Geographic distance between venture capitalists and target firms and the value of quality signals [a]

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In this paper we examine whether the value of quality signals (patent activity and founding team characteristics) transmitted by emerging biotechnology firms is influenced by the geographic distance between venture capitalists and biotechnology firms. In line with the notion that signals are more valuable to receivers in environments of elevated information asymmetries and under the premise that long distance transactions present such an environment, we empirically reveal that patent activity and founding team entrepreneurial experience are more effective in increasing venture capital investments when the distance between investors and investees is elevated. Our results, therefore, corroborate the rationale that because tacit knowledge circulates mostly within local circles, it diminishes the value of signals for local transactions as a priori knowledge about potential target firms is more easily assessed by investors. Our study contributes to the literature on the factors that drive the value of signals, on the literature that studies the function of patents and other forms of intellectual property as a means to boost firm performance and on the literature on the geography of venture capital investments.

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1. Introduction

Signaling theory builds on the premise that signals, defined as purposely sent costly pieces of information, partly reveal unobserved characteristics of the sender to an interested receiver. Credible signals, then, which are too costly to pursue for lesser quality actors, ease transacting by allowing the receiver to place more confidence on the unobserved quality of the sender and thus reduce the negative effects of information asymmetries (Amit et al., 1990; Connelly et al., 2011; Spence, 1973).[1] Precisely because the main function of signals is to increase the confidence receivers place on the senders in the face of information asymmetries, signals should not only be more likely to occur in the presence of high uncertainty (Roberts and Khaire, 2009), but they should also carry a higher value for receivers in environments of elevated information asymmetries (Janney and Folta, 2003).

Indeed, there is empirical support for that expectation. Stuart et al. (1999) find that signals, in the form of prominent alliance partners, are effective in transactions that involve young firms with limited track records. Janney and Folta (2006) conclude that signals, in the form of private placements of equity, are more relevant for those young firms that are subject to higher uncertainty. Park and Mezias (2005) show that the stock market relies more heavily on alliances as signals when the level of industry uncertainty is high. Arthurs et al. (2009), in the context of initial public offerings, report that the higher the uncertainty surrounding a given firm, the more effective the signals it transmits. Finally, Hsu and Ziedonis (2013) and Hoenen et al. (2014) find that the signaling function of patent activity is more effective in inducing venture

[1] Extended literature demonstrates the effectiveness of signals in communicating value to customers, investors, potential employees and possible alliance partners (e.g. Chung and Kalnins, 2001; Cohen and Dean, 2005; Davila et al., 2003; Higgins and Gulati, 2006; Mishra et al., 1998; Ozmel et al., 2012).

capital investments for early rounds of financing, when information asymmetries between venture capitalists and target firms are elevated.

Prior studies, then, have contextualized the level of information asymmetries and have approximated the value receivers ascribe to signals by studying the age of the sender, the uncertainty of its environment and the degree of familiarity between senders and receivers. However, little attention has been paid to an additional transactional characteristic that can significantly determine the degree of information asymmetries between transacting parties and can ultimately shape the value receivers place on signals: the geographic distance between the sender and the receiver of the signal.

Information asymmetries increase with distance (Coval and Moskowitz, 1999; Ivkovic and Weisbenner, 2005; Portes et al., 2001). It is therefore important to know whether the value receivers ascribe to signals also increases with the distance between two transacting parties, and we examine this question in this study. Because knowledge is sticky and hence difficult to move across space (von Hippel, 1994), the marginal cost of knowledge transmission is an increasing function of distance. This explains why larger distances may discourage the transmission of (tacit) knowledge (Audretsch, 1998) and could lead to increases in information asymmetries. Given that the costs of signaling do not typically vary with geographic distance, signals may be even more relevant and valuable for transactions between geographically distant parties.

To study this proposition, we analyze two signals often employed by emerging knowledge-intensive firms that can lack a track record: patent activity, including patent applications and granted patents, and the entrepreneurial experience and academic status of firm founders. Using data from first round venture capital investments in 586 U.S-based emerging biotechnology firms from 2001 to 2011, we associate the amount of capital raised by each firm through first round of financing with its patent activity and indicators of serial entrepreneurship and academic excellence among firm founders prior to the investment. Methodologically, to test whether the geographic distance between venture capitalists and the biotechnology firms they invest in conditions the impact of those signals on the firm funding level, we interact the measures of signals with the measures of the distance between the two parties and examine the statistical significance of the combined measure. We also control for many factors that can influence the size of venture capital investment in a given firm, including the market value of patents which arises from the monopoly rights they afford. We therefore first approximate the signaling value of patents and then investigate how such value is affected by the distance between the investor and the recipient. Along the same lines, by separating out the effects of academic and entrepreneurial experience of firm founders we also examine what venture capitalists value most when they invest in firms founded by academics.

Our focus on emerging firms is consistent with the notion that signaling is more important during the early stages of firm growth, when the typical lack of a track record and increased level of information asymmetries make the evaluation of investment targets a thorny task. As such, it is at this stage we expect venture capitalists to place more value to quality signals. We break new ground by examining whether the value that venture capitalists place on signals depends on their distance with target firms. We also complement previous studies that have examined the effect of signals in attracting distant investors in later stages of firm growth where the venture capitalist is already in the firm and the next stepping stone for the company is the attraction of additional investors, often via an initial public offering (Mäkelä and Maula, 2008; Powell et al., 2002; Ragozzino and Reuer, 2011).

Relatedly, we contribute to the literature on the function of patents and other forms of intellectual property for attracting firm financing (e.g. Audretsch et al., 2012; Block et al., 2014; Conti et al., 2013; Greenberg, 2013; Hoenen et al., 2014; Hsu and Ziedonis, 2013). These studies analyze a number of issues, including whether patents act as a signal and whether the signaling function of patents is more pronounced during early stages of firm growth, but do not examine the impact of the geographic distance between agents on the strength and value of the signal. Accordingly, our work improves the understanding of the conditions where patents lead to greater external funding for a given firm. Furthermore, our study offers a novel test on whether patents act primarily as a signal or whether they are valued by their investors mostly for the monopoly rents they can bring about. If patents act mainly as a signal, then we would not expect them to have as significant an impact on venture capital investments in short distance transactions. Locally circulated knowledge about a given firm can reduce the degree of information asymmetries between investors and potential investees (Asheim and Gertler, 2005; Bathelt et al., 2004; Florida and Kenney, 1988) and hence mitigate the need for signals as well as the value that investors may place on them. In contrast, if patents are valued mostly for the exclusion rights they carry, we would expect them to increase venture capital funding even for investors who allocate funds to nearby firms.

Finally, our work informs the literature on the geography of venture capital investments (Gupta and Sapienza, 1992; Kolympiris et al., 2011; Lutz et al., 2013; Powell et al., 2002; Sorenson and Stuart, 2001). While venture capital firms have a general preference to invest locally (Cumming and Dai, 2010; Powell et al., 2002; Sorenson and Stuart, 2001), here we investigate whether signals can induce larger investments in distant targets at their early stages of firm growth.

We focus on venture capital investments in biotechnology for several reasons. First, biotechnology firms are frequent investment targets of venture capitalists reflecting not only the potential for high returns but also their need for external capital, which is difficult to meet through bank lending and other forms of traditional finance due to inherent risks in the industry (Baum and Silverman, 2004; Gompers and Lerner, 2001). Second, long distance venture capital investments occur in the industry with some frequency. East/West Cost investors fund West/East Coast firms (Powell et al., 2002). Third, the lengthy R&D cycles of biotechnology coupled with strict regulatory regimes prohibit emerging firms from developing an early track record which can approximate future performance. The very same structural characteristics of biotechnology startups lead venture capitalists investing in this industry to often rely on signals (Higgins et al., 2011; Janney and Folta, 2003). All in all, these circumstances suggest that if the value venture capitalists place on signals is influenced by the geographic distance of their potential targets we should be able to detect such an influence in that industry.

We proceed as follows: In section 2, we explore the existing literature and discuss our theoretical expectations. In sections 3 and 4 we discuss the methodology and the dataset of the empirical study. In section 5, we present our empirical results and we conclude in section 6.

2. How geographic distance can influence the effectiveness of signals

In their most common form, venture capital firms (VCFs) raise funds from institutional investors such as pension funds and university endowments, invest these funds in new ventures that have the potential to yield high returns and, in large part, tie their compensation to the performance of the investment targets (Zider, 1998). Because VCFs seek high returns they tend to invest in relatively young promising companies in knowledge-based industries, such as biotechnology, in which the risks are pronounced but the returns, if realized, can also be considerable (Gompers and Lerner, 2001, 2004).

Mainly because of the long research cycles in biotechnology, firms in this industry rarely have a track record in their early stages of development. Even when these firms are fully aware of their potential, they typically possess private information regarding their quality, which is not easily discerned by the VCFs (Amit et al., 1990; Gompers, 1995; Gompers and Lerner, 2004; Sahlman, 1990). In turn, such information asymmetries complicate the investment decisions of VCFs because the problem of adverse selection is ever-present (Akerlof, 1970; Amit et al., 1990; Mishra et al., 1998).[2] In order to mitigate adverse selection VCFs typically invest in rounds of financing. Under this scheme, funds are provided in separate sequential points in time and financing continues only if firms meet certain, mainly technical, milestones (Gompers, 1995). Information asymmetries between VCFs and target firms are therefore more acute before the first round of financing as VCFs have not previously worked with the firm and the level of familiarity between investors and investees is low. It follows that because first round investments present an environment of exacerbated uncertainty, it is in this round we expect VCFs to place more value to signals. This is why we focus our discussion and subsequent empirical analysis on this round.

To prevent investments in 'lemons' VCFs are highly selective and put substantial time and effort in scouting firms and evaluating the promise of their investments targets (Amit et al., 1990; Baum and Silverman, 2004). This time and effort is primarily devoted towards assessing

[2] Uncertain market conditions, complex regulatory regimes and a general scarcity of tangible assets exacerbate the issue (Carpenter and Petersen, 2002; Gompers and Lerner, 2001). Also note that under certain conditions 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).

the quality of the firm before the first investment takes place. However, in the case of knowledge-based young firms, overall quality and promise are tightly linked to the quality of knowledge supporting their research efforts. Precisely because knowledge quality can be tacit (Johnson et al., 2002), the selection process of VCFs can become increasingly difficult when the target firm is at a distance as tacit knowledge is more easily gained when investors and investees are closely located (Coval and Moskowitz, 1999; Foray, 2004; von Hippel, 1994). For this reason, VCFs circulate knowledge about investment targets via networks which are often built on social capital, interpersonal contacts and other spatially bounded means of knowledge transfer (Bygrave, 1988; Florida and Kenney, 1988). It follows that the *ex ante* evaluation of untested target firms that are under consideration for first time investments is generally easier when these firms are located nearby.[3] Spatial proximity assists VCFs in gathering (tacit) knowledge about the target firms and decreases the level of information asymmetries. Indeed, empirical evidence indicates that VCFs have a general preference for local investments (Chen et al., 2011; Cumming and Dai, 2010; Powell et al., 2002; Sorenson and Stuart, 2001; Tian, 2011). [4]

Notwithstanding the general tendency for local investments, VCFs do engage in long distance financing (Powell et al., 2002), especially when the promise of the target firm is significant. In such cases, VCFs use alternative strategies to cope with the associated information asymmetries. Most frequently, for first round investments, but sometimes in later rounds too, VCFs use syndication schemes in which they co-invest with one or more local VCF(s) (Fritsch and Schilder, 2008; Sorenson and Stuart, 2001). Beyond syndication, VCFs may also rely on

[3] Note that contrary to other forms of capital infusion, the involvement of VCFs in target firms extends to providing advice, management support and other value-added activities (Sahlman, 1990). Spatial proximity is also relevant for those activities (Lerner, 1995) because it can ease the oversight of the target firms.

[4] In related evidence outside the venture capital industry, the number of local investments in the portfolio of fund managers is disproportionally large (Coval and Moskowitz, 1999) and fund managers perform better when investing in these local funds (Coval and Moskowitz, 2001).

signals as a way to mitigate the effects of information asymmetries for long distance first round transactions (Busenitz et al., 2005; Toole and Turvey, 2009). Indeed, there is evidence that VCFs are more likely to invest in distant firms in which other VCFs have previously invested (Mäkelä and Maula, 2008; Powell et al., 2002; Ragozzino and Reuer, 2011). This behavior is consistent with the idea that VCFs use signals in distant transactions and indicates the trust VCFs show to the investment choices of their peers. However, little is known about the value placed by VCFs on the *ex ante* signals sent by start-ups prior to first round financing.

All in all, given that receivers of signals place more value to them in environments characterized by increased information asymmetries (Arthurs et al., 2009; Hoenen et al., 2014; Hsu and Ziedonis, 2013; Ozmel et al., 2012; Stuart et al., 1999) we expect signals to be more effective in raising the amount of first round financing for distant transactions when compared to transactions between closely located VCFs and target firms. We build this expectation on the observation that short distance transactions are typically less susceptible to the sort of information asymmetries that underpin most first round investments.

2.1 Signals used by biotechnology firms before the first round of financing

A relevant question then is which signals are available to biotechnology firms during their early stages of growth and more specifically before the first round of financing? These signals need to satisfy three main conditions. First, they need to be observable and costly to imitate (Spence, 1973). Second, they need to adequately convey the knowledge available to emerging biotechnology firms since their tangible assets are limited (Hicks, 1995). Third, they need to be valued by VCFs so that they lead to increases in the level of first round of financing.

One way by which biotechnology firms can convey their knowledge is through certain characteristics of their founder(s). Founder characteristics are observable through firm presentations, websites and other information featuring the biographies of the founding team. They are also costly. For instance, the opportunity costs of eminent university professors and other high profile professionals who are often among the founders of biotechnology firms are high (Audretsch and Stephan, 1996; Zucker et al., 1998). As such, founder characteristics meet condition 1 described above. Founder characteristics can also convey knowledge because high technology firms at the early development stages often resemble the qualities of their founders (Cooper and Bruno, 1977). Hence, high profile professionals can leverage their reputation to convey the underlying quality of their firms (Bonardo et al., 2011; Certo, 2003) and as such founder characteristics meet condition 2 above. But what kinds of founder characteristics are valued by venture capitalists so that condition 3 is also met? Within the broad literature documenting the effects of founders on firm growth (Ding, 2011; Hannan et al., 2006; Klepper, 2002; Roberts et al., 2011), a number of studies has shown that VCFs prefer to invest in entrepreneurs with earlier business experience (Gompers et al., 2010; Hsu, 2007; Mueller et al., 2012; Wright et al., 1997). This is likely so because experience can help entrepreneurs cope with recurring problems, enhance their ability to spot profitable opportunities and the like (Baron and Ensley, 2006). For academic founders, previous business/entrepreneurial experience may therefore be important (Lockett and Wright, 2005).

VCFs may also value the academic prominence of founders of early stage biotechnology firms as an additional signal of their knowledge. Because of the knowledge-intensive character of biotechnology, the core technological innovations upon which the firms are built often rely on academics (Wright et al., 2004) who are regularly founders of biotechnology firms (Zucker et al., 1998). Importantly, preeminent academic scientists tend to start successful biotechnology firms (Zucker et al., 1998). When considering these observations together with the favorable attitude of VCFs towards firms founded/managed by individuals with high academic achievements (Engel and Keilbach, 2007; Hsu, 2007; Mueller et al., 2012) we conclude that the presence of academics in the founding team, especially eminent ones, may serve as a signal of quality for biotechnology firms with limited track record.

Patent activity is yet another signal that biotechnology firms can use. Patent information is freely available from public sources but patents themselves are costly to acquire and maintain (Graham et al., 2009). Hence, patents conform to the basic characteristics of a signal. But do patents convey knowledge and are they valued by VCFs? A number of studies have demonstrated that VCFs are attracted to firms with patent activity (Audretsch et al., 2012; Conti et al., 2013; Engel and Keilbach, 2007; Hoenen et al., 2014; Hsu and Ziedonis, 2013). Patents also convey knowledge for two main reasons: First, they represent inventions and innovations (Acs et al., 2002; Igami, 2013) which are the outcomes of knowledge development efforts. Second, the patent acquisition process entails interactions with patent examiners so that the prior art of the submitted application is adjusted, and the claims of the patents are clarified and placed within the context of existing technologies and innovations. As such, the patent application process compels firms to keep up to date with the latest scientific developments in rapidly evolving fields such as biotechnology, enhance their knowledge and refine their technology development strategies.

In sum, we expect patent activity, as well as the entrepreneurial experience and academic prominence in the founding team to act as signals that can help firms to increase their first round of investment as they are costly, observable, they transmit knowledge and they are valued by venture capitalists. We expect these signals to be more effective and valuable in long distance transactions because it is in these types of transactions that information asymmetries are elevated and hence venture capitalists place more value to signals.

3. Methods

To test whether signals are more effective and valuable for long distance transactions between VCFs and biotechnology firms we build econometric models in which the level of funding raised during the first round of financing is regressed on variables that measure patent activity and founding team characteristics prior to the investment. To explicitly test the impact of geographic distance on the effectiveness of these signals in stimulating larger investments, we include a variable that measures the distance between the VCF and the target firm and we interact this variable with the signals we study. We expect the interaction terms to be positive, indicating that signals are more valuable for long distance transactions.

Formally, the model takes the following form:

$$\ln(Y_i) = X_i\beta + \varepsilon \qquad (1)$$

where the dependent variable Y_i is the natural logarithm of the amount of funds received by the focal firm i in the first round of venture capital funding, X_i is the design matrix including the variables we discuss below and the βs are the associated coefficients.

The first signal we study is patent activity which we measure with the patent applications submitted by the firms in our sample prior to the first round financing they received and with the patents granted to the firms during the same period. More specifically, following previous works that constructed patent variables in the same way (e.g. Czarnitzki et al., 2007; Toole and

Czarnitzki, 2007) each of the two measures takes the value of 1 if the firm had applied for a patent or was granted a patent before the investment occurred and 0 otherwise. [5] [6]

The reason we employ two measures of patent activity is that the signal transmitted by granted patents can be meaningfully different than the signal transmitted by patent applications. For instance, throughout the examination process patent applications may signal a firm that is not sitting idle but it updates its knowledge and extends its experience by revising the claims of the patent, populating the list of prior art with new references, and refining its innovation strategy. These are important considerations since knowledge in biotechnology is continuously updated and breakthroughs may come from newer discoveries at any time (see Humphries, 2010; McNamee and Ledley, 2012 for specific examples). As such, new knowledge development is crucial and patent applications may capture such a process more effectively than granted patents. Instead, granted patents can signal a firm that has developed original knowledge and has gone through the patent application process successfully in the past. Conceptually, then, we expect granted patents to approximate the knowledge a company has already developed and owns while patent applications to approximate the knowledge a company is developing. It is interesting to note that there is empirical evidence which reinforces the potential for differential signaling function of

[5] To avoid double-counting if an application is granted patent rights before the first round of financing, we measure only the granted patent as a measure of patent activity and not the application.

[6] Originally we used the count of patents and applications as our measures of patent activity. However, constructing the interaction terms using the counts and including them in the empirical specifications increased the multicollinearity index well above the safe threshold of 30 and hence raised inference concerns. When we measured patent activity with dummy variables (and constructed the interaction terms) the index dropped significantly to below 30. Importantly, the dummy variables are roughly equivalent to continuous measures of patent activity as the latter are heavily left skewed with the vast majority of the firms having no patent activity. As such, we opt to use the dummy variables because they lead to lower multicollinearity indices, and, hence higher confidence in inference. Still, in section 5.2 we present estimates from models omitting from the analysis firms with inflated records of patent activity. The results are qualitatively similar to the baseline estimates we present in Table 3. Alternatively, we could omit certain control variables in order to reduce the multicollinearity index. That option raises significant concerns on the interpretation of our findings due to omitted variable bias. Such bias is particularly relevant in our application as teasing out the signaling function of patents is challenging mainly because a host of factors can explain the growth of venture capital funds for a given firm.

granted patents and patent applications. Specifically, a few studies have shown that patent applications are more effective than granted patents in shortening the time that venture capitalists invest in a firm and in increasing the amount of funds invested (Baum and Silverman, 2004; Haeussler et al., 2014; Hoenen et al., 2014).

Because we are interested in the signaling value of patent activity, we need to account for the market value of monopoly rights that patents offer, which can also attract investors and raise the amount of invested capital. Estimating with precision the market value that patent monopoly rights can bring about is a difficult task partly because the true market value of an invention is often unobservable and, if observed, it is difficult to attribute solely to the patent that protects the invention. A setting in which patent market value can be closely approximated is at patent auctions where patents are traded between interested parties. This setting is appropriate not only because the auction price is observed but also, and perhaps more importantly, because what is traded is only the patent and not its owner. Accordingly, it is unlikely that the signaling function of granted patents drive their auction prices. Crucially, the price paid for a patent in such auctions correlates strongly with an observed feature of the patent: the number of times the patent is cited by later patents (forward citations) (Fischer and Leidinger, 2014; Odasso et al., 2014; Sneed and Johnson, 2009). Based on this evidence, and with an eye on previous works demonstrating the relevance of forward citations as a measure of patent value (e.g. Gambardella et al., 2008; Harhoff et al., 2003), we employ forward citations as a measure of the economic value of a patent. Because older patents have a longer time frame to gather forward citations we measure forward citations per year.

The second signal we examine is the entrepreneurial experience and academic standing of the founding team. We employ two different empirical specifications to more extensively test their potential impacts. Specification 1 employs the signal used in Hoenen et al. (2014). In particular, we approximate the academic standing and business experience of the founding team with a dummy variable that takes the value of 1 if a member of the founding team has high academic standing and/or earlier experience in founding a firm (*Foundersignal*). In Specification 2 we use two separate measures to characterize the standing of the founding team. The first measure, *Entrepreneurialsignal,* indicates whether one of the members of the founding team has previously started a firm.[7] The second measure, *Academicsignal,* assumes increasing values with the highest academic rank held by members of the founding team and ranges from 0 to 5 with 0 indicating that there is no academic in the founding team, 1 through 4 indicate increasing professorial standing (a lecturer, an assistant, an associate and a full professor) while 5 indicates that a member of the founding team holds a distinguished and/or named professorship and/or is a member of the Academy of Sciences and/or has won a Nobel Prize.

To test our expectation that signals are more valuable for long distance transactions we include an additional variable which measures (in logarithmic form) the distance between the funding VCF and the target firm (for syndicate investments we measure the distance to the closest VCF).[8] We then interact the distance variable with the signal measures described above and expect a positive sign for these interaction terms.

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[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 repeated interactions with an entrepreneur, because private information regarding the entrepreneur is gained in earlier investment. However, in general the frequency of such repeated interactions is relatively low (Bengtsson, 2013; Wright et al., 1997).

[8] We do not expect distance to have a linear effect on the effectiveness of signals. For instance, a move from the 5th to the 6th mile should not have the same meaning as a move from, say, the 1005th to the 1006th mile even though in both cases the change (1 mile) is the same. This is why we use the natural log of distance. To calculate the distances we use the straight distance formula (arcos(sin(lat1).sin(lat2)+cos(lat1).cos(lat2).cos(long2−long1)) ×3963). For the (short) distances that we look at, the straight line distance closely resembles the driving distance but unlike the driving distance, it does not change over time due to newly constructed roads and other residential developments. This is relevant for our application because we study transactions that spread over a decade and, hence, need comparable distances across time. In cases where more than one VCF invested in the focal firm we measure the distance to the closest VCF because in syndication schemes the closest VCF typically assumes most of the oversight and consulting roles (Ferrary, 2010; Fritsch and Schilder, 2012) .

3.1 Control Variables

The design matrix X in equation 1 above includes a number of control variables which can influence the level of first round financing each firm receives.[9] Each VCF investment that a firm receives is proportional to the valuation of the firm *ex ante* and the equity level the VCFs collects. It follows that we need to account for both of those factors but finding direct measures for such factors is empirically challenging. As such, we use two separate indicators that can approximate the conceptual variables. Specifically, we first include dummy variables (*seed, early,* and *expansion*) that correspond to the growth stage of the firm when the VCF investment took place.[10] Because the valuation of firms, *ex ante,* increases with the stage of firm growth (Cumming and Dai, 2011) these indicators should approximate firm valuation. Importantly, early and later stage investments by VCFs are also associated with different equity levels acquired (Beaton, 2010; Kaplan and Strömberg, 2003). As such, the dummy indicators should be correlated with the amount of equity secured by VCFs. Given the increased valuation of firms at later stages of firm growth, we expect a positive sign for the indicators representing later stages of firm growth. We also construct a second indicator to approximate the level of equity VCFs receive for their investments. Because VCFs with stronger reputation typically receive larger equity than investors with weaker reputation for similar investments (Hsu, 2004) we also include a variable that reflects the Lee et al. (2011) reputation score of the highest ranked funding VCF of the first round of financing (*VCFreputation*).

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[9]Additional discussion on the impact of certain control variables included in our model on venture capital funding is presented in some of previous work (Hoenen et al., 2014).

[10] Seed stage funds are typically small amounts directed primarily towards proving a concept. Early stage funds are directed mainly towards product development. Funds directed towards the expansion stage are used, in large part, to boost market entry or strengthen R&D (Jeng and Wells, 2000). There are also funds directed towards later stage financing, such as buy-outs or acquisitions.

The availability of funds from the VCFs may also influence the amount invested in the first round of financing, overall. Because such availability is often largely determined by the number of investors that spread the risks of their investments (i.e. by the syndication size) (Lockett and Wright, 2001) as well as by the capital available to the investors (Gupta and Sapienza, 1992; Tian, 2011) we include two variables that measure the number of investors as well as their average size (*SyndicateInvestors, SyndicateSize*), and expect positive signs for both coefficients.

We also include the age of the focal firm at the round of financing (*Age*) as a control variable in the model. We do not form strong priors with regard to the direction the age of firms can move the amount of funds received because VCFs may evaluate positively older firms due to higher experience and survival but they may also view negatively older firms that have not received previous financing.

To incorporate in the analysis year-to-year variations, such as "hot IPO market" periods (Lowry and Schwert, 2002), that can encourage or discourage venture capital investments at an aggregate level we include in our empirical models a set of year dummies that match with the year in which the investment took place. We do not form expectations for the signs of their coefficients.

Agglomeration externalities (e.g. knowledge spillovers and network effects) can also help biotechnology firms improve their performance and thus increase their funding levels (Coenen et al., 2004; Döring and Schnellenbach, 2006; Gittelman, 2007; Kolympiris et al., 2011). To account for such effects we include the following variables in the model: a) *UniversitiesInMSA* which measures the number of universities that perform biotechnology related research and are located in the same Metropolitan Statistical Area as the focal firm and b) several indicators that measure the density of VCFs (*VCFarea 0010*, *VCFarea 1020)* and the number of patents granted to biotechnology firms (*PATENTarea 0010*, *PATENTarea 1020*) within 0–10 and 10–20 miles from the origin firm, respectively. We expect positive signs for the corresponding coefficients.

4. Data Sources and Presentation

To conduct the analysis we started by sourcing all venture capital first round investments by independent VCFs in dedicated biotechnology firms from 2001 up to 2011[11] using Thomson Reuter's SDC Platinum Database (SDC). Appendix Table 1 describes the construction of each variable we use in some detail. In the remaining part of this section, we focus on the variables we employ in our empirical models as shown in Table 1.

---Table 1 about here---

The sample we employ draws upon Hoenen et al. (2014).[12] As noted above, a noteworthy change from Hoenen et al. (2014) is that in Specification 2 we use a sharper way to account for the signaling function of the founding team as we decompose the *Foundersignal* variable into two separate indicators: *EntrepreneurialSignal* and *AcademicSignal.* We collected the data for both of these variables by visiting the websites of the sample firms.

[11] We start our analysis in 2001 because before then the United States Patent and Trademark Office (USPTO) did not publish patent applications. Also note that the dataset does not include investments from corporate venture capital. As well, while SDC reports the total amount invested in each round, it does not report the round investment per venture capital firm. As such, we cannot weight the distance to the closest VCF by the amount it invested. While this issue does not hold for the majority of the sample firms because they received first round investment only from one VCF (see Table 1), the finding that in syndicated investments the closest VCF is typically the one conducting the main scouting for investment targets (Fritsch and Schilder, 2012) alleviates concerns about the effect of this non-weighting on the estimated parameters.

[12] The main finding from that study was that having applied for a patent increased the level of first round of financing for biotechnology firms by 7.7 percent while patent activity had no impact on the level of funds raised during the second round of financing.

In total, the dataset includes 586 first round venture capital investments in 586 biotechnology firms. As shown in Table 1 the average distance between the recipient firms and the closest VCFs investing in such firms is 400 miles. Given that almost half of the observations are within a 20 miles threshold level (median: 20.63) the sample average is influenced by a small number of firms that received investments from VCFs located across the country. On average, the sample firms received $7.2 million in the first round of financing which was realized for half of the firms when they were less than 1.3 years old. The average $7.2 million investment is, however, inflated by few firms that attracted significantly more funds than the rest (e.g. the modal value is $1million).

With regards to the signals we study, the vast majority of the firms did not have any patent activity before the first round of financing. 66 firms had applied for at least one patent and 32 were granted at least one patent before the investment.[13]

The *Foundersignal* indicates that 1 out of 5 firms had at least one member in the founding team with entrepreneurial experience and/or with academic standing. In particular, approximately 1 out of 10 founders had earlier entrepreneurial experience while a sizeable portion of sample firms were (co)founded by academicians, a small share of which of preeminent status. Most founding teams, however, did not include an academic or a serial entrepreneur.

As it pertains to the regional environment, on average, a firm in the sample was surrounded by high patent activity and 39 VCFs located within a 20 miles radius. Figure 1

[13] The heavy representation of firms without patent activity in the sample supports our empirical choice to employ corresponding dummy variables. More specifically, 531 firms did not have any applications, 29 firms had 1 application, 9 firms had 2 applications, 14 firms had between 2 and 7 applications and 2 firms had 10 and 13 applications respectively. Granted patents had a similar left skewed distribution as well. The fact that the sample includes firms with varying degrees of patent activity is relevant in that it mitigates potential concerns of overstressing the significance of patents that could result from the tendency of better firms to patent more and generally better protect their intellectual property assets (Helmers and Rogers, 2011).

explains, in large part, these statistics as it shows that the majority of the sample firms were located in traditional biotechnology clusters of the East and West Coast of the United States. Nevertheless, a meaningful share of the firms was located outside the traditional biotechnology hubs in locations such as Austin, TX and Boulder, CO. This latter observation implies that our results are not specific to the traditional biotech clusters.

---Figure 1 and Table 2 about here---

In Table 2 we present the correlation coefficients for the variables described above. While in general the correlation coefficients assume low values, those between the level terms of the signal variables and the interaction terms between the signals and the distance are high (0.5, 0.75, 0.79, 0.81, 0.83). This suggests that there may be some overlap in the information provided by the level and interaction terms on the dependent variable. As we explain below, this point becomes relevant when we opt to not include the level terms in our baseline specifications.

5. Results

5.1. Baseline Model

Table 3 includes the estimates from the baseline specifications in which we omit the level terms.

---Table 3 about here---

Model 1 does not include the interaction terms we use to test our theoretical expectations. We include it for comparison purposes to Models 2 and 3, which present the coefficients from Specifications 1 and 2, respectively. We cluster the standard errors at the state level.[14] We do so to account for the possibility that firms located in the same state underperform or overperform

[14] Inference remains unchanged even when we employ White's heteroskedasticity robust standard errors.

jointly due to unobserved state-specific features promoting innovation, such as the quality of entrepreneurial coaching provided by local agencies, and because we expect the distance measures to be more similar among firms in the same state. The F-tests across all empirical models as well as the adjusted R^2 suggest that our empirical models have explanatory power. The multicollinearity condition index is below the generally regarded as safe threshold of 30 (Belsley et al., 1980).

We first evaluate whether geographic distance influences the value of the *Foundersignal* to VCFs in Model 2 (Table 3). In this model, the slope coefficient associated with distance between the firm and the nearest VCF is allowed to change when founders are eminent and/or have business experience. Based on the fitted model, we find that the coefficient of the interaction term is significantly positive (0.0981), and the marginal effect of distance on VC funding levels more than doubles when the firm's founder is eminent/experienced. Hence, we find empirical support for the hypothesis that geographic distance influences the signaling value of the founding team characteristics, as measured by the *Foundersignal* indicator. This result is also consistent with simple averages as firms that were founded by serial entrepreneurs and/or eminent academics received, on average, \$4.2 million more funding than the rest of the firms in our sample.

Next, we evaluate whether the academic standing and previous experience with starting a firm among firm founders have different value as signals and whether they are more effective in raising the amount of first round financing for distant transactions. In Models 3a-3c we use two separate measures to characterize the standing of the founding team: *AcademicSignal* and *EntrepreneurialSignal*. We evaluate the relevance of first for each of these signals separately (in Models 3a and 3b) and then jointly (in Model 3c).

While *AcademicSignal*Distance* is statistically significant and positive (0.0129) in Model 3a, the marginal effect of distance on VC funding levels when the firm's founder has high academic standing does not increase appreciably due to the weak quantitative impact of this signal. In contrast, when we estimate the joint impact of distance and the firm founders' business experience on the VC funding levels, through *EntrepreneurialSignal*Distance* in Model 3b, the result is quite different. Based on the fitted version of this model, we find that the estimated coefficient on this variable is significantly positive (0.088) and the marginal effect of distance on VC funding levels increases by 75% when the firm's founder is a serial entrepreneur. These results are confirmed when both indicators are included in Model 3c as their coefficients remain roughly the same. In addition, the *AcademicSignal* interaction is now statistically not different from zero. Taken together these results suggest that business experience as a signal matters more when the distance between investors and recipients increases while academic prominence does not seem to have such an effect.

In all of the Models 2 and 3, the estimated coefficient on the interaction term between patent applications and distance is significantly positive and varies between 0.0655 and 0.0733 in value. As such, the marginal effect of distance on VC funding levels increases (depending on the model) by 50-70% when the firm has patent applications. The positive and statistically significant coefficient of the interaction term between patent applications and distance is therefore also supportive of the theoretical expectation that the larger the distance, the larger the positive effect of patent applications on the level of venture capital funds received by the firms in the sample.

The interaction term between granted patents and distance in all empirical models (Models 2 and 3) is very small in size and, for the most part, statistically not different from zero. The insignificance of granted patents as a signal is an interesting result, especially since patent applications are found to have signaling value. By definition, applications do not have an exclusion value because patent claims are not finalized until the patent issues. As such, patent applications may be a stronger signal than granted patents because they convey both a learning-by-doing process and a fine-tuning process (Hoenen et al., 2014). The learning-by-doing process refers to the fact that every patent needs to conform to the same criteria of novelty, usefulness and non-obviousness. Accordingly, the more often a firm submits patent applications the more likely it will learn how to satisfy these three criteria. The fine-tuning process refers to the interactions between applicants and patent officers after an application is submitted. Following the initial application, firms learn more about the prior art in their technology development area from communication with the patent examiner, redefine their claims, and overall get exposed to a process that can deepen and update their knowledge. This deepening and updating of knowledge is particularly important in fast evolving industries such as biotechnology where breakthroughs are often the result of the very latest techniques and cutting edge discoveries (see Humphries, 2010; McNamee and Ledley, 2012 for specific examples). Hence, while a granted patent may represent what a firm has learned, an application may better signify what a firm is learning. Given that learning processes are important for fast-evolving industries, patent applications in biotechnology may be a stronger signal because investors value firms that can evolve over time by keeping up with the latest developments in the industry and do not sit idle.

It is worth noting, that the estimated coefficients in Model 3c where all the interaction terms of the signals with distance are included suggest that the marginal effect of distance on VC funding levels increases by 125% when the firm's founder is a serial entrepreneur *and* the firm has patent applications. The individual effects of the two signals are distinct and remain stable across all specifications. Hence, our findings suggest that signals increase the level of venture capital funding primarily in environments where information asymmetries are more pronounced, and hence investors place more value on them, such as when the geographic distance between the VCF and the target firm is extended. For distant target firms, VCFs appear less able to assess the quality of the firm in question (Rosiello and Parris, 2009; Sorenson and Stuart, 2001; Zook, 2002) and as a means to mitigate the effects of the associated increase in information asymmetries they tend to rely on signals transmitted by firms seeking for investments.

Importantly, our findings also shed new light on the ongoing discussion whether patent activity is valued by investors primarily as a signal or as a means to gain monopoly rights (Hoenig and Henkel, 2014). The granted patents signal and the forward citations control proxy for the economic value of patents are statistically insignificant across specifications. Therefore, similar to previous works (Hoenen et al., 2014; Hsu and Ziedonis, 2013) our findings are supportive of the explanation that patents serve, in large part, a signaling function. More to it, if patents were valued more for the exclusion value they carry, then we would expect them to attract investors even in environments of reduced information asymmetries. Short distance investments are an example of such an environment. Yet, what we consistently find is that patent activity does not increase VC investments for short distance transactions, which then provides evidence in favor of a signaling function. Perhaps, what can explain this finding is that specifically for patents covering drug-related inventions (hence the sorts of patents we study), infringements are common (Lanjouw and Schankerman, 2001). Accordingly, while in principle the exclusion value afforded by the monopoly rights of a patent is present, VCFs might be discounting such value in light of potential infringements.

With regards to the control variables we include in the analysis, the results indicate that older firms receive more funds and firms receiving seed stage investments receive less (*firmage* *and seed*). The number of VCFs in the syndication also increases the amount of investment received by firms in the sample while the reputation of VCFs has no effect. The density of VCFs within a 10 miles radius from the recipient firm increases the level of first round financing for the firms in the sample as well. Finally, several other control variables, including the number of universities in the metropolitan statistical area (MSA) and the density of granted patents, do not affect the level of investments.

5.2. Sensitivity analysis of baseline results

The estimated empirical models presented in Table 3 are very stable. The coefficients of all the signal and control variables have been largely unchanged across the various specifications. Still, to further test the robustness of our baseline empirical results we conducted a number of additional sensitivity tests. In Table 4 we present the estimates for these robustness checks only for Specification 2 (model 3c) and we note that the results are qualitatively similar for Specification 1 as well.[15]

---Table 4 about here---

Because we rely on a sample of firms that received venture capital investments, our estimates could suffer from selection bias if the sample firms were more likely to receive funds than other firms in the first place. To check whether this potential bias influences our results in sensitivity test 1 we construct a Heckman selection model where in the first stage we model the

[15] In Hoenen et al. (2014) we demonstrate the robustness of the model without the interaction terms to a number of observations that include a) different time frames of analysis and, b) different measures of patent quality. We obtain similar results when we conduct the same tests here. Along the same lines, on top of the tests we present in section 5.2, we also conducted a) a test where we employ the density of VCFs in a region as an alternative proxy for the existence of environments characterized by strong information asymmetries and b) a test where we replace the minimum distance to the VCF with the average distance (in case of syndicate investments). By and large, our estimates are qualitatively similar to the estimates reported in Table 3.

probability that a firm receives venture capital and in the second stage we conduct the baseline analysis. In the set of regressors in the first stage we include variables such as patents, founder's status and receipt of government grants that have been previously shown to affect the chances of receiving venture capital (Kaplan and Strömberg, 2004; Lerner, 1999; MacMillan et al., 1986). To source the sample of firms that had not received venture capital funds we relied on proprietary data from InKnowVation reflecting all biotechnology firms that had won grants from the Small Business Innovation Research (SBIR) program from 1983 to 2006.[16] The dataset included firm-specific information such as patents and year of foundation as well as an indicator of whether or not the SBIR winner firms received venture capital investments, with the majority of those firms not having received funds from VCFs.[17] The estimates of Heckman selection model remain similar in magnitude, sign and statistical significance to our baseline estimates and indicate that any potential selection bias does not materially change our findings.

[16] The dataset included all life science winners. In order to identify the biotechnology firms we performed a keyword search on the business description of all the firms. We used almost 400 keywords with about 100 of them characterizing the vast majority of the firms in the dataset (Kolympiris et al., 2014). These keywords included glycosylation, oligo-nucleotide, mutation, antigen, recombinant allergens, biofiltration, glycosylation, Bacillus thuringiensis, polymerase chain reaction (PCR), chondrocyte differentiation, biosynthesis, recombinant enzymes, genetic engineering, stem cells, bioprocessing, genetic, biotic stress, genetic parameters, chimeraplasty, introgression, biomedicine, reverse transcriptase, glycoprotein, directional cloning, western blot, combinatorial biocatalysis, arabidopsis, gene (DNA) sequencing.

[17] Instead of using the age variable in the first stage of the Heckman model we use the year of foundation. We do so because for the age variable to be meaningful in our application we would need to model the probability that a firm receives venture capital investment within a specific period of time. However, by definition, such period of time does not exist for firms that did not receive venture capital investments. For the selection equation, we also use only granted patents as measures of patent activity in the first stage because a number of recipient firms received the award before 2001 and as such the full list of submitted applications is not available as it was not recorded by the USPTO. The selection of the remaining variables in the first stage of the Heckman model is guided, primarily, by findings of previous literature. To illustrate, for the selection equation we include the SBIR and the location dummies based on the findings that SBIR winners are more likely to attract venture capital funds (Lerner, 1999) and that firms located in Massachusetts or California are more likely to attract funds (Lerner, 1999). The relationship of those factors with the amount of venture capital raised in the first round was not replicated in the existing literature. As such, we consider these factors as relevant for the first but not for the second stage of the Heckman model. Factors for which empirical evidence is scarce, we theorize, are relevant for both stages (e.g. *FounderSignal*) and are included in both stages (we opt for *FounderSignal* and not *AcademicSignal* and *EntrepreneurialSignal* because of better model fit). Finally, when we include different groups of variables in the selection equation we find that the results remain largely unchanged.

If the amount invested in a biotechnology firm is endogenously determined with the distance between the VCF and the firm, our estimates would suffer from endogeneity bias.[18] For instance, if local investors could not provide sufficient amounts of capital to local firms, the only option for such firms would be to raise funds from distant investors. In such a case, distance and the amount raised (our dependent variable) would be determined simultaneously. To test whether distance is an endogenous variable we performed the Hausman endogeneity test described in Wooldridge (2010, p. 119) and present the second stage estimates in test 2.[19] The coefficient of the residuals of the first stage is not statistically significant, thus, rejecting endogeneity. This implies that our estimates are not plagued by endogeneity bias. Further, the magnitude, sign and statistical significance of the signal interactions remain qualitatively similar to the baseline estimates.

To measure the effects of the regional environment and clustering in general, we include variables measuring the density of VCFs and patent activity within a 20 miles radius from the focal firm. However, clusters are not defined solely by geography but also through professional and social ties (Casper, 2007). It is, thus, possible that nearby firms might not belong in a cluster or that firms located further away are still part of the cluster. To address this possibility, in sensitivity test 3 we replace the variables describing the regional environment with variables that take the value of 1 for firms located in the MSAs of the three traditional biotech clusters in the US: Boston, San Diego and San Francisco. As shown in Table 3, the estimates of this sensitivity test are nearly identical to the estimates of the baseline specification.

[18] We thank an anonymous reviewer for bringing up this point.
[19] More specifically, we first run the reduced form regression with distance as the dependent variable against the exogenous variables and use the residuals of this regression as an explanatory variable in our baseline model.

As we explained above, we opted to represent patent activity in our baseline model with dummy variables that take the value of 1 if the firm was granted a patent or had applied for a patent before the investment and 0 otherwise. We did so chiefly because of multicollinearity concerns and because the left skewed distribution of patent activity made the dummy variables we used roughly equivalent to continuous measures. In sensitivity tests 4 and 5 we put this modelling choice to test. In those tests we omit firms with well above average patent applications, thus, checking whether these outliers drive our estimates. In both tests the results are qualitatively similar to the baseline estimates and hence provide additional support to our representation of patent activity with dummy variables.

Finally, in tests 6 and 7 we test for the separate significance of the interaction terms – patent activity measures and distance as well as founder characteristics and distance—as those are tested jointly in the baseline model. The coefficients are similar to the baseline coefficients we present in Table 3. Patent applications and the entrepreneurial experience interaction variables remains significant and granted patents and academic eminence interaction variables remain insignificant.

5.3. Model specifications that include levels

Our baseline specification is informative and stable. However, it is based on our choice to exclude the level terms of signals from the model and test the significance of the interaction terms of signals with distance on funding levels, alone. Our choice is driven by the high correlation between levels and interaction terms. This high correlation, however, may raise concerns as to what sort of impacts the interaction terms are picking up when included alone. In order to examine this issue further, in Appendix Table 2 we present estimates from specifications that a) include only the level terms, b) include the level and associated interaction terms one by one and c) include all the level and interaction terms. We derive three main conclusions from Appendix Table 2 and from comparing it to Table 3. First, the magnitudes of the interaction terms in Table 3, which omits the level terms, and the magnitudes of the interaction terms in the models of Appendix Table 2, which include the level terms, are similar. The stability of the interaction terms across specifications suggests that these variables represent separate effects that are not influenced by the presence or the absence of the level terms in the models. Second, in Appendix Table 2 we observe a material increase in the standard errors of the founder signal interaction terms. Given the high correlations it is likely that the level terms, as intercept shifters, and the slope shifters provided by the Distance* founder signal interactions could represent similar patterns in the funding data and, for these cases, the models could be over-specified leading to inflated variance of those estimators and, eventually, incorrect inference. Finally, none of the level terms is significant when the interaction terms are included in the specifications. An F-test of joint significance for the level terms also failed to reject the hypothesis that, as a set, these effects are equal to 0; the F-test for specification 1 (Model 8 in Appendix Table 2) was 0.27 with a p-value of 0.85 and the F-test for specification 2 (Model 9 in Appendix Table 2) was 0.43 with a p-value of 0.79. It is important to note, that because these F-statistics have values below 1, inclusion of the level terms would actually reduce the adjusted R^2 in the fitted models (Wooldridge, 2009 p. 201). These three main reasons guide our baseline specification above and support the omission of the level terms as: a) the baseline model explains a larger portion of the variance, it is more parsimonious and it is less likely to suffer from inference concerns; and b) the inferences on our testable hypotheses are not meaningfully affected by the omission of the level terms.

6. Conclusion and Discussion

A long stream of literature based on signaling theory has analyzed the factors that make signals more valuable to receivers. The general consensus in this literature is that signals are more valuable to receivers when transmitted in environments of elevated information asymmetries between senders and receivers, such as when firms are untested and when industries are risky. However, despite extensive evidence of increasing information asymmetries between transacting parties over geographic distance, the value of signals relative to geographic distance remains largely unknown. Against this background, and keeping in mind that signals are often more relevant for early stages of firm growth, in this paper we pose the following question: are signals of start-up firm quality more valuable to distant than nearby investors and, if so, do they lead to higher investments?

To address the question we examine venture capital investments in 586 US-based biotechnology firms over a 10 year period. In line with the notion that information asymmetries are more pronounced in long distance transactions we find that firm patent activity and the business experience of the founder team carry a stronger signaling value for long distance transactions.

Overall, our empirical results corroborate the idea that because tacit knowledge circulates mostly within local circles, it diminishes the value that receivers place on signals for local transactions. Notably, our analysis sheds new light on why patents and patent applications of start-up firms attract investors. If patents were valued mostly for their monopoly rights, we would expect them to attract investors, equally, in environments of low and high information asymmetries. If, however, they were valued primarily as a signal of unobserved firm quality, we would expect them to attract investors, chiefly, when information asymmetries are pronounced.

We find strong support for the latter argument: patent activity, especially patent applications, seems to attract venture capitalists mostly because of its signaling function.

Our study also has managerial and policy implications. For instance, for start-up firms located outside the traditional venture capital hubs seeking early stage venture capital investments, our study suggests that signals can help them overcome any potential disadvantages of their location. This finding is particularly relevant because, early stage firms are often tempted to relocate to increase their access to financial resources (Tian, 2011). In contrast, potential senders of signals located close to intended receivers, may benefit more from conveying quality information through local networks. Our study shows that in close proximity the value of signals tends to diminish and, hence, the costs of signaling may outweigh the potential benefits. 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 assist local firms with signaling, through certification or award programs or technical assistance for patent and grant acquisition, this could attract distant venture capital and therefore contribute to the innovativeness and economic growth of the region (Samila and Sorenson, 2011).

We close with a note on the limits of our study and on potential extensions. Our focus on biotechnology is largely motivated by the spatial configuration and the types of investments that occur in the industry, which present a suitable setting for studying the strength of signals across different distances between senders and receivers. The spatial configuration of the biotechnology industry and of investments in it may not be representative of other industries thereby limiting the generality of our conclusions. Extending the analysis to different industries could leverage the presence of shorter research cycles, differential locations, industry structures, and overall information asymmetries and risks thereby providing opportunities for new signals and additional insights.

A potential limitation of our work is that common factors could affect the location of biotechnology firms and venture capital firms. For instance, biotech firms with low patent activity aware of its signaling value to distant investors could purposefully locate close to VCFs. If that holds, the analysis would be subject to an identification concern.[20] Existing empirical evidence from a broad set of industries indicates that the effect of regional venture capital activity *per se* on firm births is not strong (Samila and Sorenson, 2010, 2011). Specifically for biotechnology the impact of venture capital activity on firm births is either non-existent (Kolympiris et al., 2015) or weakly positive and lessens even more when other factors (e.g. university presence) are explicitly considered (Stuart and Sorenson, 2003). While such evidence suggests that the concern at hand is not particularly acute, the possibility cannot be fully ruled out.

The focus of the study coupled with data limitations does not allow us to use sharper measures of the regional environment in which the focal firms are located. Relevant measures could account for the ties between nearby organizations and the overall network structure surrounding the firms receiving funding. Along the same lines, investigating whether social and industrial distance between investors and recipient firms impacts the effects of geographic distance on the valuation of signals *a la* Sorenson and Stuart (2001) is a fruitful avenue for further work.

Finally, the correlation of the signals and their interactions with the distance between VCFs and target firms in our data set constraints, somewhat, our model specification. Our empirical tests

[20] Along the same lines, an additional identification concern could arise if venture capitalists encourage firms to apply for patents. Given that we measure patent activity before the first round of investment, this would hold only for cases under which the venture capitalist plays a role in the decision process of the firm before the investment. However, because of the well-established *ex ante* scanning function and *ex post* coaching function of venture capitalists, this sort of identification is not a particularly strong concern in our work.

provide some comfort on the robustness of our results but future work could explore further their separate effects.

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Table 1. Descriptive Statistics of Selected Variables Used in the Empirical Models.

Variable Description	N	MEAN	STD. DEV	MIN.	MEDIAN	MAX.	MODE
Investment size	586	7.21	11.04	0.001	3.56	100.00	1.00
Patent applications	66						
Granted patents	32						
Forward citations	586	0.06	0.44	0.00	0.00	6.83	0.00
Founder signal	119						
Entrepreneurial signal	61						
Academic signal[1]	**d=0**	**d=1**	**d=2**	**d=3**	**d=4**	**d=5**	
	445	5	4	9	49	74	
Distance between firm and closest VCF	586	398.49	747.92	0.00	20.63	3146.00	0.01
Seed	248						
Early	246						
Expansion	78						
Firm age	586	2.54	3.12	0.00	1.37	27.73	0.00
VCF reputation	586	0.36	0.45	0.00	0.00	1.00	0.00
Syndicate investors	586	2.61	1.84	1.00	2.00	13.00	1.00
Syndicate size	586	366.99	616.60	0.00	75.47	4155.00	0.00
Number of universities located in the MSA	586	9.30	8.09	0.00	9.00	37.00	17.00
Density of VCFs in 0 to 10 miles from the firm	586	23.46	29.36	0.00	10.00	103.00	1.00
Density of VCFs in 10 to 20 miles from the firm	586	15.21	25.37	0.00	5.00	127.00	0.00
Number of patents granted to biotechnology firms located 0 to 10 miles from the firm	586	126.55	155.87	0.00	61.00	531.00	0.00
Number of patents granted to biotechnology firms located 10 to 20 miles from the firm	586	69.73	115.16	0.00	18.00	608.00	1.00

[1]The variable takes the value of 0 if none of the founding team members had an academic title, 1 if a member of the founding team is an instructor or lecturer, 2 if a member of the founding team is an assistant professor, 3 if a member of the founding team is an associate professor, 4 if a member of the founding team is a full professor, 5 if a member of the founding team holds a distinguished and/or named professorship and/or is a member of the Academy of Sciences and/or has won a Nobel Prize.

Note: 64 observations in 2001, 60 observations in 2002, 52 observations in 2003, 49 observations in 2004, 66 observations in 2005, 74 observations in 2006, 78 observations in 2007, 63 observations in 2008, 33 observations in 2009, 39 observations in 2010 and 8 observations in 2011

Table 2. Correlation matrix for variables used in the analysis

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Patent applications	1	1.00																							
Granted patents	2	0.22	1.00																						
Founder signal	3	-0.03	0.03	1.00																					
Academic signal	4	-0.02	0.00	0.62	1.00																				
Entrepreneurial signal	5	-0.02	0.02	0.68	0.14	1.00																			
Distance between firm and closest VCF	6	0.10	0.07	0.00	-0.06	0.04	1.00																		
Distance between firm and closest VCF * Patent applications	7	*0.81*	0.24	-0.04	-0.02	0.01	0.28	1.00																	
Distance between firm and closest VCF * Granted patents	8	0.12	*0.50*	0.09	0.08	-0.01	0.13	0.17	1.00																
Distance between firm and closest VCF * Founder signal	9	-0.02	0.06	*0.79*	0.44	0.60	0.24	0.01	0.15	1.00															
Distance between firm and closest VCF * Academic signal	10	0.02	0.04	0.47	*0.75*	0.13	0.25	0.07	0.16	0.61	1.00														
Distance between firm and closest VCF * Entrepreneurial signal	11	0.02	0.05	0.56	0.10	*0.83*	0.19	0.05	0.01	0.74	0.20	1.00													
Forward citations	12	0.08	0.59	0.01	-0.02	0.02	0.02	0.11	0.27	0.04	0.01	0.04	1.00												
Seed	13	-0.17	-0.13	0.01	0.03	-0.01	-0.13	-0.15	-0.04	0.00	0.02	-0.05	-0.10	1.00											
Early	14	0.04	-0.05	0.02	0.01	0.03	0.01	-0.01	-0.07	-0.02	-0.04	0.02	0.00	-0.73	1.00										
Expansion	15	0.19	0.26	-0.05	-0.05	-0.03	0.15	0.22	0.17	0.03	0.03	0.03	0.16	-0.34	-0.33	1.00									
Firm age	16	0.34	0.31	-0.02	-0.01	-0.03	0.19	0.35	0.24	0.05	0.06	0.02	0.11	-0.25	-0.08	0.43	1.00								
VCF reputation	17	-0.12	-0.08	0.17	0.13	0.12	-0.15	-0.11	-0.03	0.08	0.03	0.05	-0.03	-0.03	0.12	-0.14	-0.13	1.00							
Syndicate investors	18	0.03	-0.01	0.04	0.01	0.10	-0.09	0.03	-0.04	-0.02	-0.07	0.05	-0.06	-0.16	0.16	0.01	-0.09	0.36	1.00						
Syndicate size	19	-0.06	-0.12	0.09	0.10	0.04	0.10	-0.03	-0.06	0.11	0.11	0.05	-0.07	0.13	-0.06	-0.13	-0.12	0.28	0.09	1.00					
Number of universities located in the MSA	20	-0.02	-0.04	0.03	0.01	-0.01	-0.14	-0.09	-0.08	-0.06	-0.08	-0.06	-0.10	-0.05	0.09	-0.07	0.00	0.06	0.03	0.05	1.00				
Density of VCFs in 0 to 10 miles from the firm	21	-0.04	-0.07	0.11	0.15	0.01	-0.24	-0.10	-0.07	-0.04	-0.01	-0.07	-0.08	0.06	0.01	-0.09	-0.10	0.19	0.11	0.15	0.45	1.00			
Density of VCFs in 10 to 20 miles from the firm	22	-0.04	-0.02	-0.04	-0.06	-0.02	-0.02	-0.06	-0.04	-0.05	-0.07	-0.03	-0.04	-0.07	0.08	-0.02	-0.08	0.09	0.02	0.04	0.20	0.06	1.00		
Number of patents granted to biotechnology firms located 0 to 10 miles from the firm	23	0.01	-0.04	0.01	0.09	0.01	0.00	0.00	-0.07	-0.03	0.04	-0.02	-0.01	0.03	0.03	-0.08	-0.16	0.12	0.10	0.18	0.03	0.28	0.13	1.00	
Number of patents granted to biotechnology firms located 10 to 20 miles from the firm	24	-0.02	-0.04	-0.03	0.00	-0.02	-0.02	-0.04	-0.04	-0.06	-0.03	-0.05	-0.06	-0.03	0.04	-0.04	-0.10	0.05	0.02	0.07	0.09	0.25	0.64	0.16	1.00

Table 3. Baseline Estimates. The dependent variable is the natural logarithm of the amount of venture capital funding in the first round of financing.

			Specification 1		Specification 2					
Model	**Model 1 (No signals)**		**Model 2 (Including founder signal only)**		**Model 3a (Including academic signal only)**		**Model 3b (Including entrepreneurial signal only)**		**Model 3c (Including both entrepreneurial and academic signals)**	
Variable	Coefficient	Standard errors	Coefficient	Standard errors	Coefficient	Standard errors	Coefficient	Standard errors	Coefficient	Standard errors
Intercept	13.3103	0.3477 ***	13.2968	0.3714 ***	13.2875	0.3616 ***	13.2841	0.3505 ***	13.2781	0.3625 ***
Distance between firm and closest VCF	0.1016	0.0280 ***	0.0806	0.0299 **	0.0875	0.0307 ***	0.0881	0.0288 ***	0.0812	0.0315 **
Distance between firm and closest VCF * Granted patents			-0.0129	0.0062 **	-0.0120	0.0062	-0.0100	0.0060	-0.0114	0.0061
Distance between firm and closest VCF * Patent applications			0.0733	0.0188 ***	0.0656	0.0179 ***	0.0655	0.0186 ***	0.0658	0.0178 ***
Distance between firm and closest VCF * Founder signal			0.0981	0.0196 ***						
Distance between firm and closest VCF * Academic signal					0.0129	0.0061 **			0.0106	0.0068
Distance between firm and closest VCF * Entrepreneurial signal							0.0886	0.0280 ***	0.0789	0.0308 **
Forward citations	-0.0554	0.0958	-0.0287	0.0835	-0.0165	0.0793	-0.0365	0.0853	-0.0282	0.0792
Seed	-0.9806	0.2483 ***	-0.9299	0.2506 ***	-0.9600	0.2412 ***	-0.9169	0.2651 ***	-0.9325	0.2629 ***
Early	-0.2413	0.1820	-0.2094	0.2052	-0.2360	0.1943	-0.2045	0.2108	-0.2135	0.2155
Expansion	-0.1253	0.3156	-0.0968	0.3078	-0.1228	0.3018	-0.0923	0.3093	-0.1011	0.3111
Firm age	0.0640	0.0231 ***	0.0608	0.0233 **	0.0607	0.0227 **	0.0615	0.0230 **	0.0613	0.0230 **
VCF reputation	0.2904	0.1707	0.2697	0.1623	0.2961	0.1648	0.2961	0.1669	0.2824	0.1649
Syndicate investors	0.3732	0.0547 ***	0.3687	0.0526 ***	0.3709	0.0537 ***	0.3627	0.0532 ***	0.3668	0.0526 ***
Syndicate size	0.0003	0.0001	0.0003	0.0001	0.0003	0.0001	0.0003	0.0002	0.0003	0.0001
Number of universities located in the MSA	-0.0010	0.0102	-0.0004	0.0100	-0.0003	0.0101	-0.0008	0.0103	-0.0002	0.0101
Density of VCFs in 0 to 10 miles from the firm	0.0112	0.0031 ***	0.0110	0.0031 ***	0.0110	0.0031 ***	0.0113	0.0032 ***	0.0111	0.0031 ***
Density of VCFs in 10 to 20 miles from the firm	0.0027	0.0023	0.0030	0.0025	0.0031	0.0024	0.0029	0.0024	0.0031	0.0024
Number of patents granted to biotechnology firms located 0 to 10 miles from the firm	0.0008	0.0004	0.0007	0.0004	0.0007	0.0004	0.0007	0.0004	0.0007	0.0004
Number of patents granted to biotechnology firms located 10 to 20 miles from the firm	0.0008	0.0004	0.0007	0.0004	-0.0005	0.0005	-0.0005	0.0005	-0.0005	0.0005
Year Dummies included	YES		YES		YES		YES		YES	
Obervations	586		586		586		586		586	
Adjusted R^2	0.3997		0.4116		0.4056		0.4073		0.4085	
F test for overall model significance	157.9900 ***		152.1700 ***		228.6300 ***		196.6400 ***		225.35 ***	
Multicollinearity Condition Index	27.4842		28.0051		28.0077		27.8823		28.1721	
Joint test of significance: Distance between firm and closest VCF * Founder signal(s)[1] & Distance between firm and closest VCF * Patent applications			16.1300 ***		9.8100 ***		8.6800 ***		7.3200 ***	
Joint test of significance: Distance between firm and closest VCF * Granted Patents & Distance between firm and closest VCF * Patent applications			9.8500 ***		9.4400 ***		7.5200 ***		9.3100 ***	
Joint test of significance: Distance between firm and closest VCF & Distance between firm and closest VCF * Founder signal(s)[1]			28.1200 ***		12.8600 ***		20.7600 ***		36.4200 ***	
Joint test of significance: Distance between firm and closest VCF & Distance between firm and closest VCF * Patent applications			15.1500 ***		14.3500 ***		14.0800 ***		12.9500 ***	

Standard errors are clustered at the state level

* Significant at 5%. ** Significant at 1%.

[1]For model 3, the founder signal in the joint tests of significance refers to the academic and entrepreneurial signal

Table 4. Sensitivity Analysis. The dependent variable is the natural logarithm of the amount of venture capital funding in the first round of financing.

	1		2		3		4	
Model	Heckman Selection Model [1]		Hausman test for endogeneity		Regional environment with dummy variables for traditional biotechnology clusters		Omit firms with more that four patent applications	
Variable	Coefficient	Standard errors	Coefficient	Standard errors	Coefficient	Standard errors	Coefficient	Standard errors
Intercept	13.2210	0.3806 ***	12.6878	0.8759 ***	13.7132	0.4232 ***	13.2886	0.3676 ***
Distance between firm and closest VCF	0.0787	0.0302 ***	0.2069	0.1717	0.0534	0.0320	0.0830	0.0316 **
Distance between firm and closest VCF * Granted patents	-0.0107	0.0057	-0.0114	0.0061	-0.0119	0.0065 *	-0.0144	0.0059 **
Distance between firm and closest VCF * Patent applications	0.0741	0.0175 ***	0.0658	0.0178 ***	0.0635	0.0170 ***	0.0599	0.0178 ***
Distance between firm and closest VCF * Academic signal	0.0122	0.0068	0.0106	0.0068	0.0123	0.0072 *	0.0108	0.0066
Distance between firm and closest VCF * Entrepreneurial signal	0.0724	0.0318 **	0.0789	0.0308 **	0.0705	0.0308 **	0.0803	0.0328 **
Forward citations	-0.0152	0.0708	-0.0282	0.0792	-0.0488	0.0706	-0.0146	0.0820
Seed	-0.8591	0.2527 ***	-0.8133	0.2675 ***	-0.9327	0.2603 ***	-0.9401	0.2621 ***
Early	-0.1280	0.2222	-0.1811	0.2169	-0.1828	0.2137	-0.2225	0.2157
Expansion	0.0108	0.3080	-0.1224	0.3207	-0.0654	0.3469	-0.1137	0.3140
Firm age	0.0706	0.0226 ***	0.0473	0.0237	0.0557	0.0266 **	0.0597	0.0224 **
VCF reputation	0.2757	0.1558	0.3796	0.2299	0.3763	0.1806 **	0.2733	0.1654
Syndicate investors	0.3678	0.0523 ***	0.3757	0.0591 ***	0.3731	0.0536 ***	0.3680	0.0537 ***
Syndicate size	0.0003	0.0001	0.0002	0.0001	0.0003	0.0002 **	0.0003	0.0001
Number of universities located in the MSA	-0.0005	0.0097	0.0018	0.0096			0.0001	0.0100
Density of VCFs in 0 to 10 miles from the firm	0.0110	0.0030 ***	0.0138	0.0053 **			0.0112	0.0031 ***
Density of VCFs in 10 to 20 miles from the firm	0.0031	0.0022	0.0033	0.0025			0.0031	0.0024
Number of patents granted to biotechnology firms located 0 to 10 miles from the firm	0.0007	0.0003 **	0.0006	0.0005			0.0007	0.0004
Number of patents granted to biotechnology firms located 10 to 20 miles from the firm	-0.0005	0.0005	-0.0006	0.0006			-0.0005	0.0005
First stage residuals of Distance between firm and closest VCF			-0.1257	0.1574				
Firm located in Boston					1.1250	0.2584 ***		
Firm located in San Francisco					0.3837	0.1303 ***		
Firm located in San Diego					0.1341	0.1102		
Year Dummies included	YES		YES		YES		YES	
Obervations	586		586		586		578	
Adjusted R^2			0.4085		0.3779		0.4055	
F test for overall model significance			225.3500 ***		14.6700 ***		195.5600 ***	
Multicollinearity Condition Index	28.1721		75.5719		24.3924		27.9837	
Joint test of significance: Distance between firm and closest VCF * Founder signals & Distance between firm and closest VCF * Patent applications	29.3400 ***		7.3200 ***		8.8800 ***		6.7100 ***	
Joint test of significance: Distance between firm and closest VCF * Granted Patents & Distance between firm and closest VCF * Patent applications	22.2500 ***		9.3100 ***		10.0500 ***		8.5700 ***	
Joint test of significance: Distance between firm and closest VCF & Distance between firm and closest VCF * Founder signals	118.2600 ***		8.5600 ***		27.5700 ***		34.2300 ***	
Joint test of significance: Distance between firm and closest VCF & Distance between firm and closest VCF * Patent applications	30.6000 ***		11.0700 ***		8.4900 ***		11.7500 ***	
Wald test for Rho (correlation coefficient between error terms of the two equations) = 0	3.7300							

Standard errors are clustered at the state level

** Significant at 5%. *** Significant at 1%.

[1] Appendix Table 3 presents the first stage

Table 4 continued. Sensitivity Analysis. The dependent variable is the natural logarithm of the amount of venture capital funding in the first round of financing.

Model	5		6		7	
	Omit firms with more that five patent applications		Omit patent activity signal interactions		Omit academic and entrepreneurial signal interactions	
Variable	Coefficient	Standard errors	Coefficient	Standard errors	Coefficient	Standard errors
Intercept	13.2751	0.3633 ***	13.2958	0.3639 ***	13.3395	0.3389 ***
Distance between firm and closest VCF	0.0824	0.0317 **	0.0865	0.0315 ***	0.0941	0.0280 ***
Distance between firm and closest VCF * Granted patents	-0.0116	0.0060				
Distance between firm and closest VCF * Patent applications	0.0692	0.0187 ***			0.0612	0.0187 ***
Distance between firm and closest VCF * Academic signal	0.0105	0.0070	0.0089	0.0073		
Distance between firm and closest VCF * Entrepreneurial signal	0.0799	0.0322 **	0.0819	0.0308 **		
Forward citations	-0.0144	0.0834	-0.0637	0.0925	-0.0722	0.0903
Seed	-0.9282	0.2633 ***	-0.9674	0.2688 ***	-0.9720	0.2441 ***
Early	-0.2131	0.2174	-0.2256	0.2136	-0.2415	0.1813
Expansion	-0.1013	0.3098	-0.1113	0.3263	-0.1396	0.3031
Firm age	0.0610	0.0230 **	0.0642	0.0238 **	0.0551	0.0229 **
VCF reputation	0.2759	0.1640	0.2587	0.1690	0.3066	0.1723
Syndicate investors	0.3672	0.0525 ***	0.3729	0.0529 ***	0.3672	0.0538 ***
Syndicate size	0.0003	0.0001	0.0003	0.0001	0.0003	0.0001
Number of universities located in the MSA	-0.0001	0.0101	-0.0003	0.0100	-0.0004	0.0103
Density of VCFs in 0 to 10 miles from the firm	0.0112	0.0031 ***	0.0111	0.0031 ***	0.0112	0.0032 ***
Density of VCFs in 10 to 20 miles from the firm	0.0031	0.0024	0.0030	0.0023	0.0028	0.0024
Number of patents granted to biotechnology firms located 0 to 10 miles from the firm	0.0007	0.0004	0.0008	0.0004	0.0007	0.0004
Number of patents granted to biotechnology firms located 10 to 20 miles from the firm	-0.0005	0.0005	-0.0005	0.0005	-0.0005	0.0005
First stage residuals of Distance between firm and closest VCF						
Firm located in Boston						
Firm located in San Francisco						
Firm located in San Diego						
Year Dummies included	YES		YES		YES	
Obervations	581		586		586	
Adjusted R^2	0.4063		0.4045		0.4015	
F test for overall model significance	231.8600 ***		140.7900 ***		142.4600 ***	
Multicollinearity Condition Index	28.0500		27.9250		27.6536	
Joint test of significance: Distance between firm and closest VCF * Founder signals & Distance between firm and closest VCF * Patent applications	7.4100 ***					
Joint test of significance: Distance between firm and closest VCF * Granted Patents & Distance between firm and closest VCF * Patent applications	9.5800 ***					
Joint test of significance: Distance between firm and closest VCF & Distance between firm and closest VCF * Founder signals	34.2300 ***		31.9400 ***			
Joint test of significance: Distance between firm and closest VCF & Distance between firm and closest VCF * Patent applications	13.6700 ***				16.7800 ***	
Wald test for Rho (correlation coefficient between error terms of the two equations) = 0						

Standard errors are clustered at the state level

** Significant at 5%. *** Significant at 1%.

[1]Appendix Table 3 presents the first stage

Appendix Table 1. Construction of Variables

Variable Code	Description	Construction
Patent applications	Takes the value of 1 if the biotechnology firm had at least on submitted patent application from foundation to the first round of investment	Obtained from Google Patents® which indexes granted patents and patent applications from the United States Patent and Trademark Office (USPTO).
Granted patents	Takes the value of 1 if the biotechnology firm had at least on granted patents from foundation to the first round of investment	Obtained from Google Patents® which indexes granted patents and patent applications from the United States Patent and Trademark Office (USPTO).
Forward citations	Average number of forward patent citations per year of patents granted between firm foundation and the first round of investment	The number of times each of the patents in the dataset was cited by other patents was obtained from Google Patents®. For each firm the average number of citations across all granted patents of the firm was calculated and divided by by the difference (in years) between early summer of 2012 (when the variable was constructed) and the date that the patent was granted.
Founder signal	Dummy with the value 1 if a member of the founding team holds a distinguished and/or named professorship and/or is a member of the Academy of Sciences and/or has won a Nobel Prize and/or had previously founded a firm	Biographical information about the founders was collected from the website of each firm and biographies provided at the personal websites of the founders.
Entrepreneurial signal	Dummy variable wich takes the value 1 if a member of the founding team has previously founded other firms	Biographical information about the founders was collected from the website of each firm and biographies provided at the personal websites of the founders.
Academic signal	Categorical variable that indicates the highest academic appointment within the founding team	Biographical information about the founders was collected from the website of each firm and biographies provided at the personal websites of the founders.
Investment stage	Stage of firm growth for the first round investment (seed, early, expansion, later, other)	Obtained from Thomson Reuter's SDC Platinum Database.
Firm age	Age of the focal firm at the first round of investment	Obtained from Thomson Reuter's SDC Platinum Database.
VCF reputation	Average reputation score of the participating venture capital firms	The yearly ranking of VCFs was obtained from http://www.timothypollock.com/vc_reputation.htm. DBFs whose funding VCFs at the time of the financing round were not ranked, were coded as 0. DBFs whose highest ranked VCF was also the highest ranked of all VCFs were coded as 1. For other VCFs, the following formulla was used: 1-(rank/total number of VCFs)
Syndicate Size	Average sum the funding venture capital firms had raised prior to investing in the focal firm (1,000,000)	Obtained from Thomson Reuter's SDC Platinum Database.
Syndicate Investors	Number of venture capital firms participating in the first round of investment	Obtained from Thomson Reuter's SDC Platinum Database.
Distance to closest funding VCF	Distance of the focal firm to the closest funding participating venture capital firm (miles)	Addresses of target firms and VCFs were obtained from Thomson Reuter's SDC Platinum Database.The addresses were converted to coordinates at http://batchgeo.com. Subsequently, these coordinates were plugged in the distance formula: Distance = ar cos(sin(lat1).sin(lat2)+cos(lat1).cos(lat2).cos(long2−long1)) ×3963
Universities in the MSA	Total number of biotechnology research intensive universities located in the Metropolitan Statistical Area of the focal firm	Lists of institutions of biotechnology-related research grants were obtained from the National Institutes of Health, the Association of University Technology Managers and the Chronicles of Higher Education. The addresses of all institutions were then assigned to MSAs using the zip code-to MSA list provided by the U.S. Bureau of Economic Analysis.
Density of VCFs, 0 - 10 miles	Density of venture captital firms in 0 to 10 miles from the focal firm	The number of VCFs within 0 to 10 miles from the DBF were summed, using the above described methods to obtain the discance between the DBF and VCFs
Density of VCFs, 10 - 20 miles	Density of VCFs in 10 to 20 miles from the focal firm	The number of VCFs within 10 to 20 miles from the DBF were summed, using the above described methods to obtain the discance between the DBF and VCFs
Patent production 0 - 10 miles	Number of patents granted to biotechnology firms located 0 to 10 miles from the focal firm before the first financing round	Google Patents® was used to measure the yearly total number of patents assigned to each DBF. The patents that were granted before each round of financing to DBFs within 0 to 10 and from the origin DBF were sumed (using the above described coordinates and the distance formula).
Patent production 10 - 20 miles	Number of patents granted to biotechnology firms located 10 to 20 miles from the focal firm before the first financing round	Google Patents® was used to measure the yearly total number of patents assigned to each DBF. The patents that were granted before each round of financing to DBFs within 10 to 20 and from the origin DBF were sumed (using the above described coordinates and the distance formula).
year_r1_2011 (...) year_r1_2001	Dummy variables for the year of investment, between 2011 and 2001.	Obtained from Thomson Reuter's SDC Platinum Database.

See Hoenen et al. (2014) for a detailed description of the construction of the variables.

Appendix Table 2. Specifications with interaction terms entering the models one at a time. The dependent variable is the natural logarithm of the amount of venture capital funding in the first round of financing.

Model	Model 1. Specification 1 (including founder signal) with only level terms		Model 2. Specification 2 (including academic and entrepreneurial signal) with only level terms		Model 3 (including only the level and the interaction term for granted patents)		Model 4 (including only the level and the interaction term for patent applications)		Model 5 (including only the level and the interaction term for the founder signal)	
Variable	Coefficient	Standard errors	Coefficient	Standard errors	Coefficient	Standard errors	Coefficient	Standard errors	Coefficient	Standard errors
Intercept	13.2531	0.3862 ***	13.245	0.3721 ***	13.2683	0.3527 ***	13.3389	0.3411 ***	13.2953	0.3730 ***
Granted patents	-0.2564	0.2538	-0.2356	0.2600	0.0508	0.2699				
Patent applications	0.2776	0.1361 **	0.2734	0.1322 **			0.0086	0.2129		
Founder signal	0.3570	0.1084 ***							0.1391	0.2154
Academic signal			0.0356	0.0255						
Entrepreneurial signal			0.3755	0.1358 ***						
Distance between firm and closest VCF	0.0991	0.0283 ***	0.0993	0.0279 ***	0.1049	0.0281 ***	0.0942	0.0300 ***	0.0906	0.0295 ***
Distance between firm and closest VCF * Granted patents					-0.0100	0.0069				
Distance between firm and closest VCF * Patent applications							0.0599	0.0321		
Distance between firm and closest VCF * Founder signal									0.0595	0.0462
Distance between firm and closest VCF * Academic signal										
Distance between firm and closest VCF * Entrepreneurial signal										
Forward citations	-0.0007	0.1055	-0.0051	0.1098	-0.0232	0.1126	-0.0722	0.0903	-0.0668	0.0957
Seed	-0.9684	0.2581 ***	-0.9657	0.2648 ***	-0.9549	0.2458 ***	-0.9721	0.2447 ***	-0.9730	0.2586 ***
Early	-0.2529	0.2009	-0.2488	0.2068	-0.2281	0.1851	-0.2420	0.1835	-0.2287	0.1997
Expansion	-0.1146	0.3321	-0.1084	0.3290	-0.1032	0.3108	-0.1399	0.3014	-0.1089	0.3319
Firm age	0.0600	0.0240 **	0.0595	0.0239 **	0.0693	0.0224 ***	0.0550	0.0237 **	0.0639	0.0237 ***
VCF reputation	0.2520	0.1658	0.2617	0.1674	0.2988	0.1624	0.3069	0.1755	0.2391	0.1688
Syndicate investors	0.3726	0.0538 ***	0.3682	0.0547 ***	0.3726	0.0564 ***	0.3672	0.0539 ***	0.3758	0.0534 ***
Syndicate size	0.0003	0.0001	0.0003	0.0001	0.0003	0.0001	0.0003	0.0001	0.0003	0.0001
Number of universities located in the MSA	-0.0008	0.0098	-0.0005	0.0100	-0.0017	0.0102	-0.0004	0.0103	-0.0006	0.0098
Density of VCFs in 0 to 10 miles from the firm	0.0107	0.0031 ***	0.0109	0.0031 ***	0.0113	0.0031 ***	0.0112	0.0032 ***	0.0109	0.0031 ***
Density of VCFs in 10 to 20 miles from the firm	0.0031	0.0024	0.0032	0.0024	0.0027	0.0024	0.0028	0.0024	0.0029	0.0024
Number of patents granted to biotechnology firms located 0 to 10 miles from the firm	0.0008	0.0004	0.0007	0.0004	0.0007	0.0004	0.0007	0.0004	0.0008	0.0004
Number of patents granted to biotechnology firms located 10 to 20 miles from the firm	-0.0005	0.0005	-0.0005	0.0005	-0.0005	0.0005	-0.0005	0.0005	-0.0004	0.0005
Year Dummies included	YES		YES		YES		YES		YES	
Obervations	586		586		586		586		586	
Adjusted R^2	0.4057		0.4044		0.3999		0.4004		0.4053	
F test for overall model significance	206.3600 ***		219.2700 ***		210.3500 ***		183.7300 ***		146.1000 ***	
Multicollinearity Condition Index	28.2467		28.5164		27.6741		27.9275		28.2807	

Standard errors are clustered at the state level

* Significant at 5%. ** Significant at 1%.

Appendix Table 2 continued. Specifications with interaction terms entering the models one at a time. The dependent variable is the natural logarithm of the amount of venture capital funding in the first rou

Model	**Model 6 (including only the level and the interaction term for the academic signal)**		**Model 7 (including only the level and the interaction term for the entrepreneurial signal)**		**Model 8. Specification 1 (including founder signal) with level and interaction terms**		**Model 9. Specification 2 (including academic and entrepreneurial signal) with level and interaction terms**	
Variable	Coefficient	Standard errors	Coefficient	Standard errors	Coefficient	Standard errors	Coefficient	Standard errors
Intercept	13.2960	0.3634 ***	13.2883	0.3514 ***	13.2808	0.3724 ***	13.2607	0.3689 ***
Granted patents					-0.0336	0.2762	-0.0394	0.2883
Patent applications					-0.0309	0.2140	-0.0054	0.2258
Founder signal					0.1176	0.2142		
Academic signal	0.0137	0.0197					0.0109	0.0231
Entrepreneurial signal			0.1961	0.2953			0.1962	0.2958
Distance between firm and closest VCF	0.0950	0.0307 ***	0.0948	0.0284 ***	0.0828	0.0321 **	0.0848	0.0340 **
Distance between firm and closest VCF * Granted patents					-0.0127	0.0067	-0.0111	0.0067
Distance between firm and closest VCF * Patent applications					0.0778	0.0323 **	0.0667	0.0287 **
Distance between firm and closest VCF * Founder signal					0.0760	0.0469		
Distance between firm and closest VCF * Academic signal	0.0086	0.0069					0.0087	0.0079
Distance between firm and closest VCF * Entrepreneurial signal			0.0534	0.0630			0.0429	0.0644
Forward citations	-0.0540	0.0932	-0.0658	0.0964	-0.0201	0.1041	-0.0183	0.1090
Seed	-0.9956	0.2446 ***	-0.9546	0.2716 ***	-0.9291	0.2520 ***	-0.9348	0.2631 ***
Early	-0.2497	0.1871	-0.2181	0.2092	-0.2091	0.2062	-0.2152	0.2157
Expansion	-0.1328	0.3179	-0.0970	0.3319	-0.0909	0.3138	-0.0934	0.3155
Firm age	0.0630	0.0234 **	0.0650	0.0235 ***	0.0616	0.0238 **	0.0618	0.0238 **
VCF reputation	0.2696	0.1698	0.2651	0.1698	0.2609	0.1616	0.2725	0.1642
Syndicate investors	0.3772	0.0541 ***	0.3685	0.0546 ***	0.3689	0.0538 ***	0.3661	0.0548 ***
Syndicate size	0.0003	0.0001	0.0003	0.0002	0.0003	0.0001	0.0003	0.0001
Number of universities located in the MSA	-0.0004	0.0100	-0.0009	0.0101	-0.0005	0.0098	-0.0002	0.0100
Density of VCFs in 0 to 10 miles from the firm	0.0110	0.0030 ***	0.0112	0.0032 ***	0.0109	0.0032 ***	0.0110	0.0031 ***
Density of VCFs in 10 to 20 miles from the firm	0.0030	0.0023	0.0028	0.0023	0.0030	0.0025	0.0032	0.0025
Number of patents granted to biotechnology firms located 0 to 10 miles from the firm	0.0007	0.0004	0.0008	0.0004	0.0007	0.0004	0.0007	0.0004
Number of patents granted to biotechnology firms located 10 to 20 miles from the firm	-0.0005	0.0005	-0.0005	0.0005	-0.0004	0.0005	-0.0005	0.0005
Year Dummies included	YES		YES		YES		YES	
Obervations	586		586		586		586	
Adjusted R^2	0.4003		0.4032		0.4087		0.4048	
F test for overall model significance	127.8400 ***		183.4500 ***		297.17 ***		466.93 ***	
Multicollinearity Condition Index	28.3454		27.9000		28.9221		29.412	

Standard errors are clustered at the state level

* Significant at 5%. ** Significant at 1%.

Appendix Table 3. First stage of Heckman selection model corresponding to sensititivity test 1 in Table 4

	Coefficient	Standard errors	
Intercept	-154.0243	17.42438	***
SBIR award (1 for firms that received an award, 0 otherwise)	-3.8363	0.3935	***
Firm located either in MA or CA	0.2146	0.0827	***
Founder signal	0.3398	0.1225	
Number of patents granted to a firm up to 2006 for SBIR firms or up to the first round of investment for VC-backed firms.	0.0014	0.0019	***
The year of foundation of the focal firm	0.0783	0.0087	***
Inverse mills ratio	-0.1636		

Significant at 5%.* Significant at 1%.

Figure 1. Location of biotechnology firms in the sample