The Importance of Geographical Distance for the Effectiveness of Information Signals: Evidence from the Venture Capital Industry

MSc Thesis –final report

Student:	Ronald Seele
Reg. nr:	880614756060
MSc programme:	Management, Economics and Consumer Studies
Supervisors	Dr. C. Kolympiris (Management Studies Group)
	J.M. Denolf MA (Management Studies Group)
Course code:	MST-80433 (33 ECTS)
Presentation date:	September 19th, 2013

Abstract

Information signals partly reveal unobserved characteristics of an agent in a market situation. The effectiveness of signaling increases in the level of information asymmetries between the sender and receiver of the signal. Prompted by decreasing information asymmetries in geographical proximity, we argue that the effectiveness of signaling is expected to diminish in the proximity between the sender and receiver. We test this hypothesis by the use of a dataset of more than 580 investments of venture capital firms (VCFs) in early stage dedicated biotechnology firms (DBFs). Our results reflect that the number of pending patent applications of the DBF, the entrepreneurial experience and the academic status of the founding team substantially increase the level of first round venture capital funding. However, this effect is subjected to the distance between the VCF and the DBF. For local investments signaling does not affect the amount of venture capital funding, while signaling positively influences the level of funding for DBFs that are funded by nonlocal VCFs. We argue that information asymmetries are lower for local investments because VCFs are better able to assess the quality of nearby DBFs through local networks. As such VCFs only rely on information signals only for long distance investments.

1. Introduction

One of the basic principles of signaling theory is that signals, defined as pieces of information purposely sent by an insider to a less informed outsider to communicate the credibility of the sender, partly reveal unobserved characteristics of an agent in a market situation (Amit et al., 1990; Connelly et al., 2011; Deeds et al., 1997; Spence, 1973). The development of signaling theory is often traced back to Spence (1973), who argued that education fulfills a signaling function regarding the productivity of a prospective employee, hereby affecting the hiring decisions of employers if the true productivity is unobservable. Subsequently, information signals have been found significant in a wide array of cases. For example, signaling enables firms to communicate value to customers (Cao and Prakash, 2011; Chung and Kalnins, 2001; Mishra et al., 1998), investors (Cohen and Dean, 2005; Higgins and Gulati, 2006), potential employees (Davila et al., 2003) and potential alliance partners (Ozmel et al., 2013).

Prompted by the theoretical relevance of signaling theory, a substantial body of empirical literature has focused on the factors that influence the effectiveness of information signals. For instance, the timing of the signaling event has been shown to matter. Signals towards investors are most relevant for young firms, because at this point the uncertainty regarding the quality is highest (Stuart et al., 1999). Along the same lines, the focal signal is influenced by the frequency of previous signals, because regular signaling reduces fluctuation in information and hereby displays the credibility of the firm over time (Janney and Folta, 2003). Multiple signals can on the other hand also substitute for each other, which decreases the value of the individual signal (Arthurs et al., 2008; Ozmel et al., 2013). The environment in which the signal takes place is also important. Studied in the context of the crash of the e-commerce sector, the level of environmental munificence is found to affect the strength and meaning of a signal (Park and Mezias, 2005). Signals are likewise more important when industry uncertainty, as measured in industry age and availability of resources, is higher (Janney and Folta, 2006; Sanders and Boiwie, 2004). Lastly, in the context of international trade, signals become more relevant as competition increases (Cao and Prakash, 2011).

The studies mentioned above typically examine the circumstances under which the relevance of signaling increases. A topic that received little attention in this context is how signaling effectiveness is influenced by the geographical distance between agents. Given that information asymmetries increase in distance (Coval and Moskowitz, 1999, 2001; Ivković and Weisbenner, 2005; Portes et al., 2001), one could reasonably assume that the effectiveness of signaling also increases in distance. Only few studies have addressed these geographical dynamics of information signals (Mäkelä and Maula, 2008; Powell et al., 2002; Ragozzino and Reuer, 2011) and found that signaling increases the likelihood that a firm secures funding from an investor located at long distance.

More specifically, these studies report how involvement of local venture capital firms (VCFs) acts as a signal for peers. Firms backed by a local VCF and firms with more connections to various types of organizations, have a higher chance of being funded by VCFs from outside the local area (Powell et al., 2002)[1]. Similarly, the involvement of a local VCF fulfills a signaling function towards cross-border VCFs (Mäkelä and Maula, 2008). Firms acquired by investors shortly after the initial public offering, are on average located further away from the acquirer when previous involvement of VCFs is observed as signal (Ragozzino and Reuer, 2011). Because earlier venture capital funding is used as information signal, the studies named above involve investments directed at later development stages of the firm, when signaling effectiveness is generally lower (Hoenen et al., 2013).

Other studies employ different types of information signals and are as a consequence more likely to include investment directed towards firms in early development stages (Mueller et al., 2012; Lerner, 1999). These studies focus on the venture capital access of firms located inside or outside geographical agglomerations. University spinouts in the UK located outside high economic growth areas have to send additional signals to attract venture capital funding, in order to overcome increased information asymmetries (Mueller et al., 2012). In contradiction, firms who received government funding in the form of Small Business Innovation Research (SBIR) grants are more likely

[1] The study of Powell et al. (2002) covers the differences in characteristics between local or nonlocal funded firms. While it is found that nonlocal funded firms have more collaborations with diverse types of organizations compared to locally funded firms, it is not specified to what extent this is caused only by signaling function of collaborations.

to attract follow-up venture capital funding only in regions with substantial venture capital activity (Lerner, 1999). The latter finding indicates that signals are particularly relevant when agents are already co-located.

What is still largely unknown is whether geographical distance between the firm and the investor alters the effectiveness of signals, in terms of increasing the level of investment, in the early development stages of the firm. The contribution of our present study to literature is therefore threefold: (1) the focus is on the initial relation between the investor and the firm, in the first round of venture capital funding. The study consequently involves firms in early development stages, when information asymmetries are most pronounced. Investors in such early stage firms hold a closer geographical scope for their investments (Gupta and Sapienza, 1992). (2) While earlier work studied the effects of signaling in long distance investments, our study addresses the difference in signaling effectiveness between local and nonlocal funded firms, based on the geographical distance between the firm and investor. (3) As a methodological improvement regarding the earlier named studies, we use the amount of received investment as indicator for the effectiveness of the signal, instead of the likelihood of receiving investment. Hereby we use a sharper measure for the capability of a firm to attract funding[2].

Against this background we use the interactions between VCFs and dedicated biotechnology firms (DBFs), in the first round of venture capital funding, as a template. Several aspects of the venture capital industry strengthen its suitability for this study. First, the interactions between VCFs and DBFs are in particular characterized by high information asymmetries, caused by long and expensive R&D cycles, uncertain outcomes, and difficult evaluation because of the complex science-based knowledge (Carpenter and Peterson, 2002; Deeds et al., 1997; DiMasi et al. 2003). Second, given that these information asymmetries are often associated with the distance between agents,

[2] Earlier studies unanimously focussed on the likelihood that a firm is funded at long distance, given the information signals that are observed. This neglects the fact that the effectiveness of a signal also increases if it makes the firm able to raise a higher level of funding. Since the firms in our dataset are rather homogeneous in terms of industry and development stage, differences in the level of funding are likely to be caused by specific firm actions, such as their signaling activities.

the geography of investment is an important aspect of venture capital investments. VCFs typically have a preference for investments in geographical proximity, sometimes referred to as local bias in venture capital (Chen et al., 2011; Chen et al., 2010; Cumming and Dai, 2010; Powell et al., 2002; Sorenson and Stuart, 2001). Third, empirical evidence for the significance of signaling in the venture capital industry is widely available (for an overview, see Connelly et al., 2011). VCFs rely on these signals in order to distinguish between high quality and low quality firms in the presence of information asymmetries (Amit et al., 1990).

The premise of this study is that the effectiveness of an information signal, in terms of increasing the level of venture capital funding, diminishes in the geographical proximity between the VCF and the DBF. To measure this effect we use the patent activities and the founding team credibility of the focal DBF as information signals. In our empirical model we associate the level of venture capital funding in the first round with the signaling activity prior to the investment. By employing the model at different distance levels between the VCF and the DBF, we are able to identify whether the effectiveness of signals varies over geographical distance. Several control variables are included regarding specific characteristics of the portfolio firm and the VCF in order to increase the explanatory power of our model. For our empirical study we make use of a dataset of 582 venture capital investments to U.S. biotechnology firms, in the period between 2001 and 2011.

We proceed as follows. In section 2 of this paper we explore the existing literature. Section 3 and 4 cover respectively the methodology and the dataset of the empirical study. The results of the empirical study are discussed in section 5 and finally, in section 6 our conclusions will be drawn and we give recommendations for further research.

2. Literature Study

We define Venture Capital Firms (VCFs) as “the professional asset management activity that invests funds raised from institutional investors, or wealthy individuals, into promising new ventures with a high growth potential” (Da Rin et al., 2013). Firms that are funded by a VCF (portfolio firms) are nurtured to growth by the provided financial and human capital, after which the VCF exits, mainly through sale or public offering (Da Rin et al., 2013; Metrick and Yasuda, 2011; Zider, 1998). The relatively young portfolio firms are associated with high risk, resulting in limited access to debt financing (Carpenter and Petersen, 2002; Gompers and Lerner, 2004; Gompers and Lerner, 2001; Zider, 1998). In contrast with debt financing, venture capital has no upper limit on the returns from successful investments (Carpenter and Petersen, 2002), whereby VCFs can compensate the high failure rate with high returns, which are estimated to be between 25% and 35% (Zider, 1998). By their investments in young promising firms that would otherwise have little access to funding, VCFs fulfill an important role in innovation and economic growth (Kenney, 2011; Kortum and Lerner, 2000; Samila and Sorenson, 2010).

In the relation between VCFs and target firms, the latter typically possess private information regarding their quality, which is not available to the VCFs (Amit et al. 1990; Gompers 1995; Gompers and Lerner, 2004; Sahlman, 1990). These so-called information asymmetries, derived from the fact that information in an agency dilemma is imperfect (Stiglitz, 1985; 2000), severely complicate the investment process of VCFs because the ex-ante uncertainty is higher. Information asymmetries arise because young firms, particularly in high-tech industries such as biotechnology, often have little possibilities to transmit their quality to the VCF because they deal with a lack of track record, uncertain market conditions and few tangible assets (Berger and Udell, 1998; Carpenter and Petersen, 2002; Gompers and Lerner, 2001). Also a firm might have incentives to purposely withhold information, either because private information implicates the entrepreneurial opportunity that it is trying to protect, or because the entrepreneur might want to conceal negative information regarding the quality of the firm (Shane and Cable, 2002; Shane and Venkataraman, 2000).

Under asymmetric information the problem of adverse selection arises, related to the unobserved quality of the firm ex-ante (Akerlof, 1970; Amit et al., 1990; Mishra et al., 1998)[3]. To

[3] VCFs also deal with moral hazard problems, concerning the unobserved actions of a portfolio firm in the post-investment phase. An entrepreneur might have incentives to behave in a way that increases his private benefits at the expense of the VCF. Information asymmetries make it increasingly difficult to monitor whether the behavior of the portfolio firm is also in the best interest of the VCF (Gompers, 1995; Gompers & Lerner, 2001; Mishra et al., 1998; Sahlman, 1990).

prevent investing in ‘lemons’, VCFs are highly selective and put substantial time and effort in scouting firms and evaluating the quality of investments targets (Amit et al., 1990; Baum and Silverman, 2004). This selection process is increasingly difficult at distance because information regarding the quality of an investment is often tacit and therefore not publicly available (Coval and Moskowitz, 1999; Von Hipple, 1994). Local networks, built by personal relations and face-to-face contact, facilitate the diffusion of information because of which tacit knowledge is likely to circulate at close proximity (Dahl and Pedersen, 2004; Jaffe et al., 1993; Desrochers, 2001; Breschi and Lissoni, 2003; Huggins and Johnston, 2010; Sorenson, 2005). Such proximity effects of knowledge transfer are often studied in the context of geographical agglomerations between similar types of organizations (Beaudry and Breschi 2003; Coenen et al., 2004; Dahl and Pedersen, 2004; Döring and Schnellenbach, 2006; Gittelman, 2007). However, also VCFs often use local information in their assessment of potential investment targets (Florida and Kenney, 1988; Rosiello and Parris, 2009; Shane and Cable, 2002; Sorenson and Stuart, 2001; Zook, 2002). Hence, information asymmetries and related adverse selection problems are typically lower for local investments.

Ex-post, VCFs use intense monitoring and participate in the management of the portfolio firm, hereby decreasing the initial information asymmetries (Gompers and Lerner, 2001; Sahlman, 1990). In the post-investment stage, VCFs often take place in the board of a new venture driven by the need to monitor the portfolio firm (Hellmann and Puri, 2002; Lerner, 1995; Sahlman, 1990). Also VCFs provide the portfolio firm with value-adding activities such as advice and management support (Da Rin et al., 2013; Sahlman, 1990). These activities involve on-site inspection and face-to-face interaction, demanding regular visits from the VCF to the portfolio firm (Gorman and Sahlman, 1989). Because the associated costs and time for traveling obviously increase in distance, monitoring is more difficult for long distance investments (Bengtsson and Ravid, 2009; Chen et al., 2010; Sorenson and Stuart, 2001). For example, VCFs are twice as likely to be involved in the management of the portfolio firm when located within a 5 miles radius compared to a 500 miles radius (Lerner, 1995).

VCFs anticipate on these higher monitoring costs ex-ante and direct lower levels of first round funding towards nonlocal portfolio firms (Tian, 2011).

Collectively these arguments suggest that spatial proximity between VCFs and their portfolio firms decreases information asymmetries and thus the related agency problems. As a consequence VCFs typically have a preference for local investments and much empirical work underlines this ‘local bias’ in the venture capital industry. Firms located close to VCFs are more likely to obtain venture capital funding (Cumming and Dai, 2010; Powell et al., 2002; Sorenson and Stuart, 2001), gain a higher level of funding per round (Tian, 2011) and a higher level of total funding (Chen et al., 2011). On the same line a higher concentration of VCFs in the direct proximity of a new venture increases the total amount of venture capital funding (Kolympiris et al., 2011) [4].

Notwithstanding the empirical evidence for a local bias in venture capital, VCFs engage in long distance investments as well. In such cases VCFs use numerous strategies to overcome the related adverse selection problems. For example, they share the financing of a long distance firm with one or more other VCFs, referred to as syndication of investment (Fritsch and Schilder, 2008; Sorenson and Stuart, 2001), or increase the number of stages in which the portfolio firm receives its funding (Tian, 2011). A method that is less studied as a way to mitigate information asymmetries shaped by long distance is signaling. Despite the extensive scientific attention for signaling in the venture capital industry, little is known about the relation between geographical distance and information signals.

The starting point of signaling theory is that the sender of a signal knows its own quality but this quality is unobservable for the intended receiver. By revealing pieces of information as secondary indicator of its legitimacy, the sender is able to transmit a part of this unobservable quality

[4] In evidence from outside the venture capital industry, the number of local investments in the portfolio of fund managers is disproportionally large (Coval & Moskowitz, 1999) and fund managers perform better when investing in these local funds (Coval & Moskowitz, 2001). Also, the profit of a fund manager increases when located in areas with a lot of investment targets at close distance, because the investor is better able to make investment decisions at close distance (Christoffersen & Sarkissian, 2009). Households are more likely to invest in proximate funds and gain a higher return from these investments (Ivković and Weisbenner, 2005) and assets trade is more likely to happen between countries located in closer proximity (Portes et al., 2001)

to the receiver (Amit et al., 1990; Spence, 1973). Hereby signals reduce information asymmetries between the agents. In order for a signal to be credible, the cost of signaling should be negatively correlated with the quality of the sender, so that low quality agents have no incentives to send high quality signals (Connelly et al., 2011; Spence, 1974). In the context of this study, high quality firms can signal at a cost that is lower than the benefits in terms of an increased level of venture capital funding. Low quality firms on the other hand signal at a cost that does not outweigh the benefits. Hence, high quality firms can increase their access to venture capital funding, because VCFs can distinguish high quality firms by their signaling activity (Amit et al., 1990). A wide range of empirical studies tested which signals are used in the venture capital industry, for example; the percentage of internal ownership (Busenitz et al., 2005), patents activity (Audretsch et al., 2012; Baum and Silverman, 2004; Cao and Hsu, 2011; Conti et al., 2013; Engel and Keilbach, 2007; Hoenen et al., 2013), SBIR awards (Lerner, 1999; Toole and Turvey, 2009) and characteristics of the founding team (Engel and Keilbach, 2007; Gompers et al., 2010; Hsu, 2007; Mueller et al., 2012; Patzelt, 2010; Wright and Ennew, 1997).

Because of the utility of signals to reduce information asymmetries, the value of such signals naturally increases when information asymmetries are high (Stuart et al., 1999). For instance, signals are more important in young and uncertain industries (Sanders and Boiwie, 2004) and when the time between signals is longer (Janney and Folta, 2003). Along the same lines information asymmetries are more severe at long distance. Signals on the other hand should by their nature be observable (Connelly et al., 2011) and hence can be easily transmitted over distance. We accordingly propose that signaling is a viable strategy for firms to resolve information asymmetries related to geographical distance and secure investment from nonlocal VCFs. Inversely, the value of an information signal is expected to diminish if information asymmetries decrease. For instance, information signals become insignificant after the first round of funding (Hoenen et al., 2013) and when substitute signals are observed (Arthurs et el., 2008; Ozmel, 2013). We anticipate that VCFs have more access to information regarding the quality of a nearby firm, and accordingly put less reliance on information signals. The relevance of signaling is therefore mitigated for firms in the proximity of VCFs. Combined, the following hypothesis is defined:

The effectiveness of information signals, in terms of raising the level of investment in the first round of funding, is stronger for firms that received nonlocal venture capital funding than for firms that received local venture capital funding.

We extend existing empirical evidence which claims that firms located at long distance can increase their chances of receiving funding by sending information signals (Mäkelä and Maula, 2008; Powell et al., 2002; Ragozzino and Reuer, 2011). In the next section we explain the methods used to test our hypothesis.

3. Methods

In our empirical analysis, we use ordinary least squares regression (OLS) to study the level of first round venture capital funding of DBFs that are funded either by local or nonlocal VCFs, subjected to the signaling activity of the DBF before the funding is received. We built upon the work of Hoenen et al. (2013), who employed a similar model and dataset to study the diminishing signaling value of patents over rounds of funding. In line with this study the following basic model is used:

$$\ln(Y_{id}) = X_i\beta + \varepsilon$$

Here, the dependent variable Y_{id} is the natural logarithm of the amount of funding received by the individual DBF i in the first round of venture capital funding, for DBFs funded by VCFs located at distance $d = 1$ or $d = 2$. The term X_i is a vector of firm specific independent variables, which is identical for both $d = 1$ and $d = 2$. The vector consists of information signals as explanatory variables and a set of control variables regarding characteristics of the DBF, the VCF and the environment. Concerning the distance levels, we distinguish between DBFs funded by local ($d = 1$) and nonlocal ($d = 2$) VCFs. As partition between these distance levels, we apply the '20-minute' rule which implies that VCFs only fund firms located within a 20 minute drive[5]. While it is shown that this rule is not always obeyed (Bengtsson and Ravid, 2009; Tian, 2011), VCFs do take such distance levels

[5] Stross, R., "It's not the people you know. It's where you are." The New York Times, 10/22/2006.

into account and hold different standards for firms located outside the local area (Tian, 2011). Accordingly, $d = 1$ is defined as investments were the closest funding VCF in the syndication is located within a 20 miles radius from the DBF. $d = 2$ is defined as investments outside a 20 miles radius from the closest funding VCF[6]. While in particular the distance to the lead investor in the syndication is important (Lutz et al., 2013), we presume that the closest VCF in the syndication is generally the lead investor.

We utilize the exact model that is used by Hoenen et al. (2013) as model 1 and an adjusted form as model 2. The starting point of our analysis is the model employed to all firms in our database, regardless of the distance between the VCF and the DBF; these models are labelled as model 1a and 2a. Subsequently, we employ the model only for observations where $d = 1$, labelled as model 1b and 2b. Finally, model 1c and 2c include only observation where $d = 2$. In the remainder of this section the information signals used as explanatory variables are described. The control variables obtained from the model of Hoenen et al. (2013), and are listed in table 1.

As independent variables we employ two distinct information signals; the patent activity and the founding team characteristics of the focal DBF. Empirical evidence suggests a positive relation between the number of patents and the access to venture capital. Firms funded by VCFs possess more patents before the first round of venture capital (Engel and Keilbach, 2007). Firms with patents gain a higher level of venture capital funding (Baum and Silverman, 2004; Cao and Hsu, 2011; Conti et al., 2013) and more patent applications decrease the time before the first round of funding is received (Häussler et al., 2009). Moreover a combination of patents and prototypes increases the likelihood of receiving venture capital funding (Audretsch et al., 2012). We therefore include p*atent_granted* and *patent_applications* in both models as respectively the number of obtained patents and the number of pending patent applications of the DBF, before the first round of venture

[6] Aharonson et al. (2007), Kolympiris and Kalaitzandonakes (2013), Rosenthal and Strange (2003) and Wallsten (2001) report the extent of local knowledge spillovers between similar types of firms to be within at most a 1 mile radius. If we would assume that VCFs benefit from such spillovers, an additional smaller distance level should be included. The limited number of observations in our dataset within such distances does not allow us to do so. Also, our present study cover interactions between different types of organizations, were such proximity effects are not found. Hence, including such a small radius could actually mask existing relationships.

capital funding. Patent quality, approximated by the number of times a patent is cited in another patent, is found to increase the strength of patents as a signal (Häussler et al., 2009). We include *patent_cited* as the average number of times a patent has been cited by another patent.

As second information signal we address the legitimacy of the founding team. High quality entrepreneurs are not only able to attract more resources because of their skills, their characteristics also perform a signaling function (Certo et al., 2003; Cohen and Dean, 2005; Higgins and Gulati, 2006; Pollock et al., 2009). Hoenen et al., (2013) approximate the founding team legitimacy by a dummy variable that indicates whether a member of the founding team has either a distinctive academic reputation or earlier experience in founding a firm. We include this variable *foundersignal* in model 1. For model 2, we create two alternative variables as a richer measure for the founding team credibility. VCFs prefer to invest in entrepreneurs with earlier experience, because this provides the entrepreneur with a track record (Wright and Ennew, 1997). If founding team members have priorly started a successful firm the likelihood of receiving venture capital increases (Gompers et al., 2010; Hsu, 2007; Mueller et al., 2012). We include the variable *entrepreneurialsignal* to indicate whether one of the members of the founding team has previously started a firm[7]. Subsequently, we emphasize on the academic quality of the entrepreneur. The education level of the management team is positively related to the access to venture capital (Engel and Keilbach, 2007). On the same line, a professor status within the founding team contributes to the likelihood of receiving venture capital (Mueller et al., 2012) and holding a doctoral degree contributes to both the likelihood of being funded as well as the valuation of the firm (Hsu, 2007). The presence of academics and prestige education in the top management team increases firm valuation at the initial public offering (Bonardo et al., 2011; Lester et al., 2006). We include a categorical variable *academicsignal* to measure both the highest academic rank of the entrepreneurial team and whether an

[7] Alternatively, it could be argued that serial entrepreneurs have more access to venture capital because a VCF might be more willing to engage in a repeated interaction with an entrepreneur, because private information regarding the entrepreneur is gained in earlier investment. However, the frequency of such repeated interactions is relatively low in general (Bengtsson, 2013; Wright & Ennew,1997).

entrepreneurial team member is a preeminent member of the academic community (further: distinctive academic reputation).

Table 1. Control Variables of model 1 and 2 (Hoenen et al., 2013)

Variable	**Description**
investmentstage	Stage of investment at first round of VC funding (1) seed (2) early growth (3) bridge (4) late.
firmage	Age of the DBF at the first round of funding
vcfreputation	Reputation score of the highest ranked funding VCF of the first round of financing.
syndicatesize	Average size of investors, measured as the accumulated amount of earlier investments of the VCF.
syndicateinvestors	Number of investors in the first round.
distanceclosestvcf	Distance in miles between the focal DBF and the most proximate funding VCF.
universitiesinmsa	Number of universities that perform biotechnology related research and are located in the same Metropolitan Statistical Area (MSA) as the focal DBF.
vcfarea_0010	Density of VCFs in 0 to 10 miles from the focal DBF.
vcfarea_1020	Density of VCFs in 10 to 20 miles from the focal DBF.
patentarea_0010	Number of patents granted to biotechnology firms located 0 to 10 miles from the focal DBF before the first financing round.
patentarea_1020	Number of patents granted to biotechnology firms located 10 to 20 miles from the focal DBF before the first financing round.
int_patentg_r1_uni	Interaction term between patents granted and universities in MSA
year_r1_2011 *(...)* *Year_r1_2001*	Dummy variables for the year of investment of investment, between 2011 and 2001. (the omitted year is 2007)

4. Dataset

For our analysis we make use of a database measuring venture capital investments toward dedicated biotechnology firms from 2001 up to 2011[8] using Thomson Reuter's SDC Platinum Database (SDC). For an elaborate explanation of the data collection, see Hoenen et al. (2013).

[8] We exclude all observations before 2001 because there was no formal obligation for the publication of patent applications from the United States Patent and Trademark Office (USPTO), because of which patent application data are not available. To test the sensitiveness of our empirical estimates to having only observations after 2001, we employ an alternative model in section 5.2.

By means of the variable *foundersignal* from model 1 the variables *entrepreneurialsignal* and *academicsignal* are created. *Entrepreneurialsignal* is a dummy variable with the value 1 if one of the founding team members has previously started a firm. For the variable a*cademicsignal* a dummy variable is created with the value 1 if a member of the founding team has a distinguished academic reputation[9]. This dummy is merged with an indicator for the highest academic rank within the founding team. The final *academicsignal* is a categorical variable for the highest academic status in the founding team, with the levels: 1=instructor or lecturer, 2=assistant professor, 3=associate professor, 4=full professor, 5=distinguished academic reputation, 0=no academic rank. Data for both variables have been collected using the websites of the firms.

Four observations are excluded from the dataset because of outliers on the number of patent applications. These firms together hold an amount of patent applications that is almost 1/3 of the total number of patent applications in our database and we anticipate that these observations therefore have a disproportional influence on the results. Using the same procedure, Hoenen et al. (2013) found that the coefficient of patent applications doubled, however this did not change the implications of the study. Given that the outliers are even more severe when employing the model at a particular distance level (2 firms possess 40% of patent applications for nonlocal investments), such outliers could have implications for the results of our model, and are excluded beforehand. We reflect on the effects of this procedure in section 5.2.

In total, we obtain a database of 582 venture capital investments towards DBF, of which 283 are local and 299 are nonlocal. The descriptive statistics (Table 2) show that the average distance between the DBF and the VCF is 400 miles. Given that almost half of the observations is within our 20 miles partition (median: 20.6) this number is influenced by a small number of DBFs that received

[9] A founding team member holds a distinguished and/or named professorship and/or is a member of the Academy of Sciences and/or has won a Nobel Prize

investments at very long distance levels[10]. The amount of venture capital investment in the first round is on average 7.180.000 USD. The average amount of respectively local and nonlocal investments differs significantly, where the average investment is considerably smaller for locally funded firms (5.870.000 USD) than for nonlocal funded firms (8.430.000 USD). This finding is inconsistent with earlier studies, which stated that locally funded firms gain a higher level of total funding and a higher level of funding in the first round (Chen et al., 2011; Tian, 2011). However, our numbers are not corrected for the fact that the nonlocal firms in our dataset are significantly older and in a later stage of development, and therefore require higher amounts of funding (Chen et al., 2011).

Regarding the information signals, DBFs have an average of 0.21 patent applications and 0.19 granted patents at the time of the first round of funding. The average number of patent applications is higher for DBFs funded by nonlocal VCFs (0.29) than for locally funded DBFs (0.12). For the number of granted patents we find a similar pattern, with 0.33 and 0.04 granted patents for respectively nonlocal and local funded DBFs. We report a mean of 0.20 for the *foundersignal,* which is stable over distance. This indicates that 1 out of 5 firms have at least one member in the founding team with entrepreneurial experience or with a distinctive academic status. The adjusted founding team signals show that approximately 1 out of 10 entrepreneurs has earlier entrepreneurial experience, also not significantly different for local and nonlocal firms. The founding teams of locally funded firms have on average a slightly higher academic status than nonlocal funded firms (1.15 and 0.94), which is in line with the idea that firms which are more science based are less likely to be funded nonlocal (Powell et al., 2002). However this effect is small, presumably because all firms in the database are biotechnology firms and are therefore all expected to have a scientific foundation.

[10] Hoenen et al. (2013) attribute this to a small number of generally large VCFs that target firms across the country, i.e. East/West coast VCFs fund West/East coast DBFs. We control for disproportional influence of these observations in section 5.2.

Table2_1. Descriptive Statistics of the variables used in model 1 and 2, for all firms in the database

Variable name	**Obs**	**Mean**	**Standard Deviation**	**Min**	**Median**	**Max**
vcf_investment	582	7.18	11.06	0	3.52	100
patent_applications	582	0.21	0.77	0	0	8
patent_granted	582	0.19	1.45	0	0	22
patent_cited	582	0.06	0.44	0	0	6.83
foundersignal	582	0.2	0.4	0	0	1
entrepreneurialsignal	582	0.1	0.3	0	0	1
academicsignal	582	1.04	1.9	0	0	5
investmentstage	582	1.67	0.74	0	2	4
firmage	582	2.29	3.09	0	1	27
vcfreputation	582	0.36	0.45	0	0	1
syndicatesize	582	368.83	618.15	0	76.99	4155
syndicateinvestors	582	2.61	1.84	1	2	13
distanceclosestvcf	582	399.8	750.05	0	20.63	3146
universitiesinmsa	582	9.3	8.1	0	9	37
vcfarea_0010	582	23.27	29.29	0	10	103
vcfarea_1020	582	15.17	25.33	0	5	127
patentarea_0010	582	125.78	155.65	0	58.5	531
patentarea_1020	582	69.83	115.45	0	18	608
int_patentg_r1_uni	582	0.79	5.77	0	0	108

Table2_2. Descriptive Statistics of the variables used in model 1 and 2, only including DBFs funded by a VCF <20 miles

Variable name	**Obs**	**Mean**	**Standard Deviation**	**Min**	**Median**	**Max**
vcf_investment	283	5.87	9.59	0	2.62	100
patent_applications	283	0.12	0.46	0	0	4
patent_granted	283	0.04	0.19	0	0	1
patent_cited	283	0.05	0.45	0	0	6.83
foundersignal	283	0.2	0.4	0	0	1
entrepreneurialsignal	283	0.09	0.28	0	0	1
academicsignal	283	1.15	1.95	0	0	5
investmentstage	283	1.55	0.68	0	1	3
firmage	283	1.65	2.15	0	1	14
vcfreputation	283	0.44	0.46	0	0	1
syndicatesize	283	303.54	487.62	0	62.07	3970
syndicateinvestors	283	2.75	1.77	1	2	11
distanceclosestvcf	283	6.56	5.68	0	5	20
universitiesinmsa	283	10.08	7.87	0	10	37
vcfarea_0010	283	30.36	31.92	0	13	103
vcfarea_1020	283	19.17	29.18	0	6	127
patentarea_0010	283	131.8	139	0	89	523
patentarea_1020	283	85.36	128.62	0	26	608
int_patentg_r1_uni	283	0.38	2.7	0	0	37

Table2_3. Descriptive Statistics of the variables used in model 1 and 2, only including DBFs funded by a VCF >20 miles

Variable name	**Obs**	**Mean**	**Standard Deviation**	**Min**	**Median**	**Max**
vcf_investment	299	8.43	12.17	0	4	93.33
patent_applications	299	0.29	0.97	0	0	8
patent_granted	299	0.33	2	0	0	22
patent_cited	299	0.08	0.43	0	0	4.33
foundersignal	299	0.2	0.4	0	0	1
entrepreneurialsignal	299	0.12	0.32	0	0	1
academicsignal	299	0.94	1.85	0	0	5
investmentstage	299	1.79	0.78	0	2	4
firmage	299	2.89	3.68	0	2	27
vcfreputation	299	0.28	0.42	0	0	1
syndicatesize	299	430.62	715.61	0	94.97	4155
syndicateinvestors	299	2.48	1.9	1	2	13
distanceclosestvcf	299	771.99	900.53	20.41	391.83	3146
universitiesinmsa	299	8.56	8.26	0	6	37
vcfarea_0010	299	16.55	24.81	0	5	103
vcfarea_1020	299	11.38	20.39	0	3	109
patentarea_0010	299	120.09	169.95	0	29	531
patentarea_1020	299	55.13	99.42	0	12	503
int_patentg_r1_uni	299	1.18	7.6	0	0	108

5. Results

5.1. Results of the empirical model

The results of the OLS are presented in tables 3, 4 and 5. Here, model 1a and 2a represent the models where all firms are included. 1b and 2b represent the models for only local funded firms and 1c and 2c represent the models for nonlocal funded firms. The Breusch- Pagan test for heteroskedasticity is significant across all models, meaning that we find evidence that the variances in the models are not homogeneous. Because of this we make use of robust standard errors. Subsequently we also use clustered standard errors on state level, to account for the possibility that our models have a correlation of errors based on regional differences, such as variation in regulation or the level of economic growth in a region (Hoenen et al., 2013). Given that both sets of outcomes do not show severe dissimilarities, our models are robust to these different measures. The F-test displays that all models are in total significant at 0.01 level, and R^2 values between 0.53 and 0.39 reflect that all models have considerable explanatory power. The multicollinearity condition numbers between 13.2 and 15.6 do not raise concerns for any of the models.

The results of the model 1a duplicate the results of Hoenen et al. (2013). The variables *patent_applications* as well as the *foundingsignal* are significant and positively related to the level of funding received by the DBF in the first round. *Patent_granted* and *patent_cited* on the other hand are both insignificant[11]. In model 2a, the *entrepreneurialsignal* of the founding team is significant and positive, while the *academicsignal* is only significant for clustered standard errors and has a considerably lower coefficient (0.048 and 0.437 respectively). This indicates that VCFs rely more on the entrepreneurial experience than on the scientific reputation of the founding team members. We impute this to the fact that entrepreneurs in the biotechnology sector are often science based and lack management experience (Patzelt, 2010). VCFs may well consider earlier entrepreneurial experience as an indicator of management experience, and therefore as a more distinguishing measure of quality in the biotechnology industry.

[11] Although Hoenen et al. (2013) show that the joint effect of patent applications and granted patents is significant in the first round of funding.

Table 3_1. OLS Model 1 with all firms included. The dependent variable is the natural logarithm of the amount of venture capital funding in the first round of financing

Variable Name	**Coefficient**	**Heteroskedasticity robust standard errors**	**Standard errors clustered at state level**
patent_applications	0.1458	0.0685 **	0.0427 ***
patent_granted	-0.0701	0.0525	0.0498
patent_cited	-0.0892	0.0805	0.0871
foundersignal	0.4619	0.1382 ***	0.1129 ***
investmentstage	0.3732	0.0976 ***	0.0796 ***
firmage	0.0725	0.0235 ***	0.0226 ***
vcfreputation	0.2267	0.1288 *	0.1676
syndicatesize	0.0003	0.0001 ***	0.0001 *
syndicateinvestors	0.3865	0.0372 ***	0.0559 ***
distanceclosestvcf	0.0003	0.0001 ***	0.0001 ***
universitiesinmsa	0.0014	0.0080	0.0103
vcfarea_0010	0.0085	0.0023 ***	0.0029 ***
vcfarea_1020	0.0030	0.0029	0.0032
patentarea_0010	0.0008	0.0004 **	0.0004 *
patentarea_1020	-0.0002	0.0007	0.0007
int_patentg_r1_uni	-0.0057	0.0120	0.0072
year_r1_2001	0.2667	0.2153	0.2075
year_r1_2002	0.1520	0.2390	0.1687
year_r1_2003	-0.1278	0.2238	0.1725
year_r1_2004	-0.1160	0.2372	0.1690
year_r1_2005	-0.6450	0.2439 ***	0.2240 ***
year_r1_2006	-0.2002	0.2397	0.1821
year_r1_2008	0.0041	0.2494	0.2015
year_r1_2009	-0.5044	0.3712	0.2682 *
year_r1_2010	-0.1846	0.2893	0.2774
year_r1_2011	-0.4925	0.5622	0.5126
intercept	12.3092	0.2615 ***	0.4230 ***
OBS	582		
R^2	0.4144		
Adjusted R^2	0.387		
F test		15.25 ***	118.75 ***
Breusch-Pagan test for heteroskedasticity	13.92 ***		
Multicollinearity Condition Number	13.32		

Table 3_2. OLS Model 2 with all firms included. The dependent variable is the natural logarithm of the amount of venture capital funding in the first round of financing

Variable Name	**Coefficient**	**Heteroskedasticity robust standard errors**	**Standard errors clustered at state level**
patent_applications	0.1400	0.0670 **	0.0434 ***
patent_granted	-0.0598	0.0524	0.0494
patent_cited	-0.0919	0.0803	0.0868
entrepreneurialsignal	0.4370	0.1760 **	0.1513 ***
academicsignal	0.0479	0.0299	0.0243 **
investmentstage	0.3727	0.0982 ***	0.0804 ***
firmage	0.0725	0.0236 ***	0.0224 ***
vcfreputation	0.2393	0.1290 *	0.1713
syndicatesize	0.0003	0.0001 ***	0.0002 *
syndicateinvestors	0.3822	0.0374 ***	0.0573 ***
distanceclosestvcf	0.0003	0.0001 ***	0.0001 ***
universitiesinmsa	0.0020	0.0081	0.0106
vcfarea_0010	0.0087	0.0023 ***	0.0029 ***
vcfarea_1020	0.0033	0.0029	0.0032
patentarea_0010	0.0007	0.0004 *	0.0004

Table 3_2 (continued)

Variable Name	Coefficient	Heteroskedasticity robust standard errors	Standard errors clustered at state level
patentarea_1020	-0.0003	0.0007	0.0007
int_patentg_r1_uni	-0.0064	0.0120	0.0073
year_r1_2001	0.2707	0.2157	0.2112
year_r1_2002	0.1495	0.2390	0.1724
year_r1_2003	-0.1160	0.2271	0.1760
year_r1_2004	-0.1073	0.2365	0.1679
year_r1_2005	-0.6311	0.2443 ***	0.2180 ***
year_r1_2006	-0.1847	0.2399	0.1805
year_r1_2008	0.03039	0.2476	0.1955
year_r1_2009	-0.4827	0.3698	0.2646 *
year_r1_2010	-0.1698	0.2947	0.2814
year_r1_2011	-0.4252	0.5492	0.4913
intercept	12.3014	0.2647 ***	0.4270 ***
OBS	582		
R^2	0.4129		
Adjusted R^2	0.384		
F test		14.81 ***	134.66 ***
Breusch-Pagan test for heteroskedasticity	15.2 ***		
Multicollinearity Condition Number	13.5257		

Considering only DBFs where the closest funding VCF is located within 20 miles (model 1b), neither *patent_applications* nor *foundingsignal* have a significant impact on the level of funding in the first round. These results are in line with our expectations and underline previous studies stating that VCFs make use of tacit information derived from local networks, hereby reducing ex-ante uncertainty regarding the quality of the DBF (Florida and Kenney, 1988; Rosiello and Parris, 2009; Zook, 2002). The VCF therefore has less necessity to rely on signals as a strategy to mitigate adverse selection problems; hence the relevance of signaling diminishes for local investments. Our results for the *foundingsignal* also reflect that VCFs anticipate replacing board members with outsiders and thus put less emphasis on the credibility of the founding team (Hellmann and Puri, 2002; Baum and Siverman, 2004). VCFs are more likely to become involved in the board of the portfolio firm at geographical proximity (Lerner, 1995), which diminishes the effectiveness of founding team credibility as a signal. In model 2b both *entrepreneurialsignal* and *academicsignal* are insignificant, confirming the results for the *foundersignal* in model 1.

Table 4_1. OLS Model 1 for DBFs funded by a VCF <20 miles. The dependent variable is the natural logarithm of the amount of venture capital funding in the first round of financing

Variable Name	**Coefficient**	**Heteroskedasticity robust standard errors**	**Standard errors clustered at state level**
patent_applications	0.0193	0.2030	0.1960
patent_granted	0.1897	0.4601	0.4148
patent_cited	-0.0560	0.0795	0.0711
foundersignal	0.1769	0.1784	0.2378
investmentstage	0.2969	0.1442 **	0.0860 ***
firmage	0.1058	0.0528 **	0.0400 **
vcfreputation	0.4063	0.2077 *	0.2470
syndicatesize	0.0002	0.0002	0.0001
syndicateinvestors	0.3920	0.0517 ***	0.0601 ***
distanceclosestvcf	-0.0411	0.0167 **	0.0243
universitiesinmsa	0.0058	0.0132	0.0116
vcfarea_0010	0.0083	0.0037 **	0.0025 ***
vcfarea_1020	0.0085	0.0038 **	0.0038 **
patentarea_0010	0.0019	0.0005 ***	0.0004 ***
patentarea_1020	0.0001	0.0010	0.0004
int_patentg_r1_uni	-0.0071	0.0261	0.0282
year_r1_2001	0.4334	0.3086	0.2863
year_r1_2002	0.1878	0.3081	0.2046
year_r1_2003	-0.2905	0.3194	0.2703
year_r1_2004	-0.0458	0.3093	0.2312
year_r1_2005	-0.4997	0.3381	0.2464 *
year_r1_2006	-0.4200	0.3038	0.2397 *
year_r1_2008	0.2679	0.3426	0.3764
year_r1_2009	-1.1912	0.6114 *	0.7518
year_r1_2010	-0.2655	0.3726	0.3037
year_r1_2011	0.3944	0.3803	0.3625
intercept	12.1825	0.3591 ***	0.3780 ***
OBS	283		
R^2	0.526		
Adjusted R^2	0.478		
F test		13.14 ***	x
Breusch-Pagan test for heteroskedasticity	11.15 ***		
Multicollinearity Condition Number	15.4251		

Table 4_2. OLS Model 2 for firms funded by a VCF <20 miles. The dependent variable is the natural logarithm of the amount of venture capital funding in the first round of financing

Variable Name	**Coefficient**	**Heteroskedasticity robust standard errors**	**Standard errors clustered at state level**
patent_applications	0.0152	0.2016	0.1935
patent_granted	0.2465	0.4696	0.3998
patent_cited	-0.0669	0.0827	0.0886
entrepreneurialsignal	0.1488	0.2544	0.2799
academicsignal	0.0106	0.0387	0.0312
investmentstage	0.3013	0.1451 **	0.0892 ***
firmage	0.1046	0.0530 **	0.0406 **
vcfreputation	0.4151	0.2092 **	0.2466
syndicatesize	0.0002	0.0002	0.0001
syndicateinvestors	0.3901	0.0517 ***	0.0609 ***
distanceclosestvcf	-0.0405	0.0169 **	0.0235 *
universitiesinmsa	0.0061	0.0133	0.0117
vcfarea_0010	0.0085	0.0037 **	0.0025 ***
vcfarea_1020	0.0086	0.0038 **	0.0039 **
patentarea_0010	0.0018	0.0005 ***	0.0004 ***

Table 4_2 (continued)

Variable Name	Coefficient	Heteroskedasticity robust standard errors	Standard errors clustered at state level
patentarea_1020	0.0001	0.0010	0.0003
int_patentg_r1_uni	-0.0094	0.0265	0.0276
year_r1_2001	0.4152	0.3066	0.2938
year_r1_2002	0.1749	0.3061	0.2121
year_r1_2003	-0.3091	0.3192	0.2727
year_r1_2004	-0.0524	0.3085	0.2423
year_r1_2005	-0.5041	0.3386	0.2411 **
year_r1_2006	-0.4349	0.3038	0.2380 *
year_r1_2008	0.2693	0.3430	0.3794
year_r1_2009	-1.1886	0.6094 *	0.7583
year_r1_2010	-0.2775	0.3880	0.3160
year_r1_2011	0.4038	0.3916	0.3634
intercept	12.1898	0.3589 ***	0.379 ***
OBS	283		
R2	0.5252		
Adjusted R2	0.475		
F test		12.56 ***	x
Breusch-Pagan test for heteroskedasticity	11 ***		
Multicollinearity Condition Number	15.5865		

Subsequently we consider only DBFs located further than 20 miles from the nearest funding VCF (Model 1c). Both *patent_applications* and the *foundingsignal* are significant and positively affect the amount of venture capital funding received in the first round. Moreover the coefficients of these variables are considerably higher in the nonlocal model than in local model. Our results reflect that for investments in nonlocal DBFs, the VCF is less able to assess the quality (Rosiello and Parris, 2009; Sorenson and Stuart, 2001; Zook, 2002), is less likely to become involved in the management (Lerner, 1995), and is less capable of monitoring (Bengtsson and Ravid, 2009; Chen et al., 2010; Sorenson and Stuart, 2001; Tian, 2011). VCFs consequently experience increasing adverse selection problems, and allocate higher levels of funding to DBFs that are able to transmit their legitimacy through signaling. Although obtaining knowledge through local networks is theoretically a preferred strategy (Casella and Hanaki, 2006), our findings suggest that signals can partly compensate for the absence of such networks. These findings are in line with earlier studies, stating that firms can compensate for higher information asymmetries associated with geographical distance, by sending additional information signals (Mueller et al., 2012; Ragozzino and Reuer, 2011). In model 2c both the *entrepreneurialsignal* and the *academicsignal* are positive and significant, confirming the results from model 1c. In line with model 2a, the coefficients are higher for the *entrepreneurialsignal* (0.60) than for the *academicsignal* (0.10), indicating that VCFs are in particular looking for skilled managers with experience in entrepreneurship for long distance investments. This is in line with the fining that VCFs are less likely to be involved in the board of long distance portfolio firms (Lerner, 1995) and therefore rely on the quality of the founding team.

Table 5_1. OLS Model 1 for firms funded by a VCF >20 miles. The dependent variable is the natural logarithm of the amount of venture capital funding in the first round of financing

Variable Name	**Coefficient**	**Heteroskedasticity robust standard errors**	**Standard errors clustered at state level**
patent_applications	0.1602	0.0683 **	0.0583 ***
patent_granted	-0.0774	0.0499	0.0486
patent_cited	-0.1704	0.1517	0.1484
foundersignal	0.7684	0.1868 ***	0.1615 ***
investmentstage	0.3981	0.1360 ***	0.0980 ***
firmage	0.0411	0.0248 *	0.0247
vcfreputation	0.0161	0.1737	0.1584
syndicatesize	0.0003	0.0001 **	0.0002 *
syndicateinvestors	0.3779	0.0498 ***	0.0557 ***
distanceclosestvcf	0.0002	0.0001 ***	0.0001 **
universitiesinmsa	-0.0033	0.0116	0.0113
vcfarea_0010	0.0087	0.0037 **	0.0040 **
vcfarea_1020	0.0020	0.0053	0.0055
patentarea_0010	-0.0001	0.0005	0.0005
patentarea_1020	-0.0005	0.0010	0.0010
int_patentg_r1_uni	-0.0060	0.0123	0.0108
year_r1_2001	-0.0001	0.3092	0.2608
year_r1_2002	-0.0288	0.3882	0.3244
year_r1_2003	-0.1044	0.3076	0.2278
year_r1_2004	-0.3299	0.3818	0.3911
year_r1_2005	-0.9533	0.3467 ***	0.3940 **
year_r1_2006	-0.0515	0.3517	0.3035
year_r1_2008	-0.3311	0.3529	0.3359
year_r1_2009	-0.0034	0.3965	0.5007
year_r1_2010	-0.1609	0.4009	0.4193
year_r1_2011	-1.2715	1.1229	1.0669
intercept	12.8644	0.3831 ***	0.3525 ***
OBS	299		
R2	0.391		
Adjusted R2	0.333		
F test		7.71 ***	196.66 ***
Breusch-Pagan test for heteroskedasticity	9.27 ***		
Multicollinearity Condition Number	13.2285		

Table 5_2. OLS Model 2 for firms funded by a VCF >20 miles. The dependent variable is the natural logarithm of the amount of venture capital funding in the first round of financing

Variable Name	**Coefficient**	**Heteroskedasticity robust standard errors**	**Standard errors clustered at state level**
patent_applications	0.1458	0.0672 **	0.0609 **
patent_granted	-0.0644	0.0510	0.0499
patent_cited	-0.1561	0.1444	0.1364
entrepreneurialsignal	0.6180	0.2062 ***	0.1919 ***
academicsignal	0.0927	0.0444 **	0.0436 **
investmentstage	0.3852	0.1368 ***	0.1025 ***
firmage	0.0434	0.0251 *	0.0250 *
vcfreputation	0.0434	0.1755	0.1666
syndicatesize	0.0003	0.0001 **	0.0002 *
syndicateinvestors	0.3750	0.0501 ***	0.0552 ***
distanceclosestvcf	0.0002	0.0001 ***	0.0001 ***
universitiesinmsa	-0.0023	0.0120	0.0114
vcfarea_0010	0.0089	0.0037 **	0.0042 **
vcfarea_1020	0.0023	0.0052	0.0052
patentarea_0010	-0.0001	0.0005	0.0004
patentarea_1020	-0.0005	0.0010	0.0010
int_patentg_r1_uni	-0.0072	0.0126	0.0112
year_r1_2001	0.0681	0.3097	0.2756
year_r1_2002	0.0065	0.3852	0.3388
year_r1_2003	-0.0229	0.3117	0.2311
year_r1_2004	-0.2907	0.3819	0.4084
year_r1_2005	-0.8883	0.3455 **	0.3848 **
year_r1_2006	0.0705	0.3486	0.3049
year_r1_2008	-0.2423	0.3495	0.3286
year_r1_2009	0.0676	0.4062	0.5224
year_r1_2010	-0.0879	0.4086	0.4378
year_r1_2011	-1.1235	1.0769	1.0198
intercept	12.8118	0.3934 ***	0.3750 ***
OBS	299		
R2	0.3868		
Adjusted R2	0.326		
F test		7.75 ***	233.95 ***
Breusch-Pagan test for heteroskedasticity	10.11 ***		
Multicollinearity Condition Number	13.5251		

In full, we find that information signals increase the level of venture capital funding only if the distance between the VCF and the DBF is high. Because we use a natural logarithm for the dependent variable, the coefficients can be interpreted as semi-elasticities (Hoenen et al., 2013). The results indicate that one additional patent application increases the amount of received venture capital funding with approximately 15% for nonlocal investments, but not significantly for local investments. Hence, we confirm our hypothesis that information signals are more effective for nonlocal than for local investments. These findings are robust over both model 1 and 2 and over all information signals included in our model, which increases the strength of our results[12].

[12] In unreported models, Phase 1 and Phase 2 SBIR awards are included as additional information signals. These are not found significant in either the local, the nonlocal or the model at all distance levels. The contradiction with earlier studies that report SBIR awards as a significant signal (Lerner, 1999; Toole & Turvey, 2009) could be

In addition to our analysis of the information signals, the results of the OLS give insight in the behavior of the control variables. Regarding the characteristics of the DBFs, we find that *firmage* and *investmentstage* positively influence the level of funding in all models. This is as expected because older and bigger firms generally require higher investments (Chen et al., 2011; Sorenson and Stuart, 2001). We expect the magnitudes of these variables to be higher for nonlocal investments, since higher age and development stage come with a track record of the its firm credibility and therefore decrease information asymmetries associated with long distance (Stuart, 1999). This premise is indeed confirmed by *investmentstage* (coefficients: 0.40 and 0.29 for the nonlocal and local model respectively), but not by *firmage.* A explanation for the latter finding could be that older firms have larger social networks, which makes older firms better able to transmit their quality to local VCFs.

For the characteristics of the VCF, the average size of investors in the syndication increases the amount of investment in all models, while the number of participating VCFs only has a minor positive effect for nonlocal investments. Further, our results regarding the reputation of the VCF are worth emphasizing. It is expected that more reputable VCFs have bigger networks and use these to reduce information asymmetries for long distance investments (Cummings and Dia, 2010; Sorenson and Stuart, 2001). Our results, while rather unstable over the different models, pinpoint that *vcfreputation* increases the level of funding for local investments but not for nonlocal investments. If we assume that a higher reputation is an indicator for a stronger social network, our findings could reflect that VCFs rely more on their networks for local investments than for nonlocal investments. High reputable VCFs are consequently willing to allocate higher levels of funding to local DBFs than low reputable VCFs, because they are better able to assess the quality through their strong networks. This finding in in line with our argumentation regarding the diminishing signaling value for local investments.

---

caused by an inaccurate measure of the date at which the SBIR grant is received. As such we do not emphasis further on these results, however we do recite that including these variables does not cause severe fluctuation in the other variables in the models.

Regarding the environmental characteristics, the amount of VCFs between 0 and 10 miles increases the level of venture capital funding in all models, in line with Kolympiris et al. (2011). A higher number of patents granted to biotechnology firms within a 10 miles radius and more VCFs between 10 and 20 miles only increase the level of funding for DBFs located nearby the funding VCF. This could indicate that local funded DBFs are able to transmit their quality through local networks, and that the level of funding towards DBFs increases if such local networks are stronger. Finally, the number of universities in the metropolitan statistical area (MSA) does not affect the level of investment at any distance level, nor does the interaction term between universities in MSA and granted patents.

5.2. Robustness checks

In Table 6_1 till 6_11, a number of additional models are presented to test the robustness of our analysis to several assumptions. We anticipate that our results might be sensitive to the distance used to distinguish between local and nonlocal investments. While the 20 miles partition used in our analysis has a theoretical foundation, a number of alternative approximations for local investments are available in literature. We test our model for a number of such alternatives. Kolympiris et al. (2011) find that DBFs benefit from the amount of VCFs and DBFs within a 10 mile radius, attributed to the agglomeration effects that such proximities produce. Employing model 2 for DBFs funded by VCFs located within 10 miles, does not provoke severe differences regarding the significance of the signaling variables compared to model 1b and 2b. Following Powell et al. (2002), we also test the alternative of a one hour drive, approximated by a 50 miles radius. At this distance level all information signals are insignificant. Hereby the implications of our model regarding local investments are found robust for alternative interpretations of local investments.

The same alternatives are tested for nonlocal investments. Model 2 applied to DBFs funded from outside a 10 mile radius largely reproduces the outcomes of model 1c and 2c. However for the 50 miles model the results are somewhat different. At such a distance level neither *patent_applications* nor *academicsignal* are significant, which might reveal that the distance at which information signals are relevant also has an upper limit. In the context of our database, a plausible explanation is that our outcomes are influenced by the small number of very long distance investments (as identified in section 4). We therefore run the analysis while excluding observations where the distance between VCF and DBF exceeds 2000 miles. Such a procedure indeed increases the significance of patent applications outside the 50 mile radius. Likewise, an identical procedure for respectively the 10 and 20 miles distance levels increases the magnitude of both the patent applications and the entrepreneurial signal. We can therefore presume that information signals are not used by VCFs investing at very long distance investments, however the number of such long distance investments in our dataset is too low to specifically test this premise. Overall it is found that our models are rather robust for alternative measures for local and nonlocal investment.

Table 6_1. OLS Model 2 with alternative distance levels for local investments. The dependent variable is the natural logarithm of the amount of venture capital funding in the first round of financing

	<10 Miles		**<50 Miles**	
Variable Name	**Coefficient**	**Heteroskedasticity robust standard errors**	**Coefficients**	**Heteroskedasticity robust standard errors**
patent_applications	-0.0924	0.2752	0.1411	0.99
patent_granted	0.3323	0.4569	-0.2439	0.5945
patent_cited	-0.1236	0.0910	0.0263	0.0999
entrepreneurialsignal	0.2110	0.2435	0.2522	0.2274
academicsignal	0.0027	0.0435	0.0177	0.0356
investmentstage	0.3960	0.1706 **	0.3202	0.1323 **
firmage	0.1181	0.0586 **	0.1216	0.0466 ***
vcfreputation	0.3583	0.2511	0.4450	0.1915 **
syndicatesize	0.0002	0.0002	0.0003	0.0002 *
syndicateinvestors	0.3087	0.0522 ***	0.3883	0.0453 ***
distanceclosestvcf	-0.0556	0.0332 *	-0.0007	0.0074
universitiesinmsa	0.0102	0.0158	0.0111	0.0095
vcfarea_0010	0.0090	0.0042 **	0.0082	0.0029 ***
vcfarea_1020	0.0033	0.0061	0.0034	0.0033
patentarea_0010	0.0024	0.0006 ***	0.0015	0.0005 ***
patentarea_1020	0.0005	0.0016	0.0006	0.0009
int_patentg_r1_uni	-0.0157	0.0255	-0.0137	0.0377
year dummies Included		Yes		Yes
intercept	12.1568	0.4022 ***	11.7438	0.3111 ***
OBS	213		348	
R2	0.5177		0.5241	
Adjusted R2	0.447		0.484	
F test	10.66 ***		16.22 ***	
Breusch-Pagan test for heteroskedasticity	16.08 ***		17.98 ***	
Multicollinearity Condition Number	15.4215		14.7009	

Table 6_2. OLS Model 2 with alternative distance levels for nonlocal investments. The dependent variable is the natural logarithm of the amount of venture capital funding in the first round of financing

	>10 miles			>50 miles
Variable Name	**Coefficient**	**Heteroskedasticity robust standard errors**	**Coefficients**	**Heteroskedasticity robust standard errors**
patent_applications	0.1577	0.0664 **	0.0856	0.0670
patent_granted	-0.0490	0.0520	-0.0709	0.0447
patent_cited	-0.1911	0.1348	-0.0774	0.1597
entrepreneurialsignal	0.4752	0.2192 **	0.4839	0.2332 **
academicsignal	0.0834	0.0409 **	0.0733	0.0501
investmentstage	0.3534	0.1220 ***	0.3814	0.1445 ***
firmage	0.0484	0.0245 **	0.0308	0.0240
vcfreputation	0.0957	0.1585	-0.2353	0.2095
syndicatesize	0.0003	0.0001 **	0.0002	0.0001 *
syndicateinvestors	0.4382	0.0517 ***	0.3448	0.0525 ***
distanceclosestvcf	0.0003	0.0001 ***	0.0002	0.0001 *
universitiesinmsa	-0.004	0.0103	-0.0027	0.0182
vcfarea_0010	0.0091	0.0032 ***	0.0063	0.0053
vcfarea_1020	0.0055	0.0032 *	-0.0014	0.0067
patentarea_0010	-0.0001	0.0005	-0.0002	0.0005
patentarea_1020	-0.0008	0.0008	-0.0013	0.0012
int_patentg_r1_uni	-0.0110	0.0133	-0.0007	0.0098
year dummies Included		Yes		Yes
Intercept	12.5134	0.3612 ***	13.3401	0.4388 *
OBS	369		234	
R2	0.4008		0.3214	
Adjusted R2	0.353		0.232	
F test	8.7 ***		5.02 ***	
Breusch-Pagan test for heteroskedasticity	8.69 ***		6.57 **	
Multicollinearity Condition Number	13.5026		13.5966	

Table 6_3. OLS Model 2 with alternative distance levels for nonlocal investments, observations >2000 miles excluded. The dependent variable is the natural logarithm of the amount of venture capital funding in the first round of financing

	>10 miles		>20 miles		>50 miles	
Variable Name	**Coefficients**	**Heteroskedasticity robust standard errors**	**Coefficients**	**Heteroskedasticity robust standard errors**	**Coefficients**	**Heteroskedasticity robust standard errors**
patent_applications	0.2281	0.0694 ***	0.2301	0.0733 ***	0.1877	0.0724 ***
patent_granted	-0.0666	0.0496	-0.0752	0.0501	-0.0763	0.0439 *
patent_cited	-0.2991	0.1666 *	-0.2624	0.1703	-0.1394	0.1778
entrepreneurialsignal	0.5502	0.2412 **	0.7487	0.2345 ***	0.6299	0.2781 **
academicsignal	0.0798	0.0422 *	0.0854	0.0472 *	0.0700	0.0550
investmentstage	0.3647	0.1238 ***	0.3945	0.1424 ***	0.3830	0.1516 **
firmage	0.0480	0.0259 *	0.0419	0.0275	0.0285	0.0269
vcfreputation	0.0554	0.1743	0.0222	0.1951	-0.2635	0.2392
syndicatesize	0.0001	0.0001	0.0001	0.0002	0.0001	0.0002
syndicateinvestors	0.4184	0.0530 ***	0.3423	0.0486 ***	0.3203	0.0515 ***
distanceclosestvcf	0.0010	0.0002 ***	0.0008	0.0002 ***	0.0007	0.0002 ***
universitiesinmsa	0.0046	0.0109	0.0049	0.0126	0.0043	0.0198
vcfarea_0010	0.0089	0.0034 *	0.0078	0.0043 *	0.0050	0.0064
vcfarea_1020	0.0089	0.0030 *	0.0086	0.0043 **	0.0051	0.0055
patentarea_0010	0.0001	0.0005	0.0002	0.0005	0.0001	0.0006
patentarea_1020	-0.0004	0.0007	0.0004	0.0009	-0.0006	0.0011
int_patentg_r1_uni	-0.0075	0.0085	-0.0045	0.0089	-0.0006	0.0084
year dummies included		yes		yes		yes
intercept	12.3219	0.3741***	12.6823	0.4121 ***	13.2362	0.4807 ***
OBS	318		248		183	
R2	0.477		0.4742		0.4203	
Adjusted R2	0.428		0.41		0.319	
F test	10.6 ***		9.77 ***		x	
Breusch-Pagan test for heteroskedasticity	9.16 ***		11.8 ***		7.89 ***	
Multicollinearity Condition Number	13.4915		13.54		14.0289	

While our study focusses on the geographical distance between an individual VCF and DBF, our results also implicate that firms located in areas with a low number of VCFs, should be more likely to benefit from sending information signals than DBFs in areas with a high accumulation of venture capital firms. Such findings contradict with Lerner (1999) who argues that signals are only relevant in regions with high access to venture capital. While not in the scope of this study, we test whether the amount of VCFs in the proximity of the DBF also affects the relevance of signaling. In order to do so, we replace the partition based on *distanceclosestvcf* by a partition based on *vcfarea_0010*. We obtain two models; one model including only DBFs that are located in regions with more than 20 VCFs in a 10 miles radius and one model for DBFs in regions with less than 20 VCFs. The results show that both pending patent applications and entrepreneurial experience are more relevant in regions with a low number of VCFs. However, the results are less pronounced as in our model divided over *distanceclosestvcf*. These findings largely confirm that firms located outside high economic growth clusters with a limited number of proximate VCFs, can increase their access to venture capital when sending credible information signals (Mueller et al., 2012).

Table 6_4. OLS Model 2 for observations where vcf_area0010 <20. The dependent variable is the natural logarithm of the amount of venture capital funding in the first round of financing

Variable Name	**Coefficient**	**Heteroskedasticity robust standard errors**	**Standard errors clustered at state level**
patent_applications	0.1372	0.0725 *	0.0553 **
patent_granted	-0.0653	0.0551	0.0534
patent_cited	-0.0989	0.0873	0.0924
entrepreneurialsignal	0.4433	0.2285 *	0.2194 *
academicsignal	0.0465	0.0400	0.0403
investmentstage	0.4109	0.1163 ***	0.1058 ***
firmage	0.0646	0.0240 ***	0.0293 **
vcfreputation	0.3450	0.1684 **	0.2472
syndicatesize	0.0004	0.0001 ***	0.0003
syndicateinvestors	0.3960	0.0489 ***	0.0859 ***
distanceclosestvcf	0.0004	0.0001 ***	0.0001 ***
universitiesinmsa	0.0015	0.0094	0.0138
vcfarea_0010	-0.0122	0.0167	0.0141
vcfarea_1020	0.0049	0.0041	0.0058
patentarea_0010	0.0009	0.0006	0.0007
patentarea_1020	-0.0001	0.0009	0.0013
int_patentg_r1_uni	0.0028	0.0098	0.0070
year dummies included		yes	yes
Intercept	12.2412	0.3348 ***	0.4203 ***

Table 6_4 (continued)

OBS	404		
R2	0.4381		
Adjusted R2	0.3980		
F test		10.6 ***	105.55 ***
Breusch-Pagan test for heteroskedasticity	5.63 **		
Multicollinearity Condition Number	13.2173		

Table 6_5. OLS Model 2 for observations where vcf_area0010 >20. The dependent variable is the natural logarithm of the amount of venture capital funding in the first round of financing

Variable Name	**Coefficient**	**Heteroskedasticity robust standard errors**	**Standard errors clustered at state level**
patent_applications	0.0887558	0.3602	0.2997
patent_granted	-0.4252201	0.7442	0.8909
patent_cited	4.26635	2.2314 **	1.1500 ***
entrepreneurialsignal	0.1565365	0.2702	0.1209
academicsignal	0.0510329	0.0424	0.0172 **
investmentstage	0.2613448	0.1794	0.1353 *
firmage	0.080992	0.0646	0.0200 ***
vcfreputation	-0.1381069	0.2145	0.0723 *
syndicatesize	0.0000739	0.0002	0.0001
syndicateinvestors	0.3799285	0.0664 ***	0.0259 ***
distanceclosestvcf	0.0001471	0.0002	0.0002
universitiesinmsa	-0.0292759	0.0225	0.0162
vcfarea_0010	0.002125	0.0073	0.0022
vcfarea_1020	-0.0042156	0.0067	0.0029
patentarea_0010	0.0005793	0.0009	0.0007
patentarea_1020	-0.0013533	0.0014	0.0002 ***
int_patentg_r1_uni	0.0073922	0.0384	0.0173
year dummies included		yes	yes
Intercept	13.98176	0.8224 ***	0.2264 ***
OBS	404		
R2	0.4381		
Adjusted R2	0.3980		
F test		10.6 ***	x
Breusch-Pagan test for heteroskedasticity	5.63 **		
Multicollinearity Condition Number	13.2173		

Besides considerations regarding the partition method between the different models, we check the validity of some of the variables included in our models. The academic signal in Model 2 is created by merging two separate variables (see section 4). We test the legitimacy of this procedure by a model including the separated measures on which the academic signal is based. In the first model, we include a dummy with the value 1 if a member of the founding team has a distinctive academic reputation (see section 4 for a definition). The new variable does not change any of the implications of our results, but in the nonlocal model the coefficient of the new variable is considerably higher compared to the original *academicsignal* (0.66 and 0.09). In the second alternative the *academicsignal* is replaced with a categorical variable for the highest academic rank in the founding team, from non-academic rank (0) till full professor (4). This model does not show severe variations compared to the initial variable, both for the local and nonlocal model. The findings indicate that a distinctive academic status has a more pronounced impact on the level of venture capital funding than a general academic appointment. However, the coefficient for distinctive academic reputation is likely to be somewhat flawed because of the low number of positive observations for this variable. As such the height of the coefficient must be considered cautiously.

Table 6_6. Model 2 with alternative independent variables, including firms funded by a VCF <20 miles. The dependent variable is het natural logarithm of the amount of venture capital received in the first round of funding

Variable Name	**Coefficient**	**Heteroskedasticity robust standard errors**	**Coefficient**	**Heteroskedasticity robust standard errors**	**Coefficient**	**Heteroskedasticity robust standard errors**
patent_applications	0.0165	0.2025	0.0147	0.2019	-0.5865	0.2852
patent_granted	0.2139	0.4720	0.2524	0.4683	0.4272	0.4366
patent_cited	-0.0609	0.0814	-0.0679	0.0827	-0.0898	0.0791
entrepreneurialsignal	0.1389	0.2534	0.1514	0.2542	0.1571	0.2563
academicsignal					0.0006	0.0404
investmentstage	0.2999	0.1450 **	0.30156	0.1451 ***	0.3160	0.1487 **
firmage	0.1061	0.0529 **	0.1045	0.0530 **	0.0930	0.0562 *
vcfreputation	0.4123	0.2092 **	0.4159	0.2093 **	0.4015	0.2102 *
syndicatesize	0.0002	0.0002	0.0002	0.0002	0.0001	0.0002
syndicateinvestors	0.3910	0.0522 ***	0.3901	0.0516 ***	0.3950	0.0515 ***
distanceclosestvcf	-0.0406	0.0169 **	-0.0405	0.0169 **	-0.0390	0.0175 **
universitiesinmsa	0.0061	0.0133	0.0062	0.0133	0.0103	0.0140
vcfarea_0010	0.0084	0.0036 **	0.0086	0.0037 **	0.0078	0.0038 **
vcfarea_1020	0.0085	0.0038 **	0.0086	0.0038 **	0.0083	0.0038 **
patentarea_0010	0.0019	0.0005 ***	0.0018	0.0005 ***	0.0019	0.0005 ***
patentarea_1020	0.0001	0.0010	0.0001	0.0010	0.0001	0.0011
int_patentg_r1_uni	-0.0084	0.0263	-0.0097	0.0265	-0.0072	0.0244
destinctive academic reputation	0.1250	0.2135				
academic rank			0.0089	0.0444		
*int_patenta*entrepreneurs*					(omitted)	
*int_patenta*academics*					0.0553	0.0818
*int_patenta*syndicationsize*					0.0005	0.0003
*int_patenta*staging*					-0.1520	0.0964
year dummies included		yes		yes		yes
intercept	12.1796	0.3635 ***	12.1922	0.3581 ***	12.1686	0.3625
OBS	283		283		283	
R2	0.5256		0.5251		0.5306	
Adjusted R2	0.475		0.475		0.475	
F test	12.68 ***		12.54 ***		12.33 ***	
Breusch-Pagan test for heteroskedasticity	10.83 ***		11.01 ***		12.25 ***	
Multicollinearity Condition nr.	15.4908		15.5838		15.7572	

Table 6_7. Model with several alternative independent variables, including firms funded by a VCF >20 miles. The dependent variable is het natural logarithm of the amount of venture capital received in the first round of funding

Variable Name	**Coefficient**	**Heteroskedasticity robust standard errors**	**Coefficient**	**Heteroskedasticity robust standard errors**	**Coefficient**	**Heteroskedasticity robust standard errors**
patent_applications	0.1556	0.0673 **	0.1450	0.0675 **	0.2761	0.1298 **
patent_granted	-0.0746	0.0512	-0.0613	0.0510	-0.0654	0.0495
patent_cited	-0.1652	0.1429	-0.1587	0.1451	-0.1579	0.1474
entrepreneurialsignal	0.5991	0.2072 ***	0.6295	0.2061 ***	0.6071	0.2207 ***
academicsignal					0.0885	0,0498 *
investmentstage	0.3876	0.1357 ***	0.3852	0.1370 ***	0.3838	0.1393 ***
firmage	0.0425	0.0248 *	0.0435	0.0252 *	0.0384	0.0252
vcfreputation	0.0297	0.1742	0.0512	0.1757	0.0270	0.1759
syndicatesize	0.0003	0.0001 **	0.0003	0.0001 **	0.0003	0.0001 **
syndicateinvestors	0.3753	0.0505 ***	0.3734	0.0500 ***	0.3785	0.0514 ***
distanceclosestvcf	0.0002	0.0001 **	0.0002	0.0001 ***	0.0002	0.0001 **
universitiesinmsa	-0.0039	0.0117	-0.0023	0.0121	-0.0037	0.0124
vcfarea_0010	0.0085	0.0038 **	0.0091	0.0037 **	0.0091	0.0038 **
vcfarea_1020	0.0022	0.0053	0.0022	0.0052	0.0028	0.0053
patentarea_0010	-0.0001	0.0005	-0.0001	0.0005	-0.0001	0.0005
patentarea_1020	-0.0005	0.0010	-0.0005	0.0010	-0.0006	0.0010
int_patentg_r1_uni	-0.0063	0.0126	-0.0074	0.0125	-0.0096	0.0126
year dummies included		Yes		Yes		yes
intercept	12.8876	0.3836 ***	12.8150	0.3956 ***	12.8022	0.3969 ***
distinctive academic reputation	0.6621	0.2458 ***				
academic rank			0.0958	0.0522 *		
*int_patenta*entrepreneurs*					0.0836	0,1611
*int_patenta*academics*					0.0251	0,0317
*int_patenta*syndicationsize*					-0.0002	0,0001 *
*int_patenta*staging*					-0.1092	0,0663
OBS	299		299		299	
R2	0.3918		0.3851		0.3906	
Adjusted R2	0.331				0.32	
F test	7.56 ***		7.74 ***		10.11 ***	
Breusch-Pagan test for heteroskedasticity	10.08 ***		10.17 ***		9.97 ***	
Multicollinearity Condition Number	13.277		13.5667		13.6568	

We also check the behaviour of a number of interaction terms between the variables in our models. Information signals can have different meanings and can as such amplify or interfere with each other. We test for the interaction between *patent_applications* and *entrepreneurialsignal* and between *patent_applications* and *academicsignal* (although *pantentapplications*entrepreneurial* signals is omitted from the local model because of collinearity problems). Moreover we look at the interaction between the signals and alternative monitoring mechanisms used by the VCF, and include an interaction term between *syndicationsize* and *patent_applications* as well as the interaction between *patent_applications* and the level of staging (approximated by the time between round 1 and round 2). We find no significant effect of these variables for either local or nonlocal investments. Also our results show that both the information signals and control variables are robust for the addition of such interaction variables.

Finally, we test whether our results are robust for a variation in the included observations in our database. Although our full database consists of venture capital investments from 1974 till 2011, only data from 2001 onwards are used because data for patent applications are not available for earlier years. In order to test the robustness of our model for this limitation, we run the model with all years included. *Patent_applications* is omitted from this model because these are only available after 2001. Both the local and nonlocal model shows some minor deviations regarding the *academicsignal* and the control variables, but these findings do not affect any of the implications of our results. One contradicting finding is that the variable *granted_patent* is negative and significant for local investments. This result is however not duplicated in any other model, and not in line with earlier empirical work regarding the signaling value of patents (Baum and Silverman, 2004; Cao and Hsu, 2011; Conti et al., 2013). While significant, we cannot devote solid conclusions to this outcome. In total, we find that our models are rather robust to the changes of the observations that are included in the analysis[13].

[13] In an unreported model, we approximated the patent applications before 2001 by using the application dates for the granted patents, obtained from Google patent. To test the reliability of this strategy we run the model for observations after 2001, but with the new variable for patent applications. This give strongly different results for both patent applications and granted patents, because of which we judge this alternative as unreliable.

Table 6_8. OLS Model 2 with observations from 1974 till 2011, for firms funded by VCF <20 miles. The dependent variable is the natural logarithm of the amount of venture capital funding in the first round of financing

Variable Name	**Coefficient**	**Heteroskedasticity robust standard errors**	**Standard errors clustered at state level**
patent_granted	-0.3344	0.1530 **	0.1430 **
patent_cited	-0.0478	0.0771	0.0829
entrepreneurialsignal	0.0171	0.2281	0.1716
academicsignal	0.0501	0.0308	0.0208 **
investmentstage	0.3184	0.1072 ***	0.1000 ***
firmage	0.0561	0.0404	0.0263 **
vcfreputation	0.5122	0.1424 ***	0.1483 ***
syndicatesize	0.0002	0.0002	0.0002
syndicateinvestors	0.3351	0.0356 ***	0.0401 ***
distanceclosestvcf	-0.0177	0.0119	0.0185
universitiesinmsa	0.0039	0.0092	0.0107
vcfarea_0010	0.0083	0.0028 ***	0.0026 ***
vcfarea_1020	0.0058	0.0028 **	0.0035
patentarea_0010	0.0013	0.0004 ***	0.0004 ***
patentarea_1020	0.0001	0.0007	0.0005
int_patentg_r1_uni	0.0011	0.0189	0.0236
Year dummies included		yes	yes
Intercept	11.9749	0.2730 ***	0.2721 ***
OBS	499		
R2	0.4889		
Adjusted R2	0.441		
F test		11.2 ***	x
Breusch-Pagan test for heteroskedasticity	13.69 ***		
Multicollinearity Condition Number	15.0809		

Table 6_9. OLS Model 2 with observations from 1974 till 2011, for firms funded by VCF >20 miles. The dependent variable is the natural logarithm of the amount of venture capital funding in the first round of financing

Variable Name	**Coefficient**	**Heteroskedasticity robust standard errors**	**Standard errors clustered at state level**
patent_granted	-0.0557	0.0477	0.0476
patent_cited	0.1459	0.1226	0.0995
entrepreneurialsignal	0.6824	0.1818 ***	0.1843 ***
academicsignal	0.1030	0.0333 ***	0.0375 ***
investmentstage	0.3649	0.0979 ***	0.0745 ***
firmage	0.0293	0.0114 ***	0.0123 **
vcfreputation	-0.1418	0.1412	0.1422
syndicatesize	0.0004	0.0001 ***	0.0002 **
syndicateinvestors	0.3907	0.0376 ***	0.0297 ***
distanceclosestvcf	0.0002	0.0001 ***	0.0001 **
universitiesinmsa	-0.0014	0.0081	0.0058
vcfarea_0010	0.0096	0.0033 ***	0.0032 ***
vcfarea_1020	0.0027	0.0045	0.0062
patentarea_0010	0.0000	0.0005	0.0003
patentarea_1020	-0.0002	0.0007	0.0006
int_patentg_r1_uni	0.0028	0.0023	0.0023
year dummies included		Yes	Yes
Intercept	12.1979	0.2598 ***	0.2762 ***
OBS	551		
R2	0.4119		
Adjusted R2	0.362		
F test		10.99 ***	x
Breusch-Pagan test for heteroskedasticity	6.3 **		
Multicollinearity Condition Number	12.3651		

We also test the impact of the four observations that were excluded from the initial dataset, because of outliers on *patent_applications*. Given that the four excluded DBFs possess a considerable percentage of the total amount of patents in our dataset, such observations could severely change the implications of our results. We find that the results of the local model are robust against the inclusion of these observations. For the nonlocal model, we find that the variable *patent_applications* is insignificant and that the patent application signal is therefore sensitive for outliers. However, we note that both the significance level and coefficient of patent applications improve compared to the local model. Since the models largely display a similar pattern as our earlier results, we do not devote strong implications to the fact that the nonlocal model is sensible to outliers.

Table 6_10. OLS Model 2 including outliers on patent applications, for firms funded by a VCF <20 miles. The dependent variable is the natural logarithm of the amount of venture capital funding in the first round of financing

Variable Name	**Coefficient**	**Heteroskedasticity robust standard errors**	**Standard errors clustered at state level**
patent_applications	0.0445	0.0604	0.0394
patent_granted	0.0719	0.4707	0.4015
patent_cited	-0.0343	0.0817	0.0691
entrepreneurialsignal	0.1384	0.2536	0.2695
academicsignal	0.0122	0.0386	0.0313
investmentstage	0.2960	0.1451 **	0.0875 ***
firmage	0.1045	0.0514 **	0.0383 **
vcfreputation	0.4276	0.2076 **	0.2418 *
syndicatesize	0.0002	0.0002	0.0001
syndicateinvestors	0.3889	0.0516 ***	0.0615 ***
distanceclosestvcf	-0.0388	0.0167 **	0.0239
universitiesinmsa	0.0056	0.0133	0.0116
vcfarea_0010	0.0084	0.0037 **	0.0025 ***
vcfarea_1020	0.0080	0.0037 **	0.0039 **
patentarea_0010	0.0019	0.0005 ***	0.0004 ***
patentarea_1020	0.0001	0.0010	0.0004
int_patentg_r1_uni	-0.0058	0.0270	0.0264
Year dummies included		Yes	Yes
intercept	12.1502	0.3570 ***	0.3815 ***
OBS			
R2	0.5258		
Adjusted R2	0.476		
F test		12.45 ***	
Breusch-Pagan test for heteroskedasticity	11.43 ***		
Multicollinearity Condition Number	15.4482		

Table 6_11. OLS Model 2 including outliers on patent application, for firms funded by a VCF >20 miles. The dependent variable is the natural logarithm of the amount of venture capital funding in the first round of financing

Variable Name	**Coefficient**	**Heteroskedasticity robust standard errors**	**Standard errors clustered at state level**
patent_applications	0.0514	0.0364	0.0349
patent_granted	-0.0636	0.0529	0.0518
patent_cited	-0.1054	0.1328	0.1333
entrepreneurialsignal	0.5988	0.2033 ***	0.1813 ***
academicsignal	0.0961	0.0442 **	0.0433**
investmentstage	0.3894	0.1366 ***	0.1007 ***
firmage	0.0499	0.0251 **	0.0245 **
vcfreputation	0.0269	0.1747	0.1706
syndicatesize	0.0003	0.0001 **	0.0002 *
syndicateinvestors	0.3803	0.0503 ***	0.0568 ***
distanceclosestvcf	0.0003	0.0001 ***	0.0001 ***
universitiesinmsa	-0.0025	0.0120	0.0113
vcfarea_0010	0.0085	0.0037 **	0.0042 **
vcfarea_1020	0.0023	0.0052	0.0054
patentarea_0010	-0.0001	0.0005	0.0004
patentarea_1020	-0.0005	0.0010	0.0010
int_patentg_r1_uni	-0.0059	0.0131	0.0116
year dummies included		Yes	Yes
intercept	12.7664	0.3919 ***	0.3689 ***
OBS	301		
R2	0.3868		
Adjusted R2	0.326		
F test		7.65 ***	226.91 ***
Breusch-Pagan test for heteroskedasticity	9.56 ***		
Multicollinearity Condition Number	13.4405		

6. Discussion

Ever since the groundwork of signaling theory, a long stream of literature has been concerned with factors that influence the effectiveness of information signals. Such factors include among others the timing, frequency and the environment of the focal signal. It is widely accepted in these studies that the effectiveness of signaling is determined by the level of information asymmetries between the sender and receiver of the signal. However, despite extensive evidence for increasing information asymmetries over geographical distance, it remains largely unknown how the effectiveness of signaling is determined by the geographical distance between both agents. Only few earlier studies discussed such geographical dynamics of signaling, all in the context of the venture capital industry. An issue still unknown is whether the effectiveness of information signals, in terms of increasing the level of venture capital investments, varies between firms that are funded by either local or nonlocal investors. In our present study we address this particular issue for the initial interaction between the firm and the investor, when information asymmetries are most severe.

In our empirical analysis, we use a database of 582 investments of venture capital firms (VCFs) in dedicated biotechnology firms (DBFs), and test whether the patent activity and the founding team legitimacy of the focal DBF are effective information signals towards respectively local and nonlocal VCFs. Our results are in line with theoretical expectations and reflect that information signals significantly increase the level of venture capital funding when the DBF is located outside a 20 miles radius from the closest funding VCF. Prompted by increasing information asymmetries in geographical distance, adverse selection problems for such investments are more severe. Hence, VCFs allocate a higher level of funding towards nonlocal DBFs that can partly reveal their unobserved quality by sending credible information signals. In turn, signaling does not significantly increase the level of venture capital funding received by DBFs located within 20 miles from the closest funding VCF. For such investments, VCFs can evaluate the credibility of investment targets by the use of tacit information obtained through local networks, which is a preferred strategy over the reliance on signaling (Casella and Hanaki, 2006). Hence, signaling value diminishes in the proximity between agents. In full, we confirm our hypothesis that information signals are more relevant for nonlocal investments than for local investments by VCFs. These results are largely identical for pending patent applications and the entrepreneurial experience of the founding team members as information signals, and in lesser extent also for the academic status of the founding team members. Also, our results are largely identical for alternative distance radii of local and nonlocal investments. Regarding the control variables in our analysis, VCFs address higher levels of funding towards firms in later development stages, in particular when investing in a nonlocal DBF. More reputable VCFs invest higher levels of funding only towards local DBFs and regional factors such as the number of VCFs and patents in the local area, are in particular relevant when the VCF and DBF are located in the same region.

Our study primarily has a conceptual character, still a number of practical implications could be derived from our findings. First of all, for firms pursuing venture capital investment that need to transmit their legitimacy to investors. Our study provides additional evidence that firms are able to overcome the disadvantages of being located outside a typical venture capital cluster, by compensating for higher information asymmetries with additional signaling. This finding is particularly relevant because firms are tempted to relocate to increase their access to financial resources (Tian, 2011). In turn, senders of information signals located in the proximity of the intended receiver, should carefully consider whether signaling indeed delivers the expected returns. Our study shows that signaling effectiveness in such cases is low, and that agents are likely not to gain returns that outweigh the costs of signaling. For policy makers our findings imply that signaling is a way to attract venture capital from outside the region. If local governments are able to construct credible signals, for example in the form of certification or award programs, this could attract nonlocal venture capital and therefore contribute to the innovativeness and economic growth in a region.

For scholars our present work provides several possibilities for further research. As information signals can have different meanings, a coherent expansion could be to reproduce our findings for alternative information signals. More specifically, it would be worthwhile to emphasize on signals regarding the intentions of the portfolio firm instead of the quality. Given that signals such as the amount of internal ownership could mitigate moral hazard problems after the initial investment, such signals could compensate for difficult monitoring ex-post. Our results could also be extrapolated to cases outside the venture capital industry. The case of international trade appears promising, where certification is used as a way to mitigate information asymmetries between countries (Cao and Prakash, 2011). Finally, multiple control variables in our models suggest that stronger social networks are associated with a higher level of funding for local DBFs. This supports our theoretical arguments that VCFs use networks to assess the quality of local firms, but contradicts with existing studies that associate stronger networks with a higher ability of the VCF to invest at long distance (Sorenson and Stuart, 2001; Cummings and Dai, 2010). Since only indirect indicators of social networks are used in our present study, we leave this contradiction open for further research.

Finally, we are aware of several limitations of our present work. Additional control variables are tested in unreported models, but these variables where not included because data have not been found reliable or because of a large number of missing observations. Regarding the VCF characteristics; size, age and experience of the VCF determine its likelihood to invest at distance (Powel et al., 2002; Lutz et al., 2013; Gupta and Sapienza, 1992), but these were not included in our final model. The same holds for an indicator of the size of the DBF. Regarding entrepreneurial experience of the founding team, it was only measured whether a member of the founding team had previously funded a firm. A more accurate measure would be to include the success of previously funded firms. Finally, obtaining data regarding patent applications before 2001 could have substantially increased the size of our database. This would be in particular beneficial to apply our model more at narrower distance levels, whereby we could provide more refined measures of the distances at which signals are significant.

References

Aharonson, B.S., Baum, J.A.C., Feldman, M.P. (2007) Desperately seeking spillovers? Increasing returns, industrial organization and the location of new entrants in geographic and technological space. *Industrial and Corporate Change*, Vol. 16, pp. 89-130

Akerlof, G.A. (1970) The market for lemons: qualitative uncertainty and the market mechanism. *The Quarterly Journal of Economics,* Vol. 84, pp. 488–500

Amit, R., Glosten, L. and Muller, E. (1990) Entrepreneurial Ability, Venture Investments, and Risk Sharing. *Management Science,* Vol. 36, pp. 1232-1245

Arthurs, J. D., Busenitz, L. W., Hoskisson, R. E., and Johnson, R. A. (2009) Signaling and initial public offerings: The use and impact of the lockup period. *Journal of Business Venturing*, Vol. 24, pp. 360-372

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

Baum, J.A.C. and 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,* Vol. 19 pp. 411-436

Beaudry, C. and Breschi, S. (2003) Are firms in clusters really more innovative? *Economics of Innovation and New Technology*, Vol. 12. pp 325-342

Bengtsson, O., and Ravid, S. A. (2009) The geography of venture capital contracts. Available at SSRN 1361827.

Bengtsson, O. (2013) Relational venture capital financing of serial founders. *Journal of Financial Intermediation*, Vol. 22, pp. 308 - 334

Berger, A.N. and Udell, G.F. (1998) The Economics of Small Business Finance: The Roles of Private Equity and Debt Markets in the Financial Growth Cycle. *Journal of Banking and Finance*, Vol. 22, pp. 613-673

Bonardo, D., Paleari, S. and Vismara, S. (2011) Valuing University ‐ Based Firms: The Effects of Academic Affiliation on IPO Performance. *Entrepreneurship Theory and Practice* Vol. 35, pp. 755-776.

Breschi, S. and Lissoni, F. (2003) Mobility and Social Networks: Localised Knowledge Spillovers Revisited. Milan: University Bocconi, CESPRI Working Paper no. 142

Busenitz, L.W., Fiet, J.O. and Moesel, D.D. (2005) Signaling in Venture Capitalist—New Venture Team Funding Decisions: Does It Indicate Long-Term Venture Outcomes? *Entrepreneurship Theory and Practice,* Vol. 29, pp. 1-12

Cao, X., Prakash, A. (2011) Growing exports by signaling product quality: Trade competition and the cross-national diffusion of ISO 9000 quality standards. *Journal of Policy Analysis and Management*, Vol. 30, pp. 111–135

Cao, J. X., and Hsu, P. H. (2011) The informational role of patents in venture capital Financing. Available at SSRN 1678809

Carpenter, R.E. and Petersen, B.C. (2002) Capital Market Imperfections, High-Tech Investment, and New Equity Financing. *The Economic Journal*, Vol. 112, pp. 54-72

Certo, S.T. (2003) Influencing initial public offering investors with prestige: Signaling with board structures. *Academy of Management Review*, Vol. 28, pp. 432-446

Casella, A., and Hanaki, N. (2006) Why personal ties cannot be bought. *The American economic review,* Vol. 96, pp. 261-264

Champenois, C., Engel, D. and Heneric, O. (2006) What kind of German biotechnology start-ups do venture capital companies and corporate investors prefer for equity investments? *Applied Economics* Vol. 38, pp. 505–518

Chen, K., Chu, T. and Billota, R. (2011) A Spatial investigation of venture capital investment in the US biotechnology industry, 1995-2008. *GeoJournal*, Vol. 76, pp. 267-282

Chen, H., Gompers, P., Kovner, A. and Lerner, J. (2010) Buy local? The geography of venture capital. *Journal of Urban Economics*, Vol. 67, pp. 90-102

Christoffersen, S. and Sarkissian, S. (2009) City size and fund performance. *Journal of Financial Economics*, Vol. 92, pp. 252-275

Coenen, L., Moodysson, J., and Asheim, B. T. (2004) Nodes, networks and proximities: on the knowledge dynamics of the Medicon Valley biotech cluster. *European Planning Studies*, Vol. 12, pp. 1003-1018

Cohen, B.D. and Dean, T.J. (2005) Information Asymmetry and Investor Valuation of IPRs: Top Management Team Legitimacy as a Capital Market Signal. *Strategic Management Journal*, Vol. 26, pp. 683-690

Connelly, B.L., Certo, S.T., Ireland, R.D. and Reutzel, C.R. (2011) Signaling Theory: A Review and Assessment. *Journal of Management*, Vol. 37, pp. 3967

Conti, A., Thursby, M., and Rothaermel, F. T. (2013) Show Me the Right Stuff: Signals for High-Tech Startups. *Journal of Economics and Management Strategy*, Vol. 22, pp. 341-364

Coval, J.D. and Moskowitz, T.J. (1999) Home Bias at Home: Local Equity Preference in Domestic Portfolios. *The Journal of Finance*, Vol. 54, pp. 2045-2073

Coval, J. D., and Moskowitz, T. J. (2001) The geography of investment: Informed trading and asset prices. *The Journal of Political Economy*, Vol. 109, pp. 811–841

Cumming, D. and Dai, N. (2010) Local Bias in Venture Capital Investments. *Journal of Empirical Finance,* Vol. 17, pp. 362 - 380

Da Rin, M., Hellmann, T. and Puri, M. (2011) A Survey of Venture Capital Research. *Handbook of the Economics of Finance*

Dahl, M. S., and Pedersen, C. Ø. (2004) Knowledge flows through informal contacts in industrial clusters: myth or reality? *Research policy*, Vol. 33, pp. 1673-1686

Davila, A., Foster, G. and Gupta, M. (2003) Venture capital financing and the growth of startup firms. *Journal of Business Venturing,* Vol. 18, pp. 689-708

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

Desrochers, P. (2001) Geographical proximity and the Transmission of Tacit Knowledge. *The Review of Austrian Economics*, Vol. 14, pp. 25-46

DiMasi, J.A., Hansen, R.W. and Grabowski, H.G. (2003) The price of innovation: new estimates of drug development costs. *Journal of Health Economics* Vol. 22, pp. 151–185

Döring, T., Schnellenbach, J. (2006) What do we know about geographical knowledge spillovers and regional growth? a survey of the literature. *Regional Studies*, Vol. 40, pp. 375-395

Engel, D. and Keilbach, M. (2007) Firm-level implications of early stage venture capital investment—An empirical investigation. *Journal of Empirical Finance*, Vol. 14, pp. 150-167

Florida, R.L. and M. Kenney (1988) Venture capital, high technology and regional development. *Regional Studies,* Vol. 22, pp. 33-48

Fritsch, M. and Schilder, D. (2008) Does Venture Capital Investment Really Require Spatial Proximity? An Empirical Investigation. *Environment and Planning,* Vol. 40, pp. 2114-2131

Gittelman, M. (2007) Does geography matter for science-based firms? Epistemic communities and the geography of research and patenting in biotechnology. *Organization Science*, Vol. 18, pp. 724-741

Gompers, P. (1995) Optimal Investment, Monitoring, and the Staging of Venture Capital. *The Journal of Finance*, Vol. 50, pp. 1461-1489

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

Gompers, P. and Lerner, J. (2001) The Venture Capital Revolution. *The Journal of Economic Perspective*, Vol. 15, pp. 145-168

Gompers, P. P. A., and Lerner, J. (2004) *The venture capital cycle*. MIT press.

Gorman, M. and W.A. Sahlman, W.A. (1989) What do venture capitalists do? *Journal of Business Venturing* Vol. 4, pp. 231-48

Gupta, A. K., and Sapienza, H. J. (1992) Determinants of venture capital firms' preferences regarding the industry diversity and geographic scope of their investments. *Journal of Business Venturing*, Vol. 7, pp. 347-362

Häussler, C., Harhoff, D. and Müller, E. (2009) To Be Financed or Not… - The Role of Patents for Venture Capital Financing ZEW - Centre for European Economic Research Discussion

Hellmann, T. and Puri, M. (2002) Venture Capital and the Professionalization of Start-Up Firms: Empirical Evidence. *The Journal of Finance*, Vol. 57, pp 169-197

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

Hoenen, S., Kolympiris, C., Schoenmakers, W., Kalaitzandonakes, N. (2012) Do Patents Increase Venture Capital Investments between Rounds of Financing?

Hsu (2007) Experienced entrepreneurial founders, organizational capital, and venture capital funding. *Research Policy,* Vol. 36, pp. 722–741

Huggins, R., and Johnston, A. (2010) Knowledge flow and inter-firm networks: The influence of network resources, spatial proximity and firm size. *Entrepreneurship and regional development*, Vol. 22, pp. 457–484

Ivković, Z. and Weisbenner, S (2005) Local does as local is: Information content of the geography of individual investors' common stock investments. *The Journal of Finance*, Vol. 60, pp. 267-306

Jaffe, A.B., Trajtenberg, M. and Henderson, R. (1993) Geographic localisation of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics,* Vol. 10, pp. 577-598

Janney, J.J. and Folta, T.B. (2003) Signaling through private equity placements and its impact on the valuation of biotechnology firms. *Journal of Business Venturing,* Vol. 18, pp. 361-380

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

Kenney, M. (2011) How venture capital became a component of the US National System of Innovation. *Industrial and Corporate Change*, Vol. 20, pp. 1677-1723

Kolympiris, C., Kalaitzandonakes, N. and Miller, D. (2011) Spatial collocation and venture capital in the U.S. biotechnology industry. *Research Policy*, Vol. 40, pp. 1188-99

Kolympiris, C., and Kalaitzandonakes, N. (2013) Geographic scope of proximity effects among small life sciences firms. *Small Business Economics* Vol. 40, pp. 1059-1086

Kortum, S. and Lerner, J. (2000) Assessing the contribution of venture capital to innovation. *The RAND Journal of Economics*, Vol. 31, pp. 674-692

Lerner, J. (1995) VCs and the oversight of private firms. *Journal of Finance*, Vol. 50, pp. 301–318

Lerner, J. (1999) The Government as Venture Capitalist: The Long-Run Impact of the SBIR Program. *The Journal of Business*, Vol. 72, pp. 285-318

Lester, R. H., Certo, S. T., Dalton, C. M., Dalton, D. R., and Cannella, A. A. (2006) Initial public offering investor valuations: An examination of top management team prestige and environmental uncertainty. *Journal of Small Business Management*, Vol. 44, pp. 1-26

Lutz, E., Bender, M., Achleitner, A. K., and Kaserer, C. (2013) Importance of spatial proximity between venture capital investors and investees in Germany. *Journal of Business Research,* Vol. 66, pp.2346–2354

Mäkelä, M.M. and Maula, M.V.J. (2008) Attracting cross-border venture capital: the role of a local investor, *Entrepreneurship and Regional Development: An International Journal*, Vol. 20, pp. 237-25

Martin, R., Berndt, C., Klagge, B. and Sunley, P. (2005) Spatial proximity effects and regional equity gaps in the venture capital market: evidence from Germany and the United Kingdom. *Environment and Planning A*, Vol. 37, pp. 1207-1231.

Metrick, A. and Yasuda, A. (2011) *Venture Capital and the Finance of Innovation*. Second Edition

Mishra, D.P., Heide, J.B. and Stanton, G.C. (1998) Information Asymmetry and Levels of Agency Relationships. *Journal of Marketing Research*, Vol. 35, pp. 277-295

Mueller, C., Westhead, P. and Wright, M. (2012) Formal venture capital acquisition: can entrepreneurs compensate for the spatial proximity benefits of South East England and `star' golden-triangle universities? *Environment and Planning*, Vol. 44, pp. 281-296

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

Park, N.K., and Mezias, J.M. (2005) Before and after the technology sector crash: The effect of environmental munificence on stock market response to alliances of e-commerce firms. *Strategic Management Journal*, Vol. 26, pp. 987-1007

Patzelt, H. (2010) CEO human capital, top management teams, and the acquisition of venture capital in new technology ventures: An empirical analysis*. Journal of Engineering and Technology Management*, Vol. 27, pp. 131-147

Pollock, T.G., Chen, G. Jackson, E.M. and Hamrick, D.C. (2009) How much prestige is enough? Assessing the value of multiple types of high status affiliates for young firms. *Journal of Business Venturing*, Vol. 25, pp. 6-23

Portes, R., Rey, H. and Oh, Y. (2001) Information and capital flows: The determinants of transactions in financial assets. *European Economic Review*, Vol. *45*, pp. 783-796

Powell, W.W., Koput, K.W., Bowie, J.I. and Smith-Doerr, L. (2002) The Spatial Clustering of Science and Capital: Accounting for Biotech Firm-Venture Capital Relationships. *Regional Studies,* Vol. 36, pp. 291-305

Ragozzino, R. and Reuer, J.J. (2011) Geographical distance and corporate acquisitions: Signals from IPO firms. *Strategic Management Journal*, Vol. 32, pp. 876-894

Rosenthal, S.S. and Strange, W.C. (2003) Geography, industrial organization, and agglomeration. *The Review of Economics and Statistics,* Vol. 85, pp. 377-93

Rosiello, A., and Parris, S. (2009) The patterns of venture capital investment in the UK bio-healthcare sector: the role of proximity, cumulative learning and specialisation. *Venture Capital*, Vol. *11*, pp.185-211

Sahlman, W.A. (1990) The structure and governance of venture-capital organizations. *Journal of Financial Economics,* Vol. 27, pp. 473-521

Samila, S. and Sorenson, O. (2010) Venture Capital as a Catalyst to Commercialization. *Research Policy*, Vol. 39, pp. 1348 – 1360

Sanders, G.W.M. and Boiwie, S. (2004) Sorting Things Out: Valuation of New Firms in Uncertain Markets*. Strategic Management Journal*, Vol. 25, pp. 167-186

Shane, S., Cable, D. (2002) Network ties, reputation, and the financing of new ventures. *Management Science*, Vol. 48, pp. 364-381

Shane, S. and Venkataraman, S. (2000) The promise of entrepreneurship as a field of research. *Academy of management review*, Vol. 25, pp. 217-226

Sorenson, O. and Stuart, T.E. (2001) Syndication networks and the spatial distribution of venture capital investments. *American Journal of Sociology* Vol. 106, pp. 1546-1588.

Sorenson, O. (2005) Social networks and industrial geography. In *Entrepreneurships, the New Economy and Public Policy,* pp. 55-69. Springer Berlin Heidelberg.

Spence, M. (1973) Job market signaling. *Quarterly Journal of Economics,* Vol. 87, pp. 355-374

Stiglitz, J. E. (1985) Information and economic analysis: A perspective. *Economic Journal*, Vol. 95, pp. 21-41

Stiglitz, J. E. (2000) The contributions of the economics of information to twentieth century economics. *Quarterly Journal of Economics*, Vol. 115, pp. 1441-1478

Stuart, T.E., Hoang, H. and Hybels, R.C. (1999) Interorganizational Endorsements and the Performance of Entrepreneurial Ventures. *Administrative Science Quarterly,* Vol. 44, pp. 315–349

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

Toole, A.A. and Turvey, T. (2009) How does initial public financing influence private incentives for follow-on investment. *The Journal of Technology Transfer*, Vol. 34, pp. 43-58

Von Hippel, E. (1994) “Sticky information” and the locus of problem solving: implications for innovation. *Management science*, Vol. 40, pp. 429-439

Wang, S. and Zhou, H. (2004) Staged financing in venture capital: Moral hazard and risks. *Journal of Corporate Finance*, Vol. 10, pp. 131-155

Wallsten, S.J. (2001) An empirical test of geographic knowledge spillovers using geographic information systems and firm-level data. *Regional Science and Urban Economics* Vol. 31, pp. 571-99

Wright, M., Robbie, K. and Ennew, C. (1997) Venture capitalists and serial entrepreneurs. *Journal of Business Venturing,* Vol. 12, pp. 227-249

Zider, B. (1998) How venture capital works. *Harvard Business Review,* Vol. 76, pp. 131-139

Zook, M. A. (2002) Grounded capital: venture financing and the geography of the Internet industry, 1994–2000. *Journal of Economic Geography*, Vol. *2*, pp. 151-177