement of these investor-level variables (*Number of Firms, Total Amount Invested (ln)*) is right-censored, as we do not observe (potential) investments made after the data was collected in April 2018.

[33] For the bivariate correlations (Table 2.1) and summary statistics (Table 2.2) of our variables, we set the time-varying investor-level variables *Total Amount Invested (ln)* and *Number of Firms* to the value at the time of the focal investment. In the competing risk regression, these variables vary over the life span we observe the investment and estimate the instantaneous risk of experiencing an *Exit* or *Failure*.

Table 2.1 Bivariate correlations at the level of the investment (n = 52,024)

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	Pending	1.000																			
2	Failure	-0.797	1.000																		
3	Exit	-0.284	-0.354	1.000																	
4	Funding Level, t-1: [75%, .)	0.058	-0.059	0.004	1.000																
5	First Campaign Month	-0.015	-0.045	0.094	-0.494	1.000															
6	Second Campaign Month	0.030	-0.009	-0.033	0.089	-0.536	1.000														
7	> Second Campaign Month	-0.010	0.059	-0.078	0.486	-0.673	-0.264	1.000													
8	Investment Sum: [p0, p25)	0.026	-0.026	0.002	-0.052	0.010	0.028	-0.035	1.000												
9	Investment Sum: [p25, p50)	0.002	0.015	-0.027	0.009	-0.014	0.000	0.016	-0.310	1.000											
10	Investment Sum: [p50, p75)	-0.011	0.001	0.015	0.002	-0.004	0.005	0.000	-0.282	-0.330	1.000										
11	Investment Sum: [p75, p90)	-0.037	0.031	0.008	0.016	0.013	-0.024	0.006	-0.229	-0.268	-0.244	1.000									
12	Investment Sum: [p90, p100]	0.021	-0.024	0.005	0.032	-0.003	-0.014	0.015	-0.197	-0.231	-0.210	-0.170	1.000								
13	Total Amount Invested (ln)	0.010	0.028	-0.060	-0.023	0.052	-0.034	-0.030	-0.508	-0.182	0.091	0.261	0.457	1.000							
14	Number of Firms: 1	-0.022	-0.015	0.058	0.172	-0.178	0.032	0.175	-0.053	-0.024	-0.009	0.034	0.070	-0.402	1.000						
15	Number of Firms: [2, 6)	0.004	0.006	-0.016	-0.047	0.030	0.017	-0.049	-0.057	-0.010	0.037	0.026	0.007	0.058	-0.586	1.000					
16	Number of Firms: [6, .)	0.020	0.010	-0.047	-0.136	0.162	-0.053	-0.139	0.120	0.038	-0.031	-0.066	-0.085	0.376	-0.449	-0.460	1.000				
17	Distance (ln+1)	-0.019	0.017	0.001	0.037	-0.074	0.033	0.056	-0.007	-0.009	0.009	0.008	0.000	0.072	-0.088	0.039	0.054	1.000			
18	Firm Value >= p75	-0.095	0.199	-0.169	0.200	-0.157	-0.009	0.188	-0.090	0.010	-0.006	0.022	0.079	0.143	-0.010	0.017	-0.008	0.048	1.000		
19	Firm Share Offered (%)	-0.003	-0.141	0.228	-0.139	0.123	-0.016	-0.126	0.001	-0.040	0.049	0.009	-0.020	-0.057	0.035	-0.014	-0.022	0.008	-0.509	1.000	
20	Funding Goal (1000 EUR)	-0.168	0.218	-0.086	0.068	-0.145	-0.005	0.170	-0.127	-0.016	0.060	0.024	0.074	0.142	0.016	0.017	-0.036	0.072	0.473	0.165	1.000

2.3.3 Empirical strategy

To account for the fact that the status of 20,285 investments (38.99%) in our sample is still pending as of December 2020, we apply survival time techniques and run unordered competing risks regressions (Fine and Gray 1999). Our dataset contains multiple failure-time data, as two competing events (*Failure* or *Exit*) occur for the same subject under investigation, i.e., the individual crowdinvestor. In these studies, failure times are correlated within the subject, thereby violating the independence of failure times assumption required in traditional survival analysis. In the context of our study, the events of failure or exit can occur in any temporal sequence, as the investor becomes at risk of experiencing these events for each of his investments. Besides, these two distinct events are competing, as the investor cannot experience an exit once his investment failed and vice versa. One major advantage of a semi-parametric approach is the fact that we do not need an assumption on the distribution of the baseline hazard rates of *Failure* or *Exit*, i.e., the likelihood of *Failure* (*Exit*) given that the other event of interest has not yet occurred, because the analysis is reduced to binary outcomes at each time one of the two competing events occur (Cox 1972).

To test our hypotheses, we first estimate the likelihood of an investment to generate positive returns for the investor, which is the inverse probability of *Failure* (i.e., Pr(*Positive Return*) = 1 – Pr(*Failure*)). We therefore model the subhazard that an investment results in a failure, while simultaneously controlling for the hazard of the competing event of an exit. Hypothesis 1 predicts that investments at higher funding levels are positively associated with the decision-making quality of the investor. In our empirical specification, this requires

(1) the relationship between investments made at high funding levels (i.e., *Funding Level, t-1: [75%, .) = 1*) and the likelihood of *Failure* to be significantly negative.

However, if investments at high funding levels (i.e., *Funding Level, t-1: [75%, .) = 1*) are both negatively correlated with the likelihood to fail and the likelihood to exit, the performance difference to investments at lower funding levels is unclear. This is explained by the fact that investments at high funding levels consequently have a significantly higher likelihood to still be pending, compared to investments at lower funding levels (i.e., *Funding Level, t-1: [75%, .) = 0*) that are characterized by a higher likelihood to fail, but also a higher likelihood to exit.[34] In addition to the first condition, the test of Hypothesis 1 therefore requires

(2) the relationship between investments made at high funding levels (i.e., *Funding Level, t-1: [75%, .) = 1*) and the likelihood of *Exit* to be not significantly negative, i.e., not significant or significantly positive.

Hypothesis 2 predicts the positive association between investments made at higher funding levels and investment performance to be stronger for firms with a lower pre-money valuation compared to firms with a high pre-money valuation. In our empirical specification, this requires

(1) the negative relationship between investments made at high funding levels (i.e., *Funding Level, t-1: [75%, .) = 1*) and the likelihood of *Failure* to be significantly greater in magnitude for firms with a lower pre-money valuation (i.e., *Firm Valuation > p75 = 0*) compared to firms with a high pre-money valuation (i.e., *Firm Valuation > p75 = 1*).

When investigating positive returns, we do not economically differentiate between investments that are still pending or already exited. Nonetheless, the second condition for Hypothesis 1 has to be fulfilled for both groups of firms with a high and lower pre-money valuation. In our empirical specification, this requires

(2) the relationship between investments made at high funding levels (i.e., *Funding Level, t-1: [75%, .) = 1*) and the likelihood of *Exit* to be not significantly negative, i.e., not significant or significantly positive, for firms with a lower pre-money valuation (i.e., *Firm Valuation > p75 = 0*) and firms with a high pre-money valuation (i.e., *Firm Valuation > p75 = 1*).

Overall, our empirical setting does not allow for a causal interpretation of our results. Endogeneity might arise from unobserved heterogeneity. In our theory section, we argue that the degree to which investors are informed about the quality of the firm determines the timing of his or her investment

[34] In this particular situation, it might be that the positive returns due to the higher exit rate of investments at lower funding levels cover for the losses due to the higher default rate, and eventually yield a superior return for the investor than investments at higher funding levels that are more likely to generate positive returns through their ongoing profit participation.

decision, i.e., whether he or she waits for additional campaign information to be revealed. However, it might be that informed investors, although not relying on campaign information in their assessment of the firm's quality, take more time to evaluate the firm's signals and therefore might invest at high funding levels. Moreover, we do not observe a variety of firm signals that correlate with quality and, hence, focus our analysis on the pre-money valuation issued by the platform owner as an objective measurement for the firm's quality at the start of the funding campaign.

2.4 Results

In the following, we report our results. We first provide univariate statistics (Table 2.2), followed by multivariate competing risk regressions (Table 2.3). Afterwards, we provide robustness checks to test the validity of our measures (Table A2.2 in the Appendix) and run additional analyses to further investigate our findings (Table 2.4 and Table A2.3 in the Appendix).

Table 2.2 lists the summary statistics of the variables used in the analysis (investment level) and provides univariate test statistics to show differences by the timing of the focal investment.

Table 2.2 Summary statistics (by funding level at the time of the investment)

Sample specification	Full sample (n = 52,024)		Funding Level, t-1		Wilcoxon-Mann-Whitney test: (1) = (2)
			(1): [0%, 75%) (n = 38,382)	(2): [75%, .) (n = 13,642)	
	Mean	SD	Mean	Mean	p-value
Pending	0.390		0.373	0.437	0.000
Failure	0.498		0.516	0.448	0.000
Exit	0.112		0.111	0.114	0.313
Funding Level, t-1: [75%, .)	0.262		0.000	1.000	
Campaign Month 1	0.578		0.723	0.169	0.000
Campaign Month 2	0.174		0.154	0.230	0.000
> Campaign Month 2	0.249		0.123	0.601	0.000
Investment Sum: [p0, p25)	0.210		0.222	0.174	0.000
Investment Sum: [p25, p50)	0.266		0.264	0.273	0.041
Investment Sum: [p50, p75)	0.231		0.231	0.232	0.730
Investment Sum: [p75, p90)	0.165		0.161	0.175	0.000
Investment Sum: [p90, p100]	0.128		0.122	0.146	0.000
Total Amount Invested (ln)	6.054	1.851	6.080	5.982	0.000
Number of Firms: 1	0.364		0.315	0.502	0.000
Number of Firms: [2, 6)	0.376		0.389	0.337	0.000
Number of Firms: [6, .)	0.261		0.296	0.160	0.000
Distance (ln+1)	5.321	1.807	5.282	5.433	0.015
Firm Value >= p75	0.393		0.328	0.574	0.000
Firm Share Offered (%)	13.061	8.244	13.743	11.144	0.000
Funding Goal (1000 EUR)	523.783	416.570	506.905	571.269	0.000

We observe notable differences between investments made after 75 percent of the funding goal has been reached at the time of the investment (*Funding Level, t-1: [75%, .)* = 1) and investments made prior to this threshold (*Funding Level, t-1: [75%, .)* = 0). While late investments to a funding campaign do not have a significantly higher exit rate than earlier investments (11.4 percent vs. 11.1 percent; Wilcoxon-Mann-Whitney test: $p = 0.313$), they have a significantly lower failure rate (44.8 percent vs. 51.6 percent; Wilcoxon-Mann-Whitney test: $p = 0.000$) and, consequently, are also more likely to be still pending at the time of the analysis (43.7 percent vs. 37.3 percent; Wilcoxon-Mann-Whitney test: $p = 0.000$). This provides descriptive evidence for Hypothesis 1, that the decision-making quality is positively correlated with campaign information, as investments at high funding levels are more likely to generate positive returns, i.e., they have a significantly lower likelihood to fail, while not being significantly less likely to exit compared to investments at lower funding levels. Moreover, late investments are characterized by higher investment sums than earlier investments, as the proportion of very high investment sums (*Investment Sum: [p90, p100]* = 1) is slightly larger for late investments compared to earlier investments (14.6 percent vs. 12.2 percent; Wilcoxon-Mann-Whitney test: $p = 0.000$), while the proportion of very low investment sums (*Investment Sum: [p0, p25)* = 1) is lower (17.4 percent vs. 22.2 percent; Wilcoxon-Mann-Whitney test: $p = 0.000$). Lastly, we observe late investments to be done by investors with a lower total amount invested on the platform (Wilcoxon-Mann-Whitney test: $p = 0.000$) and a lower total number of investments, as the proportion of investors with only one investment in our observation period is significantly larger for later investments compared to earlier investments (50.2 percent vs. 31.5 percent; Wilcoxon-Mann-Whitney test: $p = 0.000$). Thus, we observe investors that contribute at higher funding levels to a campaign to have less investment experience on Companisto at the time of their investment but invest more money than investors that contribute at funding levels below 75 percent of the funding goal.

Table 2.3 presents the results of a competing risk regression that clusters standard errors by investor.

Table 2.3 Results of the competing risk regressions

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Event	Failure	Exit	Failure	Exit	Failure	Exit
Funding Level, t-1: [75%, .)			0.831***	1.773***	0.817***	2.006***
			(0.015)	(0.064)	(0.021)	(0.067)
Firm Value > p75			1.002	0.954	0.994	1.255***
			(0.020)	(0.048)	(0.021)	(0.064)
(Funding Level, t-1: [75%, .) X (Firm Value > p75)					1.031	0.395***
					(0.029)	(0.038)
Campaign Month 2	1.112***	0.754***	1.152***	0.609***	1.153***	0.596***
	(0.019)	(0.026)	(0.019)	(0.024)	(0.019)	(0.024)
> Campaign Month 2	1.113***	0.827***	1.228***	0.585***	1.227***	0.596***
	(0.016)	(0.032)	(0.022)	(0.027)	(0.022)	(0.028)
Investment Sum: [p25, p50)	0.995	0.957	0.999	0.944	0.999	0.941
	(0.018)	(0.038)	(0.018)	(0.037)	(0.018)	(0.037)
Investment Sum: [p50, p75)	0.911***	1.047	0.914***	1.026	0.914***	1.025
	(0.021)	(0.051)	(0.021)	(0.050)	(0.021)	(0.050)
Investment Sum: [p75, p90)	0.883***	1.131**	0.890***	1.100	0.890***	1.098
	(0.025)	(0.070)	(0.025)	(0.069)	(0.025)	(0.069)
Investment Sum: [p90, p100]	0.726***	1.303***	0.731***	1.262***	0.732***	1.260***
	(0.025)	(0.102)	(0.026)	(0.100)	(0.026)	(0.100)
Total Amount Invested (ln)	1.054***	0.990	1.055***	0.993	1.055***	0.993
	(0.007)	(0.015)	(0.007)	(0.015)	(0.007)	(0.015)
Number of Firms: [2, 6)	0.978	0.913***	0.970*	0.921**	0.970*	0.923**
	(0.016)	(0.032)	(0.016)	(0.032)	(0.016)	(0.033)
Number of Firms: [6, .)	0.873***	0.856***	0.861***	0.881**	0.862***	0.884**
	(0.020)	(0.043)	(0.020)	(0.045)	(0.020)	(0.045)
Distance (ln+1)	1.007**	1.028***	1.007**	1.025***	1.007**	1.024***
	(0.003)	(0.008)	(0.003)	(0.008)	(0.003)	(0.007)
Firm Share Offered (%)	1.000***	0.998***	1.000***	0.998***	1.000***	0.998***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Funding Goal (1000 EUR)	0.967***	1.079***	0.967***	1.075***	0.967***	1.074***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Campaign Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Investments	52,024	52,024	52,024	52,024	52,024	52,024
Number of Events	25,923	5,816	25,923	5,816	25,923	5,816
Number of Competing Events	5,816	25,923	5,816	25,923	5,816	25,923
Log Likelihood	-262045.189	-59888.080	-261991.829	-59770.019	-261991.333	-59716.494

Note: Standard errors in parentheses are clustered by investor. The coefficients represent changes of the subhazard, i.e. the probability that the specified event occur given that the competing event has not yet occurred.

* p < 0.1, ** p < 0.05, *** p < 0.01

Model 1 and 2 contain the control variables only. In Model 3 and 4, we add our key explanatory variable *Funding Level, t-1: [75%, .)*, and further add the interaction term between the variables *Funding Level, t-1: [75%, .)* and *Firm Value > p75* in Model 5 and 6. Model 1, 3 and 5 estimate the subhazard that the investment results in a failure, while controlling for the subhazard of an exit. Conversely, Model 2, 4 and 6 estimate the subhazard that the investment results in an exit, while controlling for the subhazard of a failure. We report hazard ratios, which can be interpreted as the multiplicative effect on the hazard rate, i.e., a one-unit increase in the explanatory variable equals a 100*(hazard ratio-1) percentage change of the hazard of *Failure* or *Exit* (Allison 1984). As we report exponentiated coefficients, the effects of interaction variables are multiplicative.

Considering our control variables, Models 1 and 2 show a significant negative (positive) association between the investment sum and the likelihood to fail (exit). In particular, results from Model 1 show that the 10 percent highest investments have a 27.4 percent lower likelihood to fail than the 25 percent lowest investments (Model 1: hazard ratio (HR) = 0.726; p = 0.000). In addition, the 10 percent highest investments have a 30.3 percent higher likelihood to exit than the 25 percent lowest investments (Model 2: HR = 1.303; p = 0.001). Moreover, investments made after the first month of the campaign have a significantly higher likelihood to fail and lower likelihood to exit than earlier investments. For example, investments made in the third month of the funding campaign or later have a 11.3 percent higher likelihood to fail (p = 0.000) and a 17.3 percent lower likelihood to exit (p = 0.000) than investments made during the first month of the funding campaign. Interestingly, the investments of crowdinvestors with a portfolio size of one firm (*Number of Firms* = 1) have a significantly higher likelihood to exit, but at the same time higher likelihood to fail than the investments of crowdinvestors with larger investment portfolios (*Number of Firms: [2, 6); Number of Firms [6, .)*).

In Model 3 and 4, we introduce our main variables of interest *Funding Level*, *t-1: [75%, .)* and *Firm Value > p75*. Results show that investments made after 75 percent of the funding goal is reached have a 26.9 percent lower likelihood to fail (Model 3: p = 0.000) and 77.3 percent higher likelihood to exit (Model 4: p = 0.000) than investments made prior that funding level. The effects of our control variables are consistent with Model 1 and 2. Hence, these results support Hypothesis 1, implying that investments made at higher funding levels are positively correlated with decision quality, as these investments have a significantly lower likelihood to fail, while they do not have a significantly lower likelihood to exit than investments made at lower funding levels. In fact, investments made at high funding levels also have a significantly higher exit rate, hence are more likely to have already generated a definite positive return than investments made at lower funding levels.

To test our Hypothesis 2, we interact our main variable of interest *Funding Level, t-1: [75%, .)* with the variable *Firm Value > p75* (Model 5 and 6). When investigating the likelihood to fail (Model 5), the interaction term is not significant ($p > 0.1$). Thus, the negative relationship between investments made at funding levels above 75% and the likelihood of a failure does not significantly change when comparing investments in the 25% most valuable firms to investments in firms with a lower pre-money valuation. Thus, we do not find support for Hypothesis 2 arguing that the relationship between the decision quality and the funding level at the time of the investment depends on the pre-money valuation of the firm. Nonetheless, we do observe notable differences for the effect of the *Funding Level, t-1: [75%, .)* on the likelihood to exit between investments in firms with a high pre-money valuation (*Firm Value > p75 = 1*) compared to firms with a lower pre-money valuation. Model 6 shows that for investments made into firms with a pre-money valuation below the 75th percentile (i.e., less strong signal), investments made at funding levels above 75 percent have a 101 percent higher likelihood to exit than investments made below that funding level ($p = 0.000$). This positive association significantly decreases ($p = 0.000$) and is reversed for the 25 percent most valuable firms (*Firm Value > p75* = 1), as investments made after 75 percent of the funding goal is reached have a 20.8 percent lower likelihood to exit than investments made below that funding level (HR: 2.006*0.395 = 0.792; $p = 0.015$). Given the fact that investments made after 75 percent of the funding goal is reached also have a significantly lower likelihood to fail than earlier investments into the campaigns of these firms (see Model 5), one can derive that these late investments into highly valuable firms have a higher likelihood to still be pending compared to earlier investments, thereby generating ongoing returns in case of positive firm cash flows. Conversely, investments made below the funding threshold of 75 percent have a higher likelihood to fail and to exit than late investments into highly valuable firms. We therefore observe a higher performance variance among these crowdinvestors that do not contribute at high funding levels to the funding campaigns of firms with a high pre-money valuation (i.e., strong signal).

Overall, the results illustrated above provide limited support for our hypothesis that investments at high funding levels of a campaign are positively associated with investment performance, because this positive association is confined to investments in less valuable firms, where investments at higher funding levels are negatively correlated with the likelihood to fail and positively correlated with the likelihood to exit. For the most valuable firms in our sample, the effect is unclear, as investments at high funding levels are associated with a higher likelihood to still be pending, while investments at lower funding levels are associated with a higher likelihood to either exit or fail. Thus, positive campaign information only adds to the decision quality of crowdinvestors in case of a less strong signal, i.e., firms with a lower pre-money valuation.

2.4.1 Robustness checks

To further analyze our hypotheses and assess the robustness of our results, we apply alternative measures for our main variables of interest (Table A2.2 in the Appendix). First, we use a continuous specification of our variable *Funding Level, t-1* which is truncated at 100 percent, as a funding level above 100 percent is undefined for campaigns of firms that do not decide to overreach their funding goal (Model A1 and A2).

Model A1 shows that a one percentage point increase of the *Funding Level, t-1* significantly decreases the likelihood to fail by 0.2 percent ($p = 0.000$), irrespective of the pre-money valuation of the firm. When considering exits (Model A2), a one percentage point increase of the *Funding Level, t-1* significantly increases the likelihood to exit by 1.1 percent for investments in firms below the 75th percentile ($p = 0.000$), while this effect significantly decreases for the 25 percent most valuable firms in our sample ($p = 0.000$). Investors that contribute one percentage point later than their peers to the funding campaigns of the 25 percent most valuable firms have a 0.3 percent lower likelihood to exit (HR: $1.011*0.986 = 0.997$; $p = 0.008$). Thus, these results are consistent with the results of our main regressions.

As a further robustness check, we replace the variable *Funding Level, t-1* with the number of investors that contributed earlier to the funding campaign (*Number of Investors, t-1*) in Model A3 and A4. When investigating the likelihood to fail (Model A3), an additional 100 investors that contributed earlier decreases an investment's likelihood to fail by 6.2 percent (p = 0.000) for less valuable firms (*Firm Value* > p75 = 0), while the effect is not significant for investments in the 25% most valuable firms (HR: 0.938*1.065 = 0.999; p = 0.791). Moreover, Model A4 shows that the effect of *Number of Investors, t-1* on the likelihood to exit is not significant at the 10 percent level for less valuable firms (*Firm Value > p75* = 0), while the effect significantly decreases for the 25 percent most valuable firms (p = 0.000). As a result, an additional 100 investors that contributed earlier to the focal investment significantly decreases the likelihood to exit by 6.6 percent (p = 0.000) for investments in highly valuable firms. These results replicate our main finding, that positive campaign information in terms of the number of investors at the time of the focal investment only adds to the decision quality in case of less valuable firms, where investments at higher investor counts have a higher likelihood to generate positive returns – in this case through ongoing profit participation – than investments at lower investor counts.

As a last robustness check, we replace the dummy variable *Firm Value > p75* with a dummy variable that identifies the 25 percent oldest firms in our sample (*Firm Age > p75*). Since older firms have a longer track record, information asymmetries and the potential risk of an adverse selection are generally lower (e.g., Denis 2004). Based on our theoretical foundation, one could expect the informational benefit of campaign information to be greater for the funding campaigns of firms of a younger age compared to the older firms of our sample. Results from Model A5 show that investments made after 75 percent of the funding goal is reached have a 27 percent lower likelihood to fail (p = 0.000) than investments made below that funding level in campaigns of younger firms (*Firm Age > p75* = 0). For the 25 percent oldest firms in our sample, the negative association between investments made at high funding levels significantly decreases in magnitude (p = 0.000) and is reversed, as investments made after 75 percent of the funding goal is reached have a 6.6 percent higher likelihood to fail than investments made prior to this funding level (HR: 0.73*1.46 = 1.066; p = 0.016). Moreover, Model A6 shows that investments made after 75 percent of the funding goal is reached have a 119.7 percent higher likelihood to exit (p = 0.000) than investments prior that funding level for the funding campaigns of younger firms. For investments in the 25 percent oldest firms, the positive effect of *Funding Level, t-1: [75%, .)* significantly decreases (p = 0.000) and is no longer significant (HR: 2.197*0.395 = 0.868; p = 0.132). These results support our main finding, that the positive relationship between investments made at high funding levels and investment performance is confined to firms with, in this case, higher information asymmetries. For firms that are characterized by less information asymmetries, i.e., are of older age, individuals who contribute upon positive campaign information at high funding levels actually perform worse than individuals who contribute at lower funding levels, as these late investments are characterized by a higher likelihood to fail. Hence, the informational content of campaign information generated through the investment decisions of early investors does not add to the decision quality of these investors.

2.4.2 Additional analyses

To further analyze our findings, we evaluated the extent to which our results are driven by investors that contribute to campaigns after the funding goal is reached. As investors initially do not know whether firms allow the crowd to invest more money than originally targeted, investors with a positive evaluation of the firm's quality can be expected to invest before the campaign reached its funding goal. Thus, one can assume that individuals that invest at funding levels above 100 percent to base their funding decision to a greater extent on the information of a successful campaign outcome than the firm's signals of quality. Table 2.4 descriptively shows the exit and failure rates for investments at different categories of the *Funding Level, t-1* (Panel A) and distinguishes between investments in firms with a lower pre-money valuation (Panel B: *Firm Value* > *p75* = 0) and those with a high pre-money valuation (Panel C: *Firm Value* > *p75* = 1).

Table 2.4 Exit and failure rates of the investments at different categories of the funding level

		Pending	Failure	Exit
Panel A: All investments	n	%	%	%
Funding Level, t-1: [0%, 25%)	15,461	37.15	51.55	11.31
Funding Level, t-1: [25%, 50%)	12,328	38.55	51.03	10.42
Funding Level, t-1: [50%, 75%)	10,593	36.08	52.34	11.58
Funding Level, t-1: [75%, 100%)	7,475	43.02	42.15	14.82
Funding Level, t-1: [100%, .)	6,167	44.61	48.11	7.28
Funding Level, t-1: [75%, .)	*13,642*	*43.74*	*44.85*	*11.41*
Total	52,024	38.99	49.83	11.18
Panel B: Firm Value > p75 = 0		%	%	%
Funding Level, t-1: [0%, 25%)	11,369	42.18	44.69	13.13
Funding Level, t-1: [25%, 50%)	8,552	42.48	44.21	13.31
Funding Level, t-1: [50%, 75%)	7,197	40.86	44.19	14.95
Funding Level, t-1: [75%, 100%)	4,862	46.83	33.77	19.40
Funding Level, t-1: [100%, .)	1,814	37.65	37.60	24.75
Funding Level, t-1: [75%, .)	*6,676*	*44.34*	*34.81*	*20.85*
Total	33,794	42.40	42.51	15.09
Panel C: Firm Value > p75 = 1		%	%	%
Funding Level, t-1: [0%, 25%)	4,092	23.17	70.60	6.23
Funding Level, t-1: [25%, 50%)	3,776	29.66	66.47	3.87
Funding Level, t-1: [50%, 75%)	3,396	25.94	69.61	4.45
Funding Level, t-1: [75%, 100%)	2,613	35.94	57.75	6.31
Funding Level, t-1: [100%, .)	4,353	47.51	52.49	0.00
Funding Level, t-1: [75%, .)	*6,966*	*43.17*	*54.46*	*2.37*
Total	18,230	32.67	63.40	3.93

Interestingly, we observe the baseline failure rate of investments into firms with a high pre-money valuation to be significantly higher than for investments into firms with a lower pre-money valuation (63.4 percent vs. 42.51 percent; Wilcoxon-Mann-Whitney test: $z = -45.45$, $p = 0.000$), while the exit rate is significantly lower (3.93 percent vs. 15.09 percent; Wilcoxon-Mann-Whitney test: $z = 38.523$, $p = 0.000$). The failure rate for very early investments at funding levels below 25 percent in highly valuable firms is higher (70.6 percent) compared to early investments in less valuable firms (44.69 percent). Thus, firms that send strong signals, i.e., have a high pre-money valuation, seem to attract more uninformed investors that are confident enough to invest at very low funding levels compared to firms with a lower pre-money valuation. Nonetheless, we observe the failure rate to continuously decrease for investments at higher funding levels for both firms with a high pre-money valuation and lower pre-money valuation, which is in line with our main estimates. Consistently, Model A7 in Table A2.3 in the Appendix shows that our main econometric specification for the estimation of the likelihood to fail (Model 5) is robust to the exclusion of investors that contribute after the funding goal has been reached.

When investigating the exit rate, we observe no exits for investments made at funding levels above 100 percent in firms with a high pre-money valuation, while these late investments in firms with a lower pre-money valuation have a significantly higher exit rate than investments made at earlier funding levels. It is therefore not surprising that our main econometric specification for the estimation of the likelihood to exit (Model 6) is not robust to the exclusion of these investments (see Model A8, Table A2.3). In fact, results from Model A8 show that the likelihood to exit significantly increases by 91.8 percent (HR: 1.526*1.257 = 1.918; p = 0.000) for investments at a funding level between 75 and 100 percent compared to investments at lower funding levels for investments in the 25 percent most valuable firms in our sample. This difference is even significantly higher (p = 0.019) than for investments in less valuable firms, where the likelihood to exit significantly increases by only 52.6 percent (p = 0.000) for investments at a funding level between 75 and 100 percent compared to investments at lower funding levels.

Lastly, we exploit heterogeneity among investors in terms of the size of their contributions, as the investment sum might correlate with the degree to which an investor is informed about the quality of the firm. Recent literature on the herding behavior of individuals on crowdinvesting platforms suggests that highly informed individuals invest, on average, larger amounts of money to funding campaigns than uninformed individuals (Astebro et al. 2019). In line with our theoretical arguments, we would expect informed investors to make qualitatively better decisions than their peers irrespective of the information that is generated during the funding campaign. To test this proposition, we run two additional models that compare the outcomes of contributions characterized by high investments sums (*Investment Sum > p75* = 1) to the outcomes of smaller investments (*Investment Sum > p75* = 0) depending on the funding level of the campaign. The results are shown in Models A9 and A10 (Table A2.3 in the Appendix).

When considering the event of a failure, results from Model A9 show that for funding levels below 75 percent, high investments have a 10.6 percent lower likelihood to fail than smaller investments (p = 0.000). In this case, this difference significantly decreases (p = 0.04) to 5.5 percent (p = 0.04) for funding levels above 75 percent. In addition, Model A10 shows that for funding levels below 75 percent, high investments (*Investment Sum > p75* = 1) have a 12.5 percent higher likelihood to exit (p = 0.003) than smaller investments (*Investment Sum > p75* = 0). This difference does not significantly change (p = 0.454) for investments after 75 percent of the funding goal is reached. These results provide evidence for the fact that investors that contribute high amounts of money are, on average, better informed than peer investors contributing smaller amounts of money to funding campaigns. Regardless of the timing of their investment, they make better investments decisions than their peers, although we observe this difference to decrease at high funding levels, which might be due to the value that positive campaign information provides to the decision-making of uninformed investors who wait until a sufficient funding level is reached.

To sum up, the additional analyses show that the relationship between investment performance and the funding level at the time of investment is only unclear for investments into the 25 percent most valuable firms after the funding goal has been reached, where these investments have a higher likelihood to be still pending, while earlier investments have both a higher likelihood to exit and fail. For all other investments, we find evidence for our first hypothesis that investment at high funding levels subsequently perform better than investments made at lower funding levels, as these investments have a significantly lower likelihood to fail and significantly higher likelihood to exit. Nonetheless, we do not find evidence for our second hypothesis, that the positive relationship between investments made at higher funding levels and decision quality is stronger for firms with a lower pre-money valuation compared to firms with a high pre-money valuation. First, the lower likelihood of failure for investments at high funding levels compared to lower funding levels is independent of the firm's valuation. Second, while we do observe differences for the change of the exit rate from investment at lower funding levels to high funding levels between firms with a high valuation compared to firms with a lower valuation, we are not able to economically interpret them in terms of performance, as we cannot quantify the return difference between pending investments and investments that already exited.

2.5 Discussion

The objective of this study was to theoretically examine the value of campaign information for the investment decision-making quality of crowdinvestors when separating high- from low-quality firms. Based on signaling theory, we argued that campaign information generated through early investors is valuable to uninformed investors, if these investors delay their investment decisions until informed investors have invested and then additionally join the campaign at higher funding levels. Moreover, we argued that the additional campaign information is more valuable in helping uninformed investors to distinguish high- from low-quality firms for the funding campaigns of firms with less strong signals compared to the campaigns of firms with strong signals of quality.

Accordingly, we empirically analyzed the individual outcomes of investments made at different campaign funding levels and investigated whether this relationship differs between firms with a high pre-money valuation (i.e., strong signal) compared to less valuable firms (i.e., weaker signal). Our main results show that crowdinvestors who contribute to campaigns at high funding levels (i.e., positive campaign information) make better investment decisions than investors that contribute at lower funding levels, but this relationship is confined to firms with a lower pre-money valuation. Moreover, our descriptive analyses suggest that highly valuable firms attract more uninformed investors at the start of the funding campaign, as very early contributions to the funding campaigns of these firms have a higher failure rate than early contributions in less valuable firms. Although positive campaign information seems to be valuable in terms of decreasing the likelihood to fail for investments in these highly valuable firms, the likelihood to exit also significantly decreases for investments at higher funding levels. Thus, the value of additional campaign information is unclear, as late investments at high funding levels in highly valuable firms have a higher likelihood to be still pending, while earlier investments both have a higher likelihood to fail and to exit. Our additional analyses show that this result is largely driven by investments into campaigns after the funding goal has been reached.

Our results contribute to the literature on signals on crowdinvesting platforms. Existing literature has dealt with signals on crowdinvesting platforms and suggests that uninformed individuals might have difficulties in interpreting the signals and therefore rely on the selection decisions of peer investors who contributed earlier to the funding campaign (Ahlers et al. 2015, Vismara 2018). Information cascades between investors might be detrimental if amateur investors simply mimic the investment decisions of (potentially also amateur) peers without considering the signals that young firms send (e.g., Herzenstein et al. 2011, Zhang and Liu 2012). Our results show that positive campaign information generated through earlier investor contributions complements the effect of weaker signals by reducing the uncertainty of investors and efficiently reducing information asymmetries, thereby adding to the recent discussion on the complementary effects of firm signals and the value of additional information that is revealed over time (e.g., Haeussler et al. 2014, Colombo et al. 2019b). However, the value campaign information adds to the decision quality of investors who contribute to the funding campaigns of firms with a strong signal of quality after the funding goal has successfully been reached remains economically unclear. Thus, it is important for crowdinvestors that rely on their observation of peer investors to not only consider the presence of positive campaign information, but also the various reasons (i.e., a strong signal) that may have caused this information to build.

Furthermore, this study also provides implications for policymakers, as crowdinvesting is a new and important phenomenon with a large impact on the early-stage financing opportunities of young firms. Crowdinvesting platforms allow young firms to access an additional source of external financing when other forms, such as venture capital, are unavailable. Thus, it is important to analyze the decision-making of crowdinvestors and their subsequent performance, as this financing channel might help firms to develop products and services that otherwise would not enter markets and serve customers. In this regard, this study highlights that the crowd benefits from additional campaign information generated through the earlier investments of informed investors, particularly if the firm sends weaker signals of quality. Lastly, this study also provides interesting insights for platform owners, who should be aware that their pre-money valuation of a firm significantly affects the selection behavior of crowdinvestors, although no significant correlation with investment performance could be found. Platform owners should therefore pay less attention on the promotion of the firm in terms of highlighting the pre-money valuation in the pitch deck, as this might induce the behavioral bias that investors tend to solely focus on the objective evaluation of the platform owner, but ignore other less observable signals or negative information on the firm. Instead, platforms should aim at facilitating information exchange between potential investors on their platform.

Despite these contributions, this study comes with a number of limitations, such as endogeneity arising from unobserved heterogeneity in our data. In particular, we only consider the signal of the pre-money valuation when investigating the differential effect of campaign information on the investment outcomes of the crowd, thereby neglecting the effect of other (potentially negative) information that might be overlooked by uninformed investors. This behavioral bias may constitute an interesting opportunity for further research on the selection behavior and performance of crowdinvestors. Although this study controls for heterogeneity among investors in terms of their selection behavior, we were not able to theoretically propose a direct measure for the degree to which an investor might be informed about the quality of the firm. However, our additional analyses suggest that the size of the individual investor's contribution to a funding campaign may constitute a good proxy, as these investments turn out to be more successful. Unfortunately, we were not able to control for the inherent quality of the firms in our sample through the application of fixed effects, because our small sample size of 74 funding campaigns from 68 firms does not allow the estimator to converge. We therefore emphasize other researchers to replicate our findings with more detailed data. For example, investment information from several platforms allows to investigate the quality of pre-selection of firms by platform owners, which is important in this setting, as the issued pre-money valuation significantly affects the selection behavior of the crowd.

3 Selection or Treatment: Venture Capital Investments During Recessions and the Innovation Output of Young Life-science Firms

3.1 Introduction

Venture capital (VC) investment during recessions or crises[35] is a prevalent and important research topic and the current pandemic has added fuel to the fire (e.g., Howell et al. 2021, Conti et al. 2019).

What we know from the existing literature is that recessions lead to a decrease in the supply of VC money, since VC funds have difficulties to find investors, typically pension funds, insurance companies or large banks (Gompers and Lerner 1998). A reduced availability of funds results in a decrease in the number of financing rounds and/or in the investment during a recession when compared to a situation before the recession started or was anticipated. Interestingly, the decrease in the number of deals is more pronounced in first funding rounds, whereas the decrease in the investment sums is more pronounced in later funding rounds (Block et al. 2010, Howell et al. 2021). Comparing VC investment before and after June 2008, Block et al. (2010) also find that Medical Technology/Health Care (-40%) and Biotechnology (-29.4%) are amongst the industries experiencing the highest declines in first funding rounds.

What we don't know, however, is whether the decrease in the supply of money during a recession also affects the selection criteria of VC investors, i.e., do they invest in different targets? If we were to consult the literature on economic decision theory (Edwards 1954) and work from psychology that investigates economic decision-making principles in extreme situations, such as under time pressure, we would conclude that the context of a recession is likely to change the selection behavior of VC investors. Wright (1974), for instance, shows that decision makers adopt simpler strategies and put more emphasize on negative information when decisions have to de made under time pressure. Putting more weight on negative information, in turn, makes individuals more conservative when making decisions (Hansson et al. 1974, Zur and Breznitz 1981). Nanda and Rhodes-Kropf (2013) report that start-ups that receive their initial investment during "hot" markets, i.e., a period where more capital is available, are

[35] In the following, the terms crisis and recession are used synonymously, unless otherwise stated.

more likely to go bankrupt, but conditional on going public, are valued higher on the day of their IPO, and have a higher innovation output. They explain this phenomenon with the fact that investors tend to invest in riskier projects during “hot” markets compared to periods with decreased VC activity. Thus, not surprisingly, Block et al. (2010), who examine VC investments before and during the 2008 financial crisis, speculate that lower funds during a crisis may lead to stricter investment criteria of VC firms in the selection process, as VC investors may be less willing to take risks during a recession.

Besides the lack of information about the selection criteria of VC investors, there is no evidence yet in the literature on whether times of crises affect the treatment effect of VC investors on young firms. VC investors may, for example, put more effort into supporting their portfolio firms due to the worsening economic situation during a recession, which may result in a larger observable treatment effect. This expectation would also be consistent with individuals behaving more conservatively in a crisis (Hansson et al. 1974, Zur and Breznitz 1981). One could also assume that VC investors have more resources to support their portfolio companies if they invest in fewer first rounds of financing. Another possibility is that the signal of VC funding is stronger in times of crises, which may affect the probability of the young firm to find collaboration partners and finally in better performance (Davila et al. 2003, Megginson and Weiss 1991).

A better understanding of whether VC selection and treatment are affected by a recession, is important both from the perspective of start-ups seeking funding and from a societal perspective, since venture capital is an important source of innovation and economic growth (e.g., Timmons and Bygrave 1986, Kaplan and Lerner 2010, Samila and Sorenson 2011). In particular, if there is heterogeneity in selection and treatment depending on the economic situation and if, for example, during a recession, selection is more conservative and VC investors invest more time in the treatment of young firms, then more companies with incremental rather than radical innovation could be created and survive in the short term. Radical innovation, on the contrary, may be prohibited. The latter is, however, important for long-term firm survival and societal growth (Nanda and Rhodes-Kropf 2013). In addition, start-ups need to understand the selection processes of VC investors to optimally prepare for them and thus increase their chance of funding. To give an example, BioNTech SE, a German biotechnology company that develops and manufactures active immunotherapies for patient-specific approaches to the treatment of diseases, received its first-round VC funding (€150 million seed funding[36]) in 2008, the year of the financial crisis. That BioNTech SE would eventually develop an effective COVID-19 vaccine with Pfizer Inc., was not foreseeable at the time of funding. If the company had had difficulty obtaining VC financing due to changes in the selection criteria, it would have been fatal for humanity. If a special treatment by VCs had contributed to the success or even the survival of BioNTech SE, we could be very grateful for it from today's point of view.

The challenges in addressing our research question, i.e., whether the selection criteria and/or the treatment of VC investors are affected by a recession, are two-fold. On the one hand, we lack a theory on which we could base our analysis. As mentioned above, economic decision theory (Edward 1954) together with extensions from psychology on decision making under pressure (Wright 1974, Hansson et al. 1974, Zur and Breznitz 1981) could be used. However, VC investors' financing decisions and decisions about how best to support portfolio firms (treatment) are special in that VC investors make decisions under great uncertainty and time pressure even in the absence of a crisis (McMullen and Shepherd 2006, Zacharakis and Meyer 2000, MacMillan et al. 1985). For example, when VC investors receive a business plan, they must decide whether to fund it or not, without knowing whether supposedly better business plans will be received in the next few days or until more information is revealed about the technology or the market. If an investor waits too long, a competitor closes the potentially attractive deal. Hall and Hofer (1993), for instance, state that VCs on average make a go/no-go decision in less than six minutes at the initial screening and less than 21 minutes at the proposal assessment stage. When recession is added to these extreme decision-making situations, what does that mean for the decisions of the VC investors?

The second challenge is related to methodology, i.e., the empirical separation between VC selection and treatment (e.g., Bertoni et al. 2011, Croce et al. 2013). Selection and treatment are not independent, and the analysis becomes even more complex when a contextual variable (in our case a

[36] See https://investors.biontech.de/node/6751/html#toc, accessed on January 5, 2022.

recession) is added. While the occurrence of recessions is exogenous, selection and treatment decisions are not.

To investigate whether a recession affects the selection and treatment behavior of VC investors, we use data from the VICO 4.0 dataset, which was created with the support of the VICO and RISIS projects and funded by the European Commission under the FP6, FP7 and H2020 programs. This dataset provides comprehensive geographical, industry, and accounting information on firms located in 27 European countries, the UK and Israel, which received their first VC investment between 1998 and 2015. Information on VC investors and investments were extracted from the commercial databases Zephyr, Crunchbase and Thomson ONE.

We focus our analysis on firms that were founded in or after the year 1998 and were 10 years or younger at the time of their first financing round between the first quarter of 2003 and the first quarter of 2015. We restricted our analysis to firms active in the life sciences, since this branch of science is characterized by a high patent propensity, high capital requirement and vivid start-up activity (Cohen and Walsh 2002, Nasto 2008). In addition, at least for the financial crisis around 2008, Medical Technology/Health Care and Biotechnology seem to have been particularly affected by the reduction of available VC money (Block et al. 2010). We build a control group of non-VC-backed firms, which otherwise are identical to the VC-financed companies in terms of time of foundation, age, and country of origin.

Information on patent filings, which we will use as a proxy for the innovation activities of the firms (e.g., Hsu and Ziedonis 2008, Bertoni et al. 2010, Hoenen et al. 2014), was extracted from the PATSTAT database of the European Patent Office (EPO). PATSTAT contains bibliographic patent data from more than 100 patent offices worldwide. To prevent systematic differences between firms that patent and firms that do not patent from driving our results, we restrict our sample to firms that have filed at least one patent by the end of our observation period in the first quarter of 2015.

Our final sample consists of 372 VC-backed firms that filed a total of 2,568 patents and 625 non-VC-backed firms that filed a total of 1,581 patents in the same time period. For our analyses, we use a panel dataset that includes 33,239 quarterly observations of firms. We identify recession periods by following the approach of the National Bureau of Economic Research. A recession occurs in case a significant decline in a country's economic activity (i.e., gross domestic product) that lasts more than a few months is observed.

In the econometric analysis, we use a two-step approach. First, to analyze VC selection, we conduct event history analyses to identify the determinants of a transition of life science firms into VC financing. Second, to analyze VC treatment, we apply firm-fixed-effects regressions to estimate the impact of VC investments on firm innovation. The latter is a common approach among entrepreneurship scholars studying the treatment effect of VC investments and allows to control for unobserved time-invariant heterogeneity across firms that determines both VC financing and the innovation output of a firm (e.g., Bertoni and Tykvová 2015, Colombo and Murtinu 2017, Chemmanur et al. 2014). To deal with the endogenous matching between VC investors and firms in the treatment regressions, we use an instrumental variable methodology (Semykina and Wooldrigde 2010).

Our results show that VC investors do not change their selection behavior during periods of recession, as they invest in firms with a higher patent stock, regardless of the economic situation. Considering the treatment effect of VC investments on firm innovation, we only observe a significantly smaller treatment effect of VC financing on the firm's patent stock in the two years after VC-receipt (short-term treatment effect) for firms that received first round funding during a period of recession compared to a period of non-recession, while this difference vanishes thereafter. Additionally, when not accounting for the endogenous matching between VC investor and firm, we would overestimate the effect on VC financing (treatment) on firm innovation due to unobserved heterogeneity across firms that is not captured by firm-fixed-effects.

We contribute to the literature on decision making under extreme conditions by showing that there are decision makers who do not adapt their decision-making behavior. In particular, VC investors seem to rely on established decision-making processes or heuristics and the selection criteria that work during non-recession periods. Second, we contribute to the literature on VC investment, since our results help to better understand the selection and treatment behavior of investors.

3.2 Background

The impact of VC financing on the performance of young firms is a central research topic in the entrepreneurial finance literature, since VC-backed firms have been shown to outperform non-VC-backed firms and to be an important source of innovation and economic growth (e.g., Timmons and Bygrave 1986, Kaplan and Lerner 2010, Samila and Sorenson 2011). Venture capital is a very effective financial intermediary for solving agency problems in markets with imperfectly distributed information by connecting young firms (of unobservable quality) with an innovative idea but not enough money to fund their venture, with investors who have the money but not the idea (e.g., Leland and Pyle 1977, Amit et al. 1990, Kaplan and Strömberg 2001, 2004).

3.2.1 Venture Capital Selection and Treatment

Prior to their investment, VC investors face the problem of adverse selection, as entrepreneurs seeking for VC funding are better informed about the quality of their firm than a potential VC investor and may strategically exploit this information advantage (e.g., Kaplan and Strömberg 2001, 2004, Carpenter and Petersen 2002, Denis 2004). Young innovative technology ventures often lack a track record and tangible assets that investors can evaluate, and they also face considerable technical, market, and legal uncertainty due to the nature of their inventive activity (e.g., Dewar and Dutton 1986, Jalonen 2012). To reduce information asymmetries, VC investors evaluate the unobservable quality of a young firm using signals, i.e., observable attributes that are more costly to obtain for lower quality firms relative to high quality firms, creating a signaling equilibrium that allows VC investors to identify high quality firms (Spence 1973, 2002, Stiglitz 2000).

The literature on early-stage investor selection criteria is highly diverse, but generally distinguishes between signals related to the quality of a firms' technologies and business model and to the quality of the entrepreneurial team. For technology, patents qualify as a signal. Filing for a patent is costly, and examiners at patent offices issue an objective certificate of the "quality" of an invention if the invention meets the requirements of patentability: novelty, inventive step, and commercial applicability (Deeds et al. 1997, Long 2002, Hsu and Ziedonis 2008, Haeussler et al. 2014, Hoenen et al. 2014, Farre-Mensa et al. 2020). For the founding team, affiliations with third parties, e.g., research or market alliances, which indicate access to complementary resources to develop and commercialize the firm's products or services, are an important signal (Baum and Silverman 2004, Hoenig and Henkel 2015, Plummer et al. 2016, Colombo et al. 2019). Other effective signals include educational attainment, work experience, and past entrepreneurial success, since they indicate the ability of the entrepreneurial team to handle complex situations when starting a business (e.g., Higgins and Gulati 2006, Hsu 2007, Gompers et al. 2010, Zhang 2011).

The funding decision of VC investors is a multi-stage process. The procedure can only be described as an ideal type, as each VC company carries out this review according to its own rules. The process can be roughly divided into two stages. Stage one is often called screening in the literature. The second stage is called due diligence. The screening phase begins after the first business plans or concepts received have been sorted out, e.g., due to formal deficiencies. Initial screening, which usually takes only a few minutes, rejects those business plans that do not fit into the portfolio due to a wrong focus or too little potential. Initial screening is followed by second screening. The latter can take one or several hours. The goal is a brief evaluation of the key data of the business concept. As a rule, the market, the finances, the product or technology, and the founding team are examined in more detail. Additional documents may be requested. This stage ends with a risk assessment of the funding option. If the business concept has survived the screening, a personal meeting with the founding team usually follows, and later due diligence (Wupperfeld 1996, Hall and Hofer 1993).

During the investment relationship, VC investors are primarily concerned with monitoring the actions of their portfolio companies and adding value to their business. To prevent moral hazard, e.g., founders taking (unobservable) actions out of self-interest that are not aligned with the objectives of the investors, VC investors are assigned various property rights that allow them to monitor and control their portfolio companies (Sahlman 1990, Amit et al. 1998, Kaplan and Strömberg 2004, Denis 2004). The monitoring can, however, also help young firms to allocate their resources efficiently and effectively (Amit et al. 1998, Gompers 1995). In addition, VC investors often act as coaches. For example, they offer specific value-added functions to young firms, such as strategic advice, assistance in hiring additional employees, and managerial resources (Lerner 1994, Brandner et al. 2002; see Gompers et al.

2020 for additional examples). These services should fill competence gaps of the founders and help them to become successful. This support also reduces investor risk (Gorman and Sahlman 1989, Sapienza 1992, Hellmann and Puri 2002, Baum and Silverman 2004). This particular relationship between VC investors and their portfolio companies will be referred to as treatment in the following.

In summary, it could be argued that the superior performance of VC-backed firms compared to non-VC-backed firms is related to the fact that VC investors are able to identify high quality firms (selection) and support them with value-enhancing resources (treatment).

If VC investors were to change their evaluation due to a recession situation, i.e., as speculated in the literature, choose stricter selection criteria (Block et al. 2010) or be more conservative in their choice (Nanda and Rhodes-Kropf 2013), they may use different decision criteria in screening and finally make a different selection than in a situation without recession. While on average about 20 % of the business ideas/concepts are sorted out due to form deficiencies, in screening about another 60 % of the originally submitted concepts are sorted out (Schröder 1992). In other words, VC investors select a small number of business ideas/concepts to pursue within a few hours, sometimes even within minutes. Due to the incomplete information available, the decision is often made under high uncertainty and based on experience and gut feeling (Gompers et al. 2020, Hu and Ma 2020, McMullen and Shepherd 2006).

If we observe different treatment effects from VC investors, this could be because VC investors provide different services or resources in times of recessions or that startups demand different resources or services in such times. It could also be that VC investors put more non-financial resources into supporting the portfolio companies. One motivation for this could be to compensate for lower financial resources, especially in early-stage financing (Conti et al. 2021, Block et al. 2010). They could also assume that special support helps the startups to survive economically difficult times. Pianeselli (2019), for instance suggests that VC investors invest in young firms located in geographic proximity to reduce information asymmetry and, thereby, offer more effective support. It could also be that stakeholders, e.g., potential cooperation partners, perceive VC financing in times of recessions as a special signal for the quality of the startup. This would give VC-funded companies better access to third-party resources (Davila et al. 2003, Megginson and Weiss 1991).

The question we investigate in the following is whether different selection and treatment outcomes are observed during recessions. Since we cannot directly observe the decisions and actions of VC investors, we must rely on the existing literature and our own assessment to interpret possible differences. From an empirical perspective, it is challenging to disentangle selection and treatment (e.g., Bertoni et al. 2011, Croce et al. 2013), making it difficult to assess the relative importance of these two effects (Sørensen 2007). There is empirical evidence that the treatment effect of VC investors on their portfolio firms is economically important. This is true even after controlling or correcting for selection and when considering different economic measures, such as total factor productivity, sales, number of employees or innovation output (measured by the firm's patent stock or forward citations over time) (Baum and Silverman 2004, Bertoni et al. 2011, Croce et al. 2013, Chemmanur et al. 2014, Bertoni and Tykvová 2015, Colombo and Murtinu 2017). Moreover, the existing literature assumes that early-stage investors are able to identify high-quality firms by investigating heterogeneity in selection behavior. Recent evidence suggests that VC investors consider selection as more important than to the success of their investment than their treatment (Gompers et al. 2020).[37]

3.3 Data sources and sample composition

To answer our research question, we combined information from several data sources to build a sample of VC-backed (treatment) and non-VC-backed (control) young life science firms. The life sciences were chosen, as this branch of science is characterized by a high patent propensity, high capital requirement, and vivid startup activity (Cohen and Walsh 2002). We therefore expect sufficient variation in the data to perform our analysis. In addition, at least for the financial crisis around 2008, Medical Technology/Health Care and Biotechnology seem to have been particularly affected by the reduction of available VC money (Block et al. 2010).

First, we extracted a sub-sample of VC-backed firms from the VICO dataset, which was created as part of the VICO and RISIS projects, funded by the European Commission, and which contains information on VC investments made in firms in EU-27 countries, the UK and Israel over the period

[37] Gompers et al. (2020) also distinguish deal selection from sourcing, i.e., the process of generating a pool of potential investment targets of high quality from whom to select, which has been shown to be correlated with the initial success of VC investors and is persistent over time (Nanda et al. 2020).

1998-2015, as contained in the commercial databases Zephyr, Crunchbase and Thomson ONE.[38] The dataset includes information on VC-backed firms (e.g., name, location, industry, founding date), VC investors (e.g., name, governance, location, age), and investment deals (e.g., date, round number). We restrict our sample to firms operating in the life sciences[39], that were founded in or after the year 1998 and were 10 years or younger at the time of their first financing round between the first quarter of 2003 and the first quarter of 2015. Applying these criteria results in a sample of 490 young VC-backed life science firms. Second, we extracted from ORBIS Bureau van Dijk a control group of non-VC-backed firms, which otherwise are identical to the 490 VC-backed firms in terms of time of foundation (in or after the year 1998), country of origin and industry (life sciences). We used the VICO dataset and Thomson ONE to verify that these firms did not actually receive VC financing during our observation period. Furthermore, we only kept firms that were independent in at least one year during the observation period to make sure that these firms did not receive alternative sources of equity financing, e.g., from large corporations.[40] We considered a firm as independent in a given year if the majority of shares were held by individuals and the biggest corporate or State held less than 25 percent of all shares. This resulted in a sample of 6,569 independent non-VC-backed firms operating in the life sciences.

We further restricted our sample to firms that have filed at least one patent from their foundation to the end of our observation period in the first quarter of 2015 to make sure that the sample firms pursue inventive activities.[41] Building on existing empirical studies investigating the relationship between VC financing and innovation, we use patent information to build proxies for a firm's innovation output (e.g., Hsu and Ziedonis 2008, Hoenen et al. 2014, Bertoni and Tykvová 2015). We collected patent

[38] The RISIS project resulted in a dataset containing 68,698 VC investments made by 8,761 investors in 24,238 firms. See http://risis.eu for more details.

[39] We identified firms operating in the life sciences based on the NACE codes 21 (pharmaceuticals), 7211 (biotechnology) and 266 (medical instruments).

[40] For 79.04 percent of the 6,569 non-VC-backed firms, we do not observe any missing observation of the independence status during our observation period. Our results stay robust when we only use firm-quarter observations for which we know that the focal non-VC-backed firm is independent. The results are available from the authors upon request.

[41] As a robustness check, we run regressions that estimate both the selection and treatment effect of VC with the full sample of patenting and non-patenting firms.

information from PATSTAT[42]. Since our sample firms are located in Europe, we extracted patent applications filed with the European Patent Office (EPO). We traced the firms' patent histories by matching the firm names reported in VICO with the applicant names listed in PATSTAT using various string matches, which we checked manually.[43] To avoid double counting, since one invention can be protected with more than one patent and inventions are also protected in various countries (European patents are a bundle of national patents with protection in one or more of the 38 member states[44] (as of Nov. 1, 2019)), we conducted our analysis at the patent family level, i.e., bundles of patent documents protecting the identical invention in different jurisdictions. From the initially identified 490 VC-backed firms, 372 firms (75.9 percent) have filed at least one patent, while only 625 out of 6,569 non-VC-backed firms (9.5 percent) have filed at least one patent. Overall, the 372 VC-backed firms have filed a total of 2,568 patents and the 625 non-VC-backed firms have filed a total of 1,581 patents during the observation period.

The result of this data collection effort is a unique panel dataset of 997 (372 VC-backed and 625 non-VC-backed) young life science firms that have filed at least one patent, which are observed quarterly from their foundation through the end of our observation period in the first quarter of 2015 (or through IPO, acquisition, or bankruptcy[45]), resulting in 33,239 quarterly observations of firms.

We then added bibliographic and procedural information on the respective patent families, namely technology classes, status information (i.e., grant, revocation, refusal, withdrawals), and forward citations (i.e., the number of subsequent patent filings that refer to the patents in our sample as prior art). First, to trace a firm's innovation output over time, we use a firm's *Patent Stock*, t in year-quarter t as

[42] PATSTAT, the worldwide patent statistical database provided by the European Patent Office contains bibliographical data relating to more than 100 million patent documents from leading industrialized and developing countries (see https://www.epo.org/searching-for-patents/business/patstat.html, accessed on January 3, 2022).
[43] To match firm names and patent applicant names, we first removed special characters (non-printable characters, blanks, accents, punctuation), legal suffixes (e.g., GmbH, SAS, SARL, AG), and regional indicators (e.g., Europe, UK, Deutschland). Then, we implemented a string match approach that compared to fuzzy matching techniques, limited the number of false positives. After performing the first match, we cleaned the sample of non-matched firm names by removing generic terms in the life sciences (e.g., pharmaceuticals, medical, diagnostics), and we re-ran the matching, which reduced the number of false negatives at the cost of losing some precision. Finally, we checked the matching results manually.
[44] See https://www.epo.org/about-us/foundation/member-states.html, accessed on January 3, 2022.
[45] Information on the status of the firm has been collected via VICO, Thomson One and through manual research on the firm's website.

the total number of patent families with at least one application (family member) pending or granted. Patent families for which all filings were rejected, revoked, or withdrawn or for which patent protection was not yet maintained for any family member (laps into public domain) were excluded from our analysis, since they do not represent potential value for venture capitalists. Second, we follow Hall et al. (2005) and measure the *Citation Stock*, *t*, an indicator of the technological quality of a firm's patent portfolio, using the standard declining balance formula:

$$Citation\ Stock_t = (1 - \delta) * Citation\ Stock_{t-1} + Citations_t$$

with *Citations*, *t* indicating the total number of forward citations of all patent families with a priority date in year-quarter *t*, and δ indicating a quarterly depreciation rate of 3.98 percent[46], which equals the traditionally assumed yearly depreciation rate of 15 percent (e.g., Griliches 1998, Hall et al. 2005).

Third, we build the dummy variable *Radical Invention*, *t* that equals one for companies with at least one radical invention for which a patent was filed in the time under consideration and the associated count variable *Radical Stock*, *t*. We follow the approach of Verhoeven et al. (2016), who define an invention as novel in recombination (i.e., radical) if the combination of its components and principles applied are different from those embodied in all previous inventions. We use the International Patent Classification (IPC) codes as a proxy for the knowledge components underlying an invention. An invention (i.e., all documents of a patent family) is considered radical if it contains at least one pair of IPC classes (main group level—seven-digit) that had not been combined in previous patent applications.[47] Radical inventions are important to consider. First, radical inventions are potentially a source of competitive advantage for young firms operating in the life science industry (de Vet and Scott 1992, Zucker et al. 1998, Azoulay et al. 2011, Kolympiris et al. 2014). Second, this type of invention might be particularly attractive to VC investors, as strong performers in a technology area have been shown to be more likely than weak performers to develop radical inventions (Dewar and Dutton 1986,

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[46] $Depreciation_{quarter} = \sqrt[4]{1 - 0.15} - 1 = 0.0398$

[47] For the identification of radical inventions, we rely on all 17,706,389 patent applications (8,823,589 patent families) filed at the EPO, the US Patent and Trademark Office (USPTO), and the WIPO between 1980 and 2019.

Henderson 1993). Lastly, we also build the variable *Mean Age Patents (months), t* to be able to control for the age of a firm's patent portfolio over time.

Table 3.1 shows the distribution of the 33,239 firm-quarter observations in our sample by country and VC-status at time *t* (allowing firm transitions from a non-VC-backed status to a VC-backed status), and information on their patent characteristics. The UK (27.83 percent) and Germany (19.28 percent) account for the largest number of observations. These results are consistent with Bertoni and Tykvová (2015), who investigate VC financing in the biotechnology industry. Considering patent characteristics, we find that the mean *Patent Stock, t* to be 175.24 percent (Wilcoxon-Mann-Whitney test: z = -63.39; p = 0.000) higher in observations where VC financing is already received than in observations where VC financing is not (yet) received. The same is true for the mean *Citation Stock, t* (growth = 174.06 percent; Wilcoxon-Mann-Whitney test: z = -57.49; p = 0.000) and *Radical Stock, t* (growth = 104.95 percent; Wilcoxon-Mann-Whitney test: z = -18.519; p = 0.000). Due to their skewness, we use the logarithmic values of the variables *Patent Stock, t* (mean = 2.38, sd = 6.10, skewness = 18.60), *Citation Stock, t* (mean = 16.84, sd = 54.45, skewness = 12.61) and *Radical Stock, t* (mean = 0.227, sd = 0.719, skewness = 7.56), which are increased by 1 before applying the natural logarithm.

Table 3.1 Sample composition

	All population	**Non-VC-backed**	**VC-backed**
No. of observations	33239	25332	7907
Austria	953	812	141
Belgium	487	215	272
Denmark	748	350	398
Finland	479	293	186
France	4041	2597	1444
Germany	6410	5510	900
Hungary	335	321	14
Ireland	295	249	46
Israel	2874	1616	1258
Italy	4706	4484	222
Luxembourg	180	156	24
Netherlands	363	183	180
Norway	116	87	29
Portugal	104	48	56
Spain	1049	736	313
Sweden	848	400	448
United Kingdom	9251	7275	1976
Patent measures (mean)			
Patent Stock, t	2.38	1.68	4.624
Citation Stock, t	16.84	11.91	32.641
Radical Invention, t	0.153	0.134	0.215

Note: Each observation is one firm-quarter.

Finally, we identify recession periods by following the approach of the National Bureau of Economic Research. A recession occurs in case a significant decline in a country's economic activity (i.e., gross domestic product) that lasts more than a few months is observed.[48] Accordingly, we collected quarterly and annual (quarter to quarter) GDP-growth rates for all countries where our sample firms are located.[49] Figure A3.1 in the Appendix displays the mean quarterly and annual GDP-growth rates for our sample countries. We observe periods of declining GDP growth rates during the dotcom-bubble (2000-2002), the world financial crisis (2008) and the European debt crisis (2010-2012). Negative GDP-growth rates, however, are mainly observed from early 2008 to late 2009 and in 2012. For our analysis, we define the dummy variable *Recession, t* that equals 1 if the average quarterly GDP-growth rate in a focal firm's country over the last four quarters is negative. During our sample period, 58 of 372 VC-backed firms (15.6 percent) received their first round of financing during a recession period.

3.4 Method and results

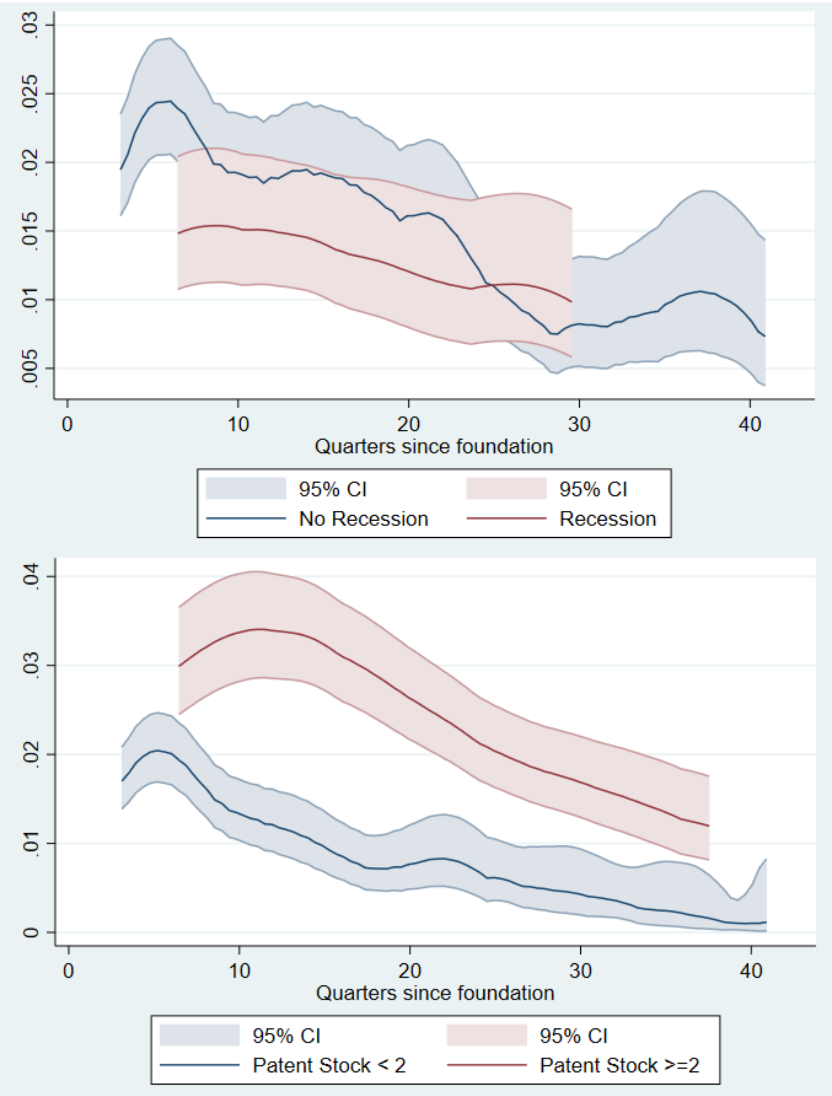
Since we need to disentangle VC selection and treatment effects to answer our research question, we use a two-step approach. First, to analyze VC selection, we conduct event history analyses to investigate the determinants of a transition of life science firms into VC financing (for a similar empirical approach to investigate VC selection, see Bertoni et al. 2011). This method is used, as our sample contains firms that are still at risk of receiving a first round of VC at the end of our observation period. Second, to analyze VC treatments, we apply firm-fixed-effects regressions to estimate the impact of VC investments on firm innovation. The latter is a common approach among entrepreneurship scholars studying the treatment effect of VC investments and allows to control for unobserved time-invariant heterogeneity across firms that determines both VC financing and the innovation output of a firm (e.g., Bertoni and Tykvová 2015, Colombo and Murtinu 2017, Chemmanur et al. 2011). Finally, we also deal with endogeneity arising from "unknown" VC selection trough application of a Heckman two-step procedure, thereby correcting for selection when estimating the treatment effect of VC financing on firm innovation (Heckman 1979).

[48] See https://www.nber.org/research/business-cycle-dating for further details.
[49] For data access, please see https://stats.oecd.org/.

3.4.1 Selection effect

We first conduct a univariate analysis on VC selection. Specifically, we non-parametrically estimate the baseline hazard rate, i.e., the conditional probability that a firm receives a first round of VC in quarter *t*, given that the firm did not yet receive VC financing. We estimate this function using kernel smoothing. Non-VC-backed firms in our sample are right censored in the first quarter of 2015, at the time of acquisition, IPO, or bankruptcy, or at 10 years of age, as we only selected VC-backed firm that were 10 years or younger at the time of their first financing round. Figure 3.1 displays hazard rates by economic situation, i.e., whether the country of the focal firm was in a recession in quarter *t* (*Recession, t* = 1), and by the firm's patent stock in quarter *t-1*, i.e., whether the firm had at least two patents, indicating the 75th percentile of the underlying distribution for all firms at risk of VC financing.

Figure 3.1 Baseline hazard rate estimates



Overall, we observe a decreasing baseline hazard rate of a first round of VC financing over time (= with increasing firm age). Interestingly, we do not observe a significant difference of the hazard rates when comparing periods of recession to periods of non-recession. Furthermore, firms with a patent stock equal to or above the 75th percentile (*Patent Stock, t-1* ≥ 2) show a significantly larger hazard to receive a first round of VC financing over time than firms with a smaller patent stock.

To investigate the effect of recessions on VC selection in a multivariate setting, we run a proportional hazard model with robust standard errors. We chose a Weibull distribution to parametrize the effect of time on the hazard of receiving a first round of VC in quarter *t*, given the decreasing baseline hazard (see Figure 3.1). The models include a number of time-varying explanatory variables. First, we are interested in the effect of the *Recession, t* dummy and its interaction with our variables characterizing firm innovation, i.e., the logged *Patent Stock (ln+1), t-1*, and *Radical Invention, t-1*.[50] As control variables, we added the variables *Mean Age Patents (months), t-1* to control for the age of the patent portfolio and *Quarter*-, *Year*- and *Country-Fixed Effects* to control for seasonal effects of VC financing and unobserved heterogeneity over time and across countries that may affect a firm's likelihood to receive a first round of VC financing.

The results are shown in Table 3.2. We report hazard ratios, which can be interpreted as the multiplicative effect on the hazard rate, i.e., a one-unit increase in the explanatory variable equals a 100*(hazard ratio-1) percentage change of the hazard of receiving a first round of VC (Allison 1984). Model 1 reports the direct effects of our explanatory variables. Models 2 and 3 add the interaction terms between the *Recession, t* dummy and *Patent Stock (ln+1), t-1* as well as the *Radical Invention, t-1* dummy.

[50] Due to the high correlation of 0.79 between the variables *Patent Stock (ln+1), t-1* and *Citation Stock (ln+1), t-1* in the pre-financing period, we decided to only include the *Patent Stock (ln+1), t-1* in our main regressions. The results stay robust when replacing the variable *Patent Stock (ln+1), t-1* with the variable *Citation Stock (ln+1), t-1* and are available from the authors upon request.

Table 3.2 Selection: First financing round

	Model 1	Model 2	Model 3
Recession, t	1.004	1.240	1.003
	[0.983]	[0.434]	[0.989]
	(0.200)	(0.341)	(0.213)
Patent Stock (ln+1), t-1	2.060	2.104	2.060
	[0.000]	[0.000]	[0.000]
	(0.173)	(0.186)	(0.173)
Radical Invention, t-1	0.918	0.916	0.917
	[0.593]	[0.585]	[0.611]
	(0.147)	(0.148)	(0.156)
Recession, t X Patent Stock (ln+1), t-1		0.781	
		[0.264]	
		(0.173)	
Recession, t X Radical Invention, t-1			1.010
			[0.981]
			(0.429)
Mean Age of Patents (months), t-1	0.985	0.985	0.985
	[0.000]	[0.000]	[0.000]
	(0.002)	(0.002)	(0.002)
Baseline Hazard	0.017	0.016	0.017
	[0.000]	[0.000]	[0.000]
	(0.013)	(0.012)	(0.013)
Shape Parameter p	0.902	0.904	0.902
	[0.031]	[0.033]	[0.031]
	(0.043)	(0.043)	(0.043)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Time Spans	23,726	23,726	23,726
Number of Firms	997	997	997
Number of Events	372	372	372
Log-Likelihood	-840.108	-839.456	-840.108

Note: This table reports the hazard ratios from a proportional hazard regression that estimates the hazard rate of a first financing round. The hazard rate is parametrized using the Weibull distribution. To test the significance level of the shape parameter p, H0: p = 1.
Brackets: p-values; Parentheses: Robust standard errors

Model 1 shows that *Recession, t* is not significantly correlated with the hazard of a first VC round, which is consistent with our univariate analysis. Considering the patent portfolio of a firm, a one unit increase of a firm's logged *Patent Stock (ln+1), t-1* significantly increases the hazard of a first VC round by 106 percent (p = 0.000). This equals a 7.1 percent increase of the hazard of a first VC round for a 10 percent increase of the patent stock (hazard ratio = exp(ln(1.1)*ln(2.06)) = 1.071). The fact that the firm has at least one radical patent (*Radical Invention, t-1* = 1) is not significantly correlated with the hazard of a first VC round. Moreover, Models 2 and 3 do not show significant interaction effects between a firm's patent characteristics and the recession dummy. Lastly, the shape parameter p is significantly smaller than 1 (p = 0.031), which indicates a decreasing hazard rate over time and is also consistent with our univariate analyses.

To sum up, we do not find VC investors to change their selection criteria during periods of recession, as they fund firms with a higher patent stock, regardless of the economic situation.

3.4.1.1 Robustness checks and additional analyses

To assess the robustness of our findings, we first use alternative measures to identify periods of recession. The dummy variable *Recession_2_quarters*, *t* is a dummy variable that equals 1 if the last two quarters indicate a negative GDP-growth rate, and the dummy variable *Recession_q_to_q*, *t* is a dummy variable that equals 1 if the yearly GDP-growth rate from quarter *t-4* to *t* is negative. The results are shown in Table A3.1 in the Appendix and are fully in line with our main regressions, i.e., the hazard of a first VC round is not significantly correlated with recession periods. Second, we test the robustness of our Weibull parametrization by using the Gompertz, and exponential distribution. Moreover, we run a semi-parametric Cox regression that does not specify the baseline hazard. The results are shown in Table A3.2. Again, the results are fully consistent with our main estimates. Third, we run the same selection models (1) by also including non-patenting firms (during our observation period), resulting in a sample of 490 VC-backed firms and 6,569 non-VC-backed firms, and (2) on the original sample of patenting firms restricted to firms founded in or after the year 2003, resulting in a sample of 286 VC-backed firms and 461 non-VC-backed firms. The latter is necessary to check whether the selection is driven by unobserved investments in the period 1998 to 2003, as we restricted our sample to firms that receive their first round of investments in or after the year 2003. The results are shown in Table A3.3 and are fully consistent with our main estimates. The magnitude of the positive association between the *Patent Stock (ln+1), t-1* and the hazard of a first financing round in the sample that also includes non-patenting firms is higher (e.g., Model A16: hazard ratio = 3.311; p = 0.000), which is not surprising.

In addition to our robustness checks, we assess whether our results are driven by distinct VC governance types. The investment behavior of governmental VC investors (GVC) substantially differs from that of private VC investors, because GVC investors have to respond to economic policy objectives and are mandated to support innovation (e.g., Bertoni et al. 2015, Betoni and Tykvová 2015). Therefore, we simultaneously model the hazards of (1) receiving a first financing round by governmental VC investors alone or syndicates with at least one governmental VC investor (i.e., GVC) and (2) receiving a first financing round by only private VC investors (independent, corporate, bank-affiliated).[51] The results are shown in Table 3.3. Model 4 reports the direct effects of our explanatory variables of interest, while Model 5 and 6 add the interaction terms between the *Recession, t* dummy and the patent characteristics *Patent Stock (ln+1), t-1* and *Radical Invention, t-1*.

Table 3.3 Selection: First financing round by type of investor governance

	Model 4		**Model 5**		**Model 6**	
Investor Type	Governmental	Private	Governmental	Private	Governmental	Private
Recession, t	0.555	1.234	0.880	1.433	0.555	1.260
	[0.134]	[0.367]	[0.804]	[0.258]	[0.156]	[0.335]
	(0.218)	(0.287)	(0.452)	(0.455)	(0.230)	(0.302)
Patent Stock (ln+1), t-1	2.413	2.011	2.514	2.043	2.413	2.006
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	(0.371)	(0.190)	(0.386)	(0.198)	(0.372)	(0.190)
Radical Invention, t-1	0.929	0.845	0.934	0.842	0.928	0.867
	[0.824]	[0.392]	[0.838]	[0.385]	[0.835]	[0.492]
	(0.309)	(0.167)	(0.312)	(0.166)	(0.331)	(0.181)
Recession, t X Patent Stock (ln+1), t-1			0.575	0.842		
			[0.216]	[0.501]		
			(0.257)	(0.216)		
Recession, t X Radical Invention, t-1					1.002	0.820
					[0.998]	[0.724]
					(0.839)	(0.460)
Mean Age of Patents (months), t-1	0.985	0.985	0.985	0.985	0.985	0.985
	[0.003]	[0.000]	[0.004]	[0.000]	[0.003]	[0.000]
	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)
Baseline Hazard	0.000	0.016	0.000	0.016	0.000	0.016
	[0.995]	[0.000]	[0.995]	[0.000]	[0.995]	[0.000]
	(0.000)	(0.013)	(0.000)	(0.012)	(0.000)	(0.013)
Shape Parameter p	0.834	0.931	0.841	0.932	0.834	0.931
	[0.124]	[0.286]	[0.141]	[0.291]	[0.124]	[0.289]
	(0.098)	(0.063)	(0.099)	(0.063)	(0.099)	(0.063)
Country FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
Quarter FE	Yes		Yes		Yes	
Time Spans	23,651		23,651		23,651	
Number of Firms	986		986		986	
Number of Events	92	269	92	269	92	269
Log-Likelihood	-318.214	-656.477	-317.388	-656.248	-318.214	-656.412

Note: This table reports the hazard ratios from a competing risk regression that simultaneously estimates the hazard rates of (1) receiving a first financing round by syndicates with at least one governmental VC investor and (2) receiving a first financing round by syndicates with only private VC investors (independent, corporate, bank-affiliated). The hazard rate is parametrized using the Weibull distribution. To test the significance level of the shape parameter p, H0: p = 1.

Brackets: p-values; Parentheses: Standard errors

[51] We exclude deals with only university-affiliated VC investors or investors with other governance structures, leading to a sample of 986 firms that receive a first financing round from syndicates with at least one governmental VC (n = 92) and syndicates with private investors only (n = 269).

For both governance structures, the results are consistent with our main finding that VC investors do not significantly change their investment behavior during periods of recession, as they fund firms with a higher patent stock, regardless of the economic situation. Nonetheless, there is slight evidence for the fact that syndicates with at least one GVC investor are more sensitive to periods of recession. The hazard of receiving a first round of GVC decreases during recessions (*Recession, t* = 1) by 44.5 percent at a significance level of 13.4 percent, while this association is not significant (p = 0.367) for private VC investors. Moreover, we tested the difference of these two hazard ratios using the chi-squared distribution. The difference is significantly different from 0 (chi-squared = 3.06; p = 0.08).

Finally, we also investigate whether the hazard of a follow-on investment is affected by the economic situation. First, we apply Weibull regressions using the time period from the first VC round to the second VC round (or right censoring) to estimate the hazard of a second VC round. Thus, the hazard rate is conditional on having received a first round of VC financing, but not yet a follow-on round. Compared to the baseline models, we also added the dummy variable *First Round Recession* that equals 1 for firms that received their first VC round during a recession period. Second, we run recurrent event analyses by considering all firm's time intervals from each financing round to the next financing round (or right censoring) as separate risk intervals (starting from *t* = 0) and apply a Weibull regression with a gamma-distributed shared frailty component at the firm-level to account for unobserved firm-specific factors that may lead to within-firm correlation between follow-on VC rounds (see Kleinbaum and Klein 2004 for an introduction to recurrent event analysis). The results are shown in Table A3.4 in the Appendix. Overall, we observe 172 firms out of the 372 VC-backed firms (45.2 percent) to receive a second VC round and 403 follow-on rounds in total (including second VC rounds) until the first quarter of 2015. Consistent with our main estimates, we observe the hazard of a second VC round (Models A22-A24) or follow-on VC round (Models A25-A27) to be not significantly correlated with recession periods, regardless of a firm's patent characteristics. Moreover, while the *Patent Stock (ln+1), t-1* is still significantly associated with the hazard of a second round of VC, this association decreases over time and is no longer significant when considering all follow-on rounds together (Model A25-A27). This is in line with the literature on decreasing signaling effects of patents over time, as VC investors update their quality expectations of young firms over time (e.g., Haeussler et al. 2014).

3.4.2 Treatment effect

To estimate the treatment effect of VC on a firm's innovation output, we consider the three innovation output measures *Patent Stock (ln+1), t*, the *Citation Stock (ln+1), t* and *Radical Stock (ln+1), t* for a focal firm at time *t*. The causality between VC financing and a firm's total innovation output over time is not evident, as our previous results suggest that VC-backed firms already filed more patents than non-VC-backed firms even before receiving their first round of VC financing. A positive association between VC investment and the growth of a firm's innovation output may simply be the result of VC selection, i.e., investors fund firms with good growth prospects based on their past patenting activity without giving them any support for their future inventive activities (Gompers and Lerner 2001, Bertoni et al. 2011, Colombo and Murtinu 2017). Moreover, innovation growth is likely to be correlated with unobserved firm characteristics, e.g., the firm's human capital. If these unobserved characteristics also correlate with the likelihood of VC financing, a spurious correlation between VC investment and firm innovation is the result. An opposite bias is also possible if firms with superior innovation growth prospects self-select out of the VC-market, finding other potential sources of financing for their innovation activities.

To deal with these endogeneity concerns, we follow Chemmanur (2011), Colombo and Murtinu (2017) and Bertoni and Tykvová (2016) and apply firm-fixed-effect OLS regressions with standard errors clustered at the firm level to control for time-invariant unobserved heterogeneity across firms. Our main explanatory variables of interest are the two variables *Post-VC Non-Recession (1,.)* and *Post-VC Recession (1,.)*, which are dummy variables that are equal to 1 for VC-backed firms financed during a period of (non-)recession from the quarter after the VC investment onwards, and 0 otherwise. Moreover, we control for the focal firm's age (*Firm's age, t (quarters)*), recession periods (*Recession, t*) and add *Quarter-, Year-Fixed Effects* to control unobserved heterogeneity over time that may affect a firm's innovation output. The firm-fixed-effect regression estimates within-firm changes of the dependent variables. Given that the (continuously increasing) dependent variables are measured on a logarithmic scale and our explanatory variables of interest *Post-VC Non-Recession (1,.)* and *Post-VC Recession (1,.)* in Model 7, 8 and 9 are dummy variables, their estimated coefficients need to be exponentiated (i.e., 100*exp(coefficient)-1) to be interpreted as percentage change of the dependent variable measuring the total innovation output in the post-financing period compared to the pre-financing period (Halvorsen and Palmquist 1980). In Models 10-12, we add the variables *Pre-VC Non-Recession (-7,0)* and *Pre-VC Recession (-7,0)* (for t = 0 in the year-quarter of the first financing round), which are dummy variables that are equal to 1 during the 2 years (= 8 quarters) prior to VC financing for all firms that received their first financing round during a period of non-recession or recession, and 0 otherwise. These variables allow to investigate the innovation growth for VC-backed firms prior selection. Accordingly, the reference period for the dependent variables in Models 10-12 is the time period from firm foundation until two years prior to the focal firm's first financing round. The results are shown in Table 3.4.

Model 7 shows that for firms that receive their first VC round during a period of non-recession, the firm's patent stock significantly increases by 40.9 percent (exp(0.343) = 1.409, p = 0.000) after VC-receipt compared to the pre-financing period. For firms that receive their first VC round during a period of recession, the patent stock increases by 45.5 percent (exp(0.375) = 1.455, p = 0.000) in the post-financing period. Moreover, we do not observe a significant difference in the growth of the patent stock between firms financed during a period of non-recession compared to a period of recession (F = 0.18, p = 0.671). Similarly, Model 8 shows positive significant growth rates of 65 percent (90.8 percent) after VC-receipt for the citation stock of firms that are financed during a period of non-recession (recession), while these growth rates are not statistically different (F = 0.90, p = 0.343). Lastly, Model 9 only shows a significant growth rate of 6.2 percent for the stock of radical patents (p = 0.000) for firms financed during a period of non-recession, while the growth rate of 4.1 percent for firms financed during a recession is not significant at standard levels of significance (p = 0.203). The two growth rates of the stock of radical patents are however not statistically different (F = 0.34, p = 0.561). A possible explanation for this result, which we cannot rule out, is the small number of firms filing a patent for a radical invention over time and the resulting lack of statistical precision.[52]

Table 3.4 Treatment effect of VC financing on firm innovation

Dependent Variable	**Model 7** Patent Stock	**Model 8** Citation Stock	**Model 9** Radical Stock	**Model 10** Patent Stock	**Model 11** Citation Stock	**Model 12** Radical Stock	**Model 13** Patent Stock	**Model 14** Citation Stock	**Model 15** Radical Stock
(1) Pre-VC Non-				0.194	0.409	0.025			
Recession (-7,0)				[0.000]	[0.000]	[0.152]			
				(0.039)	(0.092)	(0.017)			
(2) Pre-VC Recession				0.157	0.364	0.076			
(-7,0)				[0.037]	[0.025]	[0.079]			
				(0.075)	(0.162)	(0.043)			
(3) Post-VC Non-	0.343	0.501	0.060	0.465	0.758	0.076	0.088	0.125	0.033
Recession (1,.)	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.018]	[0.020]
	(0.036)	(0.078)	(0.014)	(0.053)	(0.118)	(0.022)	(0.013)	(0.053)	(0.014)
(4) Post-VC Recession	0.375	0.646	0.040	0.470	0.865	0.084	0.054	0.173	0.006
(1,.)	[0.000]	[0.000]	[0.203]	[0.000]	[0.000]	[0.101]	[0.020]	[0.076]	[0.856]
	(0.067)	(0.134)	(0.031)	(0.094)	(0.185)	(0.051)	(0.023)	(0.098)	(0.032)
Recession, t	0.013	0.036	-0.007	0.015	0.039	-0.008	-0.015	-0.005	-0.010
	[0.346]	[0.176]	[0.137]	[0.290]	[0.143]	[0.111]	[0.013]	[0.803]	[0.030]
	(0.014)	(0.027)	(0.005)	(0.014)	(0.027)	(0.005)	(0.006)	(0.020)	(0.005)
Firm's age, t (quarters)	0.017	0.018	0.003	0.016	0.017	0.003	0.048	0.064	0.006
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	(0.001)	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Constant	0.394	0.847	0.038	0.371	0.797	0.033	5.759	8.733	0.603
	[0.000]	[0.000]	[0.186]	[0.000]	[0.000]	[0.253]	[0.000]	[0.000]	[0.000]
	(0.048)	(0.096)	(0.028)	(0.046)	(0.093)	(0.029)	(0.080)	(0.229)	(0.081)
IMR, t							-2.101	-3.089	-0.222
							[0.000]	[0.000]	[0.000]
							(0.028)	(0.088)	(0.030)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-Test (1)=(2): p-value				0.659	0.807	0.274			
F-Test (3)=(4): p-value	0.671	0.343	0.561	0.962	0.619	0.883	0.185	0.661	0.436
Observations	33,239	33,239	33,239	33,239	33,239	33,239	33,239	33,239	33,239
Number of Firms	997	997	997	997	997	997	997	997	997
R-squared	0.349	0.142	0.081	0.355	0.150	0.083	0.815	0.486	0.131

Note: The firm-fixed-effect regression estimates within-firm changes of the dependent variables. In Models 7-9, the reported effects of *Post-VC Non-Recession (1,.), t* and *Post-VC Recession (1,.), t* need to be exponentiated (i.e., 100*exp(coefficient)-1) to be interpreted as percentage change or growth of the dependent variable in the post-financing period compared to the pre-financing period. Accordingly, the reference for the dependent variables in Models 10-12 is the time period from firm foundation to two years prior the focal firm's first financing round. In Models 13-15, we replicate the econometric specifications of Models 7-9, but add an inverse Mills ratio to control for unobserved selection effects. The inverse Mills ratio (*IMR, t*) is estimated using a probit regression with exclusion restriction in a survival time setting that predicts the probability of a firm to be selected by VC investors in quarter *t* (see Table A3.5 for further details).

Brackets: p-values; Parentheses: Standard errors clustered by firm in all models

[52] In the pre-financing period, 55 of the 372 VC-backed firms filed a patent for a radical invention (100 for the 625 non-VC backed firms), while we observe patents filed for a radical invention in the post-financing period for 34 firms financed in a non-recession period (n = 314) and only 3 for firms financed in a recession period (n = 58).

In Models 10-12, we additionally investigate the innovation growth in the pre-financing period by comparing the innovation output in the two years prior to VC-receipt compared to the period before, i.e., the period from foundation until two years prior to VC-receipt. In Model 10, we observe statistically significant growth rates of 21.4 percent (17 percent) for the patent stock of firms that will receive financing during a period of non-recession (recession), while these rates are not statistically different ($F = 0.20$, $p = 0.659$). In the post-financing period, the patent stock continues to grow for firms that received financing during a period of non-recession (recession) to 59.2 percent (60 percent) higher level compared to the period from firm foundation until two years prior to VC-receipt, while these rates are again not statistically different ($F = 0.00$, $p = 0.962$). In Model 11, we find similar effects of different magnitude for the growth of the citation stock of VC-backed firms in the two years prior and post VC-receipt. Model 12 only shows a significant growth of 7.9 percent for the stock of radical patents of firms that will be financed during a recession period ($p = 0.079$), but not for firms that will be financed during a period of non-recession. However, these growth rates are again not statistically different ($F = 1.2$, $p = 0.274$).

To investigate the difference in growth of the innovation output in the post-financing period compared to the two-year period prior selection, we extrapolated the estimated growth within the two years prior to VC-receipt and build the difference to the estimated post-financing growth (which shares the same reference period, i.e., the period from firm foundation until two years prior the first financing round). For the VC-backed firm's patent stock, we observe the difference in growth to be positive ($\Delta = 0.465-0.194-0.194 = 0.077$) and significant at the 10 percent level ($F = 2.80$; $p = 0.095$) only for firms financed during periods of non-recession, while this difference in growth is not significant for firms financed during recession periods ($\Delta = 0.470-0.157-0.157 = 0.156$; $F = 2.29$; $p = 0.13$). For both the citation stock and stock of radical patents (Model 11 and 12), the differences in growth in the post-financing period compared to two years prior financing are not statistically different from zero ($p > 0.15$), regardless of receiving VC financing during a period of recession or non-recession. Overall, we do not find strong evidence for the fact that VC-backed firms significantly increase their innovation output in the post-financing period compared to the two years prior to the first financing round (except for the patent stock of firms financed during a period of non-recession). Consequently, the estimated treatment effects in Models 7-9 may be endogenous to selection, as VC investors finance firms that have already shown a strong increase in their innovation output in the 2 years prior to VC financing.

In Models 13-15, we correct for time-varying unobserved heterogeneity through a Heckman two-step procedure with exclusion restriction in the selection equation (Heckman 1979), i.e., a strictly exogenous regressor that is correlated with the likelihood of VC financing, but likely uncorrelated with the error term in the firm innovation growth equation. Following the literature on panel data models with presence of endogeneity and selection (e.g., Hamilton and Nickerson 2003, Semykina and Wooldrigde 2010), we model the selection by estimating the probability of a first round of VC financing with a probit regression in a survival time setting (for a similar approach in the context of VC investments, see, e.g., Colombo and Murtinu 2017). The baseline outcome category represents the situation of no VC financing, that is, the dependent variable is always zero for non-VC-backed firms. For VC-backed firms, the dependent variable is zero for all quarters prior VC financing, equals one in the quarter of the first financing round, and is set to missing in the quarters after the first financing round. We include the same variables as in Model 1, but add the firm's age as a control variable (*Firm's age, t (quarters))*, because time from foundation is not implicitly considered by this estimator, as it is in case of (semi-)parametric survival analyses.[53] As exclusion restriction, we use the relative quarterly frequency of non-life-science VC-deals in the country of the focal firm compared to the total number quarterly non-life-science VC-deals in VICO (*Relative Frequency VC Deals in Country, t*). The activity of VC investors varies across countries and time because of changes in regulation, fundraising, exit conditions, and public markets (Gompers and Lerner 1999, Gompers et al. 2008, Groh et al. 2010). The variation in VC activity qualifies as exclusion restriction as it is correlated with the likelihood of VC financing of a given life science firm in a given country and quarter, but it does not depend on the observed and unobserved characteristics of the firm itself. The results are shown in Table A3.5 in the Appendix and are similar to our survival time analysis. Only the magnitude of the effect *Patent Stock,*

[53] Compared to the data structure underlying Model 1, we also do not exclude firms at risk of financing that are older than 10 years, as we want to predict of the probability of a VC financing for a focal firm over the entire sample period. For the same reasons, we do not include year-dummies, as our sample only reports VC-deals from the year 2003 onwards and, thus, the probabilities for the years 1998 to 2003 cannot be predicted.

t-1 is slightly smaller. Moreover, the exclusion restriction *Relative Frequency VC Deals in Country, t* is highly correlated with the likelihood of a first financing round at the 1 percent level (z = 2.83, p = 0.005), indicating that our estimates do not suffer from the weak instrument problem.

We rely on this first-step probit estimates to calculate an inverse Mills ratio (*IMR, t*) that is subsequently added to the econometric specifications of Models 7, 8 and 9, thereby correcting for selection for all firms over the whole sample period. Table 3.4 reports the results of these three additional Models 13-15. When correcting for selection, the treatment effect decreases compared to Models 7-9. For example, Model 13 shows a significant post-financing growth of “only” 9.2 percent (exp(0.088) = 1.092, p = 0.000) of the firm’s patent stock for firms financed during a period of non-recession (Model 7: 40.9 percent) and 5.5 percent (p = 0.020) for firms financed during a period of recession (Model 7: 45.5 percent). Consistently, we do not observe a significant difference in the growth of the patent stock between firms financed during a period of non-recession compared to a period of recession (F = 1.76, p = 0.185). The growth of the citation stock (Model 14) equals 13.3 percent (p = 0.018) for firms financed during a period of non-recession and 18.8 percent (p = 0.076) for firms financed during recessions. Again, these growth rates are not statistically different (F = 0.19, p = 0.661), but smaller in magnitude than in the baseline Model 8. The same holds for estimates for the growth of the stock of radical patents (Model 15), where we only find a smaller treatment effect of 3.4 percent (p = 0.020) for firms financed during a period of non-recession (Model 9: 6.2 percent).

To conclude, the baseline regressions for the treatment effect in Models 7, 8 and 9 overestimate the effect on VC financing on firm innovation. Although, our results provide evidence of a positive and significant treatment effect of VC financing on firm innovation, the magnitude of the effect is economically quite small. Given an average patent stock of 2.31 patents for VC-backed firms in the pre-financing period, a 9.2 percent increase of the patent stock as a consequence of VC financing equals a growth of only 0.2 patents of the patent stock in the post-financing period.

3.4.2.1 Robustness checks and additional analyses

We test the robustness of our estimation of the treatment effect of VC financing on firm innovation to the inclusion of non-patenting firms (during our observation period), as the above estimated treatment effect (Model 13-15) of VC financing on firm innovation may be overestimated when not including non-patenting firms, for which the treatment effect is 0 by definition. The results of these three additional models A29-A31 are shown in Table A3.6 in the Appendix. Consistent with the main estimates that also correct for selection, we find the treatment effect of VC financing on firm innovation to be quite similar in magnitude, and again, not statistically different by economic situation at the time of VC financing.

Furthermore, we investigate the dynamics of the treatment effect of VC financing on innovation growth (short- vs. long-term effect). We run the same econometric specifications of Models 13-15, but substitute the variables *Post-VC Non-Recession (1,.)* and *Post-VC Recession (1,.)* with four dummy variables that distinguish the first two years after the first financing round (*Post-VC Non-Recession (1,8)* and *Post-VC Recession (1,8)*) from the period starting from the third year after VC-receipt (*Post-VC Non-Recession (9,.)* and *Post-VC Recession (9,.)*). The results of these three additional Models 16, 17 and 18 are shown in Table 3.5 and yield interesting new evidence. When comparing the treatment effects of VC financing by economic situation at the time of VC-receipt (non-recession versus recession), we find the difference of the short-term effect of VC financing on the patent stock (Model 16) for firms financed during a period of non-recession (6.7 percent, $p = 0.000$) and recession (1 percent, $p = 0.719$) to be significantly different from 0 ($F = 3.64$, $p = 0.057$). For all other effects (short- and long-term), we do not find significant differences by economic situation at the time of VC-receipt. Moreover, we observe notable differences when investigating the difference of the short- and long-term effect of VC financing on firm innovation. For the patent stock (Model 16), we observe the difference in the long- versus short-term growth to be significantly positive only for firms that receive their first round of VC financing during a recession ($\Delta = 0.112-0.01-0.01 = 0.092$, $F = 3.20$, $p = 0.074$). Thus, we find evidence for the fact that firms financed during a period of non-recession already increase their patenting activity right after VC-receipt compared to firms financed during a recession period, while the latter increase their patenting activity in the long-term, leading to non-significantly different long-term growth rates of the patent stock by economic situation at the time of VC-receipt ($F = 0.01$, $p = 0.939$). Lastly, when considering the technological impact of the patent portfolio (Model 17), we observe the difference of the long- versus short-term growth in forward citations to be significantly greater in the period right after VC-receipt for firms financed during a period of non-recession (Δ = 0.101-0.153-0.153 = -0.205, F = 11.76, p = 0.001).

Table 3.5 Short- versus long-term treatment effect of VC financing on firm innovation

Dependent Variable	**Model 16** Patent Stock	**Model 17** Citation Stock	**Model 18** Radical Stock
(1) Post-VC Non-Recession (1,8)	0.065	0.153	0.018
	[0.000]	[0.001]	[0.140]
	(0.012)	(0.046)	(0.012)
(2) Post-VC Non-Recession (9,.)	0.114	0.101	0.049
	[0.000]	[0.125]	[0.010]
	(0.017)	(0.066)	(0.019)
(3) Post-VC Recession (1,8)	0.010	0.065	0.003
	[0.719]	[0.449]	[0.898]
	(0.027)	(0.086)	(0.027)
(4) Post-VC Recession (9,.)	0.112	0.272	0.016
	[0.000]	[0.040]	[0.697]
	(0.029)	(0.132)	(0.041)
Recession, t	-0.014	-0.004	-0.010
	[0.019]	[0.852]	[0.035]
	(0.006)	(0.020)	(0.005)
Firm's age, t (quarters)	0.048	0.065	0.006
	[0.000]	[0.000]	[0.000]
	(0.001)	(0.002)	(0.001)
Constant	5.740	8.730	0.595
	[0.000]	[0.000]	[0.000]
	(0.080)	(0.230)	(0.081)
IMR, t	-2.095	-3.088	-0.219
	[0.000]	[0.000]	[0.000]
	(0.029)	(0.089)	(0.030)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
F-Test (1)=(3): p-value	0.057	0.364	0.624
F-Test (2)=(4): p-value	0.939	0.235	0.457
F-Test (1)+(1)=(2): p-value	0.357	0.001	0.447
F-Test (3)+(3)=(4): p-value	0.074	0.334	0.801
Observations	33,239	33,239	33,239
Number of Firms	997	997	997
R-squared	0.816	0.487	0.133

Note: The firm-fixed-effect regression estimates within-firm changes of the dependent variables. The reported effects of the dummy variables capturing the short-term effect *(Post-VC Non-Recession (1,8)* and *Post-VC Recession (1,8)*) and long-term effect (*Post-VC Non-Recession (9,.)* and *Post-VC Recession (9,.)*) of VC financing on firm innovation need to be exponentiated (i.e., 100*exp(coefficient)-1) to be interpreted as percentage change or growth of the dependent variable in the defined period compared to the pre-financing period. To compare the short- versus long-term effect of VC financing on firm innovation, we extrapolated the short-term effect of VC financing and build the difference to the long-term effect. The inverse Mills ratio (*IMR, t*) controls for unobserved selection effects and is estimated using a probit regression with exclusion restriction in a survival time setting that predicts the probability of a firm to be selected by VC investors in quarter *t* (see Table A3.5 for further details).

Brackets: p-values; Parentheses: Standard errors clustered by firm in all models

3.5 Discussion

The aim of our study was to investigate whether VC selection and treatment are affected by a recession. We find that neither the selection criteria, nor the (long-term) treatment effect of VC financing on firm innovation changes during a recession. Obviously, VC investors still rely on established decision-making processes and heuristics and the selection criteria that work during non-recession periods. This result is surprising because economic decision theory and the psychological literature indicate that decision-making and behaviors change when individuals are in an extreme situation.

Moreover, we observe a significantly smaller treatment effect of VC financing on the patent stock in the two years after VC-receipt (short-term treatment effect) for firms that received first round funding during a period of recession compared to a period of non-recession. The total patenting output (long-term treatment effect), however, converges for the treatment and the control group. A possible explanation for this finding is that for young firms, even if they receive financial and non-financial resources from VC investors, it obviously takes longer for innovation output to become visible. Given that VC investors do not apply any other selection criteria, this means that it can’t be a selection effect. Possible reasons are that a difficult economic situation slows down the innovation activity of young companies (Brem et al. 2020). It could also be that the fact that less money is flowing into early-stage financing (Howell et al. 2021) can lead to longer innovation cycles. Finally, it could be that VC investors are not, as assumed, trying to compensate for the crisis with more non-monetary resources, but are providing fewer value-added functions in times of recessions than during non-recession times due to other commitments. However, these explanations are speculative in the absence of data revealing the mechanisms. Future research should take a closer look at this aspect. An equally interesting and important result is that in the long run there are no differences in innovation output between young companies that received their VC funding during times of recession vs. non-recession. The former are obviously able to catch up. This result is not only socially important and reassuring, it may also suggest that it is indeed likely to be the difficult economic situation that drives the difference in the short-term treatment effect. Lastly, the magnitude of the treatment effect on firm innovation is economically quite small when correcting for selection, which is consistent with recent survey evidence suggesting that VC investors view deal selection as being more important than their post-investment activities (Gompers et al. 2020).

We know from the VC literature that VC investments are fraught with great uncertainty and that VC investors are accustomed to hedging risk (Zhao et al. 2015). However, this uncertainty, which is related to the founding team, the market, the business model, and the technology, is very different from the uncertainty faced during a crisis or a recession, i.e., the uncertainty related to the economy (Gompers et al. 2021). A difficult economic situation, as we observed globally during the 2008-2010 financial crisis or as we are currently struggling with during the COVID-19 crisis, could lead VC investors to try to apply even stricter evaluation criteria or to invest even more time in startups (treatment) to compensate for the additional uncertainty and thus increase the probability of success. However, this is not what we observe in the data.

Why do VC investors, who in principle have to decide and act under extreme conditions, not (have to) adjust their decision criteria and behavior in an even more extreme situation like a recession or crisis? Are their selection criteria of startups already "crisis-proof"? In other words, are VC investors an example of resilient decision makers? If so, it will be interesting to examine this phenomenon in other industries and in a context other than VC funding. If these patterns can be identified in other contexts, the theoretical literature on decision making under extreme conditions would need to be expanded and revised. Other decision makers who suffer from crisis situations and adapt their decision-making behavior according to theory, i.e., decide more conservatively, may be able to learn from VC investors. A lack of willingness to take risks usually prevents innovation. But especially in times of crisis, innovation can be a salvation (e.g., COVID-19 vaccine).

Second, we contribute to the literature on VC investment, since our results help to better understand the selection and treatment behavior of investors. We know from the literature that gut feeling, and visual cues are important determinants of VC investors' selection decisions (Gompers et al. 2020, Hu and Ma 2020). Gut feeling, for example, is a decision mechanism that leads to a quick result based on intuition and experience but can hardly be explained rationally (Sadler-Smith and Shefy 2004). Also recommendations from their networks play an important role (Howell and Nanda 2019). These recommendations are based on social relationships. Generally, social ties can be a major factor supporting economic processes, such as recruiting, investment decisions, and loan-granting (Jackson 2006). Individuals may pledge social collateral for other individuals they are tied with, thus reducing informational frictions in financing and other economic transactions or processes (Karlan et al. 2009). We do know from the literature that these mechanisms are used in the selection of investment transactions. So far, we have not investigated under which conditions these mechanisms work particularly well or where they reach their limits. Future research should therefore analyze the decision-making processes of VC investors in more detail. It might be helpful to consider a range of extreme conditions, such as other types of crises, technological shocks, natural disasters, scandals, etc.

A practical implication of our research is that decisions generally need to be made increasingly quickly, whether due to competitive pressure or increasingly shorter technology life cycles. Not least for this reason, decisions are already frequently made with the support of artificial intelligence. However, artificial intelligence is only as good as the underlying algorithm. If we do not sufficiently understand decision-making processes in extreme situations, how could we program powerful algorithms for such situations in the future?

With respect to the limitations of our study, we recognize that, even though we used an instrumental variable approach to disentangle selection and treatment of VC investors, endogeneity might still arise from unobserved heterogeneity. Therefore, caution is required in interpreting our results as indicating causal links. We also recognize that our study is restricted to one industry. This may limit the generalizability of our results. Although we are confident that our results hold in other environments, future research should examine VC selection and treatment under extreme conditions in other industries and possibly also in contexts other than recessions.

General Conclusion

The objective of this thesis was to create a better theoretical and empirical understanding of the relationship between VC investors and young innovative firms. The success of VC-backed firms might be related to the fact that early-stage investors are able to select firms of high quality, but also the provision of financial and non-financial resources as well as managerial expertise. This thesis therefore investigated the relevance of specific signals, additional (positive and negative) information and external contingencies (i.e., recession periods) for the selection behavior and decision-making quality of early-stage investors, as well as the subsequent treatment effect of VC financing on firm innovation.

Considering the selection behavior, the first essay (Chapter 1) suggests that early-stage investors react differently to negative information conveyed by a strong signal of quality depending on their ability to deal with this negative information. We show that only reputable investors are more likely to invest in firms with patent(s) protecting radical inventions, but syndicate their investment. The second essay (Chapter 2) investigates the selection ability of crowdinvestors and suggests that additional positive information generated through the investment decisions of peer investors that invested earlier in the firm benefits the decision-making quality of investors that contribute later in case a firm sends a weaker signal of quality (i.e., firms with a lower valuation). Reflecting on these findings, this thesis emphasizes the complexity of the cognitive process that determines both the selection behavior and performance of early-stage investors. Introducing a new type of uncertainty related to periods of recession, the third essay (Chapter 3) shows that in times of economic contraction, investors do not adapt their selection criteria when evaluating the firm's technological quality, as they continue to invest in firms with larger patent portfolios. Similarly, we show that the long-term treatment effect of VC financing on firm innovation is not contingent on the economic situation at the time of selection, and is of small economic magnitude when correcting for the fact that early-stage investors select more innovative firms. Although all three essays are subject to endogeneity, this thesis contributes to a better theoretical and empirical understanding of the investment relationship between early-stage investors and young innovative firms.

Appendix

A1. Appendix to Chapter 1

Table A1.1 Robustness Check: Continuous measure of VC investor reputation

		Model A1	Model A2
Sample specification		First Round	Follow-on Round
Average Marginal effect of DRadical Patent on	*Counterfactual*		
P(Standalone Tie | Investor Reputation = p50; DIncremental Patent = 0)	*No Patent*	-0.001	0.001
		(0.001)	(0.001)
P(Standalone Tie | Investor Reputation = p75; DIncremental Patent = 0)		-0.001*	0.000
		(0.001)	(0.001)
P(Standalone Tie | Investor Reputation = p90; DIncremental Patent = 0)		-0.001*	-0.000
		(0.001)	(0.001)
P(Syndicated Tie | Investor Reputation = p50; DIncremental Patent = 0)		0.003**	0.000
		(0.002)	(0.001)
P(Syndicated Tie | Investor Reputation = p75; DIncremental Patent = 0)		0.004**	0.001
		(0.002)	(0.001)
P(Syndicated Tie | Investor Reputation = p90; DIncremental Patent = 0)		0.006***	0.002
		(0.002)	(0.002)
P(Standalone Tie | Investor Reputation = p50; DIncremental Patent = 1)	*Incremental Patent*	-0.001*	0.001
		(0.000)	(0.001)
P(Standalone Tie | Investor Reputation = p75; DIncremental Patent = 1)		-0.001**	0.000
		(0.000)	(0.001)
P(Standalone Tie | Investor Reputation = p90; DIncremental Patent = 1)		-0.001**	-0.000
		(0.001)	(0.001)
P(Syndicated Tie | Investor Reputation = p50; DIncremental Patent = 1)		0.003*	0.000
		(0.002)	(0.001)
P(Syndicated Tie | Investor Reputation = p75; DIncremental Patent = 1)		0.004**	0.001
		(0.002)	(0.001)
P(Syndicated Tie | Investor Reputation = p90; DIncremental Patent = 1)		0.007**	0.002
		(0.003)	(0.002)
Variables & Original Model Specification		**Model 4**	**Model 8**
Firm X Investor Dyads		74,883	73,321

Note: Standard errors in parentheses are clustered by investor. These models use the same econometric specifications as Model 4 and 8, but use a continuous specification of the reputation variable and show the marginal effects of *DRadical Patent* at different values of the underlying distribution of investor reputation.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A1.2 Robustness Check: Alternative variable specifications for VC investor reputation

		Model A3	Model A4	Model A5	Model A6
Sample specification		First Round	Follow-on Round	First Round	Follow-on Round
Average Marginal effect of DRadical Patent on	*Counterfactual*				
P(Standalone Tie | DReputable Investor (IPO 3y) = 0; DIncremental Patent = 0)	*No Patent*	-0.001	0.000		
		(0.001)	(0.001)		
P(Standalone Tie | DReputable Investor (IPO 3y) = 1; DIncremental Patent = 0)		-0.002	0.001		
		(0.001)	(0.001)		
P(Syndicated Tie | DReputable Investor (IPO 3y) = 0; DIncremental Patent = 0)		0.003*	0.001		
		(0.002)	(0.001)		
P(Syndicated Tie | DReputable Investor (IPO 3y) = 1; DIncremental Patent = 0)		0.008**	0.001		
		(0.003)	(0.002)		
P(Standalone Tie | DReputable Investor (IPO 3y) = 0; DIncremental Patent = 1)	*Incremental Patent*	-0.001	0.000		
		(0.001)	(0.001)		
P(Standalone Tie | DReputable Investor (IPO 3y) = 1; DIncremental Patent = 1)		-0.001	0.001		
		(0.001)	(0.001)		
P(Syndicated Tie | DReputable Investor (IPO 3y) = 0; DIncremental Patent = 1)		0.003*	0.001		
		(0.002)	(0.002)		
P(Syndicated Tie | DReputable Investor (IPO 3y) = 1; DIncremental Patent = 1)		0.008*	0.001		
		(0.004)	(0.002)		
P(Standalone Tie | DReputable Investor (Inv 5y) = 0; DIncremental Patent = 0)	*No Patent*			-0.001	0.001
				(0.001)	(0.001)
P(Standalone Tie | DReputable Investor (Inv 5y) = 1; DIncremental Patent = 0)				-0.001	0.000
				(0.001)	(0.001)
P(Syndicated Tie | DReputable Investor (Inv 5y) = 0; DIncremental Patent = 0)				0.003	0.002
				(0.002)	(0.001)
P(Syndicated Tie | DReputable Investor (Inv 5y) = 1; DIncremental Patent = 0)				0.008**	-0.000
				(0.003)	(0.002)
P(Standalone Tie | DReputable Investor (Inv 5y) = 0; DIncremental Patent = 1)	*Incremental Patent*			-0.001	0.001
				(0.001)	(0.001)
P(Standalone Tie | DReputable Investor (Inv 5y) = 1; DIncremental Patent = 1)				-0.001	0.000
				(0.001)	(0.001)
P(Syndicated Tie | DReputable Investor (Inv 5y) = 0; DIncremental Patent = 1)				0.003	0.002
				(0.002)	(0.002)
P(Syndicated Tie | DReputable Investor (Inv 5y) = 1; DIncremental Patent = 1)				0.009**	-0.000
				(0.004)	(0.002)
Variables & Orginal Model Specification		**Model 4**	**Model 8**	**Model 4**	**Model 8**
Firm X Investor Dyads		74,883	73,321	74,883	73,321

Note: Standard errors in parentheses are clustered by investor. These models use the same econometric specifications as Model 4 and 8, but use alternative measures for the reputation of the investor. Model A3 and A4 report the marginal effects of *DRadical Patent* for the variable *specification Reputable Investor (#IPO 3 years)*; Model A5 and A6 report the marginal effects of *DRadical Patent* for the variable specification *Reputable Investor (#investments 5 years).*

* p < 0.1, ** p < 0.05, *** p < 0.01

Table A1.3 Robustness Check: Conditional logistic regression

	Model A7	Model A8	Model A9	Model A10	Model A11	Model A12	Model A13	Model A14
Conditional on	Firm	Firm	Firm	Firm	Investor	Investor	Investor	Investor
Sample specification	First Round	First Round	Second Round	Second Round	First Round	First Round	Follow-on Round	Follow-on Round
Outcome reference: Unrealized Tie vs.	Standalone Tie	Syndicated Tie	Standalone Tie	Syndicated Tie	Standalone Tie	Syndicated Tie	Standalone Tie	Syndicated Tie
DIncremental Patent					-0.326	0.130	0.256	0.315*
					(0.212)	(0.130)	(0.394)	(0.178)
DRadical Patent					-0.305	0.397**	0.506	0.205
					(0.403)	(0.200)	(0.537)	(0.238)
DReputable Investor	-0.104	-0.103	0.082	-0.058	-0.391	-0.080	-0.094	0.443
	(0.260)	(0.180)	(0.646)	(0.378)	(0.398)	(0.261)	(0.581)	(0.299)
DIncremental Patent X DReputable Investor	0.215	-0.039	-2.421**	-0.054	0.469	-0.031	0.036	-0.285
	(0.340)	(0.232)	(1.205)	(0.430)	(0.344)	(0.229)	(0.521)	(0.268)
DRadical Patent X DReptuable Investor	0.264	0.540*	0.278	-0.724	-0.160	0.625**	0.257	-0.064
	(0.759)	(0.304)	(0.897)	(0.671)	(0.718)	(0.300)	(0.684)	(0.331)
Forward Citations (ln+1)					-0.067	0.117***	-0.172	0.084**
					(0.095)	(0.044)	(0.108)	(0.042)
Firm Age					0.032	-0.018	0.095**	-0.048**
					(0.031)	(0.020)	(0.045)	(0.021)
Number of Prior Investors							-0.075	-0.030
							(0.062)	(0.026)
DPrior Reputable Investor			-16.414	-18.251			-1.379***	-0.818***
			(832.130)	(874.399)			(0.298)	(0.122)
Months Since Last Funding							0.005	0.007**
							(0.007)	(0.003)
Industry Experience (ln+1)	-0.060	-0.038	0.067	-0.052	-0.435**	-0.288**	-0.187	-0.279**
	(0.072)	(0.045)	(0.157)	(0.079)	(0.174)	(0.124)	(0.253)	(0.135)
DPrior Investment			5.392***	5.650***			6.238***	5.936***
			(0.500)	(0.336)			(0.297)	(0.153)
Distance (ln+1)	-0.417***	-0.331***	-0.176	-0.242***	-0.356***	-0.411***	-0.499***	-0.303***
	(0.056)	(0.035)	(0.112)	(0.063)	(0.051)	(0.034)	(0.093)	(0.045)
DSame Country	2.953***	2.490***	1.948***	1.917***	4.425***	3.365***	1.381***	2.008***
	(0.257)	(0.149)	(0.498)	(0.248)	(0.407)	(0.194)	(0.397)	(0.198)
Firm Country FE	No	No	No	No	Yes	Yes	Yes	Yes
Industry (NACE) FE	No	No	No	No	Yes	Yes	Yes	Yes
Time Period Fixed FE	No	No	No	No	Yes	Yes	Yes	Yes
Firm X Investor Dyads	22,694	39,088	8,983	18,465	27,791	55,264	23,255	54,285
Log Likelihood	-647.070	-1,753.583	-154.250	-627.122	-670.997	-1,808.835	-333.678	-1,583.939

Note: The coefficients represent the changes in the log-odds. All models represent simple conditional logit analyses and are conditioned either on the firm (Models A7-A10) or the investor (Models A11-A14). They separately compare standalone ties to unrealized ties and syndicated ties to unrealized ties for either first round or follow-on round investment ties. For the model specifications A9 and A10, we confine the sample on follow-on investment ties to the second investment round, as we are not interested in the within-firm effects of our firm-specific variables over time.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A1.4 Alternative explanations

	Model A15	Model A16
Dependent variable	*Investment Sum Deal (ln)*	*Dummy Mixed Syndicate*
Estimation	OLS	Logit
Sample specification	First Round Deals	Syndicated First Round Deals
DIncremental Patent	-0.072	0.318
	0.349	0.288
DRadical Patent	0.015	0.105
	0.457	0.448
DSyndicated Deal	0.614**	
	0.245	
DIncremental Patent X DSyndicated Deal	0.486	
	0.369	
DRadical Patent X DSyndicated Deal	0.034	
	0.496	
DReputable Investor (Round)	0.781***	
	0.150	
Firm Age	0.001	0.050
	0.028	0.050
Forward Citations (ln+1)	0.253***	0.096
	0.076	0.131
Firm Country FE	Yes	Yes
Industry (NACE) FE	Yes	Yes
Time Period FE	Yes	Yes
Number of Investment Deals	394	348
R-Squared	0.323	
Log Likelihood	-639.759	-217.734

Note: Standard errors in parentheses are clustered by firm.

* p < 0.1, ** p < 0.05, *** p < 0.01

Table A1.5 Investment deals in firms with at least one radical invention by location

	VC Hub = 0		VC Hub = 1	
Panel A: VC Hubs London, Paris				
All investment rounds with	N	%	N	%
DRadical Invention = 0	834	84.16	163	90.56
DRadical Invention = 1	157	15.84	17	9.44
Total	991	100.00	180	100.00
Panel B: VC Hubs London, Paris, Stockholm, Munich, Helsinki, Amsterdam, Berlin, Dublin, Copenhagen, Bonn				
All investment rounds with	N	%	N	%
DRadical Invention = 0	682	83.48	315	88.98
DRadical Invention = 1	135	16.52	39	11.02
Total	817	100.00	354	100.00

A2. Appendix to Chapter 2

Table A2.1 Summary statistics of the firms at the time of their funding on Companisto (n = 74)

Sample specification	Full sample		Pre-money valuation		Wilcoxon-Mann-Whitney test:
			(1): < p75	(2): >= p75	(1) = (2)
	Mean	SD	Mean	Mean	p-value
Post-campaign outcomes (12/2020)					
Dummy Exit	0.11		0.11	0.10	0.824
Dummy Default	0.50		0.51	0.48	0.780
Dummy Pending	0.39		0.38	0.43	0.686
Pre-campaign characteristics					
Pre-money Valuation (1000 EUR)	3,860.00	6,148.35	1,620.38	9,512.38	0.000
Funding Goal (1000 EUR)	392.50	323.35	296.13	635.71	0.000
Firm Share Offered (Percent)	12.25	7.17	14.02	7.78	0.000
Firm Age (Months)	24.46	23.68	15.20	47.82	0.000
Campaign characteristics					
Number of Investors	738.30	407.77	620.26	1,036.19	0.000
Campaign Funding Sum (1000 EUR)	416.21	435.66	259.82	810.90	0.000
Share of Funding Goal Reached (Percent)	99.36	45.46	86.98	130.61	0.011
Dummy Overreached Funding Goal	0.22		0.11	0.48	0.001
Length of Campaign (Days)	91.28	42.00	85.34	106.29	0.046

Table A2.2 Alternative variable specifications

Event	**Model A1** Failure	**Model A2** Exit	**Model A3** Failure	**Model A4** Exit	**Model A5** Failure	**Model A6** Exit
Alternative Variable Specification	*Continuous Funding Level*		*Number of Investors*		*Firm Age*	
Funding Level, t-1 (%)	0.998***	1.011***				
	(0.000)	(0.001)				
Firm Value > p75	1.029	1.884***	0.823***	1.423***		
	(0.027)	(0.128)	(0.017)	(0.089)		
(Funding Level, t-1 (%)) X (Firm Value > p75)	1.000	0.986***				
	(0.000)	(0.001)				
Number of Investors, t-1 (100)			0.938***	0.998		
			(0.003)	(0.004)		
(Number of Investors, t-1 (100))X (Firm Value > p75)			1.065***	0.936***		
			(0.004)	(0.009)		
Funding Level, t-1: [75%, .)					0.730***	2.197***
					(0.015)	(0.085)
Firm Age > p75					0.771***	0.669***
					(0.014)	(0.040)
(Funding Level, t-1: [75%, .))X (Firm Age > p75)					1.460***	0.395***
					(0.041)	(0.038)
Campaign Month 2	1.214***	0.525***	1.242***	0.780***	1.126***	0.623***
	(0.024)	(0.022)	(0.023)	(0.032)	(0.019)	(0.023)
> Campaign Month 2	1.281***	0.555***	1.277***	0.904**	1.184***	0.509***
	(0.030)	(0.026)	(0.029)	(0.044)	(0.022)	(0.024)
Investment Sum: [p25, p50)	0.999	0.929*	0.996	0.960	1.009	0.966
	(0.018)	(0.037)	(0.018)	(0.038)	(0.019)	(0.039)
Investment Sum: [p50, p75)	0.914***	1.006	0.915***	1.049	0.916***	1.056
	(0.021)	(0.049)	(0.021)	(0.051)	(0.020)	(0.052)
Investment Sum: [p75, p90)	0.890***	1.073	0.891***	1.132**	0.905***	1.159**
	(0.025)	(0.067)	(0.025)	(0.071)	(0.025)	(0.073)
Investment Sum: [p90, p100]	0.733***	1.219**	0.737***	1.301***	0.740***	1.324***
	(0.026)	(0.097)	(0.026)	(0.103)	(0.026)	(0.106)
Total Amount Invested (ln)	1.054***	0.997	1.052***	0.991	1.055***	0.984
	(0.007)	(0.015)	(0.007)	(0.015)	(0.007)	(0.015)
Number of Firms: [2, 6)	0.973*	0.908***	0.980	0.911***	0.973*	0.941*
	(0.016)	(0.032)	(0.016)	(0.032)	(0.015)	(0.033)
Number of Firms: [6, .)	0.858***	0.904**	0.863***	0.850***	0.859***	0.904**
	(0.020)	(0.046)	(0.020)	(0.043)	(0.019)	(0.046)
Distance (ln+1)	1.008**	1.020***	1.008**	1.028***	1.008**	1.025***
	(0.003)	(0.007)	(0.003)	(0.008)	(0.003)	(0.007)
Firm Share Offered (%)	1.000***	0.999***	1.000***	0.998***	1.000***	0.999***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Funding Goal (1000 EUR)	0.968***	1.071***	0.972***	1.081***	0.965***	1.063***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Campaign Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Investments	52,024	52,024	52,024	52,024	52,024	52,024
Number of Events	25,923	5,816	25,923	5,816	25,923	5,816
Number of Competing Events	5,816	25,923	5,816	25,923	5,816	25,923
Log Likelihood	-262001.246	-59671.188	-261895.737	-59868.774	-261882.095	-59608.415

Note: Standard errors in parentheses are clustered by investor. The coefficients represent changes of the subhazard, i.e. the probability that the specified event occur given that the competing event has not yet occurred.

* p < 0.1, ** p < 0.05, *** p < 0.01

Table A2.3 Additional analyses

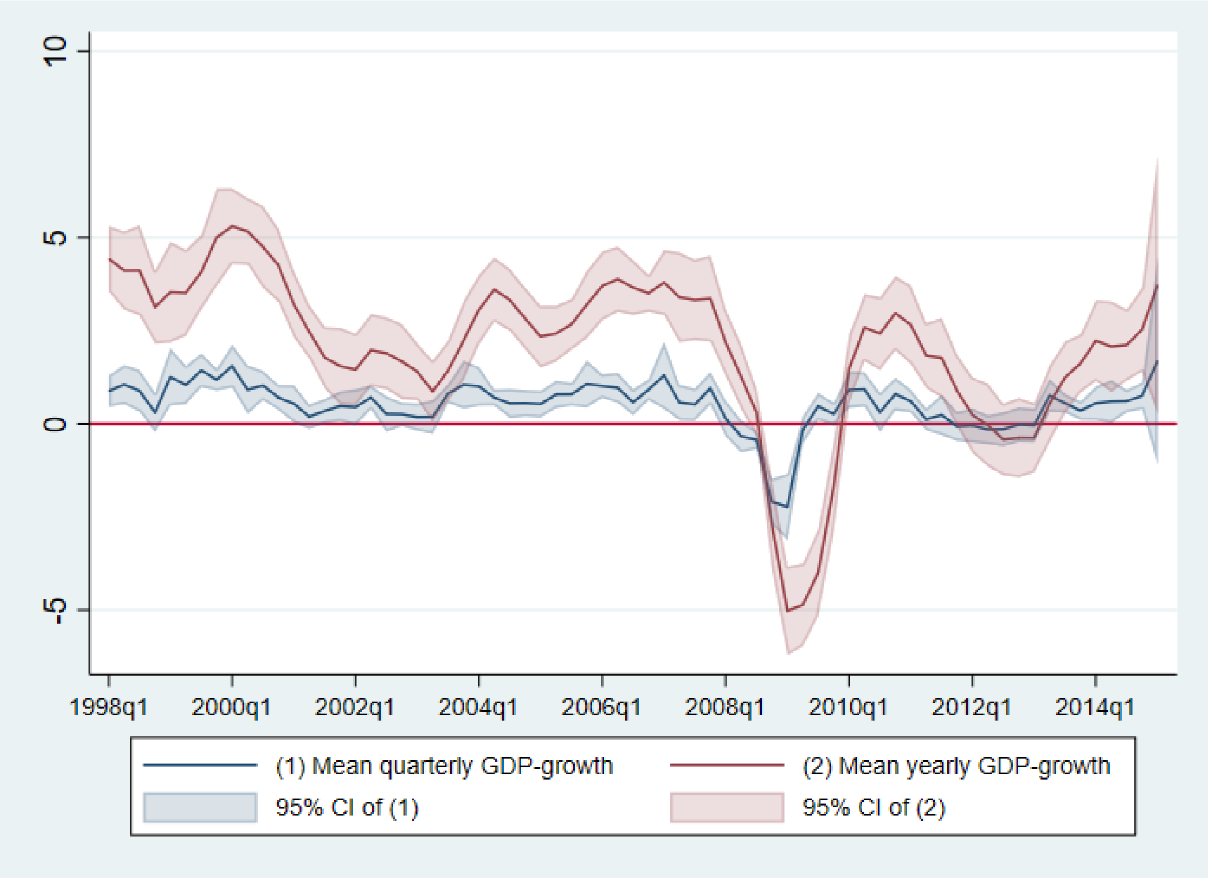
	Model A7	Model A8	Model A9	Model A10
Event	Failure	Exit	Failure	Exit
Funding Level, t-1: [75%, .)	0.686***	1.526***	0.817***	1.747***
	(0.019)	(0.065)	(0.017)	(0.071)
Firm Value > p75	0.994	1.789***	1.002	0.956
	(0.021)	(0.098)	(0.020)	(0.048)
(Funding Level, t-1: [75%, .) X (Firm Value > p75)	1.027	1.257**		
	(0.034)	(0.012)		
Investment Sum > p75			0.894***	1.125***
			(0.016)	(0.044)
(Funding Level, t-1: [75%, .)) X (Investment Sum > p75)			1.057**	1.046
			(0.029)	(0.062)
Campaign Month 2	1.129***	0.621***	1.153***	0.609***
	(0.020)	(0.025)	(0.019)	(0.024)
> Campaign Month 2	1.487***	0.453***	1.234***	0.585***
	(0.026)	(0.026)	(0.022)	(0.027)
Investment Sum: [p25, p50)	0.983	1.013		
	(0.019)	(0.043)		
Investment Sum: [p50, p75)	0.884***	1.110*		
	(0.021)	(0.059)		
Investment Sum: [p75, p90)	0.870***	1.185**		
	(0.026)	(0.082)		
Investment Sum: [p90, p100]	0.718***	1.354***		
	(0.027)	(0.120)		
Number of Firms: [2, 6)	1.011	0.799***	1.006	0.903***
	(0.017)	(0.028)	(0.015)	(0.029)
Number of Firms: [6, .)	1.002	0.700***	0.935***	0.847***
	(0.025)	(0.040)	(0.017)	(0.033)
Total Amount Invested (ln)	1.067***	0.967**	1.025***	1.007
	(0.008)	(0.016)	(0.005)	(0.010)
Distance (ln+1)	1.003	1.030***	1.007**	1.025***
	(0.004)	(0.008)	(0.003)	(0.008)
Firm Share Offered (%)	0.968***	1.090***	1.000***	0.998***
	(0.001)	(0.002)	(0.000)	(0.000)
Funding Goal (1000 EUR)	1.001***	0.100***	0.968***	1.075***
	(0.001)	(0.001)	(0.001)	(0.002)
Campaign Year Fixed Effects	Yes	Yes	Yes	Yes
Number of Investments	45,857	45,857	52,024	52,024
Number of Events	22,956	5,367	25,923	5,816
Number of Competing Events	5,367	22,956	5,816	25,923
Log Likelihood	-229174.2	- 54571.034	-262027.364	-59775.574

Note: Standard errors in parentheses are clustered by investor. The coefficients represent changes of the subhazard, i.e. the probability that the specified event occur given that the competing event has not yet occurred. Model A7 and A8 exclude investments made after the campaign successfully reached its funding goal.

* p < 0.1, ** p < 0.05, *** p < 0.01

A3. Appendix to Chapter 3

Figure A3.1 GDP-growth rates over time



Note: This figure displays the mean quarterly and yearly (quarter to quarter) GDP-growth rates for our sample countries and their respective 95% confidence intervals. Data has been collected from https://stats.oecd.org/.

Table A3.1 Selection: Alternative variable specifications for recession periods

	Model A1	Model A2	Model A3	Model A4	Model A5	Model A6
Recession_2_quarters, t	1.166	1.510	1.203			
	[0.418]	[0.138]	[0.346]			
	(0.221)	(0.420)	(0.236)			
Recession_q_to_q, t				0.998	1.233	0.997
				[0.994]	[0.447]	[0.987]
				(0.199)	(0.339)	(0.211)
Patent Stock (ln+1), t-1	2.059	2.098	2.055	2.060	2.104	2.060
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	(0.173)	(0.182)	(0.173)	(0.173)	(0.186)	(0.173)
Radical Invention, t-1	0.919	0.917	0.941	0.918	0.916	0.916
	[0.596]	[0.592]	[0.713]	[0.593]	[0.585]	[0.608]
	(0.147)	(0.148)	(0.155)	(0.147)	(0.148)	(0.156)
Recession_2_quarters, t X Patent Stock (ln+1), t-1		0.732				
		[0.245]				
		(0.197)				
Recession_2_quarters, t X Radical Invention, t-1			0.759			
			[0.601]			
			(0.401)			
Recession_q_to_q, t X Patent Stock (ln+1), t-1					0.781	
					[0.265]	
					(0.173)	
Recession_q_to_q, t X Radical Invention, t-1						1.014
						[0.974]
						(0.431)
Mean Age of Patents (months), t-1	0.985	0.985	0.985	0.985	0.985	0.985
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Baseline Hazard	0.017	0.016	0.017	0.017	0.016	0.017
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	(0.013)	(0.012)	(0.013)	(0.013)	(0.012)	(0.013)
Shape Parameter p	0.901	0.903	0.902	0.902	0.904	0.902
	[0.029]	[0.033]	[0.030]	[0.031]	[0.033]	[0.031]
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Time Spans	23726	23726	23726	23726	23726	23726
Number of Firms	997	997	997	997	997	997
Number of Events	372	372	372	372	372	372
Log-Likelihood	-839.814	-839.056	-839.680	-840.108	-839.458	-840.108

Note: This table reports the hazard ratios from a proportional hazard regression that estimates the hazard rate of a first financing round. The hazard rate is parametrized using the Weibull distribution. *Recession_2_quarters, t* is a dummy variable that equals 1 if the last two quarters have a negative GDP-growth rate. *Recession_q_to_q, t* is a dummy variable that equals 1 if the yearly GDP-growth rate from quarter *t-4* to *t* is negative. To test the significance level of the shape parameter p, H0: p = 1

Brackets: p-values; Parentheses: Robust standard errors

Table A3.2 Selection: Alternative parametrizations of the hazard rate and semi-parametric Cox regression

Regression Type	**Model A7** Exponential	**Model A8** Exponential	**Model A9** Exponential	**Model A10** Gompertz	**Model A11** Gompertz	**Model A12** Gompertz	**Model A13** Cox	**Model A14** Cox	**Model A15** Cox
Recession, t	1.005	1.254	1.006	1.005	1.212	1.002	1.025	1.236	1.028
	[0.980]	[0.412]	[0.979]	[0.982]	[0.482]	[0.993]	[0.903]	[0.432]	[0.897]
	(0.200)	(0.346)	(0.212)	(0.201)	(0.332)	(0.213)	(0.205)	(0.333)	(0.218)
Patent Stock (ln+1), t-1	2.042	2.090	2.042	2.051	2.089	2.051	2.036	2.074	2.036
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	(0.176)	(0.189)	(0.176)	(0.168)	(0.180)	(0.168)	(0.167)	(0.179)	(0.166)
Radical Invention, t-1	0.924	0.922	0.925	0.909	0.908	0.907	0.913	0.912	0.916
	[0.624]	[0.616]	[0.648]	[0.549]	[0.544]	[0.563]	[0.564]	[0.563]	[0.603]
	(0.149)	(0.149)	(0.158)	(0.144)	(0.145)	(0.154)	(0.144)	(0.145)	(0.154)
Recession, t X Patent Stock (ln+1), t-1		0.772			0.802			0.802	
		[0.248]			[0.316]			[0.309]	
		(0.173)			(0.176)			(0.174)	
Recession, t X Radical Invention, t-1			0.996			1.022			0.977
			[0.992]			[0.960]			[0.957]
			(0.422)			(0.438)			(0.420)
Mean Age of Patents (months), t-1	0.984	0.984	0.984	0.989	0.989	0.989	0.991	0.991	0.991
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Baseline Hazard	0.012	0.011	0.012	0.018	0.018	0.018			
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]			
	(0.008)	(0.008)	(0.008)	(0.013)	(0.013)	(0.013)			
Shape parameter gamma				0.972	0.972	0.972			
				[0.000]	[0.000]	[0.000]			
				(0.006)	(0.006)	(0.006)			
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Spans	23,726	23,726	23,726	23,726	23,726	23,726	23,726	23,726	23,726
Number of Firms	997	997	997	997	997	997	997	997	997
Number of Events	372	372	372	372	372	372	372	372	372
Log-Likelihood	-841.832	-841.124	-841.832	-829.903	-829.379	-829.901	-2219.595	-2219.065	-2219.593

Note: This table reports the hazard ratios when estimating the hazard of a first financing round using different parametrizations for the hazard rate. In Models A7-A9 we use the exponential distribution, while in Models A10-A12, we use the Gompertz distribution. Accordingly, we test the significance level of the shape parameter gamma for the Gompertz parametrization with H0: gamma = 1. Moreover, we run semi-parametric Cox regressions in Models A13-A15, where the baseline hazard is not specified. Brackets: p-values; Parentheses: Robust standard errors

Table A3.3 Selection: Alternative sample specifications

	Model A16	Model A17	Model A18	Model A19	Model A20	Model A21
Sample Specification	Patenting & Non-Patenting	Patenting & Non-Patenting	Patenting & Non-Patenting	Foundation after 2003	Foundation after 2003	Foundation after 2003
Recession, t	1.117	1.025	1.084	1.321	1.496	1.325
	[0.531]	[0.896]	[0.659]	[0.201]	[0.176]	[0.210]
	(0.197)	(0.191)	(0.198)	(0.287)	(0.445)	(0.298)
Patent Stock (ln+1), t-1	3.311	3.282	3.337	2.041	2.074	2.040
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	(0.340)	(0.342)	(0.337)	(0.203)	(0.218)	(0.203)
Radical Invention, t-1	0.736	0.738	0.698	0.909	0.905	0.914
	[0.264]	[0.264]	[0.230]	[0.638]	[0.624]	[0.679]
	(0.202)	(0.201)	(0.209)	(0.184)	(0.184)	(0.198)
Recession, t X Patent Stock (ln+1), t-1		1.180			0.858	
		[0.236]			[0.534]	
		(0.165)			(0.212)	
Recession, t X Radical Invention, t-1			1.430			0.964
			[0.441]			[0.939]
			(0.664)			(0.463)
Mean Age of Patents (months), t-1	1.001	1.001	1.001	0.987	0.987	0.987
	[0.518]	[0.619]	[0.568]	[0.000]	[0.000]	[0.000]
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Baseline Hazard	0.004	0.004	0.004	0.012	0.012	0.012
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	(0.003)	(0.003)	(0.003)	(0.009)	(0.009)	(0.009)
Shape Parameter p	0.720	0.721	0.719	0.974	0.976	0.974
	[0.000]	[0.000]	[0.000]	[0.626]	[0.651]	[0.627]
	(0.030)	(0.030)	(0.029)	(0.053)	(0.054)	(0.053)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Time Spans	188,647	188,647	188,647	14,946	14,946	14,946
Number of Firms	7,059	7,059	7,059	747	747	747
Number of Events	490	490	490	286	286	286
Log-Likelihood	-1663.814	-1663.236	-1663.497	-693.843	-693.633	-693.840

Note: This table reports the hazard ratios from a proportional hazard regression that estimates the hazard rate of a first financing round using different sample specifications than in our main Models 1-3. The hazard rate is parametrized using the Weibull distribution. To test the significance level of the shape parameter p, H0: p = 1.

Brackets: p-values; Parentheses: Robust standard errors

Table A3.4 Selection: Follow-on financing rounds

Event	**Model A22** Second Round	**Model A23** Second Round	**Model A24** Second Round	**Model A25** Follow-on Round	**Model A27** Follow-on Round	**Model A27** Follow-on Round
Recession, t	1.221	1.334	1.178	1.150	1.104	1.041
	[0.548]	[0.524]	[0.637]	[0.486]	[0.768]	[0.855]
	(0.407)	(0.602)	(0.408)	(0.232)	(0.368)	(0.231)
Patent Stock (ln+1), t-1	1.334	1.349	1.333	1.072	1.068	1.074
	[0.011]	[0.013]	[0.012]	[0.504]	[0.538]	[0.494]
	(0.152)	(0.163)	(0.152)	(0.112)	(0.114)	(0.112)
Radical Invention, t-1	1.236	1.238	1.197	1.033	1.032	0.968
	[0.346]	[0.341]	[0.452]	[0.877]	[0.883]	[0.881]
	(0.278)	(0.278)	(0.287)	(0.219)	(0.218)	(0.213)
Recession, t X Patent Stock (ln+1), t-1		0.930			1.028	
		[0.780]			[0.875]	
		(0.242)			(0.179)	
Recession, t X Radical Invention, t-1			1.193			1.444
			[0.731]			[0.251]
			(0.611)			(0.462)
Mean Age of Patents (months), t-1	0.986	0.986	0.986	0.990	0.990	0.990
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
First Round Recession	1.025	1.020	1.030	1.072	1.074	1.083
	[0.933]	[0.946]	[0.918]	[0.801]	[0.798]	[0.774]
	(0.296)	(0.295)	(0.298)	(0.297)	(0.297)	(0.300)
Baseline Hazard	0.003	0.003	0.003	0.004	0.004	0.004
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Shape Parameter p	1.068	1.069	1.068	1.357	1.356	1.356
	[0.309]	[0.305]	[0.308]	[0.000]	[0.000]	[0.000]
	(0.069)	(0.069)	(0.069)	(0.056)	(0.056)	(0.056)
Frailty Component theta				1.525	1.525	1.529
				[0.012]	[0.012]	[0.012]
				(0.257)	(0.257)	(0.258)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Time Spans	5,311	5,311	5,311	8,662	8,662	8,662
Number of Firms	372	372	372	372	372	372
Number of Events	172	172	172	403	403	403
Log-Likelihood	-419.548	-419.511	-419.485	-908.068	-908.055	-907.427

Note: Models A22-A24 estimate the hazard rate of a second round of VC financing using a Weibull regression with robust standard errors. In Models A25-A27, we run recurrent event analyses by considering every firm's period from financing round to financing round (or right censoring) as separate risk interval (starting from $t = 0$) and apply a Weibull regression with a gamma-distributed shared frailty component. To test the significance level of the shape parameter p and frailty component theta, H0: p = 1.

Brackets: p-values; Parentheses: Robust standard errors

Table A3.5 Selection: First-step instrument variable estimates

	Model A28
Recession, t	1.002
	[0.979]
	(0.061)
Patent Stock, t-1	1.413
	[0.000]
	(0.053)
Radical Invention, t-1	0.954
	[0.475]
	(0.062)
Average Age of Patents (months), t-1	0.996
	[0.000]
	(0.001)
Relative Frequency VC Deals in Country, t	1.020
	[0.005]
	(0.007)
Firm's age, t (quarters)	0.985
	[0.000]
	(0.002)
Constant	0.088
	[0.000]
	(0.017)
Country FE	Yes
Quarter FE	Yes
Observations	25961
Number of firms	997
Log-Likelihood	-1727.377

Note: This table reports exponentiated coefficients from a probit regression in a survival time setting. The baseline outcome category represents the situation of no VC financing, that is, the dependent variable is always 0 for non-VC-backed firms. For VC-backed firms, the dependent variable is 0 for all quarters prior VC financing, equals 1 in the quarter for the first financing round, and is set to missing in the quarters after the first financing round.

Brackets: p-values; Parentheses: Standard errors clustered by firm

Table A3.6 Treatment effect of VC financing on firm innovation (non-patenting firms included)

Dependent Variable	**Model A29** Patent Stock	**Model A30** Citation Stock	**Model A31** Radical Stock
(1) Post-VC Non-Recession (1,.)	0.111	0.088	0.035
	[0.000]	[0.032]	[0.002]
	(0.009)	(0.041)	(0.011)
(2) Post-VC Recession (1,.)	0.095	0.113	0.006
	[0.000]	[0.140]	[0.793]
	(0.016)	(0.076)	(0.023)
Recession, t	-0.064	-0.080	-0.009
	[0.000]	[0.000]	[0.000]
	(0.001)	(0.004)	(0.001)
Firm's age, t (quarters)	0.029	0.038	0.003
	[0.000]	[0.000]	[0.000]
	(0.000)	(0.001)	(0.000)
Constant	4.149	5.463	0.474
	[0.000]	[0.000]	[0.000]
	(0.045)	(0.150)	(0.054)
IMR, t	-1.407	-1.833	-0.161
	[0.000]	[0.000]	[0.000]
	(0.016)	(0.053)	(0.019)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
F-Test (1)=(2): p-value	0.381	0.778	0.274
Observations	213,827	213,827	213,827
Number of Firms	7,059	7,059	7,059
R-squared	0.774	0.430	0.114

Note: The firm-fixed-effect regression estimates within-firm changes of the dependent variables. The reported marginal effects of *Post-VC Non-Recession (1,.), t* and *Post-VC Recession (1,.), t* need to be exponentiated (i.e., 100*exp(coefficient)-1) to be interpreted as percentage change or growth of the dependent variable in the post-financing period compared to the pre-financing period. The inverse Mills ratio (IMR, t) controls for unobserved selection effects and is estimated using a probit regression with exclusion restriction in a survival time setting that predicts the probability of a firm to be selected by VC investors in quarter *t* (see Table A3.5 for further details).

Brackets: p-values; Parentheses: Standard errors clustered by firm in all models

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