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Quality signals? The role of patents, alliances, and team experience in venture capital financing

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ABSTRACT

Observable resources, particularly patents, alliances, and team experience, are known to affect a start-up's ability to attract venture capital financing. In this context they potentially fulfill a twofold function: as productive assets and, likely, as signals of characteristics of a venture that are not observable at the time of assessment. In particular, patents, alliances, and team experience may serve as signals of the unobservable quality of a venture's technology. Most existing studies based on firm-level transaction data cannot disentangle signaling from productive effects. Using a conjoint-based survey among 187 European and U.S. venture capitalists, we find they rely on research alliances and, partly, on team experience as signals of technological quality. While patents affect the venture capitalists' decision making in their property rights function, we find no indication that they serve as technology quality signals.

1. Introduction

Venture capitalists (VCs) specialize in financing young firms with a high growth potential. Such investments bear a high risk due to a lack of securities and a high level of uncertainty. In particular the start-up itself is subject to uncertainty, since for lack of a track record its quality is only imperfectly observable. Thus, in evaluating a young firm, external parties have to rely on attributes that are observable at the time of assessment and presumably correlated with further, unobserved determinants of the start-up's quality (Stuart et al., 1999).

For high technology start-ups, patents, alliances, and team experience are important instances of observable resources. In line with Spence's (1973) definition, all of them can potentially serve as signals as they are differentially costly to obtain for ventures of different quality.[1] Indeed, patents and research alliances have been argued to serve, in particular, as signals of the quality of the venture's technology (Audretsch et al., 2012; Baum and Silverman, 2004; Cao and Hsu, 2011; Conti et al., 2013; Häussler et al., 2012; Hoenen et al., 2014; Hsu and Ziedonis, 2013; Long, 2002; Mann and Sager, 2007; Stuart, 2000). Also team experience might provide a signal in this regard as a high-quality technology is more likely to attract a good team.

However, while patents, alliances, and team experience have long been recognized as relevant selection criteria for venture capital investors, actually identifying a signaling effect above and beyond the productive value of the respective resource is challenging. Most existing studies are based on firm-level transaction data and relate observable resources to venture capital funding figures. This approach provides meaningful results, however it does not allow the disentanglement of the signaling effect of these resources from their productive effect. As Mann and Sager (2007, p. 200) put it regarding patents, "we cannot untangle whether the patent or the technology that it covers best explains the results that we report." Similarly, we are not aware of any study that disentangles the signaling and productive effects of alliances and team experience. As notable exceptions, Hsu and Ziedonis (2013) and Hoenen et al. (2014) show that the effect of patents on venture capital financing is stronger in situations where signals are more urgently needed—in early funding rounds, when the venture team has no IPO experience, and when, at the IPO, the venture is not backed by a prominent VC. The authors interpret these findings as evidence of a signaling effect of patents. Yet, a clear separation of signaling and productive effects is beyond the scope of their studies since the data preclude actual ceteris paribus comparisons. Also, which quality of the start-up its patent stock actually signals—e.g., technology quality or commercial orientation—is not clear.

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[1] In Section 2.1 we explain why we emphasize signaling in the sense of Spence (1973) over decision-theoretic signaling in the interpretation of our study.

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Given the importance of high-tech start-ups for the economy, and the apparent relevance of patents, alliances, and team experience in this context, a better understanding of the role of these resources in venture capital financing is desirable from a theoretical as well as from a practical perspective. The importance of a resource as a signal has various strategic implications, in particular related to differential skills of start-ups to generate the signal and even to deliberate manipulation (e.g., Prabhu and Stewart, 2001). We thus ask: to what extent, if at all, do patents, research alliances, and team experience signal information to potential investors about the quality of a new venture's technology? And related, which of these three resource types—intellectual capital, alliances, human capital—are more important in this role?

Drawing on value appropriation and signaling theory, we develop a conjoint approach. Our research setting is the screening of business plans, the first stage of the venture capital decision making process, in which information asymmetries between entrepreneurs and VCs are high and thus signaling particularly important. We conducted a survey among 102 European VCs with an investment focus on Germany and 85 U.S. VCs, all of whom invested in high technology start-ups.[2] Participants completed a conjoint experiment in which the importance of observable start-up characteristics—patents, alliances, and the team's experience—for securing venture capital funding was tested. To isolate the signaling effect of these resources, we conducted the experiment under two scenarios. In one scenario, participants were told that the technological quality of the start-ups under consideration was unknown to them. In the other scenario, they were briefed that the firms' technologies were known to them and equally good. With the collected choice data we estimate mixed-logit models. Since no signaling regarding the start-ups' technologies is required in the scenario featuring equally good technologies, differences between the two scenarios indicate signaling effects of the respective characteristic.

Our results are surprising. Although we find a comparatively high importance of patents for securing venture capital funding, we cannot identify a signaling effect of patents. In other words, VCs value patents highly, but not as signals of the venture's technology quality. Instead, VCs seem to rely on research alliances and, partly, on team experience as signals in this regard. These findings are rather unexpected in the light of conceptual studies on a patent's signaling value (e.g., Graham et al., 2009; Long, 2002) and question received wisdom.

This study makes three contributions. First, we add to a recent stream of research on the role of observable resources in venture capital financing (Audretsch et al., 2012; Baum and Silverman, 2004; Cao and Hsu, 2011; Conti et al., 2013; Greenberg, 2013; Hoenen et al., 2014; Hsu and Ziedonis, 2013; Häussler et al., 2012; Mann and Sager, 2007). To the best of our knowledge, this study is the first to clearly separate the signaling effect of three important start-up resources from their function as productive assets, and to assess their relative importance as signals. Second, we contribute to the literature on venture capital selection criteria (e.g., Franke et al., 2008; Hall and Hofer, 1993; MacMillan et al., 1985). Third, we extend the range of applications of conjoint analysis for managerial research (e.g., Fischer and Henkel, 2013; Shepherd and Zacharakis, 1999) by combining it with a scenario approach.

2. Venture capitalists' decision making

Faced with high uncertainty and limited information in assessing new high-tech ventures, VCs need to rely on those characteristics of the start-up that are observable. They will assess the inherent value of these observable characteristics, and in addition will likely take them as a basis for drawing conclusions about unobservable characteristics of the firm. In other words, they may use observable resources as signals of unobservable quality dimensions. In the following, we first review the literature on signaling in venture capital decision making. We then turn to three specific observable resources—patents, alliances, and team experience—and discuss their functions as productive assets and as signals of the unobservable quality of a start-up's technology. Table 1 provides an overview of the pertaining studies, which are discussed in the following subsections.

2.1. Signals

Investing in young technology-based ventures is a high risk undertaking. New organizations are confronted with numerous challenges and therefore highly vulnerable, a phenomenon that Stinchcombe (1965) termed liability of newness. With their product offering still in the development phase, start-ups, especially high technology start-ups, face a high technical and commercial failure rate (Aldrich and Fiol, 1994; Tushman and Rosenkopf, 1992). In addition, start-ups are difficult for investors to evaluate since they lack a performance track record or even revenues (Penrose, 1959; Shane and Stuart, 2002).

A particular challenge for investors is to assess the quality of the new firm's technology. Information asymmetries are severe—naturally, the entrepreneurial team possesses more information about the quality of the technology than any outside investor (Shane and Stuart, 2002). "[I]nformation asymmetry", as Arthurs and Busenitz (2003, p. 147) note, "may allow an entrepreneur to engage in opportunistic behavior, more specifically, adverse selection or moral hazard [. . .] For example, the entrepreneur may attempt to 'oversell' the merits and viability of the venture [. . .] in order to secure more favorable financing terms [. . .]" Such overselling happens indeed and affects the relationship between VC and founders; as Pollack and Bosse (2014) phrase it, "[t]his information asymmetry as well as the potential for moral hazard [. . .] plagues entrepreneurs and limits the ability of potential investors to gauge the legitimacy of ventures [. . .]" Eventually, information asymmetry may hinder the establishment of an investor/start-up relationship (Leland and Pyle, 1977). In this situation, Spence's (1973) signaling theory applies.

A second reason why entrepreneurs will often overstate the merits of their venture is that they tend to be overly optimistic (e.g., Cooper et al., 1988; De Meza and Southey, 1996). This implies that some of the information needed for an objective valuation of the venture is unknown to both VC and entrepreneurs, or at least not correctly interpreted by the latter. In this case, a signal has a decision-theoretic function, providing information to both parties.

Our own interviews with VCs confirm the above effects—overselling due to asymmetric information and overstating due to over-optimism.[3] Both make external signals valuable to the VC. In the interpretation of our study we emphasize

[2] A part of this data set has also been used by Hoenig and Henkel (2012) in a study of industry differences in the use of patents and alliances as VC screening criteria.

[3] We addressed this issue with seven of our interviewees (see Section 3.1). Five of them clearly saw deliberate overselling on the part of the venture team (all quotes translated by the authors): "I think it is a principal-agent model with certain information asymmetries. Also the investors do not openly address all pitfalls in the contracts" (Interviewee 1); "Honesty: SW(OT) is often consciously omitted in selling mode" (Interviewee 2); "They regularly omit weaknesses, they always present it simpler than it is" (Interviewee 3); "The entrepreneur is in a sales pitch. Thus, positive aspects are emphasized and weaknesses are mentioned as little as possible" (Interviewee 4); "Both [conscious overselling and over-optimism] happens. In the end, the investor wants a team that can present the venture in a favorable light" (Interviewee 5). Asked about the relative importance of deliberate overselling and over-optimism, specifically with respect to the quality of the venture's

Table 1
Existing studies that discuss signals in the context of venture capital financing.

Study	Sample (location)	Method	Focus research variables	Key findings	Signaling-related results, as interpreted by the authors	Isolation of signaling effect?
Stuart et al. (1999)	301 biotech start-ups (US)	Transaction data	Alliances, patents	Positive association of strategic alliance partnerships and IPO valuations	Alliances serve as endorsement for young firms and are used by external parties to make judgments about their quality	No
Burton et al. (2002)	173 high-tech start-ups (US)	Transaction data	Team experience	Entrepreneurial experience in prominent firms positively related to the probability of attracting external financing	Entrepreneurial experience serves as a signal of the quality of the entrepreneur	No
Baum and Silverman (2004)	204 biotech start-ups (Canada)	Transaction data	Patents, alliances, team experience	All three types of resources are positively related to the amount of VC financing	Resources discussed as “signals for start-up potential,” but no differentiation between signaling and productive effects	No
Gompers et al. (2010)	9932 entrepreneurs (US)	Transaction data	Team experience	Successful experience (IPO) of the start-up team is positively related to start-up success (IPO). Also, previous success correlated with earlier VC funding	Prior success is a “public signal of quality”	No
Beckman et al. (2007)	161 high-tech start-ups	Transaction data	Team experience	Prior management experience of start-up team positively associated with ability to attract VC financing and to go public	Experience signals skill and capabilities of the management team	No
Engel and Keilbach (2007)	21,517 start-ups (Germany)	Transaction data	Patents	VC-funded firms hold higher number of patent applications at pre-funding stage than non-VC-funded firms	No direct results, but patent applications and the founders’ education levels interpreted as signals of the firm’s innovative potential	No
Heeley et al. (2007)	1413 manufacturing firms (US)	Transaction data	Patents	Patents are correlated with lower IPO underpricing in discrete technology industries and with increased underpricing in complex technology industries	In discrete technology industries patents reduce information asymmetries (signaling), while in complex technology industries the opposite holds	No
Hsu (2007)	149 technology start-ups (US)	Survey	Team experience	Prior founding experience positively related to likelihood of VC funding and venture valuation	Successful start-up experience serves as signal of entrepreneurial quality	No
Mann and Sager (2007)	1089 start-ups (US)	Transaction data	Patents	Positive correlation between patenting activity and total VC investment as well as number of financing rounds	No specific discussion of signaling vs. productive effects	No
Häussler et al. (2012)	190 biotech firms (D & UK)	Transaction data	Patents	Amount of patent applications (but not grants) positively related to early VC financing	Patents hold value both as property rights and as “seals of quality indicating a novel and inventive start-up technology”	No
Cao and Hsu (2011)	>20,000 VC-backed firms (US)	Transaction data	Patents	Pre-VC patent filings are correlated with larger VC funding and lower likelihood of failure	Results are based on informational role of patents as after VC investment patenting activity slows down	No
Conti et al. (2013)	117 start-ups (US)	Transaction data	Patents	Positive correlation of patents filed with likelihood of VC investment and amount of VC funding	Results are based on the value of patents as signals of technology quality since study is based on IT industry where patents have little productive value	No
Greenberg (2013)	188 start-ups (Israel)	Transaction data	Patents, alliances	Positive association of patent applications and alliances with firm valuation. Granted patents have larger effect than pending patents, but only for young start-ups and during early financing rounds	The event of granting constitutes a signal to investors as it reduces uncertainty	No
Hsu and Ziedonis (2013)	370 start-ups (US)	Transaction data	Patents, team experience	Positive correlation of patent stock with VC financing and IPO pricing	Stronger effect of patents in situations where quality signals are needed (lack of alternative means to convey quality, early stage of financing). Authors discuss patents as quality signals, but not specific to technology quality	Yes
Hoenen et al. (2014)	580 biotech firms (US)	Transaction data	Patents	Patent filings, but not granted patents, have a positive effect on the amount of first-round VC investments. No effects of either filings or granted patents on second-round VC investments	“As firms mature and information asymmetries [. . .] decrease, the signaling value of patent activity diminishes [. . .]”	Yes

Spencian (1973) signals, for two reasons. First, our interviews confirm that the entrepreneurs' lying to investors matters. Furthermore, over-optimism is considered to be less pronounced with respect to technology quality—the focus of our study—than with respect to the venture's overall prospects. Thus, for technology quality the issue of deliberate overselling becomes relatively more important. Second, information asymmetries matter more insofar as they affect the entrepreneur's behavior, inducing him or her to engage in activities that create the signal.[4,5]

According to Spence's (1973) signaling theory, the better informed party can send a signal of quality to the less informed party in order to reduce information asymmetries. Spence (1973) uses an example of the labor market, where job candidates obtain education to signal productive capabilities to potential employers. Signals provide a sorting mechanism in case of uncertainty or, in other words, help form opinions by serving as indicators for unobservable characteristics (Kirmani and Rao, 2000). In order to be effective, signals need to be observable and costly (Spence, 1973). Observability describes the extent to which outsiders are able to notice the signal; cost refers to the condition that the costs of signaling must be lower for parties of higher quality. For instance, it should be less costly for a high quality manufacturing firm to obtain an ISO 9000 certification than for a low quality manufacturer. Importantly for our case, while signals are often sent intentionally, parties may also send signals without being aware of it (Janney and Folta, 2003; Spence, 2002).[6]

Signaling theory holds a prominent position in entrepreneurship literature and applies well to the context of venture capital financing (Connelly et al., 2011). Since the quality of a start-up often cannot be observed directly, VCs have to rely on other sources of information, in particular on observable characteristics of the new venture (Stuart et al., 1999). VCs spend a substantial amount of time and effort on seeking and assessing these signals of a start-up's quality and potential (Amit et al., 1990; Hall and Hofer, 1993). At the same time, entrepreneurs facing the challenge of securing resources for further development invest in observable characteristics to signal the quality of their venture (Zott and Huy, 2007).

2.2. Patents

Up until the 2000s, intellectual property rights have been acknowledged as a relevant, but not very important, venture capital selection criterion (e.g., MacMillan et al., 1985). Only recently, the attention toward patents has increased with a number of studies, all based on transaction data, indicating a positive relationship between the existence of patents and venture capital financing of start-ups. Baum and Silverman (2004) demonstrate that biotechnology start-ups in possession of patent applications or patent grants receive more venture capital financing than ventures without patent protection. A study by Hsu and Ziedonis (2013) in the semiconductor industry yields similar results in that the number of patent applications a start-up holds is shown to drive its financial evaluation by VCs, especially in early funding rounds.

Examining a sample of mostly information technology start-ups from an incubator at Georgia Institute of Technology, Conti et al. (2013) find that the number of patents filed by a start-up is positively related to the likelihood of venture capital investment and the amount of funding received. For a U.S.-based sample of venture capital-backed firms from various industries, Cao and Hsu (2011) show that pre-venture capital patent filings are correlated with larger venture capital funding and lower likelihood of failure. Mann and Sager (2007) find positive correlations between patenting activity and several performance variables such as number of financing rounds or total investment for a sample of software start-ups. Analyzing a sample of German ventures, Engel and Keilbach (2007) notice that venture capital-funded firms hold a larger number of patent applications at pre-funding stage than non-venture capital-funded firms. Häussler et al. (2012) are able to prove that biotech start-ups are likely to receive venture capital earlier in cases of existing patent applications and particularly if these patents turn out to be of high quality. Greenberg (2013) finds a positive association of patent applications with firm valuation. This effect is more pronounced for granted than for pending patents, but only for the younger start-ups in her sample and during early financing rounds. Finally, empirical results by Audretsch et al. (2012) suggest that nascent ventures possessing patents have a higher probability of obtaining equity finance from VCs, but only if they possess a prototype at the same time.

The above-mentioned impact of patents on venture capital financing is explained with the two main functions of a patent for technology-based start-ups: property rights and quality signals. Regarding its productive function as a property right, a patent constitutes a legal right to exclude others from using an invention. As such, patents support the appropriation of returns from innovative activities and facilitate cooperation and bargaining with business partners (e.g., Cohen et al., 2000; Hall and Ziedonis, 2001). Indeed, a positive correlation of patent ownership and stock market valuation can be observed in general (e.g., Hall et al., 2007). Furthermore, patent ownership correlates with the business performance of start-ups in terms of asset growth (Helmers and Rogers, 2011), short time to initial public offering (IPO) (Stuart et al., 1999), and an increased likelihood of survival after IPO (Wagner and Cockburn, 2010). Additional (trade) value to both entrepreneurs and VCs may result from the possibility of selling property rights to third parties.

A patent can represent a Spencian signal of the quality of a start-up's technology as it is differentially costly to obtain and directly observable by outsiders (Long, 2002).[7] Technology entrepreneurs are well aware of the signaling value a patent may have to VCs, and report to engage in patenting activities to increase their chances of securing investment (Graham and Sichelman, 2008). The comprehensive examination by the patent office works as a certification mechanism (Häussler et al., 2012),[8] implying that granted patents

technology, one interviewee (3) quantified it as "50/50." Referring specifically to serial entrepreneurs in the U.S., Interviewee 2 noted that their overstating the venture's qualities is "rather tactics than ignorance or over-optimism." Interviewee 6 only saw little overselling ("Weaknesses are indeed downplayed by founders that are financed"; "a slight exaggeration also happens for the technology"), while Interviewee 7 saw none ("I would not say that weaknesses are consciously omitted; rather, the founders overestimate the value of their product or technology idea").

[4] Note that many common examples of Spencian signals contain elements of decision-theoretic signals, i.e., they provide information also to the sender. Obtaining a university degree with a certain grade, e.g., not only provides a signal to potential employers but also additional information to the graduate about his or her capabilities.

[5] Also most earlier studies on the topic (Audretsch et al., 2012; Cao and Hsu, 2011; Conti et al., 2013; Häussler et al., 2012; Hoenen et al., 2014; Hsu and Ziedonis, 2013; Long, 2002) are framed within Spence's (1973) signaling theory—without, however, discussing the question of Spencian versus decision-theoretic signals and why the former provides the more appropriate framing.

[6] In statistical terms, the quality of the technology represents the hidden or latent variable, while a start-up's resource constitutes a proxy from which the value of the hidden variable can be inferred, albeit with uncertainty (e.g., Bartholomew and Knott, 1999; Upton and Cook, 2002).

[7] We point out that, in contrast to some existing studies that use the term signaling more broadly in the sense of patents as indicators of future performance, we apply a narrower definition, in line with Spence (1973). We investigate the function of patents as a signal of the presently existing but unobservable quality of a start-up's technology (as, e.g., Conti et al., 2013).

[8] Häussler et al. (2012) argue that signaling on the part of the start-up and certification on the part of the patent office complement each other in providing information to potential investors. This certification may also provide new information to the entrepreneurs, and thus work as a decision-theoretic signal to both

can also serve as signals in the decision-theoretic sense. But even before the patent office makes a decision, a patent application can work as a proxy for technological quality (Baum and Silverman, 2004; Hsu and Ziedonis, 2013). We note, though, that differing opinions exist. In analyzing the effect of patent filings on IPO underpricing in the United States, Heeley et al. (2007) conclude that patents in complex product industries fail to provide a positive signal to equity investors.

The signaling function of patents is difficult to disentangle from their productive function. To our knowledge, only two studies provide evidence in this regard. Hsu and Ziedonis (2013) show for a sample of semiconductor start-ups that patent stock has a stronger positive effect on venture capital financing and IPO pricing in situations where signals are more urgently needed—when the founding team lacks reputation, the firm is in early rounds of financing, or the start-up lacks prominent investors at the IPO. Even more pronounced, using a longitudinal data set of biotech firms Hoenen et al. (2014) find that patent applications have a positive effect on venture capital financing during the first round of financing but not in the second. Since the effect of a patent's productive value on venture capital financing should, if anything, increase in later rounds (due to increasing complementarities with other resources), the authors interpret their findings as evidence of a signaling effect of patents.

Yet, a clear separation and comparison of signaling and productive effects is beyond the scope of these studies since the comparisons they are based on are not ceteris paribus comparisons. Also, which quality of the start-up its patent stock actually signals is not addressed. Our research addresses this gap, aiming to determine to what extent, if at all, patents serve as signals of the quality of a new venture's technology.

2.3. Alliances

Alliance agreements entered into by a start-up represent another important investment criterion for VCs. Not only linkages with banks or investors, but also strategic alliances, i.e., affiliations with other productive organizations, can have a substantial impact on the opportunities and constraints a new venture faces (Gulati and Higgins, 2003). Studies based on venture capital transaction data show that the number of alliances a start-up possesses is positively related to the amount of venture capital financing it receives (e.g., Baum and Silverman, 2004; Greenberg, 2013). We focus on upstream alliances, to pursue R&D, and downstream alliances, agreements with organizations down the value chain such as sales partners (e.g., Baum et al., 2000).[9] Just like patents, alliances may incorporate a productive as well as a signaling component.

Regarding the productive value, prior research shows that organizations with reputable networks of alliances benefit from collaboration and are therefore likely to outperform others. Alliances improve access to complementary resources (Chung et al., 2000). For example, a downstream agreement with a sales partner can help a start-up bring its innovative product to market. Similarly, Liebeskind et al. (1996) show that upstream alliances, e.g., with universities or other research institutes, secure valuable access to knowledge and other assets. Such assets can enable a new venture to develop technological knowledge that it could not have generated by itself (Santoro and Gopalakrishnan, 2000). Furthermore, alliances provide access to information and can thus help firms discover and exploit business opportunities (Cohen and Levinthal, 1990). Investigating the benefits of alliances for new ventures, Baum et al. (2000) find evidence that biotechnology start-ups that are able to quickly establish both upstream and downstream alliances achieve significant performance improvements during their early years of business.

With respect to the signaling function, alliances may also serve as legitimation for the new venture (Baum and Oliver, 1991; Miner et al., 1990) and consequently facilitate the acquisition of other resources such as venture capital. As potential signals of technological quality, upstream alliances, ideally with reputable research institutions or large innovative firms, are particularly relevant (Pisano, 1991). To protect their own reputations these organizations need to be selective in choosing alliance partners, and so being selected conveys a positive signal to outsiders (Stuart, 2000). In contrast, downstream relationships with sales partners or pilot customers, if they serve as quality signals at all, will relate to a broad range of quality dimensions and not specifically to the company's technology. In fact, the latter should play a very minor role in this context since a technology typically marks the beginning of a high-tech venture's value creation, while sales alliances relate to the end of this process. We thus do not expect them to exhibit a signaling effect, and use "sales alliance" as a robustness check of our method.

In line with Spence's (1973) signaling theory, alliances involve costs as a differentiator in the sense that it is easier for a high quality than for a low quality start-up to gather alliance partners. In particular, having a high-quality technology will strongly facilitate entering into an up-stream, R&D-oriented alliance. Furthermore, alliances are observable for external parties as long as they are recorded in a written agreement (and the start-up is willing to disclose this information). Thus, alliances are valid Spencian signals,[10] and third parties should refer to the affiliates of new ventures to make judgments about their quality whenever they cannot observe it directly (Stuart et al., 1999). In particular, if the quality of a start-up's technology is unknown, we propose that upstream alliances come into consideration as quality signals.

As for patents, disentangling the productive from the signaling effect of upstream alliances is challenging using transaction data. Using a different approach, we thus ask to what extent, if at all, upstream alliances serve as signals of the quality of a new venture's technology.

2.4. Team experience

A popular saying in the venture capital industry states that VCs would rather invest "in a grade A team with a grade B idea than in a grade B team with a grade A idea" (e.g., Bygrave, 1997).

parties. We argue, however, that the role as Spencian signals is dominant since founders of a technology-based start-up should normally know much more than a VC about novelty and inventive step of their invention. This argument is supported by our finding that the signaling effect of a patent application—which is solely based on information known to the start-up team—amounts to two thirds of that of a granted patent (which is thus based to *at least* two thirds on information known to the start-up team). Findings by Häussler et al. (2012) and Hoenen et al. (2014) regarding the signaling effect of pending patent applications support this argument. We further note that certification—through exams and grades—is also part of Spence's (1973) classical example of job market signaling.

[9] Note that by focusing on upstream and downstream alliances we do not consider horizontal alliances in our analysis. Upstream and downstream alliances are often regarded as most important forms of collaboration for technology start-ups and have both, in contrast to horizontal alliances, been shown to positively affect start-up performance (e.g., Baum et al., 2000).

[10] They may also have an element of decision-theoretic signals, since the fact that a research organization is willing to enter into an alliance agreement may provide new information also to the start-up team. However, most of the new information that a VC gleans from the existence of a research alliance should already be known to the start-up team. Establishing a research alliance will require that the start-up team convinces the prospective alliance partner of the value of its technology. While the potential partner may have background information that the start-up lacks, the start-up will still be more familiar with the technology and will likely know better about prospects of future development and potential risks; otherwise there would be little incentive for the other party to engage with the start-up in the first place.

Scholarly studies confirm this view, consistently finding criteria related to the start-up team among the top three evaluation criteria of VCs (Franke et al., 2008; Zacharakis and Meyer, 2000). Team experience in particular is seen as a desirable characteristic, and significantly increases a start-up's chances of receiving venture capital funding (e.g., Franke et al., 2008; Hsu, 2007). Depending on the study, authors identified management and marketing experience (Goslin and Barge, 1986), sector-specific managerial experience (Dixon, 1991; Franke et al., 2008; Muzyka et al., 1996), leadership experience (Franke et al., 2008), and experience with (successful) prior ventures (Gompers et al., 2010) as relevant. Also other team characteristics valued by VCs such as management skills and history (Tyebjee and Bruno, 1981), leadership potential (Muzyka et al., 1996), industry-related competence (Shepherd, 1999b), and familiarity with the target market (MacMillan et al., 1985) have a strong element of experience, and thus further confirm the latter's importance to VCs. Kaplan et al. (2009) find that the stated importance of the team's expertise relative to that of the business and the market declines as a firm matures. Since we focus on an early stage, their results support our treating the team's experience as one of the most important variables.

We argue that also team experience has both a productive and a signaling value for VCs. General experience should have a productive value since an experienced team is more proficient in problem solving, has entrepreneurial process knowledge, and may bring network connections helpful in developing the venture (Hsu, 2007). In addition, with experience in the focal industry the team possesses relevant knowledge of and possibly relationships with customers and suppliers (Gimeno et al., 1997), better understands how to manage industry specific product development processes (Behrens et al., 2012), and can more quickly grasp opportunities that require industry specific skills for their recognition (Feeser and Willard, 1990). Prior experience also facilitates the founding team's obtaining relevant resources through creating organizational legitimacy (Packalen, 2007, and references therein).

The signaling function of new venture team characteristics and actions has received comparatively little attention. Busenitz et al. (2005) study signals that new venture teams send by investing into their own venture; Hsu (2007) finds that, under some circumstances, the team's formal education (specifically, a doctoral degree) may serve as a signal, as may foregoing high value alternatives; and Elitzur and Gavious (2003), using a game theoretic model, show that the entrepreneur sends a positive signal to VCs by approaching an angel investor. Behrens et al. (2012) argue that managerial human capital constitutes a signal of managerial competence to investors, but given the close causal link between the two one might consider the effect a productive rather than a signaling one.

The value of team experience as a signal for less directly related, unobservable characteristics of the venture has, to our knowledge, not been studied. It seems plausible though that the new venture team's experience can serve as such a signal, and specifically of the quality of the firm's technology.[11] The argument resembles that made for alliances (Stuart, 2000). More experienced individuals should have a larger choice on the labor market, so their joining the nascent new venture—typically at a time when the venture is characterized by little more than its raw technology and the core team members—works as an endorsement. In turn, it should be less costly for a core new venture team with a high-quality than with a low-quality technology to recruit experienced additional members. As for patents and alliances, identifying a signal effect of team experience based on observational data is inherently difficult.

While team experience is a multi-dimensional construct, our methodological approach requires focusing on one of its dimensions. We thus pose our third research question: to what extent, if at all, does industry specific experience of the new venture team serve as a signal of the quality of a new venture's technology?

3. Data and methods

3.1. Conjoint analysis

In order to shed more light on the role of signals in venture capital financing, we conducted conjoint experiments[12] with venture capital investors, an approach used earlier by various authors (e.g., Franke et al., 2006, 2008; Riquelme and Rickards, 1992; Shepherd, 1999a; Zacharakis and Meyer, 1998). In our experiment, respondents are repeatedly (12 times) presented with a set of three hypothetical start-ups and directed to pick the one they are most likely and the one they are least likely to finance. By analyzing the revealed preferences, one can draw conclusions about the importance that participants attach to the different attributes.

We chose to employ this approach for three reasons. First, the use of conjoint analysis provides advantages over post hoc methodologies (Shepherd and Zacharakis, 1999; Zacharakis and Meyer, 1998). Shortcomings of traditional Likert scale surveys such as inflation of importance or biases due to individual response styles are avoided (e.g., Stening and Everett, 1984), and the respondent is not required to understand his or her own decision process (Zacharakis and Meyer, 1998). Second, choice experiments come close to real-life decision situations, and thus help to increase both the validity and the response rate of surveys.[13] Third and most important, our experimental setup excludes omitted variable biases by construction, and allows to isolate the desired signaling effect experimentally (e.g., Sprinkle, 2003).

It is an important issue in conjoint experiments to make them as realistic as possible, while making sure they are easy to understand and manageable for the respondents in terms of complexity and timing. Thus, it is imperative to clearly define the setting of the experiment and account for relevant variables only. We decided to focus on the screening stage, in which VCs select start-ups based on written business plans for further consideration. This stage is not only highly relevant for both VCs and entrepreneurs, but also well suited for a conjoint experiment, as evaluating conjoint cards comes relatively close to evaluating executive summaries of real business proposals (Franke et al., 2008). To be able to interpret the results correctly, we had to make sure that all respondents have a common reference setting in mind. Therefore, at the beginning of the experiment we introduced the general screening situation and provided a short description of the type of start-ups to be assessed (Fig. 1). This introduction had been repeatedly tested and refined in our expert interviews (see below). Note that the three firms in a choice set[14] compete on technologies that are close substitutes (and

[11] Since the information that team experience provides to the VC is based on the team members' decision to join the start-up, and thus on information known to the team members, the case of team experience is entirely one of asymmetric information.

[12] Our approach is similar to choice-based conjoint experiments, also known as discrete choice experiments. In such experiments, respondents are asked to repeatedly select their preferred option out of a set of only few stimuli (Elrod et al., 1992). Our approach constitutes a combination of this method (since respondents are repeatedly shown sets of only few stimuli and are asked to select the most and the least preferred option) with traditional full ranking methods (since respondents effectively rank all stimuli in each set).

[13] We indeed achieved very high direct response rates of 40% and 20% as explained later.

[14] In line with the literature (e.g., Chapman and Staelin, 1982) we use the term "choice set" even though respondents rank all alternatives in the set rather than choosing only the most preferred one.

Several technology start-ups present their business plan to you in order to apply for venture capital funding. They all have the same background as described below:

- Venture based on a technical invention
- Industry: Biotechnology*
- Clearly visible value proposition
- Potential users: Industrial firms
- A working prototype exists
- Applying for early stage financing

* The start-up industry was adjusted to the individual VC's previously stated area of expertise. Alternatives were biotechnology, clean technology (technical equipment), or information and communication technology (hardware).

Fig. 1. Reference setting as presented to participants.

possibly equally good) but not identical, so there is no exclusivity in the sense that a firm owning a patent could exclude the others from the market. Also, it is possible that all three own a patent.

The decision to focus on the screening stage narrows the choice of venture capital investment criteria insofar as only codifiable start-up attributes can be included in the experiment. For instance, the amount of management experience in years can be read from a written business plan, whereas the actual management skills of the team leader cannot be observed on paper. Moreover, investors evaluating business proposals will rather rely on objective characteristics, e.g., written alliance agreements,[15] as opposed to more subjective and ambiguous attributes such as "a large number of potential customers." Most business plans feature estimated financial figures such as market size and growth; however, since our research interests are centered on the resources of new ventures, we exclude any financial criteria from the experiment.

As discussed in the preceding section, prior research suggests that VCs rely on three types of start-up resources in the screening process: human, alliance, and intellectual capital. To make sure we only use variables that are relevant in practice, we conducted a pilot study that included the analysis of the relevant academic and practice-oriented literature, business plan competition guidelines, and interviews with venture capital experts, among them eight active VCs, three entrepreneurs, and nine venture capital scholars. After thorough discussions around key screening criteria and their realistic levels, we arrived at three observable start-up characteristics for our analysis: patent protection, written alliance agreements, and the start-up team's experience. For each attribute, we included three different levels in the experiment, making sure that all possible combinations of attribute levels were reasonable and realistic (Table 2).[16]

To reduce the full fractional design of $3^3 = 27$ possible combinations to a manageable number of six choice sets, we relied on an efficient fractional–factorial design generated by computerized search (Yu et al., 2009).[17] In each of the six choice sets, respondents were presented with three hypothetical start-ups and asked to select the one they would most likely and least likely, respectively, fund with venture capital. Fig. 2 depicts a choice set as presented to the survey participants.

Table 2
Start-up attributes and levels.

Attribute	Levels	Description
Patent protection	None (reference) Patent applied for Patent granted	Patent protection for the start-up's core technology, covering all relevant regions and territories
Alliances	Set of verbal agreements (reference) One written research agreement One written sales agreement	Established relationships with reputable business partners, based on a research agreement (e.g., with universities, research institutions) or sales agreement (e.g., with pilot customers, sales partners)
Team's relevant management experience	2 years (reference) 5 years 10 years	Average years of experience per team member working in a management position at a company in the respective industry

To isolate the signaling effect of patents, we conducted the experiment under two different scenarios, each containing the same six choice sets in random order. This led to a total of twelve choice sets to be addressed by each respondent. The two scenarios differed only in one respect. In the scenario "technologies unknown" VCs were briefed that they were not familiar with the quality and uniqueness of the presented start-ups' technologies, whereas in the scenario "equally good technologies" the technologies of the presented start-ups were described as equally good and known to the investor. Differences in attribute importance between the two scenarios can be interpreted as signaling effects of the firms' observable characteristics. For illustration, consider the variable "patent granted." Lacking information about the start-ups' technologies, respondents are assumed to value a start-up's patent both as a property right and as a signal of the unobservable technological quality. In contrast, in the case of "equally good technologies" VCs should value patents only for their productive function, since the technological quality of all alternatives is equal by assumption. The same reasoning applies to alliances and team experience. Thus, differences in value contribution of our focal variables can be interpreted as signaling effects with respect to the quality of a start-up's technology.

The use of controlled experiments involving the manipulation of available information is a well-established approach used across all kinds of scientific research fields to answer questions that otherwise might go unanswered (e.g., Sprinkle, 2003). Scenario-based studies are one subgroup of experiments that are frequently employed to study managerial issues in, for instance, the areas of marketing and operations management (see Rungtusanatham et al., 2011; Wason et al., 2002 for overviews). To introduce respondents to the hypothetical situation in which they are supposed to act, they are typically presented with a "scenario" (Wason et al., 2002) or "vignette" (e.g., Alexander and Becker, 1978). By reproducing a real-life decision-making situation, a well-constructed scenario enhances respondent involvement and increases the experiment's internal validity by bringing all participants onto the same page and focusing their attention on the main features of the research (Cavanagh and Fritzsche, 1985; Fredrickson, 1986). In most applications, different versions of the same basic scenario are designed by altering only one piece of information and then randomly allocated to different respondents, thus allowing for investigating intergroup differences (Alexander and Becker, 1978).

[15] Written alliance agreements may not be disclosed to the public, but it is highly plausible that the founders will find it advantageous to disclose their existence to a VC whom they approach for funding.

[16] The attribute levels we choose for patents (none, one patent applied for, one patent granted) may appear low, however, they are fully realistic. Häussler et al. (2012) report a mean of 0.46 for the time-varying binary variable "EPO application," which implies that 54% of the firm/quarter observations in their sample have no patent. Hoenen et al. (2014) report a mean of 0.18 for the number of patent applications filed by the biotech firms in their sample from foundation to the first round of investment (and not yet granted at the time of that investment), and an average number of 0.12 granted patents for the same period.

[17] The design was generated using the software package NGene 1.0 by ChoiceMetrics, Ltd.

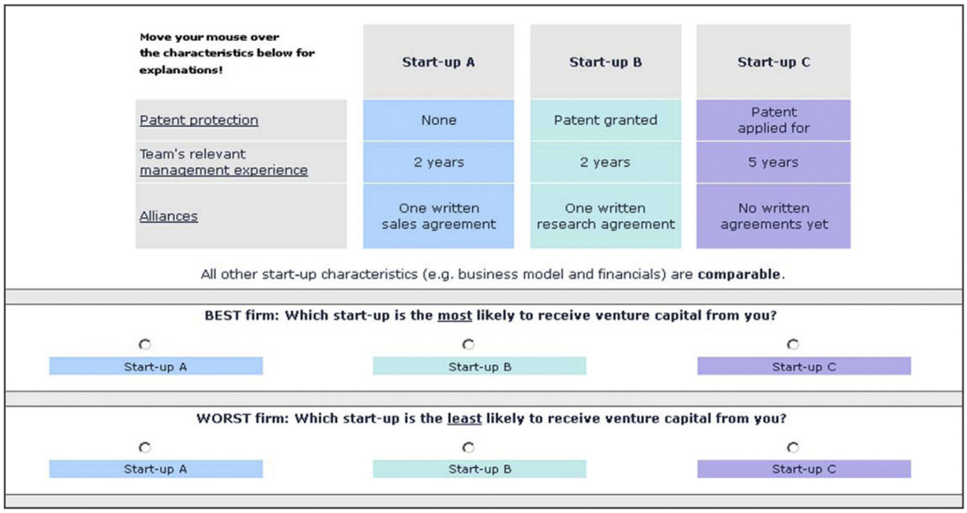

Fig. 2. Choice set as presented to participants.

Results from numerous studies in different managerial research fields show that when the scenarios are appropriately designed and validated, scenario-based experiments are an effective method for studying managerial decision making (e.g., Wason et al., 2002; Rungtusanatham et al., 2011).

For the purpose of our survey, an extensive pretest confirmed that the experimental setting including its variables and scenarios was understandable, realistic, and manageable within the suggested time frame. While the survey contained both scenarios ("technologies unknown" and "equally good technologies") for all respondents, the introduction for each scenario was illustrated with a brief example and highlighted with a different color in order to ensure internal validity and increase respondents' attention. To avoid biases, we created six different versions of the survey that differed by the order of scenarios, choice sets, and start-up attributes, and randomly assigned one version to each participant.

3.2. Sample

Our overall sample consists of 187 individual VCs from Germany and the United States. In preparation, potential respondents had been identified by searching industry associations (Bundesverband Deutscher Kapitalbeteiligungsgesellschaften–German Private Equity and Venture Capital Association [BVK], European Private Equity and Venture Capital Association [EVCA], U.S. National Venture Capital Association [NVCA]), press releases, and venture capital fund websites, making sure our population was currently active and invested in high technology start-ups at early stages. Per venture capital firm, we randomly chose a maximum of three technology-focused investment professionals to be entered into our database, leading us to a total number of 233 potential individual participants in Germany, and 285 in the U.S. Relevant VCs were first contacted by phone to establish a personal contact and to explain the conjoint experiment. Immediately afterward, we provided these investors with the link to the online survey by e-mail. A reminder was sent two to three weeks after the initial contact. As VCs have a busy schedule, we tried to design our survey to be as convenient and interesting as possible by making it available online, asking for limited demographic information only, and providing a straightforward but entertaining experiment.[18] We conducted our survey with German VCs during the first quarter of 2011 and received 110 answers in total, 102 completing the entire survey. Checking for nonresponse bias, we could not find any demographic differences between participating and non-participating VCs, neither in terms of fund size, hierarchical position, nor industry focus. With a direct response rate of 40%[19] and answers stemming from 80 different venture capital firms our sample should, thus, be representative of the German-speaking venture capital market. U.S. VCs were invited to participate in our survey during the third quarter of 2011, leading to 85 answers that all covered the entire survey. A direct response rate of 20%,[20] participants from 68 different venture capital firms, and the absence of any significant differences between respondents and non-respondents make us confident that this sample is representative of the U.S. venture capital industry. Table 3 shows that both samples contain VCs with a large variety in expertise, background, and funding experience.

3.3. Estimation

Since we asked respondents in each choice set for the start-up they would most likely fund and the one they would least likely fund, they provided us with a complete ranking of the ventures in each choice set. Beggs et al. (1981) and Chapman and Staelin (1982) were the first to present a method to analyze this kind of rank-ordered data by exploding it. More precisely, the ranking of three alternatives is decomposed into two choices: first choosing one out of three alternatives and then choosing the better of the two remaining alternatives. In our experimental setting, every respondent makes 12 choices per scenario, six times selecting the best out of three available start-ups and six times picking the better of the remaining two start-ups. What we refer to as a "choice set" in this subsection, thus, contains either three or two stimuli.

The decomposed data could then be fitted with McFadden's (1974) conditional logit model. However, estimating a conditional logit model based on (decomposed) repeated choice data is questionable in light of the assumption of independence of irrelevant

[18] As a matter of fact, we received much positive feedback on the research topic and survey design. On average, it took respondents less than 15 min to complete the survey. We believe that focusing on survey convenience and establishing a personal contact by phone was crucial to achieving a high response rate, which is considered very difficult in surveys among VC investors (Muzyka et al., 1996).

[19] Out of 233 VCs invited, 94 (40%) responded directly. Sixteen participants received the link from a colleague or other contact.

[20] 56 out of 285 VCs (20%) invited responded directly.

Table 3
Demographics of VC individuals.

	German sample (n = 102)	US sample (n = 85)
VC experience (# of start-ups funded)	Range: 1 to >20; median: 8	Range: 1 to >20; median: 10
Position	Partner: 36; principal: 22; associate: 19; senior advisor: 8; other: 15, no answer: 2	Partner: 33; principal: 19; associate: 31; senior advisor: 0; other: 2, no answer: 0
Education[a] (type of degree)	Business: 72; engineering: 30; science: 24; law: 3; other: 6	Business: 61; engineering: 22; science: 26; law: 0; other: 0
Industry focus[b]	Biotech: 29; cleantech: 34; ICT: 39	Biotech: 27; cleantech: 16; ICT: 42
Type of VC firm	Private: 70; corporate: 12; public: 14; business angel: 0; other: 6	Private: 80; corporate: 2; public: 2; business angel: 0; other: 1
VC fund size (in €/$)	<101 mio: 47; 101–500 mio: 39; >500 mio: 8; no answer: 8	<101 mio: 15; 101–500 mio: 37; >500 mio: 32; no answer: 1

[a] Multiple answers possible.
[b] As selected for experiment.

alternatives (IIA) underlying this model.[21] Mixed logit, a.k.a. random coefficient models, are extensions of conditional logit models that do not require the IIA assumption (McFadden and Train, 2000; Revelt and Train, 1998). Hence, we rely on a rank-ordered mixed logit estimator for the analysis of our venture capital choice data.

As proposed by Revelt and Train (1998), Hole (2007) and Fischer and Henkel (2013), we model the utility of alternative j in choice set t for respondent n in scenario s as a linear additive function of the alternative's observable characteristics, described by the vector x^s_{njt}, and additionally its technology quality, described by the scalar q^s_{njt}. The vector β_n and the scalar γ_n are participant-specific coefficients. The error terms ε^s_{njt} are assumed to be independently and identically distributed and to follow an extreme value distribution.

$$U^s_{njt} = \beta'_n x^s_{njt} + \gamma_n q^s_{njt} + \varepsilon^s_{njt} \quad (1)$$

Conditional on the participant-specific coefficients β_n and γ_n, the probability that respondent n selects alternative i from choice set t in scenario s can be expressed as:

$$L^s_{nit}(\beta_n, \gamma_n) = \frac{\exp[U^s_{nit}]}{\sum_{j=1}^{J} \exp[U^s_{njt}]} \quad (2)$$

In the scenario with equally good technologies ("ET"), technology quality is by definition constant across alternatives, $q^{ET}_{njt} \equiv q_0$. As a result, the terms $\gamma_n q^s_{njt}$ in Eq. (2) cancel out, allowing us to estimate β_n using STATA's mixlogit command (Hole, 2007). In contrast, in the scenario where technologies are unknown ("TU"), respondents use the available information contained in x^{TU}_{njt} as signals, or proxies, for the unobservable technology quality, q^{TU}_{njt}. We assume a linear relationship, $E[q^{TU}_{njt}|x^{TU}_{njt}] = \delta'_n x^{TU}_{njt}$. Using this expected value for q^{TU}_{njt} in the TU scenario, we obtain:

$$L^{TU}_{nit}(\beta_n, \gamma_n) = \frac{\exp[(\beta'_n + \gamma_n\delta'_n)x^{TU}_{nit}]}{\sum_{j=1}^{J} \exp[(\beta'_n + \gamma_n\delta'_n)x^{TU}_{njt}]} \quad (3)$$

As explained by Hole (2007), the (not respondent-specific) regression coefficients are obtained by calculating the probability of the entire sequence of 12 choices, integrating it over the distribution of the respondent-specific coefficients, summing it up over all respondents, and maximizing it. As a result, in the TU scenario we estimate $\beta + \gamma\delta$, while in the ET scenario we determine β, which allows us to identify $\gamma\delta$. This vector is a convolution of the vector of "signaling" coefficients, δ, and the unknown technology quality coefficient, γ. However, since the latter is a constant factor that we can safely assume to be positive—technology quality matters for VCs—its presence does not hinder the identification and comparison of signaling effects. While direct identification of $\gamma\delta$ is precluded because coefficients cannot directly be compared across non-linear models as explained below, the approach to teasing out $\gamma\delta$ carries through when we compare the average marginal effects (AMEs) across the models.

Since all start-up attributes are described by three levels, we coded each attribute into two dummy variables that indicate the deviation from the reference value. For ease of interpretation, we used the level with the presumably lowest benefit contribution per attribute as reference value: no patents, two years of experience, no written alliance agreements yet (see Table 2).

3.4. Scenario comparisons

To test for differences between the scenarios, we employ an approach suggested by Long (2009) and recently implemented by Fischer and Henkel (2012), which consists in comparing predicted probabilities.[22] We first determine a particular dummy variable's marginal effect for each scenario separately. The marginal effect of dummy variable X is defined as the difference in predicted probabilities that a hypothetical start-up A in a given choice set is chosen as best when X is switched from 0 to 1 (e.g., Hoetker, 2007), for instance from "no patent" to "patent granted." As the size of the marginal effect of X depends on both the other attributes of start-up A and all attribute levels of the two competing start-ups in the choice set, we calculate the marginal effect of X for all possible combinations of the two other attributes of start-up A and the attributes of the two competing start-ups.[23] This results, for each scenario, in $3^2 \times 3^3 \times 3^3 = 6561$ marginal effect values for each dummy variable.

We then isolate the signaling effect of a variable on technology quality by subtracting from its AME in the "technologies unknown" scenario (where signals are valuable) its AME in the "equally good technologies" scenario (where no signals are needed). In a second step, we need to assess if the differences in AMEs between the scenarios are significantly different from zero. To that end, we employ a simulation approach to measure the variance of marginal effects (King et al., 2000; Zelner, 2009).[24]

[21] According to the IIA assumption, the error terms of each respondent's choice of alternatives would have to be independently and identically distributed. This assumption, however, is likely violated with data from choice experiments, as respondents' preferences will influence the error terms in their various choice decisions in a similar way (Hausman and Wise, 1978; Layton, 2000).

[22] We estimate separate equations to test for differences between the scenarios. This approach is preferable to using interaction terms for group (here: scenario) comparisons since we cannot rule out differences in unobservable variation (Hoetker, 2007). A simple test for equality of the coefficients across the two equations, however, would not produce meaningful results since we estimate non-linear models and the amount of residual variation between the two models will in general differ (Allison, 1999). Proposed solutions by Allison (1999) and Hoetker (2007) to test for equality of residual variation between the models or compare ratios of coefficients across models are not applicable in our case.

[23] Alternatively, one could calculate the marginal effect of the focal variable while setting all other variables (of the focal start-up and of the two competing start-ups) to their respective sample mean. However, this approach makes little sense in our setting since all variables are dummy variables. Furthermore, marginal effects at the means do not account for the non-linearity of the model.

[24] Based on the results of the rank-ordered mixed logit estimations, we make 100 random draws from the distribution of the coefficient vector and repeat the calculation of the marginal effects for each drawn coefficient vector to determine confidence intervals (cf. Fischer and Henkel, 2012). We measure the significance of a difference of an average marginal effect between the two scenarios in a specific

4. Results

The results of our estimations are summarized in Table 4 and illustrated, for the combined sample, in Fig. 3. The table displays for each scenario the estimated coefficients, robust standard errors, AMEs, and the difference in AMEs between the scenarios.

We first look at the importance of each start-up attribute in the combined sample (Table 4a), defined as the normalized difference between the highest and the lowest AME across this attribute's levels (e.g., Franke et al., 2008). As the marginal effect of the least preferred attribute level is zero by construction, the highest AME of the two remaining levels measures the attribute's importance.[25] These importance values are then normalized by dividing each by the sum of all three values. When the firms' technologies are unknown, the importance values are 35% for patents, 38% for alliances, and 27% for team experience; with equally good technologies, 38%, 40%, and 22%, respectively. Overall, our results indicate for both scenarios a comparatively high importance of patent protection and alliances, and a substantially lower importance of team experience.

Coming to the core of our study, we now concentrate on the differences in AMEs between the two scenarios. Table 4a–c shows that, for all three samples, the difference between the two scenarios in the AMEs of "patent granted" is negative and not significantly different from zero. The same is true for "patent applied for." This means that—surprisingly—VCs do not put a higher emphasis on patent protection in the case of unknown technology qualities compared with a situation in which they face start-ups with known and equally good technologies. In other words, we cannot identify a signaling effect of patents.

In contrast, the AME of "research alliance" is significantly (5%, one-sided) higher, in the combined sample and the German sample, when technologies are unknown than with equally good technologies. VCs thus seem to interpret existing research alliances as signals of the unobservable quality of a start-up's technology. As expected, the difference in the AME of "sales alliance" between the scenarios is small, negative, and not significant.

Also for team experience we find significant positive differences between the scenarios (for the combined and the German sample), again suggesting a signaling effect. For both 5 years and 10 years of experience, the AME is significantly larger (5% or 10%, one-sided) when technologies are unknown.[26] Results for the U.S. sample (Table 4c) regarding differences in AMEs are consistent with those for the combined sample and the German sample with respect to sign and relative size of the various AMEs. They are not significant, though, which is likely caused by the smaller number of observations in the U.S. sample.

We perform several robustness checks to corroborate our results. One point of criticism could be that respondents might have had difficulties internalizing the change from one scenario to the other. As a result, choices made in the second half of the survey might have been biased in such a way that they differ less from those in the first half than they would have if the respondent had only done the second half of the survey. To address this potential issue, we calculate two additional estimation models, taking into account only the choices made during the first scenario by each participant. We thus implicitly divide the sample into two groups, one that only saw the scenario "equally good technologies" (ET_1, $N = 100$) and one that was only briefed to make decisions under "technologies unknown" (TU_1, $N = 87$). The results are shown in Table 4d, confirming our previous findings. For "experience 5 years," we again see a significant difference (10% one-sided) between the two scenarios. The scenario differences with regard to research alliances point in the same direction as in the main models, but are not statistically significant from zero due to the smaller number of observations.[27] Importantly, we do not observe a signaling effect of patent applications nor of granted patents, which is consistent with our earlier results. We furthermore compared subsamples defined by experience, educational background, and position within the venture capital firm, but did not find any significant differences.

As an additional robustness check, we investigated potential signaling values restricted to each industry (Table 5). While there are differences between the industries with respect to the importance VCs attach to the key start-up characteristics, these differences exist for both scenarios. The results regarding signaling values (last column in Table 5), though not significant due to smaller numbers of observations, are consistent with those obtained for the pooled sample. For patents, both filed and granted, this means that while the intrinsic property rights value is higher in biotech than in the cleantech or the ICT sector, we do not observe a signaling effect of the patent variables in any industry.[28]

5. Discussion

5.1. Summary and interpretation

By analyzing choice decisions of VCs, we investigate to what extent, if at all, they interpret a start-up's patents, research alliances, and team experience as signals of the quality of its technology. Through a comparison of two scenarios we are able to disentangle a resource's signaling from its productive value.[29] Surprisingly, no signaling effect of patents regarding the start-ups' technology quality can be identified, neither of patent applications

probability range by calculating differences in average marginal effects for each simulated coefficient vector in both groups.

[25] The importance of an attribute clearly depends on its available levels and therefore needs to be interpreted with the respective reference levels in mind. Refer to Table 2 for our choice of attribute levels.

[26] Note that the sum of the average marginal effects of the respective most preferred level of each characteristic is bounded (in general, it is below 100%). Thus, what we measure is the signaling effect of a variable *relative* to that of other variables. Also, our finding of insignificant signaling effects of the patent dummies does not preclude a positive signaling effect of these variables, which might become visible when the other, stronger signals are absent or if the number of observations is increased.

[27] When performing the same robustness check (i.e., only the first scenario for each participant) for our German sample only, we again find a significant signaling effect (5%, two-sided) for "research alliance".

[28] We conducted a further validity check based on direct questions. We asked participants to assess the importance of the various resources as signals of the quality of the start-up's technology, on a five-point Likert scale ranging from 1 (not important at all) to 5 (very important). These questions were asked as a follow-up to the original survey conducted in June 2013, which yielded 68 responses (42 from German, 26 from US respondents). Team experience came out top with an average of 4.53, followed by sales alliances (3.38) and granted patents (3.37). The signaling function of research alliances (3.09) received only a slightly higher importance level than that of patent applications (2.91). These results differ strongly from those of our conjoint experiment. However, answering Likert-type questions regarding signaling values requires a rather deep understanding on the respondent's side of his or her own decision process. This understanding will in general be limited, though, which is one of the major reasons why conjoint-based studies have been suggested in such situations (Zacharakis and Meyer, 1998; Shepherd and Zacharakis, 1999). Furthermore, the importance ranking we obtained seems to reflect the perceived importance of these resources with respect to their *overall* value (rather than only their signaling value), which once more suggests that respondents did not handle this question correctly. We thus interpret the above discrepancy as reflecting the unsuitability of Likert-type questions for assessing signals in decision making, and as further justification of our scenario- and conjoint-based approach.

[29] Note that not only a patent's productive value, but also its signaling value is of a long-term nature. While the signal itself may be short-lived, the quality it potentially signals—the quality of the start-up's technology—is of a long-term nature.

Table 4
Estimation results.

	Technologies unknown			Equally good technologies			Difference
	Coeff.	SE	AME	Coeff.	SE	AME	ΔAME
(a) Combined sample							
Patent applied for	2.383	0.230	0.193	2.983	0.244	0.232	−0.039
Patent granted	3.631	0.254	0.309	4.048	0.257	0.335	−0.026
Research alliance	1.923	0.220	0.156	1.348	0.205	0.110	0.046**
Sales alliance	4.068	0.295	0.338	4.194	0.292	0.353	−0.015
Experience 5 years	1.741	0.192	0.143	1.204	0.191	0.100	0.043**
Experience 10 years	2.812	0.256	0.241	2.270	0.258	0.192	0.049*
Obs/persons	2244	187		2244	187		
LR $\chi^2(6)$, $p > \chi^2$, log likelihood	505.43	0.000	−1381.9	478.65	0.000	−1359.0	
(b) German sample							
Patent applied for	2.618	0.327	0.198	3.184	0.363	0.222	−0.024
Patent granted	4.304	0.393	0.348	4.901	0.433	0.372	−0.024
Research alliance	2.175	0.312	0.167	1.474	0.305	0.110	0.057**
Sales alliance	4.370	0.422	0.350	4.617	0.432	0.359	−0.009
Experience 5 years	1.963	0.273	0.153	1.462	0.269	0.111	0.042*
Experience 10 years	2.878	0.349	0.233	2.259	0.362	0.174	0.059*
Obs/persons	1224	102		1224	102		
LR $\chi^2(6)$, $p > \chi^2$, log likelihood	250.37	0.000	−731.2	276.97	0.000	−714.2	
(c) U.S. sample							
Patent applied for	2.215	0.329	0.188	2.849	0.338	0.241	−0.053
Patent granted	3.035	0.342	0.264	3.331	0.311	0.291	−0.027
Research alliance	1.595	0.314	0.135	1.202	0.271	0.104	0.031
Sales alliance	3.940	0.454	0.336	3.937	0.417	0.347	−0.011
Experience 5 years	1.534	0.289	0.131	1.001	0.268	0.088	0.043
Experience 10 years	2.783	0.375	0.247	2.394	0.383	0.217	0.030
Obs/persons	1020	85		1020	85		
LR $\chi^2(6)$, $p > \chi^2$, log likelihood	256.73	0.000	−634.0	207.740	0.000	−634.9	
(d) Only first scenario combined sample							
Patent applied for	2.105	0.322	0.182	2.800	0.320	0.228	−0.046*
Patent granted	3.356	0.353	0.305	3.894	0.323	0.337	−0.032
Research alliance	1.600	0.300	0.140	1.301	0.257	0.110	0.030
Sales alliance	3.640	0.390	0.330	3.903	0.360	0.347	−0.017
Experience 5 years	1.785	0.280	0.159	1.304	0.252	0.112	0.047*
Experience 10 years	2.494	0.360	0.226	2.475	0.344	0.218	0.008
Obs/persons	1044	87		1200	100		
LR $\chi^2(6)$, $p > \chi^2$, log likelihood	234.31	0.000	−658.8	205.22	0.000	−744.5	

Notes: All coefficients are significant at $p < 0.001$. Rank-ordered mixed logit estimation. AME: average marginal effects. Simulations for estimating coefficients and calculating predicted probabilities done using 1.000 Halton draws. Simulations for calculating confidence intervals of AME done using 100 random draws of coefficients. Robust standard errors reported.

* Significance level of ΔAME: $p < 0.10$, one-sided test.

** Significance level of ΔAME: $p < 0.05$, one-sided test.

nor of granted patents. Instead, the presence of an R&D alliance and the team's relevant management experience seem to work as quality signals. To quantify these signals, we subtract a resource's effect in the scenario "equally good technologies" from its effect in the scenario "technologies unknown." For "R&D alliance," this is 0.110 subtracted from 0.156, yielding a value of 0.046. By this measure, about 29% of a research agreement's value contribution can be attributed to its signaling function, the remaining 71% to its productive function. We observe similar signaling effects for the entrepreneurial team's management experience. Sales alliances, on the other hand, appear to have no signaling effect, as expected.

The role of R&D alliances and team experience as important signals of the unobserved quality of a start-up's technology is noteworthy. Unlike patents, both—and in particular team experience—are only indirectly related to technology quality. Yet, the logic of why the existence of R&D alliances and the venture team's experience should be correlated with the start-up's technology quality is compelling, and so the signaling effects we identify are clearly plausible.

The nonexistence of technology-related patent signaling in the venture capital financing context constitutes a new insight, challenging most extant theoretical and qualitative evidence regarding the twofold role of patents.[30] This finding even stands somewhat in contrast to our own interviews with VCs. However, the conjoint analysis clearly shows that when presented with several resources as quality indicators, VCs do not rely on patents but on upstream alliances and on team experience instead. The conjoint results should be regarded as the most valid, since a conjoint analysis does not require VCs to understand their own decision process.

A closer look at signaling theory helps in the interpretation of our findings. The signaling cost differential (Spence, 1973) is arguably smaller for obtaining a patent grant (or even filing an application) than for establishing an R&D alliance or assembling an

[30] Our findings are consistent, though, with empirical results by Audretsch et al. (2012) which suggest that patents are rather valuable as property rights, while existing prototypes signal technological quality and feasibility.

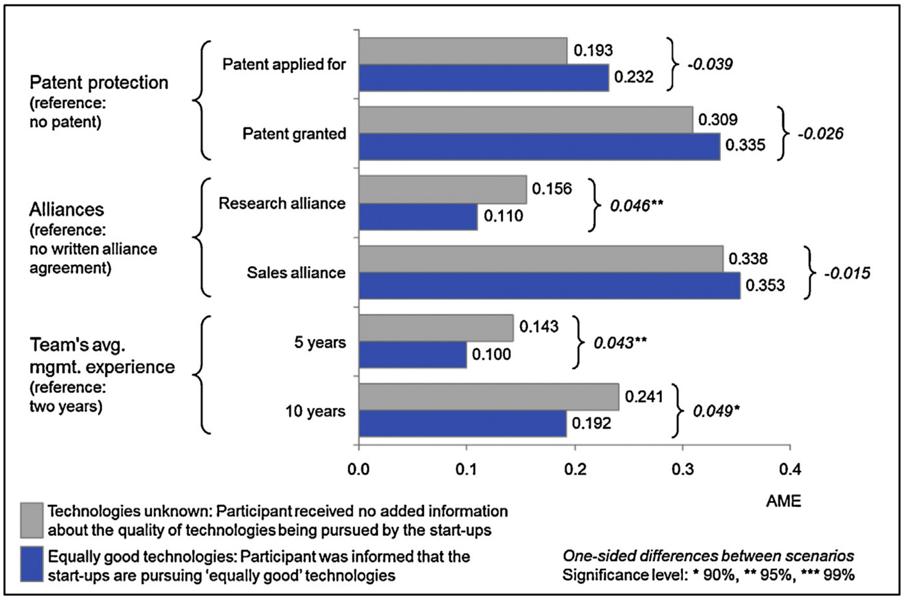

Fig. 3. Comparison of average marginal effects between scenarios (combined sample).

Table 5
Estimation results by industry.

	Technologies unknown			Equally good technologies			Difference
	Coeff.	SE	AME	Coeff.	SE	AME	ΔAME
(a) Biotech							
Patent applied for	3.430	0.506	0.230	3.784	0.447	0.273	−0.043
Patent granted	5.678	0.614	0.427	5.257	0.515	0.417	0.010
Research alliance	2.614	0.489	0.189	1.997	0.395	0.155	0.034
Sales alliance	3.347	0.434	0.247	3.759	0.441	0.306	−0.059
Experience 5 years	2.566	0.421	0.182	1.790	0.336	0.138	0.044
Experience 10 years	3.699	0.507	0.275	3.183	0.440	0.261	0.014
Obs/persons	672	56		672	56		
LR $\chi^2(6)$, $p > \chi^2$, log likelihood	109.12	0.000	−368.2	85.78	0.000	−375.6	
(b) Cleantech							
Patent applied for	2.194	0.456	0.192	2.590	0.460	0.222	−0.030
Patent granted	3.048	0.459	0.272	3.690	0.490	0.336	−0.064
Research alliance	1.447	0.361	0.125	0.763	0.343	0.070	0.055
Sales alliance	3.904	0.521	0.357	3.437	0.469	0.329	0.028
Experience 5 years	1.496	0.352	0.133	1.028	0.382	0.095	0.038
Experience 10 years	2.338	0.475	0.213	1.574	0.456	0.146	0.067
Obs/persons	600	50		600	50		
LR $\chi^2(6)$, $p > \chi^2$, log likelihood	95.64	0.000	−389.3	97.12	0.000	−388.9	
(c) ICT							
Patent applied for	1.816	0.329	0.156	2.665	0.421	0.193	−0.037
Patent granted	2.733	0.329	0.243	3.550	0.430	0.266	−0.023
Research alliance	1.860	0.346	0.155	1.389	0.364	0.101	0.054
Sales alliance	4.668	0.507	0.389	5.526	0.651	0.401	−0.012
Experience 5 years	1.364	0.286	0.117	0.973	0.317	0.074	0.043
Experience 10 years	2.501	0.380	0.225	2.192	0.464	0.166	0.059
Obs/persons	972	81		972	81		
LR $\chi^2(6)$, $p > \chi^2$, log likelihood	234.85	0.000	−575.2	270.11	0.000	−547.3	

Notes: All coefficients are significant at $p < 0.001$. Rank-ordered mixed logit estimation. AME: average marginal effects. Simulations for estimating coefficients and calculating predicted probabilities done using 1.000 Halton draws. Simulations for calculating confidence intervals of AME done using 100 random draws of coefficients. Robust standard errors reported. None of the values of ΔAME is significant.

experienced start-up team.[31] A second determinant of the relevance of a signal is its *focus*, indicating the contribution of the unobserved quality to the signal (Prabhu and Stewart, 2001).[32] Signal focus should be strongest for R&D alliances since the main determinants of achieving an R&D alliance should be perceived technology quality and, likely highly correlated with it, the team's technology competence. In contrast, both filing and grant of a patent and the presence of experienced management team members will each depend on various other additional factors. These considerations are in line with our findings that R&D alliances matter most as signals of technology quality, team experience less, and patents least.

While our results convey that patents do not act as signals of unobservable technological quality, we cannot control for other signaling functions. VCs might still draw implications from existing patents on other unobservable start-up characteristics, such as the professionalism or technical know-how of the entrepreneurial team. This explanation might reconcile our findings with results by Hsu and Ziedonis (2013) and Hoenen et al. (2014). These authors provide evidence of a distinct signaling effect of patents, but consider signals for venture quality overall while we focus on the venture's technology quality. On the other hand, there are indications that signaling effects for other characteristics than technology quality are of minor importance: our interviews with VCs reveal that patents held by young ventures are first and foremost associated with technology development and other scholars share this view (e.g., Conti et al., 2013). Then again, it is questionable to what extent VCs understand their own decision process (Zacharakis and Meyer, 1998).

Another potential explanation of the apparent contradiction between our results and those of other studies rests on correlations between resources. While our approach avoids correlations between patent endowment, alliances, and team experience by construction,[33] these variables will likely be positively correlated in real-world data. Since the VC will have a more precise assessment of team experience than a researcher in an econometric analysis, the part of team experience that is unobserved by the researcher but correlated with the start-up's patents may give rise to an omitted variable bias.

Finally, it is conceivable that the existence of a research alliance or a management team experience of 5 or even 10 years constitute signals so powerful that they eclipse any signaling effects of patents. In real data, these strong signals will often be absent such that patents might become relevant for VCs as signals of technology quality. Our data does not allow us to test this conjecture since in each choice set all three characteristics vary. However, if it was true then one would not expect to find, as we do, mostly (13 out of 14) negative signaling effects of patents, one of them (Table 4d) even significantly negative.

5.2. Contributions

From a theoretical perspective, this study makes several contributions. First, and most importantly, we add new insights to a recent stream of research on the role of signals in venture capital financing, and in particular of patents as signals (Audretsch et al., 2012; Baum and Silverman, 2004; Cao and Hsu, 2011; Conti et al., 2013; Häussler et al., 2012; Hoenen et al., 2014; Hsu and Ziedonis, 2013; Mann and Sager, 2007). We present and implement—to the best of our knowledge for the first time—a method to isolate the signaling effect of patents, alliances, and team experience in venture capital financing. By employing a scenario-based conjoint approach, we are in particular able to disentangle a patent's property right from its signaling function related to technology quality, and thereby address a limitation of transaction data based studies. Our finding that patents fail to serve as signals of technology quality is highly interesting in the light of existing studies on patents' signaling value and calls for further analysis. In particular, it suggests to open up the black box of "signaling" and to ask which start-up qualities exactly patents and other observable characteristics might signal. Strategic implications are that a start-up's skills in generating a certain signal, or even deliberately inflating it, may matter in venture capital financing, and that the VC's and the start-up's understanding of both the creation and the interpretation of signals will affect the outcome. Our research thus underlines the importance of a VC's understanding of his or her own decision process, which must not be taken for granted (Zacharakis and Meyer, 1998).

Second, we add to the existing literature on VCs' decision making (e.g., Franke et al., 2008; Hall and Hofer, 1993; MacMillan et al., 1985). More precisely, our results provide insights on the importance of the investigated start-up characteristics as venture capital selection criteria in the screening phase. The high value contribution of both research and sales alliances and patent protection in comparison to management experience is notable and may be worth further investigations.

Third, we provide an example of how to extend the usage of conjoint experiments for managerial research (e.g., Fischer and Henkel, 2013; Shepherd and Zacharakis, 1999). By changing scenarios between groups of choice sets, individual effects regarding the respective independent variables can be investigated. The size of these separated effects can be tested for significance by calculating group differences in marginal effects (Fischer and Henkel, 2012; King et al., 2000; Long, 2009).

We also note some interesting side results. In all models, existing patents and alliances are important selection criteria for VCs. This result supports previous research based on transaction data in which patents as well as alliances have been shown to drive VCs' evaluation of start-ups (e.g., Baum and Silverman, 2004; Mann and Sager, 2007). Our findings extend existing knowledge by showing that both patents and alliances are highly relevant selection criteria also in the screening of business plans (see also Hoenig and Henkel, 2012). The high relative importance of patent protection compared to other start-up attributes may seem surprising, but might be explained by two reasons. First, this study is targeted at high tech VCs featuring an experimental setting of start-ups based on technical inventions in technology-driven industries, a setting where patent protection is known to be most effective. Furthermore, our choice of the reference level of 2 years of relevant management experience might have been regarded as relatively high by the survey

[31] Note, however, that Häussler et al. (2012) and Hoenen et al. (2014) find a significant signaling effect of the number of pending patent applications and, surprisingly, in the case of Hoenen et al. (2014) no significant effect of the number of granted patents. A potential explanation of the apparent contradiction between these findings and the argument that patent filings are easy to obtain may be that serious patent applications are in fact not that easy to draft, and that start-ups refrain from submitting mock applications because doing so would backfire later. Thus, for serious applications there would indeed be a cost differential. Also, start-ups may not be fully aware of the potential signaling value of patent applications, such that (even if the cost differential was small) start-ups with good technology are more likely to have patent applications than those with low quality technology.

[32] Related to signal focus is the notion of *signal fit*, which describes how strongly the signal is correlated with the unobservable quality (Connelly et al., 2011).

[33] In our study these variables exhibit only weak correlations due to the largely orthogonal construction of the stimuli. These would be exactly orthogonal, i.e., with zero correlation between the three variables, had we used a complete design with $3 \times 3 \times 3 = 27$ different stimuli in which each stimulus appears an equal number of times. Since we use a fractional factorial design, we do have non-zero but small correlations.

respondents, which would have shifted this characteristic's importance downward.[34]

5.3. Limitations

When interpreting the results of our study, certain limitations need to be kept in mind. Conjoint experiments are always simplified models of real-world decision making, and so we had to select a limited number of selection criteria to be included in the choice sets and decided to focus on start-up resources. In the actual decision process, financial criteria such as expected growth rates or estimated market size will play a role, and the VC may have more detailed information available about the patent, the patenting process, the alliance partner, and the team. However, even though we focus on only three (objectively observable) start-up attributes, our analysis does not suffer from omitted variable bias as all excluded variables are set equal by construction. As an exception, technology quality in the 'technologies unknown' scenario may cause an omitted variable bias, but this bias is precisely what we tease out as the signaling effects of the observable variables.

Another potential issue is that introducing a change in scenarios after half of the choice sets may have been challenging for the participants. However, since we do find sensible and significant differences between the two scenarios, the change from "technologies unknown" to "equally good technology" or vice versa seems to have been understood. As further proof, results of a robustness check taking only the first scenario decisions of each participant into account are consistent with those of our main model. Restricted to the German sample, this robustness check even yields a more pronounced signaling effect of "research alliance" than the full model with both scenarios per participant, but still no effect of patents.

Finally, also with respect to the VC's relationship with the founding team our experimental approach implies a simplification. By construction, the number of years of "relevant management experience" is all the VC knows about the team; he or she thus decides as an "outsider," as is the case when the VC does not know the team before reading the business plan. We do think, though, that our results also apply to situations in which team and VC had prior interaction, or in which other information about the team is available (in particular, about successful earlier ventures, see Gompers et al., 2010). In that case, the variable "relevant management experience" in our survey has to be interpreted as comprising both the team's experience as measured in years and the VC's assessment of the team's experience as based on further information.

5.4. Conclusions

Our study provides interesting insights for entrepreneurs, policy makers, and VCs. Patents constitute a very important advertising mechanism for high tech start-ups when applying for venture capital. Hence, it is advisable for founders to invest time and money into patenting activities before approaching potential investors. However, VCs seem to appreciate patents only in their productive functions as property rights, not as signals of technology quality. Instead, they appear to rely on the existence of R&D alliances and management experience as signals of technological quality. Entrepreneurs in technology-driven industries need to be aware of that and should focus on building up their research network early. They can emphasize established research agreements in their business proposals to signal the technological quality of their firm to VCs, especially if the potential investor has never heard of the start-up before. Policy makers need to understand the various resources' signaling function in order to design competitive R&D subsidy programs such as the U.S. Government's Small Business Innovation Research[35] program effectively. VCs, finally, may take our results as a benchmark and interpret them in comparison to their own decision making.

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References

Aldrich, H.E., Fiol, C.M., 1994. Fools rush in? The institutional context of industry creation. Academy of Management Review 19 (4), 645–670.
Alexander, C.S., Becker, H.J., 1978. The use of vignettes in survey research. Public Opinion Quarterly 42 (1), 93–104.
Allison, P.D., 1999. Comparing logit and probit coefficients across groups. Sociological Methods & Research 28 (2), 186–208.
Amit, R., Glosten, L., Muller, E., 1990. Entrepreneurial ability, venture investments and risk sharing. Management Science 36 (10), 1232–1245.
Arthurs, J.D., Busenitz, L.W., 2003. The boundaries and limitations of agency theory and stewardship theory in the venture capitalist/entrepreneur relationship. Entrepreneurship Theory and Practice 28 (2), 145–162.
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.
Bartholomew, D.J., Knott, M., 1999. Kendall's Library of Statistics 7: Latent Variable Models and Factor Analysis, second ed. Wiley, Chichester, UK.
Baum, J.A.C., Calabrese, T., Silverman, B.S., 2000. Don't go it alone: alliance network composition and startups' performance in Canadian biotechnology. Strategic Management Journal 21, 267–294 (special issue).
Baum, J.A.C., Oliver, C., 1991. Institutional linkages and organizational mortality. Administrative Science Quarterly 36 (2), 187–218.
Baum, J.A.C., 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.
Beckman, C.M., Burton, M.D., O'Reilly, C., 2007. Early teams: The impact of team demography on VC financing and going public. Journal of Business Venturing 22 (2), 147–173.
Beggs, S., Cardell, S., Hausman, J., 1981. Assessing the potential demand for electric cars. Journal of Econometrics 17 (1), 1–19.
Behrens, J., Patzelt, H., Schweizer, L., Bürger, R., 2012. Specific managerial human capital, firm age, and venture capital financing of biopharmaceutical ventures: a contingency approach. Journal of High Technology Management Research 23, 112–121.
Burton, M.D., Sorensen, J.B., Beckman, C.M., 2002. Coming from good stock: career histories and new venture formation. In: Lounsbury, M., Ventresca, M. (Eds.), Research in the Sociology of Organizations—Social Structure and Organizations Revisited, vol. 19. JAI Press, Greenwich, CT, pp. 229–262.
Busenitz, L.W., Fiet, J.O., Moesel, D.D., 2005. Signaling in venture capitalist—new venture team funding decisions: does it indicate long-term venture outcomes? Entrepreneurship Theory and Practice 29 (1), 1–12.
Bygrave, W.D., 1997. The entrepreneurial process. In: Bygrave, W.D. (Ed.), The Portable MBA in Entrepreneurship. John Wiley, New York, NY, pp. 1–24.
Cao, J., Hsu, P.-H., 2011. The Informational Role of Patents in Venture Capital Financing. Working Paper, Available at SSRN: http://ssrn.com/abstract=1678809, accessed 02/09/2014
Cavanagh, G.F., Fritzsche, D.J., 1985. Using vignettes in business ethics research. In: Preston, L.E. (Ed.), Research in Corporate Social Performance and Policy. JAI Press, Greenwich, CT, pp. 279–293.

[34] A reference level of 0 years of experience instead of 2 years would not have been realistic in combination with a granted patent or existing alliance, but would have yielded higher importance values for the attribute "team experience."

[35] See http://www.sbir.gov/.

Chapman, R.G., Staelin, R., 1982. Exploiting rank ordered choice set data within the stochastic utility model. Journal of Marketing Research 19 (3), 288–301.
Chung, S., Singh, H., Lee, K., 2000. Complementarity, status similarity and social capital as drivers of alliance formation. Strategic Management Journal 21 (1), 1–22.
Cohen, W.M., Levinthal, D.A., 1990. Absorptive capacity: a new perspective on learning and innovation. Administrative Science Quarterly 35 (1), 128–152.
Cohen, W.M., Nelson, R.R., Walsh, J.P., 2000. Protecting Their Intellectual Assets: Appropriability Conditions and Why U.S. Manufacturing Firms Patent (or not). NBER Working Paper No. 7552. National Bureau of Economic Research, Cambridge, MA.
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.C., Rothaermel, F.T., 2013. Show me the right stuff: signals for high tech startups. Journal of Economics & Management Strategy 22 (2), 341–364.
Cooper, A.C., Woo, C.Y., Dunkelberg, W.C., 1988. Entrepreneurs' perceived chances for success. Journal of Business Venturing 3, 97–108.
De Meza, D., Southey, C., 1996. The borrower's curse: optimism, finance and entrepreneurship. Economic Journal 106, 375–386.
Dixon, R., 1991. Venture capitalists and the appraisal of investments. OMEGA: International Journal of Management Science 19, 333–344.
Elitzur, R., Gavious, A., 2003. Contracting, signaling, and moral hazard: a model of entrepreneurs, 'angels,' and venture capitalists. Journal of Business Venturing 18 (6), 709–725.
Elrod, T., Louviere, J.J., Davey, K.S., 1992. An empirical comparison of ratings-based and choice-based conjoint models. Journal of Marketing Research 29 (3), 368–377.
Engel, D., Keilbach, M., 2007. Firm-level implications of early stage venture capital investment – an empirical investigation. Journal of Empirical Finance 14 (2), 150–167.
Feeser, H.R., Willard, G.E., 1990. Founding strategy and performance: a comparison of high and low growth high tech firms. Strategic Management Journal 11, 87–98.
Fischer, T., Henkel, J., 2012. Capturing value from innovation—diverging views of R&D and marketing managers. IEEE Transactions on Engineering Management 59 (4), 572–584.
Fischer, T., Henkel, J., 2013. Complements and substitutes in profiting from innovation—a choice experimental approach. Research Policy 42, 326–339.
Franke, N., Gruber, M., Harhoff, D., Henkel, J., 2006. What you are is what you like—similarity biases in venture capitalists' evaluations of start-up teams. Journal of Business Venturing 21 (6), 802–826.
Franke, N., Gruber, M., Harhoff, D., Henkel, J., 2008. Venture capitalists' evaluations of start-up teams: trade-offs, knock-out criteria, and the impact of VC experience. Entrepreneurship: Theory and Practice 32 (3), 459–483.
Fredrickson, J.W., 1986. An exploratory approach to measuring perceptions of strategic decision process constructs. Strategic Management Journal 7 (5), 473–483.
Gimeno, J., Folta, T.B., Cooper, A.C., Woo, C.Y., 1997. Survival of the fittest? Entrepreneurial human capital and the persistence of underperforming firms. Administrative Science Quarterly 40 (4), 750–783.
Gompers, P., Kovner, A., Lerner, J., Scharfstein, D., 2010. Performance persistence in entrepreneurship. Journal of Financial Economics 96 (1), 18–32.
Goslin, L.N., Barge, B.,1986. Entrepreneurial qualities considered in venture capital support. In: Frontiers of Entrepreneurship Research. Babson College, Wellesley, MA, pp. 366–377.
Graham, S.J.H., Merges, R.P., Samuelson, P., Sichelman, T., 2009. High technology entrepreneurs and the patent system: results of the 2008 Berkeley Patent Survey. Berkeley Technology Law Journal 24 (4), 1255–1327.
Graham, S.J.H., Sichelman, T., 2008. Why do start-ups patent? Berkeley Technology Law Journal 23 (3), 1063–1097.
Greenberg, G., 2013. Small firms, big patents? Estimating patent value using data on Israeli start-ups' financing rounds. European Management Review 10 (4), 183–196.
Gulati, R., Higgins, M.C., 2003. Which ties matter when? The contingent effects of interorganizational partnerships on IPO success. Strategic Management Journal 24 (2), 127–144.
Hall, B.H., Thoma, G., Torrisi, S., 2007. The Market Value of Patents and R&D: Evidence from European Firms. NBER Working Paper No. 13426. National Bureau of Economic Research, Cambridge, MA.
Hall, B.H., Ziedonis, R.H., 2001. The patent paradox revisited: an empirical study of patenting in the U.S. semiconductor industry, 1979–1995. RAND Journal of Economics 32 (1), 101–128.
Hall, J., Hofer, C.W., 1993. Venture capitalists' decision criteria in new venture evaluation. Journal of Business Venturing 8 (1), 25–42.
Hausman, J.A., Wise, D.A., 1978. A conditional probit model for qualitative choice: discrete decisions recognizing interdependence and heterogeneous preferences. Econometrica 46 (2), 403–426.
Häussler, C., Harhoff, D., Müller, E., 2012. To Be Financed or Not ... – The Role of Patents for Venture Capital-financing. Working Paper. http://ssrn.com/abstract=1393725
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.
Helmers, C., Rogers, M., 2011. Does patenting help high-tech start-ups? Research Policy 40 (7), 1016–1027.
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, 956–989.
Hoenig, D., Henkel, J., 2012. On Patents and Alliances as Venture Capital Screening Criteria—Investigating Industry Differences. Working Paper. TUM School of Management, Technische Universität München http://ssrn.com/abstract=2179878
Hoetker, G., 2007. The use of logit and probit models in strategic management research: critical issues. Strategic Management Journal 28 (4), 331–343.
Hole, A.R., 2007. Fitting mixed logit models by using maximum simulated likelihood. Stata Journal 7 (3), 388–401.
Hsu, D.H., 2007. Experienced entrepreneurial founders, organizational capital, and venture capital funding. Research Policy 36 (5), 722–741.
Hsu, D., Ziedonis, R., 2013. Resources as dual sources of advantage: implications for valuing entrepreneurial-firm patents. Strategic Management Journal 34, 761–781.
Janney, J.J., Folta, T.B., 2003. Signaling through private equity placements and its impact on the valuation of biotechnology firms. Journal of Business Venturing 18 (3), 361–380.
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. Journal of Finance 64 (1), 75–115.
King, G., Tomz, M., Wittenberg, J., 2000. Making the most of statistical analyses: improving interpretation and presentation. American Journal of Political Science 44 (2), 347–361.
Kirmani, A., Rao, A.R., 2000. No pain, no gain: a critical review of the literature on signaling unobservable product quality. Journal of Marketing 64 (2), 66–79.
Layton, D.F., 2000. Random coefficient models for stated preference surveys. Journal of Environmental Economics and Management 40 (1), 21–36.
Leland, H.E., Pyle, D.H., 1977. Informational asymmetries, financial structure, and financial intermediation. Journal of Finance 32 (2), 371–387.
Liebeskind, J.P., Oliver, A.L., Zucker, L., Brewer, M., 1996. Social networks, learning, and flexibility: sourcing scientific knowledge in new biotechnology firms. Organization Science 7 (4), 428–443.
Long, C., 2002. Patent signals. University of Chicago Law Review 69 (2), 625–680.
Long, J.S., 2009. Group Comparisons in Logit and Probit using Predicted Probabilities. Working Paper. Indiana University, Bloomington, IN.
MacMillan, I.C., Siegel, R., Subba Narasimha, P.N., 1985. Criteria used by venture capitalists to evaluate new venture proposals. Journal of Business Venturing 1 (1), 119–128.
Mann, R.J., Sager, T.W., 2007. Patents, venture capital, and software start-ups. Research Policy 36 (2), 193–208.
McFadden, D., 1974. Conditional Logit Analysis of Qualitative Choice Behavior. Academic Press, New York.
McFadden, D., Train, K., 2000. Mixed MNL models for discrete response. Journal of Applied Econometrics 15 (5), 447–470.
Miner, A.S., Amburgey, T.L., Stearns, T.M., 1990. Interorganizational linkages and population dynamics: buffering and transformational shields. Administrative Science Quarterly 35 (4), 689–713.
Muzyka, D., Birley, S., Leleux, B., 1996. Trade-offs in the investment decisions of European venture capitalists. Journal of Business Venturing 11 (4), 273–287.
Packalen, K.A., 2007. Complementing capital: the role of status, demographic features, and social capital in founding teams' abilities to obtain resources. Entrepreneurship Theory and Practice 31 (6), 873–891.
Penrose, E., 1959. The Theory of the Growth of the Firm. Oxford University Press, Oxford, UK.
Pisano, G.P., 1991. The governance of innovation: vertical integration and collaborative arrangements in the biotechnology industry. Research Policy 20 (3), 237–249.
Pollack, J.M., Bosse, D.A., 2014. When do investors forgive entrepreneurs for lying? Journal of Business Venturing 29, 741–754.
Prabhu, J., Stewart, D.W., 2001. Signaling strategies in competitive interaction: building reputations and hiding the truth. Journal of Marketing Research 38 (1), 62–72.
Revelt, D., Train, K., 1998. Mixed logit with repeated choices: households' choices of appliance efficiency level. Review of Economics and Statistics 80 (4), 647–657.
Riquelme, H., Rickards, T., 1992. Hybrid conjoint analysis: an estimation probe in new venture decisions. Journal of Business Venturing 7 (6), 505–518.
Rungtusanatham, M., Wallin, C., Eckerd, S., 2011. The vignette in a scenario-based role-playing experiment. Journal of Supply Chain Management 47 (3), 9–16.
Santoro, M.D., Gopalakrishnan, S., 2000. The institutionalization of knowledge transfer activities within industry–university collaborative ventures. Journal of Engineering and Technology Management 17 (3/4), 299–319.
Shane, S., Stuart, T., 2002. Organizational endowments and the performance of university start-ups. Management Science 48 (1), 154–170.
Shepherd, D.A., 1999a. Venture capitalists' assessment of new venture survival. Management Science 45 (5), 621–632.
Shepherd, D.A., 1999b. Venture capitalists' introspection: a comparison of "in use" and "espoused" decision policies. Journal of Small Business Management 27, 76–87.
Shepherd, D.A., Zacharakis, A., 1999. Conjoint analysis: a new methodological approach for researching the decision policies of venture capitalists. Venture Capital: An International Journal of Entrepreneurial Finance 1 (3), 197–217.

Spence, M., 1973. Job market signaling. Quarterly Journal of Economics 87 (3), 355–374.
Spence, M., 2002. Signaling in retrospect and the informational structure of markets. American Economic Review 92 (3), 434–459.
Sprinkle, G.B., 2003. Perspectives on experimental research in managerial accounting. Accounting, Organizations and Society 28 (2/3), 287–318.
Stening, B.W., Everett, J.E., 1984. Response styles in a cross-cultural managerial study. Journal of Social Psychology 122 (2), 151–156.
Stinchcombe, A.L., 1965. Social structure and organizations. In: March, J.G. (Ed.), Handbook of Organizations. Rand McNally, Chicago, IL, pp. 142–193.
Stuart, T.E., 2000. Interorganizational alliances and the performance of firms: a study of growth and innovation rates in a high-technology industry. Strategic Management Journal 21 (8), 791–811.
Stuart, T.E., Huang, H., Hybels, R.C., 1999. Interorganizational endorsements and the performance of entrepreneurial ventures. Administrative Science Quarterly 44 (2), 315–349.
Tushman, M.L., Rosenkopf, L., 1992. Organizational determinants of technological change: toward a sociology of technological evolution. In: Staw, B.M., Cummings, L.L. (Eds.), Research in Organizational Behavior, vol. 14. JAI Press, Greenwich, CT, pp. 311–347.
Tyebjee, T., Bruno, A., 1981. Venture capital decision making: preliminary results from three empirical studies. In: Vesper, K.H. (Ed.), Frontiers of Entrepreneurial Research. Babson College, Wellesley, MA, pp. 281–320.
Upton, G., Cook, I., 2002. A Dictionary of Statistics. Oxford University Press, Oxford, UK.
Wagner, S., Cockburn, I., 2010. Patents and the survival of internet-related IPOs. Research Policy 39 (2), 214–228.
Wason, K.D., Polonsky, M.J., Hyman, M.R., 2002. Designing vignette studies in marketing. Australasian Marketing Journal 10 (3), 41–58.
Yu, J., Goos, P., Vandebroek, M., 2009. Efficient conjoint choice designs in the presence of respondent heterogeneity. Marketing Science 28 (1), 122–135.
Zacharakis, A.L., Meyer, G.D., 1998. Do venture capitalists really understand their own decision process? A social judgment theory perspective. Journal of Business Venturing 13, 57–76.
Zacharakis, A.L., Meyer, G.D., 2000. The potential of actuarial decision models: can they improve the venture capital investment decision? Journal of Business Venturing 15 (4), 323–346.
Zelner, B.A., 2009. Using simulation to interpret results from logit, probit, and other nonlinear models. Strategic Management Journal 30 (12), 1335–1348.
Zott, C., Huy, Q.N., 2007. How entrepreneurs use symbolic management to acquire resources. Administrative Science Quarterly 52 (1), 70–105.