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

Massimo G. Colombo
Department of Management, Economics, and Industrial Engineering
Politecnico di Milano
Piazza Leonardo da Vinci, 32
20133 Milan, Italy
Phone: +39 02 2399-2748
Email: massimo.colombo@polimi.it

Massimiliano Guerini
Department of Management, Economics, and Industrial Engineering
Politecnico di Milano
Piazza Leonardo da Vinci, 32
20133 Milan, Italy
Phone: +39 02 2399-2748
Email: massimiliano.guerini@polimi.it

Karin Hoisl*
Mannheim Business School
University of Mannheim
L5, 4
68161 Mannheim, Germany
Phone: +49 (0)621 181-1604
Email: hoisl@bwl.uni-mannheim.de

Nico Zeiner
Mannheim Business School
University of Mannheim
L5, 4
68161 Mannheim, Germany
Phone: +49 (0)621 181-1604
Email: nico.zeiner@uni-mannheim.de

* Corresponding author

Accepted for publication in Research Policy.

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

ABSTRACT

Patents are an important signal of the unobserved quality of young, innovative firms. We study patents that protect radical inventions associated with high earnings potential but also a high risk of failure. These previously disregarded signals convey positive and negative information simultaneously, i.e., strong signals that have a dark side. We argue that whether firms that send such signals are attractive investment targets for venture capital (VC) investors depends on the characteristics of the investors. Reputable VC investors are attracted to the strong quality signals of patents protecting radical inventions and are better able than other VC investors to deal with the dark side of these signals through syndication. These effects are stronger in the first financing round than in follow-on rounds, as the (positive and negative) informational value of patents protecting radical inventions diminishes over time as information asymmetries between young firms and prospective VC investors are reduced. We test these predictions using a sample of 759 young life science firms and 555 VC investors. Econometric estimates from a matching model support our predictions.

Keywords

Signals, radical inventions, high-tech startups, venture capital

Acknowledgments:

This work was supported by the RISIS project, funded by the European Union's Horizon 2020 Research and Innovation Program under grant number 824091.

1. Introduction

Startups usually have no track record and no collateral that could tip the scales in favor of acquiring funding, typically venture capital (VC) financing. They must therefore rely on signals, i.e., observable costly actions that are positively correlated with the quality of the young firm (Spence, 1973; 2002). 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[1] (Lanjouw and Schankerman, 2001; Long, 2002; Hall, 2019; Farre-Mensa et al., 2020). 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).

We focus on patents protecting *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, the quality signal of patents protecting radical inventions is *stronger* than that of patents protecting incremental inventions since radical inventions are more costly to develop and have particularly high earnings potential (Schoenmakers and Duysters, 2010; Eggers and Kaul, 2018). On the other hand, the stronger signal is accompanied by *negative information* about the greater uncertainty and longer-term payoff of radical inventions (Eggers and Kaul, 2018), i.e., patents protecting radical inventions convey strong signals with a dark side.

The dark side of a signal has gone almost unnoticed in the signaling literature. Partial exceptions are the studies by Haeussler et al. (2014) and Hegde et al. (2020), which show that patents convey additional information over time that may include "bad news," such as a less favorable assessment of the novelty of patents by patent examiners or a lack of strength of patent protection and poor market prospects for the underlying invention. What is different about the signal we study is that the *same*

[1] High-quality firms are firms that are strong performers in a technology area and that have outperformed their competitors (Ahuja and Morris Lampert, 2001; Subramaniam and Youndt, 2005; Dewar and Dutton, 1986; Henderson, 1993).

characteristics simultaneously increase (=strong signal) and decrease (=dark side) the attractiveness of a firm at a given point in time—in our case, during the first round of VC investments.

We argue that the tension between the strong signal sent by patents that protect radical inventions and the negative information that accompanies these strong signals changes the signaling role of these patents. In particular, we hypothesize that the attractiveness of the signal, and thus the likelihood of a deal between a VC investor and a young firm with patents protecting radical inventions, depends on the characteristics of the *signal receivers*, i.e., their ability to deal effectively with the challenges of radical inventions. We maintain that *reputable VC investors* are more likely than other VC investors to invest in such deals[2]. First, they are more attractive partners for supposedly high-quality firms (Hsu, 2004; Sørensen, 2007; Nahata, 2008). Second, they are attractive partners for syndication and therefore can more easily spread the risk of potentially attractive investments across multiple partners (Lerner, 1994; Plagmann and Lutz, 2019). Conversely, low-reputation VC investors need to "grandstand" to be able to raise more capital from prospective limited partners (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. In summary, the aim of this paper is to investigate how the receivers of signals react to strong signals with a dark side, i.e., which types of VC investors are attracted to startups that have patents on radical inventions and how they design those deals.

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). These 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.

[2] Reputable investors are attracted by both the technology underlying the patent and the young firm that is responsible for the technology. In an extension to the analysis, we control for several characteristics of the founding team, such as their education level and contacts with universities and industry, to rule out the possibility that it is only the characteristics of the founding team that attract the VC investor.

To answer our research question, 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. 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, 2001; Nasto 2008).

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. VC investors' worldwide investment histories covering 1980 to 2015 were extracted from the VICO and Thomson Reuters EIKON databases, which contain 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 346 of these firms had at least one (pending) patent application with the EPO before receiving their first round of VC funding, and 65 had filed at least one (pending) patent application for a radical invention.

In the econometric analysis, we use a matching model. We assess the 1,792 realized firm–VC investor ties against unrealized firm–VC investor ties that could have formed. A logit regression provides evidence that when a firm has at least one patent application protecting a radical invention, this is associated with an increase in the probability of forming a first-round investment tie with a highly reputable VC investor compared to a firm with no patents or only patents protecting incremental inventions. Second, a multinomial logit regression provides evidence that the abovementioned increase in the probability of forming an investment tie with a reputable VC investor is confined to syndicated ties. 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. Additionally, we conduct other analyses to rule out alternative explanations, such as that our results are driven by the characteristics of the entrepreneurial teams rather than patents protecting radical inventions and that our results may simply be driven by unobserved heterogeneity (i.e., lack of control for unobserved characteristics of firms).

Our work makes a new contribution to the signaling literature by analyzing signals that have thus far escaped systematic analysis: signals that simultaneously convey good and bad additional information. We show that signals with a dark side are interpreted differently by signal receivers depending on their ability to effectively deal with the dark side. Accordingly, reputable VC investors are better able to deal with the risk posed by patents protecting radical inventions than are nonreputable VC investors. This is true because the former have better opportunities for syndication, i.e., to share the risk of such an investment. We also contribute to the entrepreneurship and entrepreneurial finance literature. To date, most of the literature has debated whether the entrepreneurial team (jockey) or the technology/product (horse) matters in VC funding decisions. There is widespread agreement in the literature that it is the jockey that matters most (Gompers et al., 2010; 2020; Bernstein et al., 2017), but product and market characteristics matter as well (Bapna, 2019; Petty and Gruber, 2011). While examining how strong signals with a dark side influence VC funding, we find that the horse (in our case, patents protecting radical inventions) in conjunction with the characteristics of the VC investor (its reputation) seem to be particularly important. We also show that the sorting mechanisms that bring together VC investors and young firms change over time, namely, when the information asymmetry between investor and firm decreases, which changes the importance of the advantages and disadvantages of a strong signal with a dark side. Finally, we add to the literature by examining the effects of syndication, a key feature of VC financing, in an environment of complex signals.

2. Conceptual background and hypotheses

2.1. Funding decisions of VC investors: The role of signals

Prior to their investment, VC investors face the problem of adverse selection, as entrepreneurs seeking VC funding are better informed about the quality of their firm than a potential VC investor and may strategically exploit this information advantage (Amit et al., 1998; Carpenter and Petersen, 2002; Denis, 2004). Young firms have a limited or nonexistent track record, they lack tangible assets that can be used as collateral, 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 challenging for external investors, including VC investors, to disentangle high-quality from low-quality young firms. To reduce information asymmetries, VC investors evaluate the unobservable quality of a young firm using signals, i.e., 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 (Connelly et al., 2011; Bergh et al., 2014).

Previous studies have shown that young firms signal their quality through different mechanisms. Several studies have focused attention on the composition of firms' entrepreneurial teams. Entrepreneurs' educational attainment, work experience, and past entrepreneurial experience are important signals (Baum and Silverman, 2004; Higgins and Gulati, 2006; Hsu, 2007; Hoenig and Henkel, 2015; Plummer et al., 2016). Individuals with higher human capital command higher salaries and thus have greater opportunity costs of starting a new business because of the greater amount of money they leave on the table. Moreover, entrepreneurs' human capital indicates the ability of the entrepreneurial team to handle complex situations when starting a business. Other studies have highlighted the signaling value of endorsement by prominent organizations (Stuart et al., 1999). Effective signals of the quality of young firms include affiliations with reputable universities (Colombo et al., 2019b) and research or market alliances with leading firms (Baum and Silverman, 2004; Ozmel et al., 2013). The high reputation of the partner university or firm reassures uninformed third parties about the quality of the focal firm. These arrangements also indicate access to complementary resources to develop and commercialize the firm's products or services.

Regarding technology, patents qualify as a credible signal for young firms (Long, 2002). Filing a patent application incurs both direct and indirect costs for young firms. In addition to the nonnegligible 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 with 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). In the following, we will focus on signals related to the technology a young firm possesses, i.e., its patents.

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 notable advance in the performance of a technology (Eggers and Kaul, 2018).

Patents protecting radical inventions are 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). At the same time, patents protecting radical inventions 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 (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, p.11). In other words, even though such inventions have high market potential, firms face uncertainty in commercializing them (Gonzalez, 2006).

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). 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). The time until market launch is a function of the investment made by the firm (Reinganum, 1983).

In summary, patents protecting radical inventions reveal valuable information that *reinforces the strength* of the conveyed signal. However, these patents also *convey negative information* (*dark side of the signal)*.

2.3. How do VC investors react to a strong signal with a dark side?

Patents protecting radical inventions send a stronger quality signal than patents protecting incremental inventions (and no patents, of course). Thus, one can presume that young firms that have those patents are especially attractive to VC investors in early investment rounds, when information asymmetry is particularly high. At the same time, radical inventions convey additional bad information. What is special about strong signals with a dark side is that the *same characteristic* that makes a signal strong can also convey "bad news," which *simultaneously* increases and decreases the attractiveness of a firm for VC investments. This property distinguishes these signals from the signals considered thus far in the literature, whose value to investors changes over time due to decreasing information asymmetry (Haeussler et al., 2014; Hegde et al., 2020). Signals with a dark side lead to an immediate tension that the VC investor must face.

To solve this tension, we argue that 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. First, 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 nonfinancial 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 that own patents protecting radical inventions to be more likely to match.

The dark side of the signal is more or less troublesome depending on the ability of VC investors to deal with high uncertainty and costs. 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). Syndication allows 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), and the pooled resources of all syndicated partners facilitate providing young firms with the resources required to successfully exploit their technologies (Brander et al., 2002; Dimov and Milanov, 2010; Bayar et al., 2019).[3] 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). These arguments lead to our first two hypotheses:

Hypothesis 1. *In first-round VC investments, young firms with patents protecting radical inventions are more likely than firms without such patents (*i.e.*, firms without patents or with 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.*

[3] We admit that syndication is not the only instrument VC investors can use to manage the risk of investing in innovative young firms. Other instruments are staging their investments, investing with convertible securities, and diversifying their portfolio (Norton and Tenenbaum, 1993). We investigated staging by looking at interround duration (Tian, 2011) and running an accelerated failure time model at the entrepreneurial firm level. The results are shown in Table A8. Unfortunately, we do not have information on the type of securities VC investors use in our sample and on their diversification strategies. We acknowledge this limitation in the concluding section.

During the first financing round, information asymmetry between VC investors and young firms is particularly high since, as mentioned above, 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. Over time, young firms may be able to produce additional valuable information (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)—decreases legal uncertainty. Additionally, collaborations with strategic partners may decrease commercialization risk (Hagedoorn, 1993; Gulati, 1998). 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. This is because the extent of the information asymmetry between entrepreneurs and VC investors is reduced in follow-on rounds. Additionally, the dark side of patents protecting radical inventions 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 proposed relationships relating to first-round investments to weaken 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 standalone investment tie with a reputable VC investor is weaker in follow-on-round VC investments than in first-round VC investments.*

3. Data and method

3.1. Data source and sample

To test our hypotheses, we focus on young VC-backed firms active in the life sciences. These firms offer 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 requirements, and vivid startup activity (Cohen and Walsh, 2001). For VC investors, however, assessing the market potential of life science inventions, especially the more radical inventions, 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, 2006). 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 investigate which types of VC investors are attracted to startups that have patents on radical inventions, i.e., strong signals with a dark side, and how they design those deals, 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. 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.[4] 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

[4] 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.

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 by captive VC investors are also driven by nonfinancial objectives (Bertoni et al., 2015; Bertoni et al., 2019b). Applying these criteria results in a sample of 759 young life science firms.[5] For these firms, we observe 1,368 investment rounds between 2003 and 2015 involving 593 different independent VC investors. To alleviate the most obvious endogeneity concerns, i.e., that the human capital of the entrepreneurial team drives our results, we collected additional data on the human capital of entrepreneurs. Through a manual internet search (e.g., LinkedIn, crunchbase.com, researcher profiles on university webpages), we were able to collect data on the educational background, prior founding experience, managerial experience (C-level), and previous employers of entrepreneurial team members for 75.1 percent of our 759 sample firms.

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[6], 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. 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). We excluded a patent family if all patents of that family had been withdrawn, refused, revoked, or expired (no payment of the annual renewal fee). Patent information allows us to identify radical inventions and describe the firms' patent portfolios at the time of each VC investment round. In total, our dataset contains 423 firms that applied for patents to protect their invention(s) at the time of their respective financing round(s) and are either

[5] 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).
[6] For instance, some countries allow deferred patent examination, while others do not (Harhoff, 2016).

still in the granting process (pending) or have already been granted patents. For the first financing round, we observe 346 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 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]

3.2. Description of variables

<u>*Dependent variable*</u>

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.

<u>*Independent variables*</u>

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. To

---

[7] To be consistent in the identification of life science firms, 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 remain part of the sample and are used as a counterfactual in our matching approach. Our results are robust when excluding these firms from our sample.

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 is 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 is considered radical if any documents of a DOCDB patent family contain at least one pair of IPC classes (main group level—seven-digit) that had not been combined in previous patent applications.[9] A total of 217 of the 3,332 identified patent families owned by sample firms (6.51%) are classified as patent families with patents protecting a radical invention. Sixty-five firms (8.6%) filed at least one patent protecting a radical invention at the time of their first financing round. This number increases to 92 firms (12.1%) 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 of between 2003 and 2015.[10]

<u>Control variables</u>

Firm-level variables. In addition to our key independent variable *DRadical Patent*, 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 (*DRadical Patent=0* and *DIncremental Patent*=0). We also control for the technological impact of a firm's patent portfolio by counting the number of citations that the patents in the portfolio received from subsequent patents up to the time of the respective

[9] 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. Haeussler et al. (2014) provide results from five in-depth interviews with VC investors, which show that VC investors are aware of the information function of patent indicators and use them in their valuation. Hence, we are confident that VC investors can distinguish between patents protecting radical versus incremental inventions.

[10] 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.

investment. The citation variable is built at the patent family level, as well.[11] We use a logarithmic transformation of the number of citations (*Forward Citations (ln+1)*), as the distribution of citations is highly skewed (skewness=13.15). 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 Rev. 2 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 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 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.

[11] We built alternative measures of a firm's inventive performance: the number of distinct patent families a firm has filed (*Number Patented Inventions*) and 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.

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) and 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 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.

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)). 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 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 to be syndicated than are the investment ties with ventures without such patents, i.e., firms with patents protecting incremental inventions (=C1) or firms without patents (=C2). In our empirical specification, demonstrating this difference requires the marginal effect of *DRadical Patent* on the formation of a first-round *syndicated tie* with a reputable VC 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 nonindependence, 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.

We are aware that unobserved firm characteristics that are correlated with both the ability to develop radical inventions and the attraction of reputable VC investors can lead to a potential omitted variable bias that precludes a causal interpretation of the regression results. To alleviate this concern, we test the robustness of our results from the (multinomial) logistic regressions by applying conditional logit models that control for unobserved time-invariant firm c+haracteristics through fixed effects and report the results of these models in our main results table (Table 2).[12]

In addition, we run several robustness checks and additional analyses to rule out alternative explanations of our results. The results are summarized at the end of the next section and reported in detail in the online appendix.

4. Results

[12] We also run conditional logistic regressions that control for unobserved time-invariant VC investor characteristics and show that our main results are robust to unobserved characteristics of the VC investors. The results are available from the authors upon request.

Table 1 reports the descriptive statistics and bivariate correlations of our variables for all 148,204 potential investment ties. In 61.3 percent of firm–investor ties (realized and unrealized), the firm has a patent. In 14.1 percent of all firm–investor ties, the firm has a patent protecting a radical invention. A reputable VC investor is involved in 27.3 percent 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.

[Insert Table 1 here]

The results of the econometric estimates are illustrated in Table 2. The reported coefficients represent the changes due to a one-unit increase in the covariates in the log-odds of forming a realized (standalone or syndicated) tie to not forming any tie. Models 1-4 relate to first-round investment ties, while Models 5-8 relate to follow-on-round investment ties. Models 1 and 5 show the baseline logistic regression comparing unrealized to realized first-round (Model 1) and follow-on-round investment ties (Model 5), while Models 3 and 7 show the baseline multinomial logistic regression for first round investment ties (Model 3) and follow-on-round investment ties (Model 7), thereby distinguishing between realized standalone and syndicated ties. Next, to each column reporting the results from our ordinary (multinomial) logistic regressions, we report the results of the same sample specifications using conditional binary logit models that control for latent firm characteristics through fixed effects after checking that the assumption of the independence of irrelevant alternatives (IIA) holds.

[Insert Table 2 here]

We first report the results for first-round VC investment ties in Models 1 and 3. Considering our control variables, 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=0.028). The positive effect of *Forward Citations(ln+1)* is entirely attributable to syndicated ties (Model 3: p=0.004). 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 standalone and syndicated ties). Considering our key variables of interest, Model 1 shows a positive and significant interaction effect of the variables *DRadical Patent* and *DReputable Investor* (p=0.024), which is entirely attributable to the formation of syndicated ties compared to no tie formation (Model 3: p=0.025). When controlling for unobserved heterogeneity arising from time-invariant firm characteristics, these interaction effects remain robust, although the magnitudes and significance levels slightly decrease (Model 2: p=0.081; Model 4b: p=0.089).

When considering follow-on VC investment rounds (Models 5-8), the interaction between *DRadical Patent* and *DReputable Investor* is no longer significant. 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: β=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.

In (multinomial) logistic models, a positive coefficient of an explanatory variable does not necessarily correspond to an increase in the probability of observing a particular outcome category. In Table 3, we therefore report the average marginal effects (AMEs) of *DRadical Patent* on the probabilities of forming a first round and a follow-on VC investment tie to test Hypotheses 1 and 3 (based on Models 1 and 5) and then distinguish between standalone and syndicated ties to test Hypotheses 2 and 4 (based on Models 3 and 7).[13]

[Insert Table 3 here]

For Model 1, 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

[13] As the maximization of a conditional log-likelihood does not produce an estimation of fixed effects (i.e., unobserved heterogeneity regarding the firm), the computation of marginal effects is not adequate for Models 2, 4a-b, 6 and 8a-b (Greene and Zhang, 2019). Thus, we can only investigate changes in log-odds to test whether our results from the ordinary (multinomial) logistic regressions are robust to unobserved time-invariant heterogeneity at the firm level, which is the case.

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=0.009, p=0.009) and firms with patents protecting only incremental inventions (=C1) (*DIncremental Patent* equals 1: AME=0.010, p=0.021). We find that when a firm has at least one patent application protecting a radical invention, this is associated with a 100 (100) percent increase[14] 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 nonreputable VC investors, the AMEs of *DRadical Patent* on the probabilities of forming a first-round investment tie are not significant. Hence, our results support Hypothesis 1.

Based on the estimates of Model 3, 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=0.010, p=0.004; firms with patents protecting only incremental inventions (=C1): AME=0.011, p=0.018). Hence, if a firm filed at least one patent protecting a radical invention, this is associated with a 167 (157) 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 VC 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 standalone tie are positive and significant for both categories of our counterfactual (firms without patents (=C2): difference=0.012, p=0.004; firms with patents protecting incremental inventions (=C1): difference=0.013, p=0.013). Hence, our results also support Hypothesis 2.

To test Hypotheses 3 and 4, we consider the econometric specifications that only consider follow-on investment ties, and again, we calculate the AME of *DRadical Patent* on the probability of

---

[14] These associations are calculated based on the estimated probabilities of forming a first-round investment tie with a reputable VC investor for firms without any patent (p=0.009) and for firms with patents protecting only incremental inventions (p=0.010).

forming any realized investment tie (Model 5) and on the probabilities of forming a standalone and a syndicated investment tie (Model 7) for reputable and nonreputable VC investors. The AME of *DRadical Patent* on the probability of forming a follow-on investment tie is not significant, irrespective of the reputation of the VC investors, the type of tie (standalone 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 VC investors vanishes in follow-on rounds. Hypotheses 3 and 4 predict that the effect of the information value of radical patents will decrease in follow-on VC rounds compared to the first round, as information asymmetries between entrepreneurs and VC investors are reduced. We did not find sufficiently strong evidence in the literature that information asymmetries disappear completely in follow-on rounds (and consequently that the information value of radical patents is zero). Our empirical result in which we find no significant effect of patents protecting radical inventions on the probability of forming a (standalone or syndicated) investment tie with a reputable VC investor in follow-on rounds does not contradict these hypotheses, as the effect is not only weaker but disappears completely.

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 among *DRadical Patent*, *DReputable Investor*, and the dummy variable *DFirst Round* distinguishing first- and follow-on-round VC investment ties. We also add the triple interaction among *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. 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=0.003; firms with patents protecting incremental inventions (=C1): AME=0.011, p=0.013). Moreover, the differences between the AMEs of *DRadical Patent* on the probabilities of forming a syndicated first-round investment tie and a standalone 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=0.012) when using firms without patents as the counterfactual (=C2) and 0.011 (p=0.033) when using firms with patents protecting only incremental patents as the counterfactual (=C1).[15]

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 investments and vanish in follow-on rounds. These results do not confirm but are in line with Hypotheses 3 and 4.

Additional analyses and robustness checks

To rule out possible alternative explanations, we conducted several additional analyses and robustness checks, which are displayed in detail in the online appendix.

The most obvious alternative explanation of our results is that reputable VC investors may invest in firms with patents protecting radical inventions because of the quality of their entrepreneurial teams or affiliations and not because these VC investors are attracted by the strength of the quality signal conveyed by radical patents. If the quality of the entrepreneurial team is correlated with both the ability to develop radical inventions and the attraction of reputable VC investors, our results may simply be driven by unobserved heterogeneity. This explanation would also be in line with the literature that considers the entrepreneur (jockey) to be more important than the technology (horse) (see, e.g., Gompers et al., 2010; 2020).

We manually collected additional data on the human capital of the entrepreneurs (the data are available for 75.1 percent of the 759 firms in our sample) to build four measures that proxy the entrepreneurial and managerial quality of the entrepreneurial team and affiliations to universities and big pharmaceutical firms: (a) *DEntrepreneur PhD* that equals 1 for entrepreneurial teams with at least

[15] In this specification, the AME of *DRadical Patent* on the probability of forming a standalone first-round investment tie with a reputable VC investor is negative, even if of small economic magnitude (i.e., AME=-0.0018), and (weakly) significant (firms with no patents (=C2): AME=-0.0018, p=0.091; firms with patents protecting incremental inventions (=C1): AME=-0.0017, p=0.066). These findings provide even stronger support for 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 standalone basis.

one member who has a PhD degree at the time the firms are founded, (b) *DSerial Entrepreneur* that equals 1 for entrepreneurial teams with at least one member who already has entrepreneurial experience, (c) *DC-level Experience* that equals 1 for entrepreneurial teams with at least one member who already has managerial (i.e., C-level) experience and (d) *DEntrepreneur BigPharma* that equals 1 for entrepreneurial teams with at least one member with previous work experience in one or more of the 30 top-selling pharmaceutical firms by sales in 2010 (source: ORBIS database). We find no evidence that reputable VC investors are attracted by entrepreneurial teams that include either entrepreneurs with PhDs, serial entrepreneurs or entrepreneurs with prior C-level experience, while they are indeed more likely to invest in firms whose entrepreneurs have worked for leading pharmaceutical firms (Tables A1 – A5 in the online appendix). More importantly, our key findings that reputable VC investors in first-round investments are associated with firms that have patents protecting radical inventions and prefer to syndicate their investment rather than invest alone remain unchanged.

We control for the VCs' predisposition for risk-taking and syndication, proxied by a focal VC investor's number of first-round investments and number of syndicated investments as a share of its total number of investments in the 5 years prior to the focal investment, respectively. Table A6 in the online appendix shows that our results remain robust when adding these controls. Next, we rule out that syndication is simply a proxy for pooling financial and nonfinancial complementary resources rather than for sharing the risk between VC investors (Brander et al., 2002; Bayar et al., 2019). We find that the investment amount of syndicated investments is not higher and that syndicated investments are not more heterogeneous when firms have patents protecting radical inventions (see Table A7 in the online appendix). Furthermore, we provide evidence that VC investors do not use investment staging to address the uncertainty of patents protecting radical inventions (see Table A8).

The results shown in Table A9 rule out the possibility that the colocation of reputable VC investors and firms with patents protecting radical inventions in VC hubs may explain our results. We even show 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.

Next, we check whether our results are driven by the presence of an inflated number of unrealized ties due to our definition for firm–investor dyads that are at risk of realizing an investment tie. In particular, to alleviate problems possibly arising from the small number of realized ties compared to unrealized ties in the dataset (King and Zeng, 2001), we run a simulation where we repetitively (n=1,000) and randomly draw 10 or 5 unrealized investment ties (without replacement) out of the set of each firm's counterfactual data per investment deal instead of using all potential but unrealized ties to independent VC investors that have been active in the year of the investment round (see Sorenson and Stuart, 2008; Zhelyazkov and Tatarynowicz, 2021, for a similar approach). The results remain robust (see Table A10 in the online appendix).

Furthermore, our results do not depend on the arbitrary choice of the 75th percentile as a cutoff point to distinguish between reputable and nonreputable VC investors. In Table A11 in the online appendix, we show the consistent outcomes of a multinomial logit model that uses a continuous measure for investor reputation. Alternative measures for VC investor reputation considering a 3-year instead of a 5-year period prior to the focal investment and measuring reputation as the share of investments made by each investor in the 5 years prior to the focal investment relative to all the investments made by all VC investors in our sample in the same period also lead to robust results (Table A12 in the online appendix).

Finally, we run an additional robustness check that only takes into account lead VC investors in syndicated deals. Lead VC investors are defined as any investor who is present in the first VC round and invests in all VC rounds (or it invests in all VC rounds up to the last round in which one of the initial investors invested). The results are shown in Table A13 in the online appendix. The average marginal effects of *DRadical Patent* remain robust to our main econometric specifications shown in Table 3 in the main text.

5. Discussion

The purpose of this study was to examine which types of VC investors are attracted to startups that have patents on radical inventions, i.e., signals that simultaneously convey positive and negative information, and to investigate how VC investors deal with this tension, i.e., how they design those deals.

We offer a novel contribution to the signaling literature in that we analyze strong signals that simultaneously convey good and bad additional information (in our case, patents that protect radical inventions). The literature recognizes that signals may be of different strengths (e.g., Vanacker et al., 2020); that over time, the value of signals can change if additional information is revealed (Haeussler et al., 2014; Hegde et al., 2020); and that firms may send multiple signals that complement, reinforce, or substitute for each other (e.g., Pollock et al., 2010; Stern et al., 2014; Ozmel et al., 2013; 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). An important yet not discussed aspect of the signal we describe in this work 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 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 argue and document empirically that signal receivers (in our case, VC investors) react differently to a strong signal with a dark side depending on their ability to deal effectively with this dark side. Indeed, reputable VC investors are more likely than other VC investors to match with young innovative firms with patents protecting radical inventions and to syndicate their investments in these firms.

Second, we contribute to the entrepreneurship and entrepreneurial finance literature. First, when investing in young innovative firms, VC investors have to solve an information asymmetry problem and disentangle higher-quality firms from lower-quality firms (Amit et al., 1998). Ex ante screening plays a crucial role in this process (Gompers and Lerner, 2002). Over the last 20 years, there has been an ongoing discussion in the literature of whether the entrepreneurial team (jockey) or the technology/product (horse) matters more in VC funding decisions (Kaplan et al., 2009). There is widespread agreement in the literature that it is the jockey that matters more. Gompers et al. (2010), for instance, show that past entrepreneurial success is an important decision criterion for VC investors. This has recently been confirmed by Gompers et al. (2020). The authors surveyed 885 VC investors and found that they placed the greatest importance on the entrepreneurial team. Recent evidence from field experiments confirms this view (Bernstein et al., 2017) but also shows that firms' product and market characteristics matter (Bapna, 2019). We find that in strong signals with a dark side, the horse (technology) in conjunction with the characteristics of the VC investor seem to be particularly important. Reputable VC investors are better able than nonreputable VC investors to deal with the risk posed by patents protecting radical inventions. This is true, for example, because they have good opportunities for syndication, i.e., risk sharing. In our robustness checks, we do not find a significant effect of the entrepreneurial team.

In addition, 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 sufficiently 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, their technology and market prospects becomes 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 and more reputable VC investors, but only if investments are syndicated.

With respect to the limitations of our study, we made every effort to ensure that (time-invariant) unobserved heterogeneity did not drive our results. We also ruled out seemingly obvious alternative explanations for our findings, such as the characteristics of the entrepreneurs, since more reputable VC investors select better entrepreneurial teams (jockey), which are, at the same time, more likely to produce radical inventions. These robustness checks and 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 firms with radical inventions, some time-varying unobserved characteristics of VC investors (e.g., overconfidence of investment managers) might explain the differences between reputable and nonreputable investors. Therefore, caution is required in interpreting our results as indicating causal links. Additionally, syndication is only one means of dealing with the risk of patents on radical inventions. In our empirics, we also investigate staging by looking at interround duration. However, other means, such as the type of securities VC investors use and their portfolio diversification strategies, should be investigated in future studies. Future research that considers more fine-grained information and adopts different methodologies (e.g., field experiments) is also welcomed to further alleviate causality concerns.

Although our results are robust to different matching strategies and counterfactuals, we acknowledge that we do not observe which young, innovative firms had been evaluated and screened by which VC investors. We therefore welcome studies that have more detailed data on funded and unfunded firms that approach 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. 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 to be matched with a reputable VC investor. 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 nonreputable ones does not mean that there is no additional risk associated with these investments. This is also confirmed by our findings that reputable VC investors, rather than investing alone, decide to syndicate, i.e., share risk and consult other experts, even if it means sharing any future returns. Assessing whether this investment strategy is profitable for reputable VC investors would be an interesting extension of our research. Additionally, future research should look at the characteristics of the syndication partners to obtain 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). Finally, an interesting question that is beyond the scope of our current analysis relates to the (allegedly beneficial) outcome for invested firms of obtaining VC from more or less reputable VC investors (see, e.g., Chemmanur et al., 2011), depending on whether the focal firm developed radical or incremental patents (or no patent at all) using an endogenous switching regression model.

Despite these limitations, our study also has interesting managerial implications for entrepreneurs. Highly innovative ideas resulting in radical inventions may be punished by VC investors since nonreputable VC investors and, in particular, VC investors without syndication partners may not want to take on the risk involved in such an investment. However, young firms are heavily reliant on external financing. Due to the high risk and long-term returns associated with radical inventions, external equity financing is usually the only available source of finance. To increase their chances of obtaining external equity financing, the creators of radical inventions must understand the impact of the signal they send and the target group of potentially interested investors. Our findings also have implications for VC investors. Both reputable and nonreputable VC investors could improve their investment decisions by better understanding the forces driving these decisions. Our results may also help coinvestors increase their bargaining power in syndicates if they are aware of their importance in funding young firms with patents protecting radical inventions.

Our study also has implications for policy-makers. Radical inventions are of particular interest since they are the “driving forces of technological, industrial and societal change” (Schoenmakers and Duysters, 2010, p.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 inventions. 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., 2019a) may help solve this problem. Otherwise, breakthrough inventions may never be developed or brought to market, i.e., turned into innovations. Finally, our results show that the patent system plays an important role in financing young firms with radical inventions. It provides information that itself can provide signals, but it also conveys additional information to the signals that interacts with the VC investors' characteristics. In other words, patent offices have an important informational function that they should be aware of, in addition to incentivizing inventors by granting time-limited exclusion rights.

REFERENCES

Adams, J., 1990. Fundamental Stocks of Knowledge and Productivity Growth. Journal of Political Economics 98, 673–702.

Ahuja, G., Morris Lampert, C., 2001. Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. Strategic Management Journal 22 (6-7), 521–543.

Amit, R., Brander, J., and Zott, C. 1998. Why do venture capital firms exist? Theory and Canadian evidence. Journal of Business Venturing 13, 441-466.

Tushman, M.L., Nelson, R.R. 1990. Introduction: Technology, organizations, and innovation. Administrative Science Quarterly 35 (1), 1-8.

Arrow, K., 1962. Economic Welfare and the Allocation of Resources for Inventions. The Rate and Direction of Inventive Activity: Economic and Social Factors. Princeton University Press, Princeton, NJ.

Arts, S., Veugelers, R., 2015. Technology familiarity, recombinant novelty, and breakthrough invention. Industrial Corporate Change 24 (6), 1215–1246.

Audretsch, D.B., Bönte, W., Mahagaonkar, P., 2012. Financial signaling by innovative nascent ventures: The relevance of patents and prototypes. Research Policy 41 (8), 1407–1421.

Azoulay, P., Graff Zivin, J.S., Manso, G., 2011. Incentives and creativity: evidence from the academic life sciences. RAND Journal of Economics 42 (3), 527–554.

Bapna, S., 2019. Complementarity of Signals in Early-Stage Equity Investment Decisions: Evidence from a Randomized Field Experiment. Management Science 65 (2), 933-952

Baum, J. A., Silverman, B. S., 2004. Picking winners or building them? Alliance, intellectual, and human capital as selection criteria in venture financing and performance of biotechnology startups. Journal of Business Venturing 19 (3), 411-436.

Bayar, O., Chemmanur, T.J., Liu, M.H., 2019. How to Motivate Fundamental Innovation: Optimal Interactions between Entrepreneurs, Venture Capitalists, and the Government. Venture Capitalists. Working Paper. Available at SSRN: https://papers.ssrn.com/sol3/Papers.cfm?abstract_id=2799490, accessed on December 30, 2022.

Begg, C.B., Gray, R., 1984. Calculation of Polychotomous Logistic Regression Parameters Using Individualized Regressions. Biometrika 71 (1), 11-18.

Bergh, D.D., Connelly, B.L., Ketchen, D.J., Shannon, L.M., 2014. Signalling theory and equilibrium in strategic management research: An assessment and a research agenda. Journal of Management Studies 51 (8), 1334–1360.

Bernstein, S., Korteweg, A., Laws, K., 2017. Attracting early-stage investors: Evidence from a randomized field experiment. The Journal of Finance 72 (2), 509-538.

Bertoni, F., Colombo, M.G., Quas, A., 2015. The patterns of venture capital investment in Europe. Small Bussines Economics 45 (3), 543–560.

Bertoni, F., Colombo, M.G., Quas, A., 2019a. The role of governmental venture capital in the venture capital ecosystem: An organizational ecology perspective. Entrepreneurship Theory & Practice 43 (3), 611–628.

Bertoni, F., Colombo, M.G., Quas, A., Tenca, F., 2019b. The changing patterns of venture capital investments in Europe. Journal of Industrial and Business Economics 46 (2), 229–250.

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

Bygrave, W.D., 1987. Syndicated investments by venture capital firms: A networking perspective. Journal of Business Venturing 2 (2), 139–154.

Cao, J., Hsu, P.H., 2011. The informational role of patents in venture capital financing. Working Paper. Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1678809, accessed on Dec. 30, 2022.

Carpenter, R.E., Petersen, B.C., 2002. Capital market imperfections, high-tech investment, and new equity financing. The Economic Journal 112 (477), F54-F72.

Chemmanur, T.J., Krishnan, K., Nandy, D.K., 2011. How does venture capital financing improve efficiency in private firms? A look beneath the surface. The Review of Financial Studies 24 (12), 4037-4090.

Chen, H., Gompers, P., Kovner, A., Lerner, J., 2010. Buy local? The geography of venture capital. Journal of Urban Economics 67 (1), 90–102.

Cohen, W.M., Walsh, J.P., 2001. Public research, patents and implications for industrial R&D in the drug, biotechnology, semiconductor and computer industries. In: Wessner, C. (ed.) Capitalizing on New Needs and New Opportunities: Government-Industry Partnerships in Biotechnology and Information Technologies. The National Academies Press, Washington, DC: 223–243.

Colombo, M.G., D'Adda, D., Quas, A., 2019a. The geography of venture capital and entrepreneurial ventures' demand for external equity. Research Policy 48 (5), 1150–1170.

Colombo, M.G., Meoli, M., Vismara, S., 2019b. Signaling in science-based IPOs: The combined effect of affiliation with prestigious universities, underwriters, and venture capitalists. Journal of business Venturing 34 (1), 141–177.

Colombo, M.G., Shafi, K., 2016. Swimming with sharks in Europe: When are they dangerous and what can new ventures do to defend themselves?. Strategic Management Journal 37 (11), 2307–2322.

Connelly, B.L., Certo, S.T., Ireland, R.D., Reutzel, C.R., 2011. Signaling Theory: A Review and Assessment. Journal of Management 37 (1), 39–67.

Conti, A., Thursby, M., Rothaermel, F.T., 2013a. Show me the right stuff: Signals for high-tech startups. J. Econom. Management Strategy 22 (2), 341–364.

Conti, A., Thursby, J., Thursby, M., 2013b. Patents as signals for startup financing. Journal of Industrial Economics 61 (3), 592–622.

Dahlin, K.B., Behrens, D.M., 2005. When is an invention really radical? Defining and measuring technological radicalness. Research Policy 34 (5), 717–737.

De Prijcker, S., Manigart, S., Collewaert, V., Vanacker, T., 2019. Relocation to get venture capital: a resource dependence perspective. Entrepreneurship, Theory & Practice 43 (4), 697–724.

De Vet, J.M., Scott, A.J., 1992. The Southern Californian medical device industry: Innovation, new firm formation, and location. Research Policy 21 (2), 145–161.

Deeds, D.L., Decarolis, D., Coombs, J.E., 1997. The impact of firm specific capabilities on the amount of capital raised in an initial public offering: Evidence from the biotechnology industry. Journal of Business Venturing 12 (1), 31–46.

Denis, D.J. 2004. Entrepreneurial finance: an overview of the issues and evidence. Journal of Corporate Finance 10 (2), 301-326.

Dewar, R.D., Dutton, J.E., 1986. The adoption of radical and incremental innovations: An empirical analysis. Management Science 32 (11), 1422–1433.

Dimov, D., Milanov, H., 2010. The interplay of need and opportunity in venture capital investment syndication. Journal of Business Venturing 25 (4), 331–348.

Drover, W., Wood, M.S., Corbett, A.C., 2018. Toward a cognitive view of signaling theory: individual attention and signal set interpretation. Journal of Management Studies 55 (2), 209–231.

Dushnitsky, G., Shaver, J.M., 2009. Limitations to interorganizational knowledge acquisition: The paradox of corporate venture capital. Strategic Management Journal 30 (10), 1045–1064.

Eggers, J.P., Kaul, A., 2018. Motivation and ability? A behavioral perspective on the pursuit of radical invention in multi-technology incumbents. Academy of Management Journal 61 (1), 67–93.

Ettlie, J.E., Bridges, W.P., O'Keefe, R.D., 1984. Organization strategy and structural differences for radical versus incremental innovation. Management Science 30 (6), 682–695.

Farre-Mensa, J., Hegde, D., Ljungqvist, A., 2020. What is a patent worth? Evidence from the US patent "lottery". The Journal of Finance 75 (2), 639-682.

Fleming, L., 2001. Recombinant uncertainty in technological search. Management Science 47 (1), 117–132.

Gompers, P.A., 1996. Grandstanding in the venture capital industry. Journal of Financial Economics 42 (1), 133–156.

Gompers, P. A., Gornall, W., Kaplan, S. N., Strebulaev, I. A., 2020. How do venture capitalists make decisions?. Journal of Financial Economics 135 (1), 169-190.

Gompers, P., Kovner, A., Lerner, J., Scharfstein, D. 2010. Performance persistence in entrepreneurship. Journal of Financial Economics 96 (1), 18-32.

Gompers, P.A., Lerner, J., 2002. The money of invention: How venture capital creates new wealth. Ubiquity, 2002(January), 1.

Gonzalez, R.A., 2006. From the lab to the market: The commercialization strategy of patented inventions, Academy of Management Proceedings 1, pp. H1-H6.

Gulati, R. 1998., Alliances and networks. Strategic Management Journal 19 (4), 293-317.

Guler, I., 2007. Throwing good money after bad? Political and institutional influences on sequential decision making in the venture capital industry. Administrative Science Quarterly 52 (2), 248-285.

Greene, W., Zhang, Q., 2019. Nonlinear and related panel data models. Panel Data Econometrics. (Academic Press), 45–96.

Hagedoorn, J., 1993. Understanding the rationale of strategic technology partnering: Interorganizational modes of cooperation and sectoral differences. Strategic Management Journal 14 (5), 371-385.

Hall, B.H., 2019. Is there a role for patents in the financing of new innovative firms?. Industrial Corporate Change 28 (3), 657–680.

Hannan, M.T., Freeman, J., 1984. Structural inertia and organizational change. American Sociological Review 49 (2), 149–164.

Hargadon, A., Sutton, R.I., 1997. Technology brokering and innovation in a product development firm. Administrative Science Quarterly 42 (4), 716–749.

Harhoff, D., 2016. Patent quality and examination in Europe. American Economic Review 106 (5), 193–197.

Harhoff, D., Narin, F., Scherer, M., Vopel, K., 1999. Citation frequency and the value of patented inventions. The Review of Economics and Statistics 81 (3), 511–515.

Harhoff, D., Scherer, F.M., Vopel, K., 2003. Citations, family size, opposition and the value of patent rights. Research Policy 32 (8), 1343–1363.

Hausman, J., McFadden, D., 1984. Specification tests for the multinomial logit model. Econometrica 52 (5), 1219–1240.

Haeussler, C., Harhoff, D., Mueller, E., 2014. How patenting informs VC investors–The case of biotechnology. Research Policy 43 (8), 1286–1298.

Hegde, D., Ljungqvist, A., Raj, M., 2020. Quick and Dirty Patents. Available at SSRN: 3511268.

Heeley, M.B., Matusik, S.F., Jain, N., 2007. Innovation, appropriability, and the underpricing of initial public offerings. Academy of Management Journal 50 (1), 209–225.

Henderson, R., 1993. Underinvestment and incompetence as responses to radical innovation: Evidence from the photolithographic alignment equipment industry. The RAND Journal of Economics 24 (2), 248–270.

Higgins, M.C., Gulati, R., 2006. Stacking the deck: The effects of top management backgrounds on investor decisions. Strategic Management Journal 27 (1), 1–25.

Hill, C.W., Rothaermel, F.T., 2003. The performance of incumbent firms in the face of radical technological innovation. Academy of Management Review 28 (2), 257–274.

Hoenen, S., Kolympiris, C., Schoenmakers, W., Kalaitzandonakes, N., 2014. The diminishing signaling value of patents between early rounds of venture capital financing. Research Policy 43 (6), 956–989.

Hoenig, D., Henkel, J., 2015. Quality signals? The role of patents, alliances, and team experience in venture capital financing. Research Policy 44 (5), 1049–1064.

Hsu, D.H., 2004. What do entrepreneurs pay for venture capital affiliation?. The Journal of Finance 59 (4), 1805–1844.

Hsu, D.H., 2007. Experienced entrepreneurial founders, organizational capital, and venture capital funding. Research Policy 36 (5), 722-741.

Hsu, D.H., Ziedonis, R.H., 2008. Patents as quality signals for entrepreneurial ventures. Academy of Management Proceedings 2008 (1), 1–6.

Hsu, D.H., Ziedonis, R.H., 2013. Resources as dual sources of advantage: Implications for valuing entrepreneurial-firm patents. Strategic Management Journal 34 (7), 761–781.

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

Junkunc, M.T., 2007. Managing radical innovation: The importance of specialized knowledge in the biotech revolution. Journal of Business Venturing 22 (3), 388–411.

Kaplan, S.N., Sensoy, B.A., Strömberg, P., 2009. Should investors bet on the jockey or the horse? Evidence from the evolution of firms from early business plans to public companies. The Journal of Finance 64 (1), 75-115.

King, G., Zeng, L., 2001. Logistic regression in rare events data. Political Analysis 9 (2), 137–163.

Kolympiris, C., Kalaitzandonakes, N., Miller, D., 2014. Public funds and local biotechnology firm creation. Research Policy 43 (1), 121–137.

Lanjouw, J.O., Schankerman, M., 2001. Characteristics of patent litigation: a window on competition. The RAND Journal of Economics 32 (1), 129–151.

Lavie, D., 2006. Capability reconfiguration: An analysis of incumbent responses to technological change. Academy of Management Review 31 (1), 153–174.

Lerner, J., 1994. The syndication of venture capital investments, Financial Management, 16–27.

Long, C., 2002. Patent signals. University Chicago Law Review 69 (2), 625–679.

Nahata, R., 2008. Venture capital reputation and investment performance. Journal of Financial Economics 90 (2), 12–151.

Nanda, R., Rhodes-Kropf, M., 2017. Financing risk and innovation. Management Science 63 (4), 901-918.

Nanda, R., Samila, S., Sorenson, O., 2020. The persistent effect of initial success: Evidence from venture capital. Journal of Financial Economics 137 (1), 231–248.

Nasto, B., 2008. Chasing biotech across Europe. Nature Biotechnology 26 (3), 283–288.

Nelson, R.R., Winter, S.G., 1982. An evolutionary theory of economic change. Harvard University Press, Cambridge, Massachusetts.

Norton, E., Tenenbaum, B.H., 1993. Specialization versus diversification as a venture capital investment strategy. Journal of Business Venturing 8 (5), 431-442.

O’Connor, G.C., McDermott, C.M., 2004. The human side of radical innovation. Journal of Engineering Technology Management 21 (1-2), 11–30.

Ozmel, U., Reuer, J.J., Gulati, R., 2013. Signals across multiple networks: How venture capital and alliance networks affect interorganizational collaboration. Academy of Management Journal 56 (3), 852–866.

Petty, J.S., Gruber, M., 2011. "In pursuit of the real deal": A longitudinal study of VC decision making. Journal of Business Venturing 26 (2),172-188.

Plagmann, C., Lutz, E., 2019. Beggars or choosers? Lead venture capitalists and the impact of reputation on syndicate partner selection in international settings. Journal of Banking and Finance 100, 359–378.

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

Pollock, T.G., Chen, G., Jackson, E.M., Hambrick, D.C., 2010. How much prestige is enough? Assessing the value of multiple types of high-status affiliates for young firms. Journal of Business Venturing 25 (1), 6–23.

Pollock, T.G., Lee, P.M., Jin, K., Lashley, K., 2015. (Un) tangled: Exploring the asymmetric coevolution of new venture capital firms’ reputation and status. Administrative Science Quarterly 60 (3), 482–517.

Raffo, J., Lhuillery, S., 2009. How to play the “Names Game”: Patent retrieval comparing different heuristics. Research Policy 38 (10), 1617–1627.

Reinganum, J.F., 1983. Uncertain innovation and the persistence of monopoly. American Economic Review 73 (4), 741–748.

Rizzo, U., Barbieri, N., Ramaciotti, L., Iannantuono, D., 2020. The division of labour between academia and industry for the generation of radical inventions. Journal of Technology Transfer 45 (2), 393–413.

Rosenberg, N., 1974. Science, Invention and Economic Growth. The Economic Journal 84 (333), 90–108.

Schoenmakers, W., Duysters, G., 2010. The technological origins of radical inventions. Research Policy 39 (8), 1051–1059.

Schumpeter, J.A., 1934. The Theory of Economic Development. Harvard University Press, Cambridge, Massachusetts.

Sorenson, O., Stuart, T.E., 2008. Bringing the context back in: Settings and the search for syndicate partners in venture capital investment networks. Administrative Science Quarterly 53 (2), 266–294.

Sørensen, M., 2007. How smart is smart money? A two-sided matching model of venture capital. The Journal of Finance 62 (6), 2725–2762.

Spence, M., 1973. Job market signaling. Quarterly Journal of Economics 87, 355–374.

Spence, M., 2002. Signaling in retrospect and the informational structure of markets. American Economic Review 92 (3), 434–459.

Stern, I., Dukerich, J.M., Zajac, E., 2014. Unmixed signals: How reputation and status affect alliance formation. Strategic Management Journal 35 (4), 512–531.

Stuart. T.E, Hoang, H., Hybels, R.C., 1999. Interorganizational endorsements and the performance of entrepreneurial ventures. Administrative Science Quarterly 44 (2), 315–349.

Subramaniam, M., Youndt, M.A., 2005. The influence of intellectual capital on the types of innovative capabilities. Academy of Management Journal 48 (3), 450–463.

Tian, X., 2011. The causes and consequences of venture capital stage financing. Journal of Financial Economics 101 (1), 132-159.

Trajtenberg, M., 1990. A penny for your quotes: patent citations and the value of innovations. The RAND Journal of Economics 21 (1), 172-187.

Tushman, M.L., Anderson, P., 1986. Technological discontinuities and organizational environments. Administrative Science Quarterly 31 (3), 439–465.

Vanacker, T., Forbes, D.P., Knockaert, M., Manigart, S., 2020. Signal strength, media attention, and resource mobilization: evidence from new private equity firms. Academy of Management Journal 63 (4), 1082–1105.

Verhoeven, D., Bakker, J., Veugelers, R., 2016. Measuring technological novelty with patent-based indicators. Research Policy 45 (3), 707–723.

Wright, M., Lockett, A., 2003. The structure and management of alliances: syndication in the venture capital industry. Journal of Management Studies 40 (8), 2073–2102.

Zhelyazkov, P.I., Tatarynowicz, A., 2021. Marriage of unequals? Quality heterogeneity, market heat, and the formation of status-asymmetric ties in the venture capital industry. Academy of Management Journal 64 (2), 509–536.

TABLES

Table 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
1	DIncremental Patent	0.472		0	1	**1**												
2	DRadical Patent	0.141		0	1	-0.383	**1**											
3	DReputable Investor	0.273		0	1	0.005	0.003	**1**										
4	Number Forward Citations	12.874	73.385	0	1366	0.165	0.463	0.002	**1**									
5	Firm Age	4.014	3.218	0	16	0.136	0.183	-0.010	0.454	**1**								
6	Number of Prior Investors	1.390	2.164	0	14	0.161	0.133	0.000	0.348	0.376	**1**							
7	DPrior Reputable Investor	0.211		0	1	0.113	0.112	-0.002	0.226	0.246	0.612	**1**						
8	Months Since Last Funding	8.620	15.292	0	122	0.080	0.112	-0.011	0.289	0.442	0.424	0.319	**1**					
9	Industry Experience	12.227	25.434	0	262	0.008	0.001	0.618	0.001	-0.009	0.004	0.001	-0.009	**1**				
10	DPrior Investment	0.006		0	1	0.015	0.017	0.031	0.037	0.033	0.100	0.022	0.042	0.054	**1**			
11	DFirst Round	0.505		0	1	-0.138	-0.147	-0.001	-0.292	-0.391	-0.649	-0.522	-0.570	-0.005	-0.077	**1**		
12	Distance	2,266.28	2,627.72	0	17,324.35	0.014	0.036	-0.013	0.036	0.026	-0.005	-0.032	-0.013	0.013	-0.088	0.011	**1**	
13	DSame Country	0.126	0.332	0	1	-0.009	-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 Round* 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 2 - *Results of the (multinomial) logistic regressions*

	Model 1	Model 2	Model 3		Model 4a	Model 4b	Model 5	Model 6	Model 7		Model 8a	Model 8b
Sample specification	First Round	First Round	First Round		First Round	First Round	Follow-on Round	2nd Round	Follow-on Round		2nd Round	2nd Round
Empirical specification	Logit	Cond. Logit	Multinomial Logit		Cond. Logit	Cond. Logit	Logit	Cond. Logit	Multinomial Logit		Cond. Logit	Cond. Logit
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
DIncremental Patent	-0.073		-0.386*	0.055			0.235		0.228	0.226		
	(0.107)		(0.232)	(0.112)			(0.176)		(0.316)	(0.183)		
DRadical Patent	0.148		-0.490	0.345*			0.178		0.170	0.163		
	(0.173)		(0.356)	(0.189)			(0.218)		(0.484)	(0.220)		
DReputable Investor	-0.155	-0.129	-0.079	-0.192	-0.104	-0.139	0.208	-0.020	0.069	0.194	0.082	-0.058
	(0.156)	(0.156)	(0.256)	(0.189)	(0.232)	(0.202)	(0.248)	(0.326)	(0.363)	(0.283)	(0.605)	(0.389)
DIncremental Patent X DReputable Investor	0.134	0.081	0.315	0.073	0.215	0.021	-0.185	-0.303	0.100	-0.198	-2.421	-0.054
	(0.176)	(0.204)	(0.316)	(0.202)	(0.330)	(0.259)	(0.255)	(0.418)	(0.397)	(0.277)	(1.926)	(0.464)
DRadical Patent X DReputable Investor	0.612**	0.533*	-0.022	0.722**	0.264	0.575*	0.036	-0.340	0.124	0.080	0.278	-0.724
	(0.271)	(0.305)	(0.630)	(0.321)	(0.904)	(0.338)	(0.331)	(0.535)	(0.538)	(0.352)	(0.860)	(0.722)
Forward Citations (ln+1)	0.087**		-0.049	0.121***			0.084**		-0.046	0.107**		
	(0.040)		(0.098)	(0.042)			(0.043)		(0.094)	(0.043)		
Firm Age	-0.002		0.036	-0.015			-0.023		0.073**	-0.045**		
	(0.018)		(0.030)	(0.020)			(0.019)		(0.035)	(0.021)		
Industry Experience (ln+1)	-0.049	-0.043	-0.052	-0.048	-0.060	-0.037	-0.054	-0.026	0.195*	-0.103*	0.067	-0.052
	(0.038)	(0.043)	(0.076)	(0.046)	(0.068)	(0.053)	(0.056)	(0.075)	(0.112)	(0.061)	(0.169)	(0.084)
Distance (ln+1)	-0.259***	-0.357***	-0.295***	-0.245***	-0.417***	-0.331***	-0.088*	-0.223***	-0.146*	-0.077	-0.176	-0.242***
	(0.031)	(0.039)	(0.046)	(0.036)	(0.065)	(0.047)	(0.050)	(0.072)	(0.076)	(0.051)	(0.148)	(0.082)
DSame Country	2.858***	2.604***	3.297***	2.720***	2.953***	2.490***	1.549***	1.926***	1.504***	1.552***	1.948***	1.917***
	(0.149)	(0.141)	(0.266)	(0.173)	(0.259)	(0.168)	(0.197)	(0.269)	(0.349)	(0.207)	(0.595)	(0.301)
DPrior Investment							6.133***	5.588***	6.660***	6.054***	5.392***	5.650***
							(0.157)	(0.391)	(0.313)	(0.155)	(0.685)	(0.475)
Number of Prior Investors							-0.043*		-0.302***	-0.007		
							(0.025)		(0.095)	(0.024)		
DPrior Reputable Investor							-0.742***	-17.199***	-0.900***	-0.712***	-16.414***	-18.251***
							(0.165)	(0.572)	(0.296)	(0.165)	(1.739)	(0.590)
Months Since Last Funding							0.005*		-0.002	0.007***		
							(0.003)		(0.007)	(0.003)		
Firm Country FE	Yes	No	Yes		No	No	Yes	No	Yes		No	No
Industry (NACE) FE	Yes	No	Yes		No	No	Yes	No	Yes		No	No
Time Period Fixed FE	Yes	No	Yes		No	No	Yes	No	Yes		No	No
Firm X Investor Dyads	74,883	61,782	74,883		22,694	39,088	73,321	27,448	73,321		8,983	18,465
Log Likelihood	-3264.323	-2406.838	-3670.014		-647.070	-1753.472	-2557.098	-785.627	-2987.586		-154.250	-627.122

Note: The coefficients represent the changes in the log-odds. The reference outcome are unrealized investment ties. Models 1 and 5 show the baseline logistic regression comparing unrealized to realized first round (Model 1) and follow-on round investment ties (Model 5), while Models 3 and 7 show the baseline multinomial logistic regressions for first round (Model 3) and follow-on round investment ties (Model 7), thereby distinguishing between realized standalone and syndicated ties. In these models, the standard errors are clustered at the level of the investor. Model 2, 4a-b, 6 and 8a-b represent simple conditional logit analyses and are conditioned on the firm with standard errors clustered at the level of the firm. They separately compare realized ties (Model 2 and 6), standalone ties (Model 4a and 8a) and syndicated ties (Model 4b and 8b) to unrealized investment ties. In Model 6 and 8a-b, we confine the sample of 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 3 - *Average Marginal Effects of patents protecting radical inventions on the type of investment tie*

		Model 1	**Model 3**	**Model 5**	**Model 7**
Sample Specification		First Round	First Round	Follow-on Round	Follow-on Round
Average Marginal Effect of DRadical Patent on	*Counterfactual*				
(1) the probability of a **realized tie** with a **reputable** VC investor	*Firms without patents*	0.009***		0.002	
		(0.004)		(0.002)	
(2) the probability of a **realized tie** with a **less reputable** VC investor	*Firms without patents*	0.002		0.001	
		(0.002)		(0.001)	
(1) - (2)		0.008**		0.000	
		(0.004)		(0.002)	
(3) the probability of a **realized tie** with a **reputable** VC investor	*Firms with incremental patents only*	0.010**		0.002	
		(0.004)		(0.002)	
(4) the probability of a **realized tie** with a **less reputable** VC investor	*Firms with incremental patents only*	0.001		0.001	
		(0.002)		(0.002)	
(3) - (4)		0.008**		0.000	
		(0.004)		(0.003)	
(5) the probability of a **syndicated tie** with a **reputable** VC investor	*Firms without patents*		0.010***		0.001
			(0.004)		(0.002)
(6) the probability of a **syndicated tie** with a **less reputable** VC investor	*Firms without patents*		0.003*		0.001
			(0.002)		(0.001)
(7) the probability of a **standalone tie** with a **reputable** VC investor	*Firms without patents*		-0.001		0.000
			(0.001)		(0.001)
(8) the probability of a **standalone tie** with a **less reputable** VC investor	*Firms without patents*		-0.001		0.000
			(0.001)		(0.001)
(5) - (7)			0.012***		0.001
			(0.004)		(0.002)
(9) the probability of a **syndicated tie** with a **reputable** VC investor	*Firms with incremental patents only*		0.011**		0.001
			(0.005)		(0.002)
(10) the probability of a **syndicated tie** with a **less reputable** VC investor	*Firms with incremental patents only*		0.003		0.001
			(0.002)		(0.002)
(11) the probability of a **standalone tie** with a **reputable** VC investor	*Firms with incremental patents only*		-0.001		0.001
			(0.001)		(0.001)
(12) the probability of a **standalone tie** with a **less reputable** VC investor	*Firms with incremental patents only*		-0.001*		0.000
			(0.001)		(0.001)
(9) - (11)			0.013**		0.001
			(0.005)		(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 by using the delta method, leaving all variables except for the variables of interest at their observed value. Models 1 and 3 only consider potential first round investment ties, while Models 5 and 7 only consider potential follow-on investment ties. Models 1 and 5 report the Average Marginal Effects of *DRadical Patent* on the probability of a realized investment tie. Models 3 and 7 report the Average Marginal Effects of *DRadical Patent* on the probabilities of a standalone and syndicated tie with varying investor reputations.

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

APPENDIX

Additional analyses and robustness checks

A possible alternative explanation of our results is that reputable VC investors may invest in firms with patents protecting radical inventions because of the quality of their entrepreneurial teams or affiliations, such as to universities or reputable third parties (e.g., big pharmaceutical firms) and not because these VC investors are attracted by the strength of the quality signal conveyed by radical patents. In particular, if the quality of the entrepreneurial team is correlated with both the ability to develop radical inventions and the attraction of reputable VC investors, our results may simply be driven by unobserved heterogeneity (i.e., lack of controls for the characteristics of entrepreneurial teams). This explanation would also be in line with the literature that considers the entrepreneur (jockey) more important than the technology (horse) (see, e.g., Gompers et al. 2010, 2020).

Our conditional logit models show that the estimated log-odd ratios in our main models are robust to the effect of time-invariant unobservable firm characteristics on the likelihood of a realized (standalone or syndicated) investment tie compared to no tie formation. However, these models are not sufficient to rule out endogeneity concerns at the level of the interaction between firms with patents protecting radical inventions and reputable VC investors.

To alleviate these concerns, we manually collected additional data on the human capital of the entrepreneurs (the data are available for 75.1 percent of the 759 firms in our sample) to build four measures that proxy the entrepreneurial and managerial quality of the entrepreneurial team and affiliations to universities and big pharmaceutical firms: (a) *DEntrepreneur PhD* that equals 1 for entrepreneurial teams with at least one member who has a PhD degree at the time the firms are founded, (b) *DSerial Entrepreneur* that equals 1 for entrepreneurial teams with at least one member who already has entrepreneurial experience, (c) *DC-level Experience* that equals 1 for entrepreneurial teams with at least one member who already has managerial (i.e., C-level) experience and (d) *DEntrepreneur BigPharma* that equals 1 for entrepreneurial teams with at least one member in the 30 top-selling pharmaceutical firms by sales in 2010 (source: ORBIS database).[16]

Descriptive analysis shows that the majority of entrepreneurial teams have at least one member with a PhD (67.89 percent – this is not surprising given that we use a sample of young life science firms, where the proportion of employees with PhDs is generally particularly high due to the science-dependent nature of this technology). A total of 28.42 percent of the entrepreneurial teams have a member with prior entrepreneurial experience, 31.23 percent of the entrepreneurial teams have a member with C-level experience, and 11.75 percent of the entrepreneurial teams have a member with work experience in a big pharmaceutical firm. Firms with patents protecting radical inventions (at the time of the first financing round) are not more likely to come from entrepreneurial teams with at least one PhD, serial entrepreneur, entrepreneur with prior C-level experience, or big pharma experience. A Wilcoxon-Mann–Whitney test shows that the share of entrepreneurial teams with at least one PhD, serial entrepreneur, entrepreneur with C-level experience, or entrepreneur with work experience in a big pharmaceutical firm in the sample of firms with patents protecting radical inventions is not significantly different from the sample of firms without such patents (PhD: 72.58 percent compared to 66.59 percent, z=-0.896, p=0.370; serial entrepreneur: 37.10 percent compared to 27.33 percent, z=-1.598, p=0.110; C-level experience: 32.26 percent compared to 31.45 percent, z=-0.128, p=0.898; big pharmaceutical firm experience: 6.45 percent compared to 11.93 percent, z=1.279, p=0.201).

Second, we added the four dummy variables *DEntrepreneur PhD*, *DSerial Entrepreneur*, *DC-level Experience*, *DEntrepreneur BigPharma* and their respective interactions with *DReputable Investor* to our matching model to test whether (a) signals identifying entrepreneurial teams with higher quality are also associated with investments from reputable VC investors and (b) whether the observed association between patents protecting radical inventions and reputable VC investors (in syndicated first round investment ties) remains robust when signals regarding the human capital of the entrepreneurial team are included. The

[16] High bivariate correlations between these three variables are not a concern. The highest correlation is observed between *DSerial Entrepreneur* and *DC-level Experience* (corr=0.391).

results are reported in Table A1, where we display the AMEs of the relevant variables (the results of the estimates of Models A1 and A2 are available from the authors upon request). We find no evidence that reputable VC investors are attracted by entrepreneurial teams that include either entrepreneurs with PhDs, serial entrepreneurs or entrepreneurs with prior C-level experience (Model A1). Only for entrepreneurial teams whose members have worked for leading pharmaceutical firms does the likelihood of the formation of an investment tie with a reputable VC investor increase significantly (AME=0.007, p=0.023). Nonetheless, our key findings that reputable VC investors in first round investments are associated with firms that have patents protecting radical inventions (see again Model A1) and prefer to syndicate their investment rather than invest alone (Model A2) remain unchanged.

Table A1 - *Average Marginal Effects of human capital characteristics of the entrepreneurial team and patents protecting radical inventions on the type of investment tie when controlling for the association between high quality entrepreneurial teams and reputable VC investors*

		Model A1	**Model A2**
Sample Specification		First Round	First Round
Average Marginal Effect of DEntrepreneur PhD on	*Counterfactual*		
(1) the probability of a **realized tie** with a **reputable** VC investor	*Entrepreneurial teams without PhD*	0.000 (0.002)	
(2) the probability of a **realized tie** with a **less reputable** VC investor		-0.001 (0.001)	
Average Marginal Effect of DSerial Entrepreneur on			
(3) the probability of a **realized tie** with a **reputable** VC investor	*Entrepreneurial teams without serial entrepreneur*	-0.001 (0.002)	
(4) the probability of a **realized tie** with a **less reputable** VC investor		0.000 (0.001)	
Average Marginal Effect of DC-level Experience on			
(5) the probability of a **realized tie** with a **reputable** VC investor	*Entrepreneurial teams without C-level experience*	0.002 (0.002)	
(6) the probability of a **realized tie** with a **less reputable** VC investor		-0.001 (0.001)	

Table A1 - *continued*

Average Marginal Effect of DEntrepreneur BigPharma on			
(7) the probability of a **realized tie** with a **reputable** VC investor	*Entrepreneurial teams without leading pharma firm experience*	0.007**	
		(0.003)	
(8) the probability of a **realized tie** with a **less reputable** VC investor		-0.001	
		(0.002)	
Average Marginal Effect of DRadical Patent on			
(9) the probability of a **realized tie** with a **reputable** VC investor	*Firms without patents*	0.008**	
		(0.003)	
(10) the probability of a **realized tie** with a **less reputable** VC investor		0.003	
		(0.002)	
(9) - (10)		0.005	
		(0.004)	
(11) the probability of a **realized tie** with a **reputable** VC investor	*Firms with incremental patents only*	0.007**	
		(0.004)	
(12) the probability of a **realized tie** with a **less reputable** VC investor		0.003	
		(0.002)	
(11) - (12)		0.005	
		(0.004)	
(13) the probability of a **syndicated tie** with a **reputable** VC investor	*Firms without patents*		0.009**
			(0.004)
(14) the probability of a **syndicated tie** with a **less reputable** VC investor			0.004**
			(0.002)
(15) the probability of a **standalone tie** with a **reputable** VC investor			-0.001
			(0.001)
(16) the probability of a **standalone tie** with a **less reputable** VC investor			-0.001
			(0.001)
(13) - (15)			0.011**
			(0.004)
(17) the probability of a **syndicated tie** with a **reputable** VC investor	*Firms with incremental patents only*		0.009**
			(0.004)
(18) the probability of a **syndicated tie** with a **less reputable** VC investor			0.004*
			(0.002)
(19) the probability of a **standalone tie** with a **reputable** VC investor			-0.001
			(0.001)
(20) the probability of a **standalone tie** with a **less reputable** VC investor			-0.001
			(0.001)

Table A1 - *continued*

(17) - (19)			0.010** (0.005)
Firm X Investor Dyads		55,742	55,742

Note: Standard errors in parentheses are clustered by investor. This table reports the Average Marginal Effects of *DEntrepreneur PhD, DSerial Entrepreneur*, *DC-level Experience, DEntrepreneur BigPharma* and *DRadical Patent* on the probability of a realized/syndicated or standalone first round investment tie. Compared to the baseline regressions in Model 1 and 3, we added the four human capital variables *DEntrepreneur PhD, DSerial Entrepreneur*, *DC-level Experience*, *DEntrepreneur BigPharma* and their associated interaction terms with *DReputable Investor*. The Average Marginal Effects are calculated by using the delta method, leaving all variables except for the variables of interest at their observed value.

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

Third, we considered the three-way interaction between *DEntrepreneur PhD* (*DSerial Entrepreneur*, *DC-level Experience* and *DEntrepreneur BigPharma*), *DRadical Patent* and *DReputable Investor* to test whether the positive AME of *DRadical Patent* on the probability of a realized (syndicated) first round investment tie with a reputable VC investor depends on the human capital of the entrepreneurial team. Our results turn out to be largely independent of the characteristics of the entrepreneurial team (see Tables A2 – A5). In fact, the AME of *DRadical Patent* on the probability of establishing a tie with a reputable VC investor does not differ significantly depending on whether the entrepreneurial team consists of PhD entrepreneurs, serial entrepreneurs, entrepreneurs with managerial experience, or entrepreneurs with work experience in big pharmaceutical firms. If anything, the AME of the *DRadical Patent* is smaller and less significant when the entrepreneurial teams have higher human capital. For example, when entrepreneurial teams contain a serial entrepreneur, the marginal effect of *DRadical Patent* on the probability of a realized tie with a reputable investor is smaller and is no longer significant compared to entrepreneurial teams without serial entrepreneurs (see Table A3: Model A5).[17]

[17] We also tested the robustness of these new results by creating an additional human capital variable indicating entrepreneurial teams with at least one entrepreneur with a PhD from a prestigious university (top 20 university in the QS-Rating of Life Sciences & Medicine in Europe or worldwide; source: https://www.topuniversities.com/ university-rankings/university-subject-rankings/2018/life-sciences-medicine). These results are very close to those presented here. They are available from the authors upon request.

Table A2 - *Average Marginal Effects of patents protecting radical inventions on the type of investment tie for varying VC investor reputation and whether one of the founding entrepreneurs has a PhD*

		Model A3	Model A4
Sample Specification		First Round	First Round
Average Marginal Effect of DRadical Patent on	*Counterfactual*		
(1) the probability of a **realized tie** with a **reputable** VC investor for entrepreneurial teams **with PhD**	*Firms without patents*	0.007*	
		(0.004)	
(2) the probability of a **realized tie** with a **reputable** VC investor for entrepreneurial teams **without PhD**		0.010**	
		(0.005)	
(1) - (2)		-0.003	
		(0.006)	
(3) the probability of a **realized tie** with a **reputable** VC investor for entrepreneurial teams **with PhD**	*Firms with incremental patents only*	0.006	
		(0.004)	
(4) the probability of a **realized tie** with a **reputable** VC investor for entrepreneurial teams **without PhD**		0.010*	
		(0.006)	
(3) - (4)		-0.004	
		(0.007)	
(5) the probability of a **syndicated tie** with a **reputable** VC investor for entrepreneurial teams **with PhD**	*Firms without patents*		0.007*
			(0.004)
(6) the probability of a **syndicated tie** with a **reputable** VC investor for entrepreneurial teams **without PhD**			0.012**
			(0.005)
(5) - (6)			-0.005
			(0.006)
(7) the probability of a **syndicated tie** with a **reputable** VC investor for entrepreneurial teams **with PhD**	*Firms with incremental patents only*		0.006
			(0.004)
(8) the probability of a **syndicated tie** with a **reputable** VC investor for entrepreneurial teams **without PhD**			0.017*
			(0.010)
(7) - (8)			-0.011
			(0.011)
Firm X Investor Dyads		55,742	55,742

Note: Standard errors in parentheses are clustered by investor. The Average Marginal Effects are calculated by using the delta method, leaving all variables except for the variables of interest at their observed value. While Model A1 reports the Average Marginal Effects of *DRadical Patent* on the probability of a realized first round investment tie, Model A2 reports the Average Marginal Effects of *DRadical Patent* on the probability of a syndicated first round tie with varying investor reputation and PhD degree of the entrepreneurial team. Compared to the baseline regressions in Model 1 and 3, we added the human capital variable *DEntrepreneur PhD* and build the triple interaction terms *DRadical Patent X DReputable Investor X DEntrepreneur PhD, DIncremental Patent X DReputable Investor X DEntrepreneur PhD,* and simple interaction terms *DReputable Investor X DEntrepreneur PhD*, *DRadical Patent X DEntrepreneur PhD* and *DIncremental Patent X DEntrepreneur PhD*.

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

Table A3 - *Average Marginal Effects of patents protecting radical inventions on the type of investment tie for varying VC investor reputation and whether one of the founding entrepreneurs is a serial entrepreneur*

		Model A5	**Model A6**
Sample Specification		First Round	First Round
Average Marginal Effect of DRadical Patent on	*Counterfactual*		
(1) the probability of a **realized tie** with a **reputable** VC investor for entrepreneurial teams **with serial entrepreneur**	*Firms without patents*	0.004 (0.005)	
(2) the probability of a **realized tie** with a **reputable** VC investor for entrepreneurial teams **without serial entrepreneur**		0.010** (0.004)	
(1) - (2)		-0.007 (0.007)	
(3) the probability of a **realized tie** with a **reputable** VC investor for entrepreneurial teams **with serial entrepreneur**	*Firms with incremental patents only*	0.004 (0.006)	
(4) the probability of a **realized tie** with a **reputable** VC investor for entrepreneurial teams **without serial entrepreneur**		0.009** (0.005)	
(3) - (4)		-0.005 (0.008)	
(5) the probability of a **syndicated tie** with a **reputable** VC investor for entrepreneurial teams **with serial entrepreneur**	*Firms without patents*		0.005 (0.004)
(6) the probability of a **syndicated tie** with a **reputable** VC investor for entrepreneurial teams **without serial entrepreneur**			0.012*** (0.004)
(5) - (6)			-0.007 (0.006)
(7) the probability of a **syndicated tie** with a **reputable** VC investor for entrepreneurial teams **with serial entrepreneur**	*Firms with incremental patents only*		0.007 (0.008)
(8) the probability of a **syndicated tie** with a **reputable** VC investor for entrepreneurial teams **without serial entrepreneur**			0.010** (0.005)
(7) - (8)			-0.004 (0.009)
Firm X Investor Dyads		55,742	55,742

Note: Standard errors in parentheses are clustered by investor. The Average Marginal Effects are calculated by using the delta method, leaving all variables except for the variables of interest at their observed value. While Model A5 reports the Average Marginal Effects of *DRadical Patent* on the probability of a realized first round investment tie, Model A6 reports the Average Marginal Effects of *DRadical Patent* on the probability of a syndicated first round tie with varying investor reputation and whether the entrepreneurial team has at least one serial entrepreneur. Compared to the baseline regressions in Model 1 and 3, we added the human capital variable *DSerial Entrepreneur* and built the triple interaction terms *DRadical Patent X DReputable Investor X DSerial Entrepreneur, DIncremental Patent X DReputable Investor X DSerial Entrepreneur* and simple interaction terms *DReputable Investor X DSerial Entrepreneur*, *DRadical Patent X DSerial_Entrepreneur* and *DIncremental Patent X DSerial Entrepreneur*.

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

Table A4 - *Average Marginal Effects of patents protecting radical inventions on the type of investment tie for varying VC investor reputation and whether one of the founding entrepreneurs has C-level experience*

		Model A7	**Model A8**
Sample Specification		First Round	First Round
Average Marginal Effect of DRadical Patent on	*Counterfactual*		
(1) the probability of a **realized tie** with a **reputable** VC investor for entrepreneurial teams **with C-level experience**	*Firms without patents*	0.003 (0.006)	
(2) the probability of a **realized tie** with a **reputable** VC investor for entrepreneurial teams **without C-level experience**		0.009** (0.004)	
(1) - (2)		-0.006 (0.007)	
(3) the probability of a **realized tie** with a **reputable** VC investor for entrepreneurial teams **with C-level experience**	*Firms with incremental patents only*	0.003 (0.005)	
(4) the probability of a **realized tie** with a **reputable** VC investor for entrepreneurial teams **without C-level experience**		0.010** (0.005)	
(3) - (4)		-0.007 (0.006)	
(5) the probability of a **syndicated tie** with a **reputable** VC investor for entrepreneurial teams **with C-level experience**	*Firms without patents*		0.004 (0.005)
(6) the probability of a **syndicated tie** with a **reputable** VC investor for entrepreneurial teams **without C-level experience**			0.011*** (0.004)
(5) - (6)			-0.007 (0.006)
(7) the probability of a **syndicated tie** with a **reputable** VC investor for entrepreneurial teams **with C-level experience**	*Firms with incremental patents only*		0.003 (0.004)
(8) the probability of a **syndicated tie** with a **reputable** VC investor for entrepreneurial teams **without C-level experience**			0.012** (0.006)
(7) - (8)			-0.008 (0.006)
Firm X Investor Dyads		55,742	55,742

Note: Standard errors in parentheses are clustered by investor. The Average Marginal Effects are calculated by using the delta method, leaving all variables except for the variables of interest at their observed value. While Model A7 reports the Average Marginal Effects of *DRadical Patent* on the probability of a realized first round investment tie, Model A8 reports the Average Marginal Effects of *DRadical Patent* on the probability of a syndicated first round tie with varying investor reputation and whether one of the entrepreneurs has C-level experience. Compared to the baseline regressions in Model 1 and 3, we added the human capital variable *DC-level Experience* and built the triple interaction terms *DRadical Patent X DReputable Investor X DC-level Experience*, *DIncremental Patent X DReputable Investor X DC-level Experience*, and simple interaction terms *DReputable Investor X DC-level Experience*, *DRadical Patent X DC-level Experience* and *DIncremental Patent X DC-level Experience.*

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

Table A5 - *Average Marginal Effects of patents protecting radical inventions on the type of investment tie for varying VC investor reputation and whether one of the founding entrepreneurs has prior work experience in a leading pharmaceutical firm*

		Model A9	**Model A10**
Sample Specification		First Round	First Round
Average Marginal Effect of DRadical Patent on	*Counterfactual*		
(1) the probability of a **realized tie** with a **reputable** VC investor for entrepreneurial teams **with leading pharma firm experience**	*Firms without patents*	0.015 (0.012)	
(2) the probability of a **realized tie** with a **reputable** VC investor for entrepreneurial teams **without leading pharma firm experience**		0.007** (0.003)	
(1) - (2)		0.008 (0.012)	
(3) the probability of a **realized tie** with a **reputable** VC investor for entrepreneurial teams **with leading pharma firm experience**	*Firms with incremental patents only*	0.017 (0.015)	
(4) the probability of a **realized tie** with a **reputable** VC investor for entrepreneurial teams **without leading pharma firm experience**		0.006* (0.003)	
(3) - (4)		0.011 (0.014)	
(5) the probability of a **syndicated tie** with a **reputable** VC investor for entrepreneurial teams **with leading pharma firm experience**	*Firms without patents*		0.019 (0.012)
(6) the probability of a **syndicated tie** with a **reputable** VC investor for entrepreneurial teams **without leading pharma firm experience**			0.008** (0.003)
(5) - (6)			0.011 (0.011)
(7) the probability of a **syndicated tie** with a **reputable** VC investor for entrepreneurial teams **with leading pharma firm experience**	*Firms with incremental patents only*		0.021 (0.016)
(8) the probability of a **syndicated tie** with a **reputable** VC investor for entrepreneurial teams **without leading pharma firm experience**			0.007* (0.004)
(7) - (8)			0.014 (0.014)
Firm X Investor Dyads		55,742	55,742

Note: Standard errors in parentheses are clustered by investor. The Average Marginal Effects are calculated by using the delta method, leaving all variables except for the variables of interest at their observed value. While Model A9 reports the Average Marginal Effects of *DRadical Patent* on the probability of a realized first round investment tie, Model A10 reports the Average Marginal Effects of *DRadical Patent* on the probability of a syndicated first round tie with varying investor reputation and whether one of the entrepreneurs has prior work experience in a leading pharmaceutical firm. Compared to the baseline regressions in Model 1 and 3, we added the human capital variable *DEntrepreneur BigPharma* and built the triple interaction terms *DRadical Patent X DReputable Investor X DEntrepreneur BigPharma, DIncremental Patent X DReputable Investor X DEntrepreneur BigPharma,* and simple interaction terms *DReputable Investor X DEntrepreneur BigPharma*, *DRadical Patent X DEntrepreneur BigPharma* and *DIncremental Patent X DEntrepreneur BigPharma.*
* p < 0.1, ** p < 0.05, *** p < 0.01

Moreover, we rule out the concern that our results are simply driven by the geographical proximity between the VC investor and the firm. To do so, we identified the 10 percent closest VC investor-firm dyads in our sample and run a three-way interaction model. Again, we do not see a significant difference of the AMEs of *DRadical Patent* depending on whether the firm and VC investor are geographically closely located or not. These results are available from the authors upon request.

Our next models aim at ruling out different alternative explanations at the level of the investor. In our theoretical reasoning, we argue that the dark side of the signal of patents that protect radical inventions is less troublesome for reputable VC investors, as these investors are better able to deal with the high uncertainties and costs associated with radical inventions, e.g., through syndication. One could argue that our dummy variable *DReputable Investor* does not (sufficiently) capture the risk preferences of VC investors (e.g., risk seeking/neutral/averse). Additionally, one could argue that reputable versus non-reputable VC investors generally differ in their predisposition to form syndicated ties, i.e., not just in case of an investment in young firms with patents protecting radical inventions. A generally higher willingness to take risks and/or a general preference for syndication may be alternative explanations for why reputable VCs self-select into deals that finance "riskier" inventions and why they form a syndicate.

To rule out these alternative explanations, we built two additional variables. The variable *Share_FirstRound* measures a focal VC investor's number of first round investments as a share of its total number of investments in the 5 years prior to the focal investment and qualifies as a proxy for the VC's predisposition for risk-taking, since early-stage investments are more risky than later stage investments. Indeed, later stage startup firms have a proven track record, and more information is available to investors (including information on the technology and early-stage investments). The variable *Share_Syndicated* measures a focal VC investor's number of syndicated investments as the share of its total number of investments in the 5 years prior the focal investment and proxies the VC's predisposition for syndication. We added these two variables as controls to our regression models. Table A6 reports the AMEs of *DRadical Patent* on the probabilities of a standalone investment tie and standalone or syndicated investment ties for first round and follow-on round investments. The AMEs are consistent with those displayed in our main models M1, M3, M5 and M7.[18] We also tested the robustness of our AMEs of *DRadical Patent* to the additional inclusion of the interaction terms between *Share_FirstRound* and *Share_Syndicated* with *DRadical Patent*. Again, the AMEs of *DRadical Patent* are consistent with our main models (results are available from the authors upon request).

[18] Moreover, the results from the regressions show that the variable *Share_FirstRound* is significantly positively correlated with the realization of a first round investment tie (beta=0.75, p=0.000) and significantly negatively correlated with the realization of a follow-on round investment tie (beta=-0.91, p=0.000), while the variable *Share_Syndicated* is significantly positively correlated with the realization of a syndicated investment tie compared to no investment tie formation in first round investments (beta=0.069, p=0.002) and follow-on round investments (beta=0.50, p=0.062).

Table A6 - *Average Marginal Effects of patents protecting radical inventions on the type of investment tie when controlling for the VC investor's predisposition for risk-taking and syndication*

		Model A11	Model A12	Model A13	Model A14
Sample Specification		First Round	First Round	Follow-on Round	Follow-on Round
Average Marginal Effect of DRadical Patent on	*Counter-factual*				
(1) the probability of a **realized tie** with a **reputable** VC investor	*Firms without patents*	0.009**		0.002	
		(0.003)		(0.002)	
(2) the probability of a **realized tie** with a **less reputable** VC investor		0.002		0.001	
		(0.002)		(0.001)	
(1) - (2)		0.007**		0.001	
		(0.003)		(0.002)	
(3) the probability of a **realized tie** with a **reputable** VC investor	*Firms with incremental patents only*	0.009**		0.002	
		(0.004)		(0.002)	
(4) the probability of a **realized tie** with a **less reputable** VC investor		0.002		0.001	
		(0.002)		(0.002)	
(3) - (4)		0.008*		0.001	
		(0.004)		(0.003)	
(5) the probability of a **syndicated tie** with a **reputable** VC investor	*Firms without patents*		0.009***		0.001
			(0.003)		(0.002)
(6) the probability of a **syndicated tie** with a **less reputable** VC investor			0.003*		0.000
			(0.002)		(0.001)
(7) the probability of a **standalone tie** with a **reputable** VC investor			-0.001		0.001
			(0.001)		(0.001)
(8) the probability of a **standalone tie** with a **less reputable** VC investor			-0.001		0.000
			(0.001)		(0.001)
(5) - (7)			0.010***		0.000
			(0.004)		(0.002)
(9) the probability of a **syndicated tie** with a **reputable** VC investor	*Firms with incremental patents only*		0.010**		0.001
			(0.004)		(0.002)
(10) the probability of a **syndicated tie** with a **less reputable** VC investor			0.003		0.000
			(0.002)		(0.002)
(11) the probability of a **standalone tie** with a **reputable** VC investor			-0.001		0.001
			(0.001)		(0.001)
(12) the probability of a **standalone tie** with a **less reputable** VC investor			-0.001*		0.000
			(0.001)		(0.001)
(9) - (11)			0.011**		0.000
			(0.005)		(0.002)
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 by using the delta method, leaving all variables except for the variables of interest at their observed value. To test the robustness of our main models M1, M3, M5 and M7 to the inclusion of an investor's predisposition for risk-taking and syndication, we created the variables (1) *Share_FirstRound* as the number of a focal VC's first round investments as a share of his total number of investments in the 5 years prior to the focal investment, and (2) *Share_Syndication* as the number of a focal VC's number of syndicated investments as a share of his total number of investments in the 5 years prior to the focal investment, and added these two variables as controls when rerunning models M1, M3, M5 and M7. Models A11and A12 only consider potential first round investment ties, while Models A13 and A14 only consider potential follow-on investment ties. Models A11 and A13 report the Average Marginal Effects of *DRadical Patent* on the probability of a realized investment tie. Models A12 and A14 report the Average Marginal Effects of *DRadical Patent* on the probabilities of a standalone and syndicated tie with varying investor reputation.

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

Our next two models aim at ruling out that syndication might not only help at sharing the risk between VC 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). As discussed in our theory section, radical inventions require high investment sums and complementary assets to finance the uncertain development process until commercialization. To disentangle risk sharing and resource pooling for first round VC investments, we conduct two additional analyses at the investment round level (see Table A7). First, we investigate whether the total amount of financing that a firm receives in a first round VC investment (*Round Amount (log)*) that is syndicated (*DSyndicated Deal*) is higher when the firm has patents protecting radical inventions (i.e., when *DRadical Patent*=1). Model A15 in Table A7 does not show any evidence in support of this claim. Syndicated deals are associated with higher investment amounts independent of whether firms have patents protecting radical or incremental inventions or no patents. The interaction term between *DSyndicated Deal* 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).

Table A7 - *Alternative explanations for VC syndication*

	Model A15	Model A16
Dependent variable	Round Amount (log)	Dummy Mixed Syndicate
Sample specification	First Round Deals	Syndicated First Round Deals
Empirical specification	OLS	Logit
DIncremental Patent	-0.069	0.412
	(0.349)	(0.289)
DRadical Patent	0.024	0.021
	(0.458)	(0.450)
DSyndicated Deal	0.603**	
	(0.245)	
DIncremental Patent x DSyndicated Deal	0.507	
	(0.369)	
DRadical Patent x DSyndicated Deal	0.042	
	(0.495)	
DReputable Investor (First Round)	0.780***	
	(0.150)	
Firm Age	0.002	0.050
	(0.028)	(0.050)
Forward Citations (ln+1)	0.250***	0.101
	(0.076)	(0.133)
Firm Country FE	Yes	Yes
Industry (NACE) FE	Yes	Yes
Time Period FE	Yes	Yes
Number of Investment Deals	394	348
R-Squared	0.324	
Log Likelihood	-639.438	-217.092

Note: Standard errors in parentheses are clustered by firm.
* p < 0.1, ** p < 0.05, *** p < 0.01

Moreover, VC investors might not use syndication as the only instrument to deal with the uncertainty of patents protecting radical inventions, rather they may also use other instruments (e.g., staging). We consider staging by looking at inter-round duration (Tian 2011) and running an accelerated failure time model at the entrepreneurial firm level (parametrization of the hazard rate: Weibull distribution). The results are shown in Table A8. In particular, we estimated whether the duration between the first and second financing rounds decreases for firms with patents protecting radical inventions (at the time of the first financing round). However, we do not observe that firms with such a type of patent are associated with a shorter inter-round duration. Instead, the fact that at least one reputable VC investor invested in the first round decreases the duration between the first and second rounds by 42.9 percent (Model A17).

Table A8 - *Staging*

	Model A17
Event	2nd Round
DRadical Patent (First Round)	0.719
	(0.211)
DReputable Investor (First Round)	0.571***
	(0.109)
Forward Citations (ln+1), t-1	1.027
	(0.079)
Firm Age (First Round)	1.092
	(0.045)
Baseline Hazard	504.661***
	(191.721)
Shape Parameter p	0.825***
	(0.037)
Firm Country FE	Yes
Industry (NACE) FE	Yes
Time Period FE, t	Yes
Number of Time Spans (months)	34,209
Number of Firms	702
Number of Events	241
Log-Likelihood	-723.076

Note: This table reports the results from an accelerated failure time model that estimates the time from the first to the second financing round. The baseline hazard rate is parametrized using the Weibull distribution. We report time ratios. To test the significance level of the shape parameter p, H0: p = 1. Robust standard errors are reported in parentheses.

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

Another possible alternative explanation of our results is related to the geographic distribution of firms and VC investors. 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.[19] 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 A9, 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 (10.00 percent compared to 16.04 percent; Wilcoxon-Mann–Whitney test: z=2.082; p=0.0374). 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.[20]

Table A9 - *Frequency table of investment deals in firms with at least one patent protecting a radical invention by location*

	VC Hub = 0		**VC Hub = 1**	
Panel A: VC Hubs London, Paris				
All investment deals with	N	%	N	%
DRadical Patent = 0	832	83.96	162	90.00
DRadical Patent = 1	159	16.04	18	10.00
Total	991	100.00	180	100.00
Panel B: VC Hubs London, Paris, Stockholm, Munich, Helsinki, Amsterdam, Berlin, Dublin, Copenhagen, Bonn				
All investment deals with	N	%	N	%
DRadical Patent = 0	680	83.23	314	88.70
DRadical Patent = 1	137	16.77	40	11.30
Total	817	100.00	354	100.00

[19] For example, out of the 25 VC investors with the strongest reputations (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.

[20] As additional 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.

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) by repeatedly (n=1,000) and randomly selecting from the set of counterfactual data from each young firm per investment round 10 or 5 unrealized investment ties (without replacement) instead of using all potential but unrealized ties to independent VC investors that have been active in the year of the investment round. The results of 1,000 simulations of Models 3 (first round investments) and 7 (follow-on round investments) obtained by using random sampling without replacement are shown in Table A10.

Table A10 - *Descriptive statistics of 1000 simulations with random draws of counterfactuals with replacement*

		Model 3							**Model 7**						
Sample specification		First Round							Follow-on Round						
Average Marginal Effect of Radical Patent on	Counter-factual	# Repetitions	# Unrealized Ties	# Realized Ties	mean AME	sd AME	mean p-value	# p-value >= 0.1	Repetitions	Unrealized Ties	Realized Ties	mean AME	sd AME	mean p-value	# p-value >= 0.1
the probability of a **syndicated tie** with a **reputable** VC investor	*Firms without patents*	1,000	5780	770	0.072	0.011	0.025	13	1,000	5,930	1,022	-0.004	0.007	0.752	1,000
		1,000	2890	770	0.111	0.021	0.035	48	1,000	2,965	1,022	-0.009	0.012	0.710	999
the probability of a **syndicated tie** with a **less reputable** VC investor		1,000	5780	770	0.025	0.006	0.127	524	1,000	5,930	1,022	-0.007	0.003	0.564	1,000
		1,000	2890	770	0.042	0.010	0.118	468	1,000	2,965	1,022	-0.012	0.005	0.551	1,000
the probability of a **standalone tie** with a **reputable** VC investor		1,000	5780	770	-0.023	0.003	0.053	95	1,000	5,930	1,022	-0.002	0.001	0.833	1,000
		1,000	2890	770	-0.045	0.005	0.032	22	1,000	2,965	1,022	-0.003	0.002	0.817	1,000
the probability of a **standalone tie** with a **less reputable** VC investor		1,000	5780	770	-0.016	0.002	0.086	329	1,000	5,930	1,022	0.000	0.001	0.947	1,000
		1,000	2890	770	-0.028	0.003	0.078	258	1,000	2,965	1,022	0.000	0.001	0.946	1,000
the probability of a **syndicated tie** with a **reputable** VC investor	*Firms with incre-mental patents only*	1,000	5780	770	0.078	0.014	0.041	42	1,000	5,930	1,022	-0.003	0.006	0.771	1,000
		1,000	2890	770	0.117	0.025	0.050	104	1,000	2,965	1,022	-0.008	0.011	0.707	1,000
the probability of a **syndicated tie** with a **less reputable** VC investor		1,000	5780	770	0.025	0.007	0.162	674	1,000	5,930	1,022	-0.007	0.003	0.565	1,000
		1,000	2890	770	0.040	0.011	0.158	621	1,000	2,965	1,022	-0.013	0.005	0.536	1,000
the probability of a **standalone tie** with a **reputable** VC investor		1,000	5780	770	-0.022	0.002	0.033	23	1,000	5,930	1,022	-0.002	0.001	0.826	1,000
		1,000	2890	770	-0.042	0.003	0.018	3	1,000	2,965	1,022	-0.004	0.003	0.794	1,000
the probability of a **standalone tie** with a **less reputable** VC investor		1,000	5780	770	-0.011	0.001	0.052	120	1,000	5,930	1,022	0.000	0.001	0.948	1,000
		1,000	2890	770	-0.020	0.002	0.046	66	1,000	2,965	1,022	0.000	0.001	0.947	1,000

Note: This table presents descriptive results from 1,000 simulations of Model 3 and Model 7, 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 1,000 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 investment round of a young firm, the mean AMEs of *DRadical Patent* are equal to 7.2 percent (mean p-value equal to 0.025) and 7.8 percent (mean p-value equal to 0.041) when we use counterfactual firms with no patents and 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 A18 and A19 in Table A11, 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.[21] 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 (Model A18). Moreover, we do not find any significant association between *DRadical Patent*, *DReputable Investor* and the type of investment deal in the follow-on rounds (Model A19). Furthermore, we build an alternative reputation measure considering a 3-year instead of a 5-year period prior to the focal investment (Models A20 and A21 in Table A12). We also measure VC investor reputation as the share of investments made by each investor in the 5 years prior to the focal investment relative to all the investments made by all VC investors in our sample in the same period (Models A22 and A23 in Table A12; see Pollock et al. 2015). The results are shown in Table A12 and, again, support our previous results.

[21] As mentioned earlier, the underlying distribution of VC 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.

Table A11 - *Average Marginal Effects of patents protecting radical inventions on the type of investment tie for a continuous measure of VC investor reputation*

		Model A18	**Model A19**
Sample specification		First Round	Follow-on Round
Average Marginal effect of Dummy Radical Patent on	*Counterfactual*		
the probability of a **syndicated tie** at **Investor Reputation = p90**	*Firms without patents*	0.007***	0.002
		(0.002)	(0.002)
the probability of a **syndicated tie** at **Investor Reputation = p75**		0.005***	0.001
		(0.002)	(0.001)
the probability of a **syndicated tie** at **Investor Reputation = p50**		0.004**	0.000
		(0.002)	(0.001)
the probability of a **standalone tie** at **Investor Reputation = p90**		-0.002*	-0.000
		(0.001)	(0.001)
the probability of a **standalone tie** at **Investor Reputation = p75**		-0.001*	0.000
		(0.001)	(0.001)
the probability of a **standalone tie** at **Investor Reputation = p50**		-0.001*	0.000
		(0.001)	(0.001)
the probability of a **syndicated tie** at **Investor Reputation = p90**	*Firms with incremental patents only*	0.008**	0.002
		(0.003)	(0.002)
the probability of a **syndicated tie** at **Investor Reputation = p75**		0.005**	0.001
		(0.002)	(0.001)
the probability of a **syndicated tie** at **Investor Reputation = p50**		0.004**	0.000
		(0.002)	(0.001)
the probability of a **standalone tie** at **Investor Reputation = p90**		-0.001**	-0.000
		(0.001)	(0.001)
the probability of a **standalone tie** at **Investor Reputation = p75**		-0.001**	0.000
		(0.000)	(0.001)
the probability of a **standalone tie** at **Investor Reputation = p50**		-0.001**	0.001
		(0.000)	(0.001)
Variables & Original Model Specification		**Model 3**	**Model 7**
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 3 and 7, but use a continuous specification of the reputation variable and show the Average 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 A12 - *Average Marginal Effects of patents protecting radical inventions on the type of investment tie for alternative specifications of VC investor reputation*

		Model A20	**Model A21**	**Model A22**	**Model A23**
Sample specification		First Round	Follow-on Round	First Round	Follow-on Round
Average Marginal Effect of DRadical Patent on	*Counterfactual*				
		0.009**	0.001		

the probability of a **syndicated tie** with a **reputable** VC investor (IPO 3y)	*Firms without patents*	(0.004)	(0.002)		
the probability of a **syndicated tie** with a less **reputable** VC investor (IPO 3y)		0.004**	0.001		
		(0.002)	(0.001)		
the probability of a **standalone tie** with a **reputable** VC investor (IPO 3y)		-0.002	0.001		
		(0.001)	(0.001)		
the probability of a **standalone tie** with a less **reputable** VC investor (IPO 3y)		-0.001	0.000		
		(0.001)	(0.001)		
the probability of a **syndicated tie** with a **reputable** VC investor (IPO 3y)	*Firms with incremental patents only*	0.009**	0.001		
		(0.004)	(0.002)		
the probability of a **syndicated tie** with a less **reputable** VC investor (IPO 3y)		0.004*	0.001		
		(0.002)	(0.002)		
the probability of a **standalone tie** with a **reputable** VC investor (IPO 3y)		-0.002	0.001		
		(0.001)	(0.001)		
the probability of a **standalone tie** with a less **reputable** VC investor (IPO 3y)		-0.001*	0.000		
		(0.001)	(0.001)		
the probability of a **syndicated tie** with a **reputable** VC investor (Inv 5y)	*Firms without patents*			0.008***	-0.000
				(0.003)	(0.002)
the probability of a **syndicated tie** with a less **reputable** VC investor (Inv 5y)				0.003*	0.002
				(0.002)	(0.002)
the probability of a **standalone tie** with a **reputable** VC investor (Inv 5y)				-0.001	0.000
				(0.001)	(0.001)
the probability of a **standalone tie** with a less **reputable** VC investor (Inv 5y)				-0.001	0.001
				(0.001)	(0.001)
the probability of a **syndicated tie** with a **reputable** VC investor (Inv 5y)	*Firms with incremental patents only*			0.009**	-0.000
				(0.004)	(0.002)
the probability of a **syndicated tie** with a less **reputable** VC investor (Inv 5y)				0.003*	0.002
				(0.002)	(0.002)
the probability of a **standalone tie** with a **reputable** VC investor (Inv 5y)				-0.001	0.000
				(0.001)	(0.001)
the probability of a **standalone tie** with a less **reputable** VC investor (Inv 5y)				-0.001*	0.001
				(0.001)	(0.001)
Variables & Original Model Specification		**Model 3**	**Model 7**	**Model 3**	**Model 7**
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 3and 7 but use alternative measures for the reputation of the investor. Model A20 and A21 report the Average Marginal Effects of *DRadical Patent* for the variable specification *Reputable Investor (#IPO 3 years)*; Model A22 and A23 report the Average Marginal Effects of *DRadical Patent* for the variable specification *Reputable Investor (#investments 5 years)*.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A13 - *Average marginal effects of patents protecting radical inventions on the type of investment tie when only considering lead VC investors in a deal*

		Model A24	**Model A25**	**Model A26**	**Model A27**
Sample Specification		First Round	First Round	Follow-on Round	Follow-on Round
Average Marginal effect of DRadical Patent on	*Counterfactual*				
(1) the probability of a **realized tie** with a **reputable** VC investor	*Firms without patents*	0.007** (0.003)		0.001 (0.001)	
(2) the probability of a **realized tie** with a **less reputable** VC investor	*Firms without patents*	0.000 (0.002)		0.001 (0.001)	
(1) - (2)		0.007** (0.003)		0.000 (0.001)	
(3) the probability of a **realized tie** with a **reputable** VC investor	*Firms with incremental patents only*	0.007** (0.003)		0.001 (0.001)	
(4) the probability of a **realized tie** with a **less reputable** VC investor	*Firms with incremental patents only*	0.000 (0.001)		0.001 (0.001)	
(3) - (4)		0.007** (0.003)		0.000 (0.001)	
(5) the probability of a **syndicated tie** with a **reputable** VC investor	*Firms without patents*		0.086*** (0.003)		0.000 (0.001)
(6) the probability of a **syndicated tie** with a **less reputable** VC investor	*Firms without patents*		0.001 (0.001)		0.000 (0.001)
(7) the probability of a **standalone tie** with a **reputable** VC investor	*Firms without patents*		-0.001 (0.001)		0.001 (0.001)
(8) the probability of a **standalone tie** with a **less reputable** VC investor	*Firms without patents*		-0.001 (0.001)		0.001 (0.001)
(5) - (7)			0.010*** (0.004)		-0.001 (0.001)
(9) the probability of a **syndicated tie** with a **reputable** VC investor	*Firms with incremental patents only*		0.082** (0.004)		0.000 (0.001)
(10) the probability of a **syndicated tie** with a **less reputable** VC investor	*Firms with incremental patents only*		0.001 (0.001)		0.000 (0.001)
(11) the probability of a **standalone tie** with a **reputable** VC investor	*Firms with incremental patents only*		-0.001 (0.001)		0.001 (0.001)
(12) the probability of a **standalone tie** with a **less reputable** VC investor	*Firms with incremental patents only*		-0.001* (0.001)		0.001 (0.001)
(9) - (11)			0.010** (0.004)		-0.001 (0.001)
Firm X Investor Dyads		74,766	74,766	72,582	72,582

Note: Standard errors in parentheses are clustered by investor. The average marginal effects are calculated by using the delta method, leaving all variables except for the variables of interest at their observed value. Models A24 and A25 only consider potential first round investment ties, while Models A26 and A27 only consider potential follow-up investment ties. Models A24 and A26 report the marginal effects of *DRadical Patent* on the probability of a realized investment tie. Models A25 and A27 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

Finally, we run an additional robustness check that only takes into account lead VC investors in syndicated deals. Considering non-lead VC investors might indeed create noise in the estimates. For example, if reputable lead VC investors convince non-reputable VC investors to invest in firms with patents protecting radical inventions, results would be downward biased because of realized ties between non-reputable non-lead VC investors and firms with patents protecting radical inventions. Following previous studies, lead VC investors are generally defined as any VC investor who is present in the first VC round and invests in all VC rounds (or it invests in all VC rounds up to the last one in which one of the initial investors invested). Results are shown in the Table A13. The average marginal effects of *DRadical Patent* stay robust to our main econometric specifications shown in Table 3 in the main text.

REFERENCES

Bayar, O., Chemmanur, T.J., Liu, M.H., 2019. How to Motivate Fundamental Innovation: Optimal Interactions between Entrepreneurs, Venture Capitalists, and the Government. Venture Capitalists. Working Paper. SSRN.

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

De Prijcker, S., Manigart, S., Collewaert, V., Vanacker, T., 2019. Relocation to get venture capital: a resource dependence perspective. Entrepreneurship, Theory & Practice, 43(4), 697–724.

Gompers, P. A., Gornall, W., Kaplan, S. N., Strebulaev, I. A., 2020. How do venture capitalists make decisions?. Journal of Financial Economics, 135(1), 169-190.

Gompers, P., Kovner, A., Lerner, J., Scharfstein, D. 2010. Performance persistence in entrepreneurship. Journal of Financial Economics, 96(1), 18-32.

King, G., Zeng, L., 2001. Logistic regression in rare events data. Political Analysis, 9(2), 137–163.

Sorenson, O., Stuart, T.E., 2008. Bringing the context back in: Settings and the search for syndicate partners in venture capital investment networks. Administrative Science Quarterly, 53(2), 266–294.

Tian, X., 2011. The causes and consequences of venture capital stage financing. Journal of Financial Economics, 101(1), 132-159.

Zhelyazkov, P.I., Tatarynowicz, A., 2021. Marriage of unequals? Quality heterogeneity, market heat, and the formation of status-asymmetric ties in the venture capital industry. Academy of Management Journal, 64 (2), 509–536.