Do Patents Increase Venture Capital Investments between Rounds of Financing?

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Abstract:

This MSc thesis investigates the role of patents in attracting venture capital funds over multiple investment rounds. Previous studies have provided empirical evidence that patents help firms to attract venture capital funds by signaling positive characteristics. However, what received less attention is how this relationship develops over time. We argue that the information asymmetries investors are faced with, and thus the strength of patents as a signaling agent, reduce over time as investors and target firms become more acquainted with each other.

To test our theoretical expectations we draw upon a rich dataset of more than 1500 US-based biotechnology firms that received funds from VCFs from 1974 to 2011. In the empirical part of the paper we place our attention to the first and second round of financing a focal firm receives mainly because it is in these rounds that information asymmetries between investors and target firms are expected to be potent. As expected, our results show that one additional pending patent application increases the round 1 amount invested to a given biotechnology firm by approximately 12 percent. For round 2 we find no significant relationship between patents and the size of the second investment. To improve the robustness of our models, we specify a range of variables controlling for characteristics of the target firms and venture capital firms, patent quality, regional effects and endogeneity.

1. Introduction

Patents are instrumental for the performance of a given firm as they often lead to improvements in innovation, productivity and market value (Bloom and Van Reenen 2002; Griliches 1981; Hall 2004; Hall et al. 2005). The linkage between patents and firm growth has been attributed largely to monopolistic market rights and future technology options conferred by patents, protection from competitors, increase in the survival rate of the firm that is granted a patent as well as to improvements in the negotiating position of patent holders with partners, investors and remaining stakeholders (Blind et al. 2006; Gans et al. 2002; Giuri et al. 2007; Harabi 1995; Helmers and Rogers 2011; Levitas and Chi 2010; Silverman and Baum 2002; Teece 2000)[1].

A relatively less studied driver of the relationship between patents and firm growth is that external investors such as venture capital firms (VCFs) are attracted to firms with patents. Indeed, there are theoretical reasons to expect such relationship (Graham et al. 2009; Heeley et al. 2007; Long 2002). For instance, especially in knowledge intensive industries, firms that seek external finance are often difficult to evaluate mainly because they lack a track record and they are confronted with technical, scientific and regulatory challenges that are either unknown *ex ante* or difficult to tackle *ex post* (Harhoff 2011). Accordingly, a patent can signal the potential of a firm to external investors as it can demonstrate that the firm has successfully been through a technical process that can eventually lead to outcomes with commercial value (Hagedoorn et al. 2000; Heeley et al. 2007). Further, because patents confer monopolistic rights, investors may place a market value to these rights and consequently invest in the firm that possesses them.

To corroborate such theoretical expectations a handful of empirical studies document that patents attract prominent VCFs, prompt VCFs to invest faster and generally increase the amount invested by VCFs to target firms (Baum and Silverman 2004; Häussler et al. 2009; Hsu

[1] On a macro level, patents have been associated with increasing national economic growth and the development and diffusion of knowledge (Blind and Jungmittag 2008; Shapiro and Hassett 2005).

and Ziedonis 2011; Mann and Sager 2007) [2]. In this literature, the effect of patents on venture capital has typically been studied on a single event in time such as the amount of venture capital raised by a target firm over a certain period of time. As a result, what has gone largely unnoticed is whether the role of patents in attracting VCFs reduces over time as investors and target firms become more acquainted with each other. This inquiry is the point of departure for the present study.

To form our theoretical expectation we reflect upon the main arguments behind the relationship between patents and venture capital attraction. These arguments hinge, in large part, on a reduction of information asymmetries between VCFs and target firms. But, if such reduction lessens as VCFs and target firms become more familiar over time, then the value of patents in attracting venture capital investments should decrease. To study the abovementioned argument we leverage the strategy of VCFs to invest to target firms with sequential rounds of financing. That is, VCFs provide funds to a particular firm only if the firm has met certain milestones that relate, mainly, to technical progress (Gompers 1995). This sequential structure of VC investments allows us to detect patterns that would otherwise not be apparent. More specifically, each additional round of financing can typically reduce the information asymmetries between VCFs and the target firm because VCFs gather additional information about the firm through monitoring, management and other forms of hands-on involvement in the firms they invest in (Gompers 1995; Ruhnka and Young 1987; Wang and Zhou 2004). Accordingly, the effect of patents on attracting venture capital should diminish as firms move to the next round of financing because VCFs have relatively more information about the target firm when compared with the information they have when they make their original investment[3].

To test our theoretical expectations we employ a rich dataset that measures patent activity (patents and patent applications) from firm birth to the first round of financing and from

[2] There is also evidence linking patents to successful Initial Public Offerings (e.g. Cockburn and MacGarvie 2009; Heeley et al. 2007).

[3] Hsu and Ziedonis (2011) also report that patents are more important for the attraction of venture capital at early rounds of financing. As we explain in detail section 2, our study differs in a number of ways from Hsu and Ziedonis (2011) and these include different measures of patent activity and a different focus of the stage of financing.

the first round of financing to the second round of financing for more than 1500 U.S.-based biotechnology firms that received funds from VCFs from 1974 to 2011. We place our attention to the first two rounds of financing because in these rounds information asymmetries between investors and target firms are expected to be potent. Therefore, by concentrating on these rounds we can detect the impact of information asymmetries on the effectiveness of patent activity as a signal. We focus on biotechnology because it is a knowledge intensive industry in which information asymmetries between investors and firms are expected to hold (Janney and Folta 2003). Corollary to the knowledge intensive character of the industry, patents are popular among biotechnology firms (Fligstein 1996). Further, biotechnology is an industry that receives (staged) venture capital investments heavily, which reflect the risky nature of the industry as well as the associated high returns (Baum and Silverman 2004; Gompers and Lerner 2001). Collectively, these industry characteristics suggest that if patent activity serves as a signal for investors which reduces over time, such observation should be apparent in biotechnology.

In the empirical part of the paper we construct models that associate patent activity before and after the focal round of financing with the amount invested per round to each firm and we control for regional and investing VCF-specific characteristics that can also be relevant for the growth of venture capital funds. To separate the function of patents as a signal that can attract investors from the market value of patents that can also attract investors, we account for the market value of patents. Along the same lines, to isolate the strength of patents as a signal from additional signals a focal firm can employ, we include variables that indeed echo remaining signals such as the inclusion of distinguished scientists in the board of directors.

The main impetus behind our work is the relative lack of research, despite strong theoretical arguments, on the expected diminishing value of patents in attracting venture capital as investors reduce information asymmetries with target firms over time. Nevertheless, the present paper also has policy implications and can offer managerial prescriptions. For instance, assessing whether patents actually attract venture capital investments is of direct interest to managers of biotechnology firms who, at least in the early stages of firm growth, are typically confronted with a lack of capital from traditional sources of finance such as bank and equity agreements. With regard to policy implications, the number of patents and patent applications have increased substantially over the years (Kim and Marschke 2004; Kortum and Lerner 1999), but so have the costs associated with processing patents. Such costs are instrumental in driving concerns over the usefulness of the current patent system especially with regard to the degree that it puts smaller firms in disadvantage (Bessen and Meurer 2008; Jaffe and Lerner 2004). Assessing whether patents increase private sector investments towards small firms and whether such increase is affected by the familiarity between VCFs and target firms, needs to be taken into account when policy makers and other interested parties consider revising or maintaining the current patent system.

We proceed with the rest of the paper as follows: In section 2 we review the literature with regard to the functions of VCFs and how patents can act as signal and form our theoretical expectations. In sections 3 and 4 we present our methodology and data sources respectively. In section 5 we present our results and we conclude in section 6.

2. How patents can act as signals to investors

In their most common form of arrangement, venture capital firms pool together small portions of funds maintained by different institutional investors such as pension funds and university endowments. Using these portions they make investments upon which they tie their compensation and the financial returns to the institutional investors. Largely because what VCFs manage is typically a small chunk of the pie maintained by a focal institutional investor, the risk exposure of each institutional investor is relatively small. Accordingly, VCFs can afford to invest in risky ventures that have the potential to yield returns in the range of 25 to 35 percent or above so that they maximize their compensation as well as the compensation of the institutional investors (Zider 1998).

A popular investment target for VCFs is young firms in high technology areas such as biotechnology. These firms have historically demonstrated a potential for high returns (Carpenter and Petersen 2002) but they are confronted with highly complex scientific problems, associated long research cycles and challenging legal environments (DiMasi and Grabowski 2007; Häussler and Zademach 2007) that collectively raise the degree of risk they carry. Further, these industry characteristics along with the typical newness of the target firm, make it difficult for the firm at hand to have an established record that either generates some cash flows or it is indicative of future cash flows. Accordingly, insofar as the target firm is knowledgeable of its potential, it is often difficult for firms to convey that potential to VCFs, which can create a mismatch about firm-specific information possessed by VCFs and by the target firm. As a result, the relationship between VCFs and target firms before an investment takes place is commonly prone to information asymmetries (Cumming 2005; Sahlman 1990).

To overcome such information asymmetries, firms that seek investors often use signals that partly fill in for the lack of an established record and can portrait the potential of the firm (Zhang and Wiersema 2009). In fact, whenever information asymmetries are present, VCFs tend to rely on signals of this sort before they make investment decisions (Amit et al. 1990; Higgins and Gulati 2006) because *a priori* the separation of high-quality start-ups from lesser firms can become prohibitively difficult (Davila et al. 2003). Indeed, a number of studies demonstrate that signals reduce information asymmetries (e.g. Cohen and Dean 2005; Janney and Folta 2003; Mishra et al. 1998).

The next relevant inquiry is whether patents can act as a signal. Strong signals need to be observable and costly to imitate (Cohen and Dean 2005; Spence 1973). Additionally, signals which are governed by strong institutions and hence conform to a certain institutional standard tend to increase in value (Janney and Folta 2003). This holds largely because conformity typically reduces the variation among the signals and thus can alleviate the impact that the subjectivity of the receiver can bring to the valuation of the signal (Fischer and Reuber 2007; Perkins and Hendry 2005). By extension, patents appear to meet the requirements for a signal because they are freely available (making them easy to observe), are costly to acquire (Graham et al. 2009) and are governed strictly. Particularly for the case of firms in knowledge intensive industries where information asymmetries are typically strong (Chaddad and Reuer 2009) and, accordingly, signals are a major means to convey the market potential for a firm, patents are expected to have increased value as they relate to invention and often to innovation that can then lead to commercial outcomes (Acs et al. 2002; Griliches 1998).

In line with the theoretical expectation that patents can act as a signal to investors, empirical evidence suggests that patents do serve such a function. Baum and Silverman (2004) found a positive association between the number of patents and patent applications for a focal Canadian biotechnology firm with the total amount raised by investors before the firm had an Initial Public Offering. In the same vein, Mann and Sager (2007) employed software firms as their case study and reported a strong correlation between patents and a number of variables that measures attraction of venture capital such as the number of financing rounds and the total investment. Finally, Häussler et al. (2009) drawing upon a sample of 190 German and British biotechnology firms, found that larger stocks of patent applications shorten the time that a given firm receives venture capital financing for the first time.

Collectively, Baum and Silverman (2004), Mann and Sager (2007) and Häussler et al. (2009) have provided empirical insights that patents generally act as a signal to investors. What is difficult to infer from these studies is whether and how the value of patents as a signal diminishes once the *a priori* unobserved quality of the firm is assessed by the investors. To approach this question we confer to the literature that analyzes how VCFs decrease information asymmetries once they have invested in a focal firm. The starting point of this literature is usually that information asymmetries lead to agency problems (Fama 1980; Jensen and Meckling 1976). In turn, a major task of VCFs is to reduce agency problems of this sort. A popular mechanism that VCFs use towards that end is to provide funds in rounds (Neher 1999; Wang and Zhou 2004). Under this mechanism, target firms receive funds of a particular round of financing conditional on having received funds (and having met certain research milestones) of a previous round. Between rounds, VCFs spend a considerable amount of time in being actively involved in the day-to-day operations of the target firm via consulting and monitoring (Gorman and Sahlman 1989; Rosenstein et al. 1993). In doing so, VCFs follow the progress of the target firm, evaluate its prospects and generally get acquainted with the firm they have invested in. It follows that information asymmetries between VCFs and target firms should decrease as the abovementioned process unfolds. In environments with reduced information asymmetries the value of signals tends to decrease (Gulati and Higgins 2003; Higgins and Gulati 2006). By extension, once a VCF is familiar with the target firm, the effectiveness of patents as signals that can attract additional funds should be limited. Empirical tests for this proposition are scarce.

Hsu and Ziedonis (2011) find that an increased portfolio of patent applications increases the probability that a given firm receives its first investment from a prominent VCF. Further, they conclude that the same portfolio of patent applications associates with increases in firm value and a positive change in the share price at initial public offering. In its own right, the scarcity of research on the issue at hand calls for more research. Alongside, to complement the insights of Hsu and Ziedonis (2011) and evaluate the robustness of their findings we introduce a number of changes. For instance, Hsu and Ziedonis (2011) employ the cumulative stock of patents applications a company carries from its birth up to focal round of financing as their measure of patent activity. Instead, we partition patent applications to those that have been filed before a focal round and to those that have been filed after the focal round and when the firm at hand is seeking its next round of financing. This way, we are able to not only test whether patent activity has a differential effect on attracting venture capital over time, but also on whether the timing of the filling of an application mediates which applications are more sensitive to considerations of this kind. Further, instead of focusing only on patent applications as a measure of patent activity, we also measure the number of patents granted to a focal firm. Patents and patent applications differ in subtle, yet important ways (Gans et al. 2008; Popp et al. 2004) which indicates that both forms of patent activity need to be considered separately for the question at hand. For instance, contrary to granted patents, patent applications are open to revisions. The implication is that in highly evolving fields such as biotechnology, applicants often start with claims that are broad enough to create uncertainty for competitors, which in turn can discourage them from entering a particular research field (Harhoff and Wagner 2009; Popp et al. 2004). On the other hand, what is eventually patented is commonly the most fruitful area from the broad claims of a pending application (Popp et al. 2004) which implies that granted patents can also carry significant value. The question then becomes whether the attraction of investors is sensitive to the different advantages offered by granted patents and pending patent applications. Indeed existing evidence supports the existence of such sensitivity and indicates that patent applications are stronger than patents in attracting venture capital faster and at larger volume (Baum and Silverman 2004; Häussler et al. 2009). Finally, while Hsu and Ziedonis (2011) study whether patents attract prominent investors and whether the market value of the firm increases with patent applications, we study whether a focal firms raises more venture capital funds per round if it engages in patent activity. We expect our measure to complement the work of Hsu and Ziedonis (2011) because it can approximate whether and how much patent activity can attract venture capital funds not only from prominent investors but also from VCFs with less reputation. Further, while the market value measures of Hsu and Ziedonis (2011) refer to later stages of firm growth, our per round measures concentrate on relatively earlier stages of firm growth where signals such as patents maybe more relevant for firms to communicate their potential to investors.

3. Methods and Procedures

Consistent with our theoretical framework, the empirical model needs to associate the patent activity of a focal firm with the growth of its venture capital funds while information asymmetries between investors and the target firm reduce over time. We operationalize patent activity with the number of patents and patent applications the focal firm has been granted or filled respectively. To capture whether the effectiveness of patent activity as a signal indeed reduces as a result of a decrease in information asymmetries we build two empirical specifications. In the first specification, where we expect information asymmetries to be strong, patent activity is regressed on the sum of venture capital funds raised by a given firm at the first round of financing. In the second specification, where we expect a reduction of information asymmetries, patent activity is regressed on the sum of venture capital funds raised by a given firm at the second round of financing. Formally, the two models are specified as follows:

$$\ln(y_{ij=1}) = X_{ij=1}\beta + \varepsilon \quad (1)$$

$$\ln(y_{ij=2}) = X_{ij=2}\beta + \varepsilon \quad (2)$$

where the dependent variable y_{ij} is the natural log of the total amount of VC funding raised by DBF *i* at round *j* and X_{ij} is a vector of round-specific variables that can affect the growth of venture capital funds for a particular firm.

In the proceeding discussion we first present the independent variables that test our main theoretical expectations, followed by an illustration of the variables that capture the market value of the patents. Then, we move to the variable that links the funds of different rounds of financing and addresses endogeneity concerns and the variables that depict additional signals that a given firm can employ besides patents. We conclude the section with a presentation of the variables that account for the features of the investors and the characteristics of the regional environment along with remaining control variables that we collectively expect to influence the level of venture capital funds raised by a given firm.

As previously introduced, we capture patent activity with the number of patents and patent applications awarded to and filed by a given firm. For the first round of financing in (1) we measure patents and patent applications from firm birth until the date of that financing round and expect a positive sign for the corresponding coefficient which would indicate that patent activity acts as a signal that increases the level of venture capital funds for the focal firm (*PatentApp_1* and *PatentGrant_1*). For the second round of financing we maintain our measures of patent activity in (1) as independent variables and also add two independent variables that measure the number of patents and patent applications granted or filled from the date of the first round of investment until the date of the second round of investment (*PatentApp_2* and *PatentGrant_2*). We do so in order to be able to test not only whether the strength of patent activity as a signal reduces over time, but also on whether the timing of patent activity is sensitive to such considerations. In line with our discussion in section 2, we expect the patent activity before the second round of investment to not exert an influence on the growth of venture capital funds for the focal firm.

In order to evaluate whether patents act as a signal that can attract venture capital funds, we need to account for the market value of patents because VCFs may invest in a firm in order to capitalize on the future cash flows that can result from patents of high quality and subsequent market value. Accordingly, similar to previous literature (Harhoff et al. 2003; Häussler et al. 2009), we approximate patent quality with a variable that measures the average number of times the patents owned by the focal firm have been cited in other patents (i.e. forward citations) [4] (*PatentCiteYear_1*). In (2), where we model the investments of the second round, we partition the forward citations to those that correspond to patents granted from firm birth up to the first round and to those that correspond to patents from the date of the first round until the date of the second round (*PatentCiteYear_2*). We expect patents of higher value to attract funds in both investment rounds.

The patent activity of a focal firm before the first round of financing is by definition unaffected by the involvement of VCFs in the firm. But, the patent activity before the second round of investment can be influenced by the consulting role that VCFs assume once they invest in a firm. To account for such potential specification bias, we include in (2) the lagged dependent variable (i.e. the dependent variable in (1) which is the total amount invested in the first round of investment – *VCF_Investment_1*) (Baum and Silverman 2004; Jacobson 1990). Given that the amount per round generally increases with more advanced rounds (Gompers 1995), we expect a positive sign for this variable.

Besides patent activity, firms without a proven track record can employ additional signals to convey their potential to generate wealth for investors because signals can differ in their strength (Gulati and Higgins 2003; Lee 2001). The signals that firms without a track record send typically leverage the reputation of the team around the firm. For example, because

[4] More recent patents tend to receive fewer citations compared to older patents due to the effective time a patent may need until it becomes visible. To account for this possibility we divide the average number of forward citations for the patents of a given firm by the difference (in years) between early summer of 2012 (when the variable was constructed) and the date that the patent was granted.

firms in high technology industries usually center around their founding team (Gompers et al. 2010), the reputation and the previous business history of the founders are often used as a signal (Certo 2003; Elitzur and Gavious 2003) as, for instance, habitual entrepreneurship if often perceived as a sign of high human capital (Ucbasaran et al. 2003). Accordingly, both in (1) and (2) we include a variable that takes the value of 1 if one of the founders of the focal firm is a preeminent member of the academic community[5] or/and has started a firm previously (*FounderSignal*). Along the same lines, once the venture capital investment has been made the eminence of the investors can also act as a signal under the premise that over time successful investors develop skills that allow them to effectively identify firms with potential (Casamatta and Haritchabalet 2007; Sorenson and Stuart 2001). By extension, in (2) we include a variable that depicts the Lee et al. (2011) reputation score of the highest ranked funding VCF of the first round of financing (*VCFreputation*_1). In line with the discussion in section 2, we expect *FounderSignal* to influence the total amount invested in the first round of financing and this effect to die off for the second round. For *VCFreputation*_1 we also expect to associate positively with the total venture capital amount raised in the second round of financing.

To couple the signaling function that funding VCFs can exert, their availability of funds can also be decisive for the growth of venture capital funds for a given firm. The availability of funds is determined in large part by the number of investors per firm and the size of each investor. VCFs with ample pools of capital usually invest higher amounts per target firm (Gupta and Sapienza 1992; Tian 2011). At the same time, VCFs often co-invest to a target firm with other VCFs. Such co-investment schemes are often referred to as syndications and are build mainly in order to spread the risks that arise from investments in largely unknown firms (Lockett and Wright 2001), which implies that larger syndication arrangements can afford individual syndication members to invest higher amounts to the target firm. Collectively, receiving funds from wealthier VCFs through syndication is expected to increase the total amount raised by a given firm. Accordingly, in (1) and (2) we include two variables that

[5] We code an academic founder as eminent if she holds a distinguished and/or named professorship and/or is a member of the Academy of Sciences and or/has won a Nobel Prize.

measure the number of investors per round as well as their average size and expect positive signs for both coefficients (*SyndicateInvestors1, SyndicateInvestors2, SyndicateSize1, SyndicateSize2*). The last variable we include in the empirical models that relates to the funding VCFs, is the distance between the most physically proximate funding VCF and the target firm (*DistanceClosestVCF*). Spatial proximity between target firms and investors typically eases the monitoring functions of VCFs which suggests that information asymmetries between the two involved parties typically reduce (Sorenson and Stuart 2001; Zook 2005). By extension, reduced information asymmetries can lead to higher investments per round. To corroborate this proposition Tian (2011) finds that more distant VCFs tend to invest smaller amounts per financing round. It follows that we expect a negative sign for the coefficient in question.

Moving to the variables that describe the regional environment, agglomeration externalities such as knowledge spillovers, pecuniary benefits (e.g. strengthening of labor pool) and network effects have been shown to positively influence a number of performance metrics for high technology firms including the growth of venture capital funds (Coenen et al. 2004; Gittelman 2007; Kolympiris et al. 2011). Importantly, existing research has demonstrated that agglomeration economies of different strength emanate from different organizations such as universities, firms in the same industry as well as firms in supporting industries (Döring and Schnellenbach 2006). In this vein, we include in (1) and (2) five variables that account for such considerations. Following previous literature that shows that the impact of universities on regional economies spans up to the Metropolitan Statistical Area (MSA) level (Abel and Deitz 2012; Anselin et al. 2000; Varga 2000), we construct a variable that measures the number of universities that perform biotechnology related research and are located in the same MSA with the focal firm (*UniversitiesInMSA*); the expected sign for this variable is positive. To account for potential proximity effects from the presence of VCFs that arise in large part from the knowledge that VCFs and their networks create (Gompers 1995; Shane and Cable 2002), we follow Kolympiris et al. (2011) and for each round of financing we construct two variables that measure the density of VCFs in 0 to 10 and 10 to 20 miles from the origin firm respectively (*VCFarea_0010_1*, *VCFarea_1020_1*, *VCFarea_0010_2*, *VCFarea_1020_2*) . To capture the benefits a given firm can reap from the proximity to overperforming firms in the same industry (Beaudry and Breschi 2003), for each round of financing we include in (1) and (2) two variables that measure the number of patents granted to biotechnology firms located 0 to 10 and 10 to 20 miles from the origin firm before the focal financing round (*PATENTarea_0010_1, PATENTarea_1020_1*, *PATENTarea_0010_2*, *PATENTarea_1020_2*). We expect positive signs for the corresponding coefficients.

Before we proceed to the last set of variables we include in the empirical models, we note that besides the regional characteristics we discussed above, there are qualitative and often unobserved regional features that can also affect the performance of a given firm and its subsequent growth of venture capital funds. These features can expand beyond the geographic boundaries of 10 or 20 miles and refer mainly to attitudes towards risky investments or the efficacy of state services or private consulting organizations that can assist firms in improving their performance[6]. Largely because of the qualitative nature of these factors, representing them through associated variables is a task with mounting difficulties. As we explain in detail in Section 5 we employ appropriate estimation techniques to account for such considerations.

To complement the aforementioned variables we expect to influence the growth of venture capital funds for a given firm, we include in (1) and (2) two control variables. The first variable measures the age of the focal firm at the round of financing (*Age1, Age2*). Older firms may have more experience and they have survived for longer time and these features can be evaluated positively by VCFs. On the other side, VCFs may consider older firms too risky to invest at the early rounds of financing either because the firm could have developed routines that are difficult to adjust or because lack of previous finance, despite the age effect, might be received as a negative signal. Therefore, we do not have strong priors with regard to the direction the age variable can move the growth of a funds for the focal DBF. The second control variable we include in our empirical specifications is a linear trend that assumes increasing values for rounds of financing that took place at later years. We construct two trend

[6] Examples of such organizations are the Larta Institute in California and the District of Columbia and Foresight S&T in Rhode Island.

variables that correspond to each of the rounds of financing we focus on (*Trend_1*, *Trend_2*). We include the linear trends to account for the general increase of the size of venture capital investments over time and we expect positive signs for *Trend_1* and *Trend_2*.

4. Data sources and presentation

To perform our empirical analyses, we relied on data from desk research, public sources and Thomson Reuter's SDC Platinum Database (SDC) which provided a dataset that measured all venture capital investments toward biotechnology firms from 1974 up to 2011. From SDC we sourced the address and founding date of each DBF, the amount invested per round, the date of financing round, the investors per round as well as their address and previous investments. We used this information to construct our dependent variables and *Age1*, *Age2*, *SyndicateInvestors1*, *SyndicateInvestors2*, *SyndicateSize1*, *SyndicateSize2*, *DistanceClosestVCF*, *VCFarea_0010_1*, *VCFarea_1020_1*, *VCFarea_0010_2*, *VCFarea_1020_2*. For *DistanceClosestVCF*, *VCFarea_0010_1*, *VCFarea_1020_1*, *VCFarea_0010_2*, *VCFarea_1020_2* we needed to calculate the distance between target firm and investors and the density of VCFs in a region respectively[7]. To do so, we converted the addresses of target firms and VCFs to coordinates at http://batchgeo.com. Subsequently, we plugged these coordinates in the distance formula[8] we employ and constructed the corresponding variables.

For our independent variables (*PatentApp_1, PatentGrant_1, PatentApp_2, PatentGrant_2)* we employed Google Patents ® which indexes granted patents and patent applications from the United States Patent and Trademark Office (UPSTO)[9]. We searched for

[7] The density of VCFs did not include the funding VCFs of the origin firm.
[8] We employed the general formula of the spherical law of cosines which corrects for Earth's spherical shape: $\text{Distance}_{12} = ar\cos(\sin(\text{lat}_1).\sin(\text{lat}_2)+\cos(\text{lat}_1).\cos(\text{lat}_2).\cos(\text{long}_2-\text{long}_1)) \times 3963$
[9] Please see http://www.uspto.gov/news/pr/2010/10_22.jsp for an official USPTO press release regarding its cooperation with Google Patents.

every patent and grant application where the focal firm was listed as the applicant/assignee[10]. Using the application and granted date we allocated patent activity between rounds. It is important to note that before November 29, 2000 there was no formal obligations for the publication of patent applications from the UPSTO[11]. Therefore, prompted by previous findings which suggest that 85 to 90 percent of patent applications turn to patents (Baum and Silverman 2004; Quillen and Webster 2001) and in order to include early years in the analysis we opt for two approaches. In the first approach, the values of the variable that measures patent applications before 2001 is calculated by multiplying the corresponding number of patents by 0.78, which is the percentage of patent applications that turned to patents for applications filled before the second round of financing for applications after 2001 in our sample, where we had full information both on patents and patent applications. In the second approach, which we present in the Appendix, the values of the variable that measures patent applications before 2001 are calculated with a linear extrapolation from a trend coefficient and an intercept that we estimated from regressing patent applications to a year trend. Both approaches yield qualitatively similar results, which adds confidence to our estimates[12].

To construct *PatentCiteYear_r1*and *PatentCiteYear_r2* we visited the website of UPSTO to count the number of times each of the patents in our dataset was cited by other patents. Then, for each firm we calculated the average number of citations for each granted patent. As noted in footnote 4 to account for the tendency of older patents to be cited more heavily, we divided the average number of forward citations for the patents of a given firm by the difference (in years) between early summer of 2012 (when the variable was constructed) and the date that the patent was granted.

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[10] In a number of cases the name of the assignee differed across patents as, for instance, “inc.” was missing or it was replaced by “inc”. To ensure that the validity of our measure was not prone to such issues we double-checked the number of patents using a number of variations of the name of each firm.
[11] Please see http://www.uspto.gov/news/pr/2001/01-13.jsp for the official announcement.
[12] Alternatively, we could opt for focusing our attention only on patenting activity that occurred after November 29, 2000. By adopting this approach we would implicitly assume that the signaling value of patenting activity would be confined to the years after 2000. But, we have no theoretical reasoning for such argument. In fact, as seen in Tables 2 and 3, the trend variable in the empirical results is highly significant, which suggests that timing is important for our application.

To collect bibliographical information for the academic founders we visited the website of each firm and complemented this search with (a) listings in Marquis Who's Who, (b) listings in Women and Men of Science and (c) academic founders' biographies provided at their personal websites. Using these sources, firms whose founder(s) had started a firm previously and/or held a distinguished and/or named professorship and/or were a member of the Academy of Sciences and or/has won a Nobel Prize took the value of 1 in the *FounderSignal* dummy variable.

To build *VCFreputation_1* we first consulted the yearly reputation rankings of VCFs maintained at http://www.timothypollock.com/vc_reputation.htm (Lee et al. 2011). DBFs whose funding VCFs at the timing of the financing round were not ranked were coded as 0. DBFs whose highest ranked VCF was also the highest ranked of all VCFs was coded as 1. To illustrate how we calculated the between cases we provide an example under which the highest ranked VCF of the focal DBF was ranked as 250th in the year in question. First, we divide 250 by 1000 which yields 0.25 and then we subtract 0.25 from 1 to have 0.75, which is the value of the *VCFreputation_1* variable for this hypothetical example. Using the same methodology, if the highest ranked VCF was ranked 150th, the value of the *VCFreputation_1* variable would be 0.85.

To construct *UniversitiesInMSA* we used the list of recipient institutions of biotechnology-related research grants maintained at the website of the National Institutes of Health. We complemented this list with comparable listings from the Association of University Technology Managers and the Chronicles of Higher Education. All three sources had information on the main address of each institution and whenever information was missing we visited the website of each institution to collect the address. The addresses were then assigned to MSAs using the zip code-to MSA list provided by the U.S. Bureau of Economic Analysis.

Finally, to build *PATENTarea_0010_1, PATENTarea_1020_1, PATENTarea_0010_2,* and *PATENTarea_1020_2* we first visited the UPSTO website to measure the yearly total number of patents assigned to each DBF. Then, we summed over the patents that were granted before the focal financing to DBFs within 0 to 10 and 10 to 20 miles from the origin DBF (using the coordinates and the distance formula previously described).

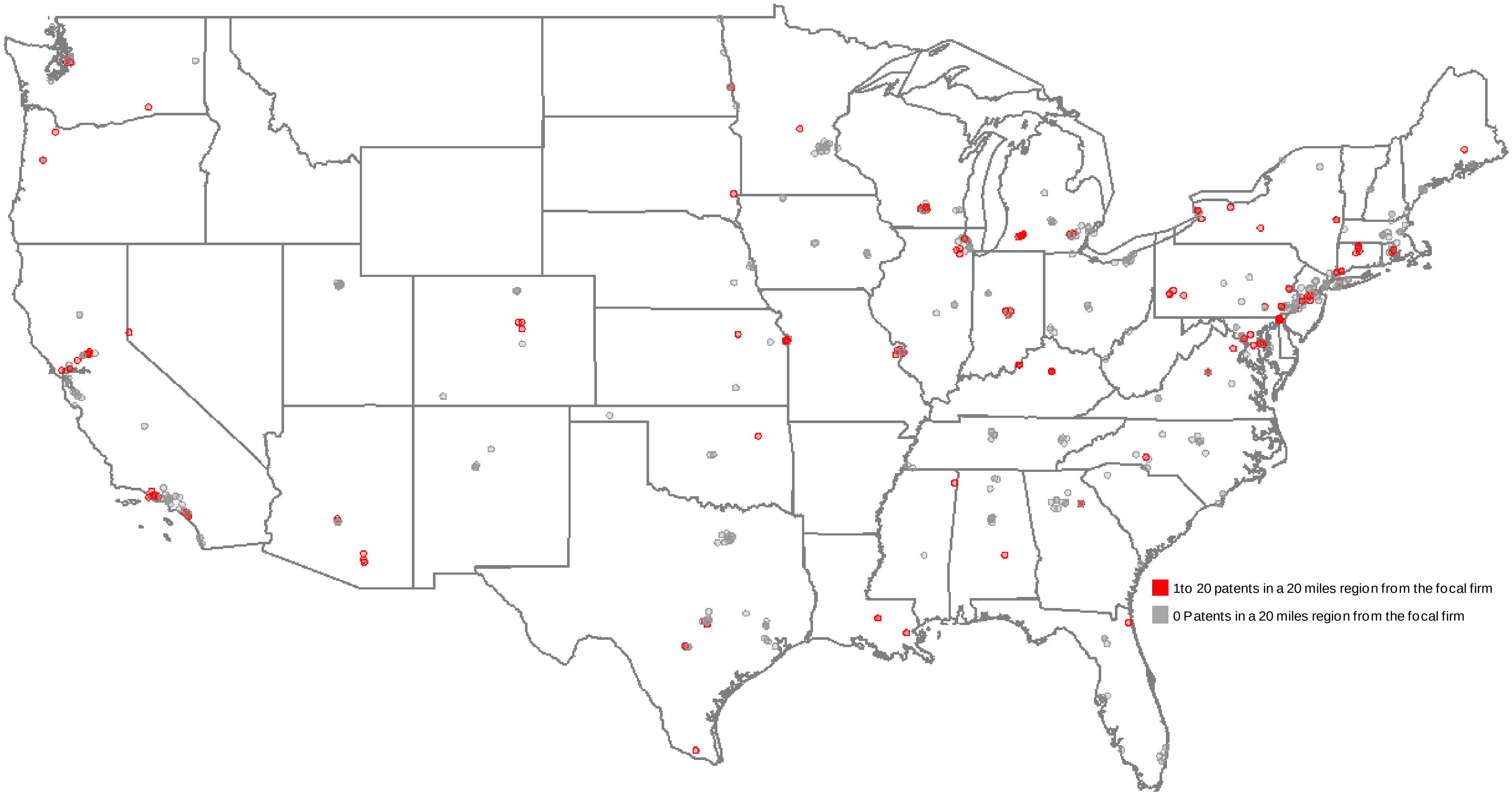

Figure 1a. Density of patents surrounding the focal biotechnology firm in a 0 to 20 miles radius.

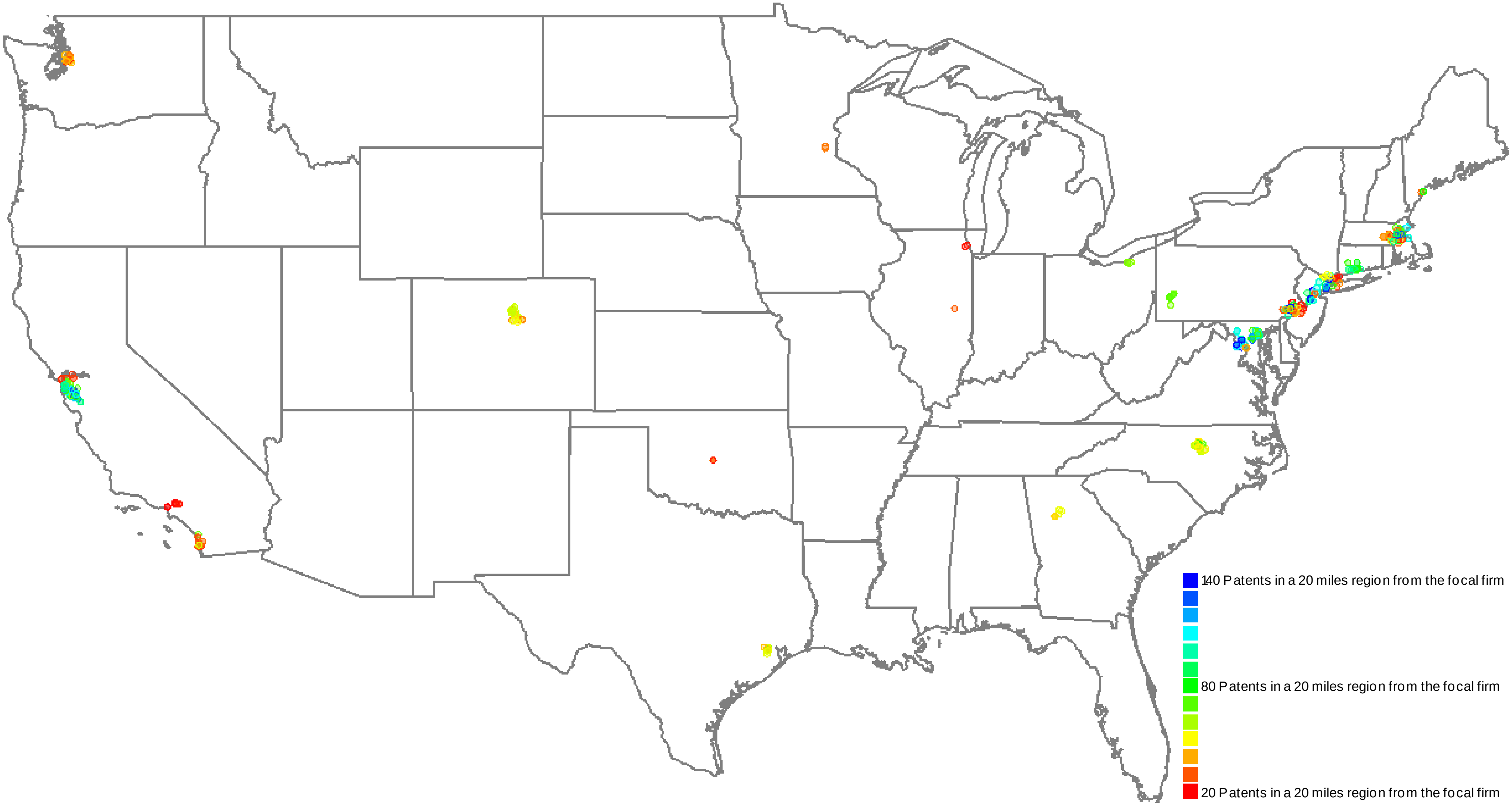

Figure 1b. Density of patents surrounding the focal biotechnology firm in a 0 to 20 miles radius.

Figure 1c. Density of patents surrounding the focal biotechnology firm in a 0 to 20 miles radius.

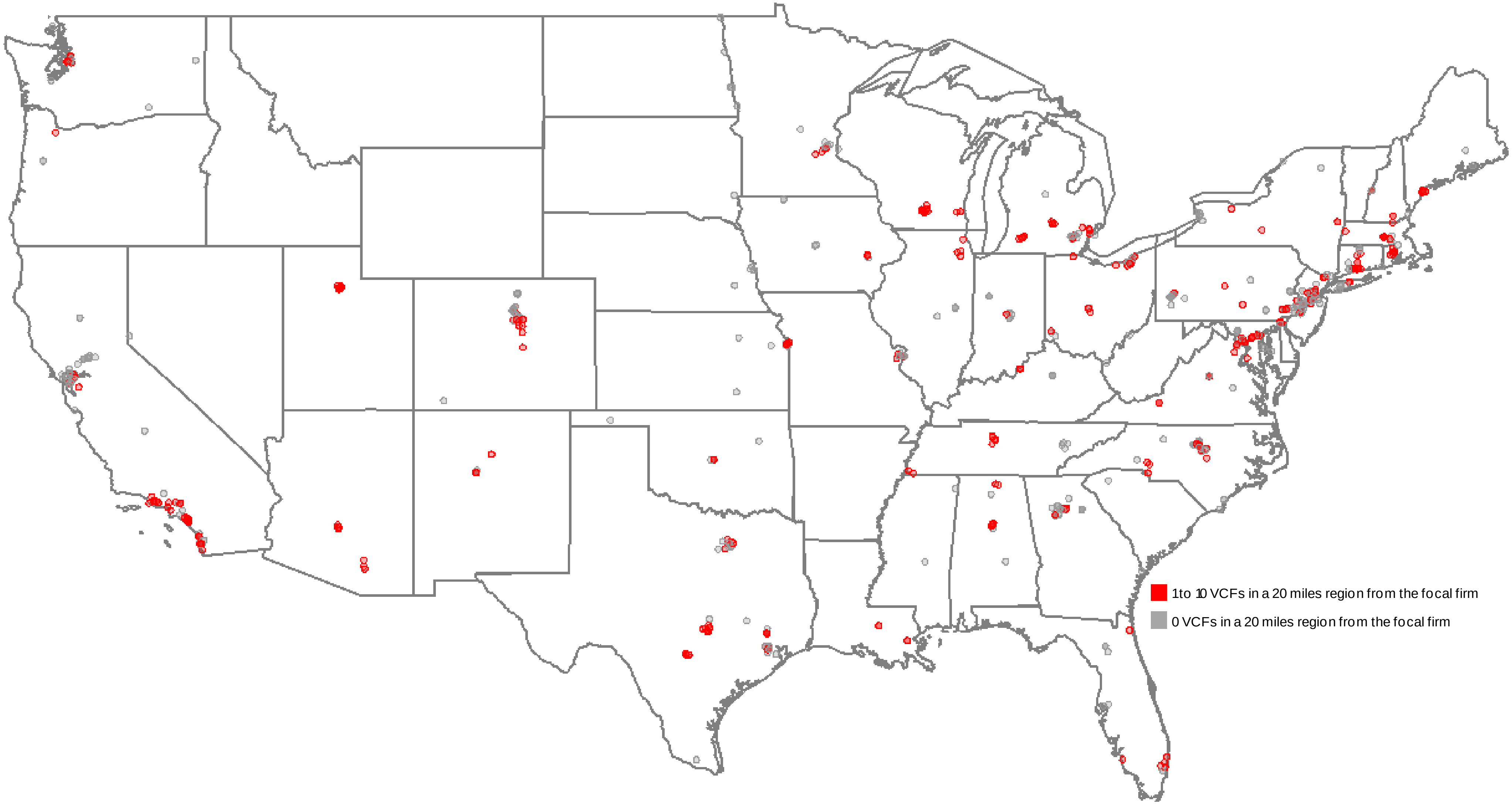

Figure 2a. Density of VCF surrounding the focal biotechnology firm in a 0 to 20 miles radius.

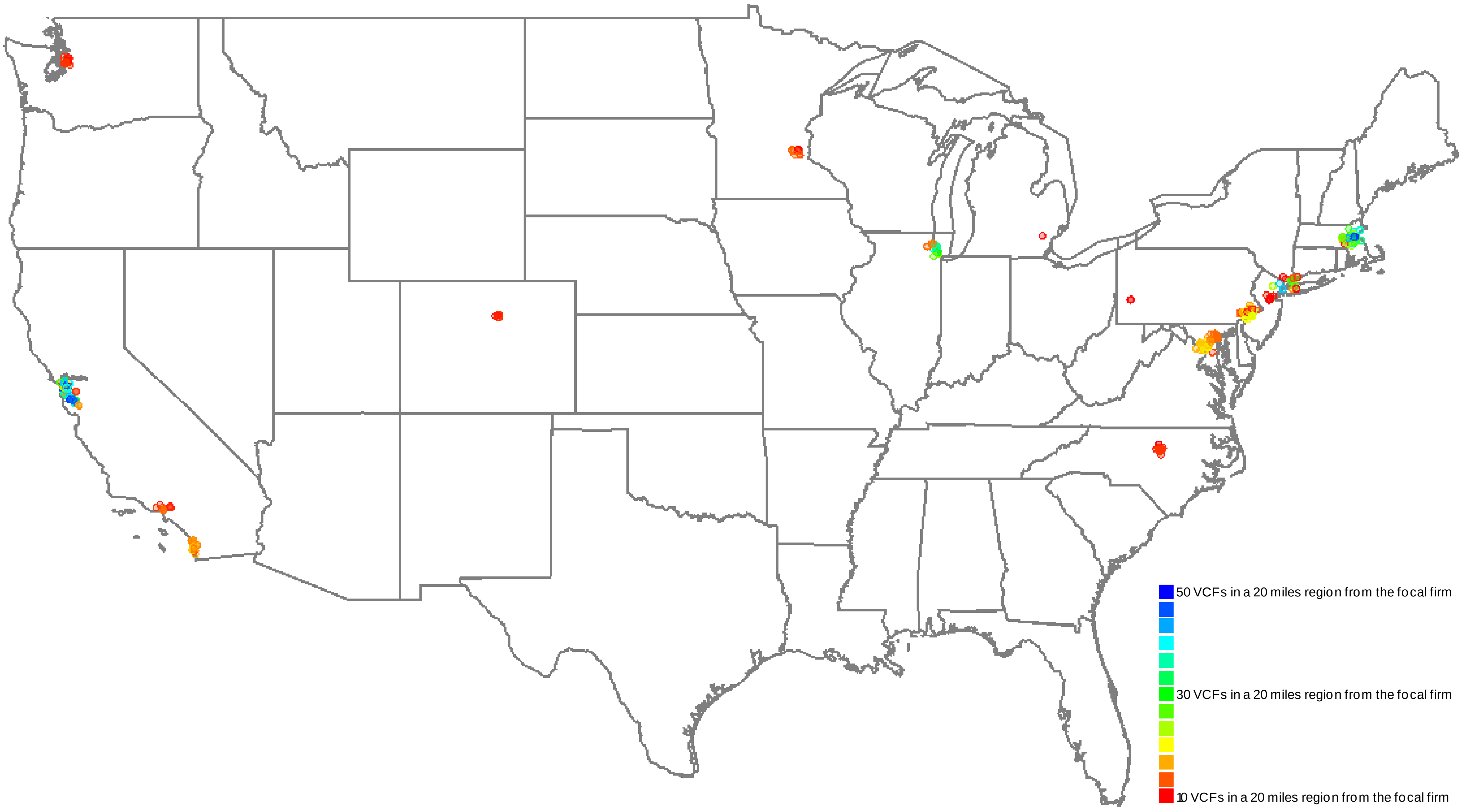

Figure 2b. Density of VCFs surrounding the focal biotechnology firm in a 0 to 20 miles radius.

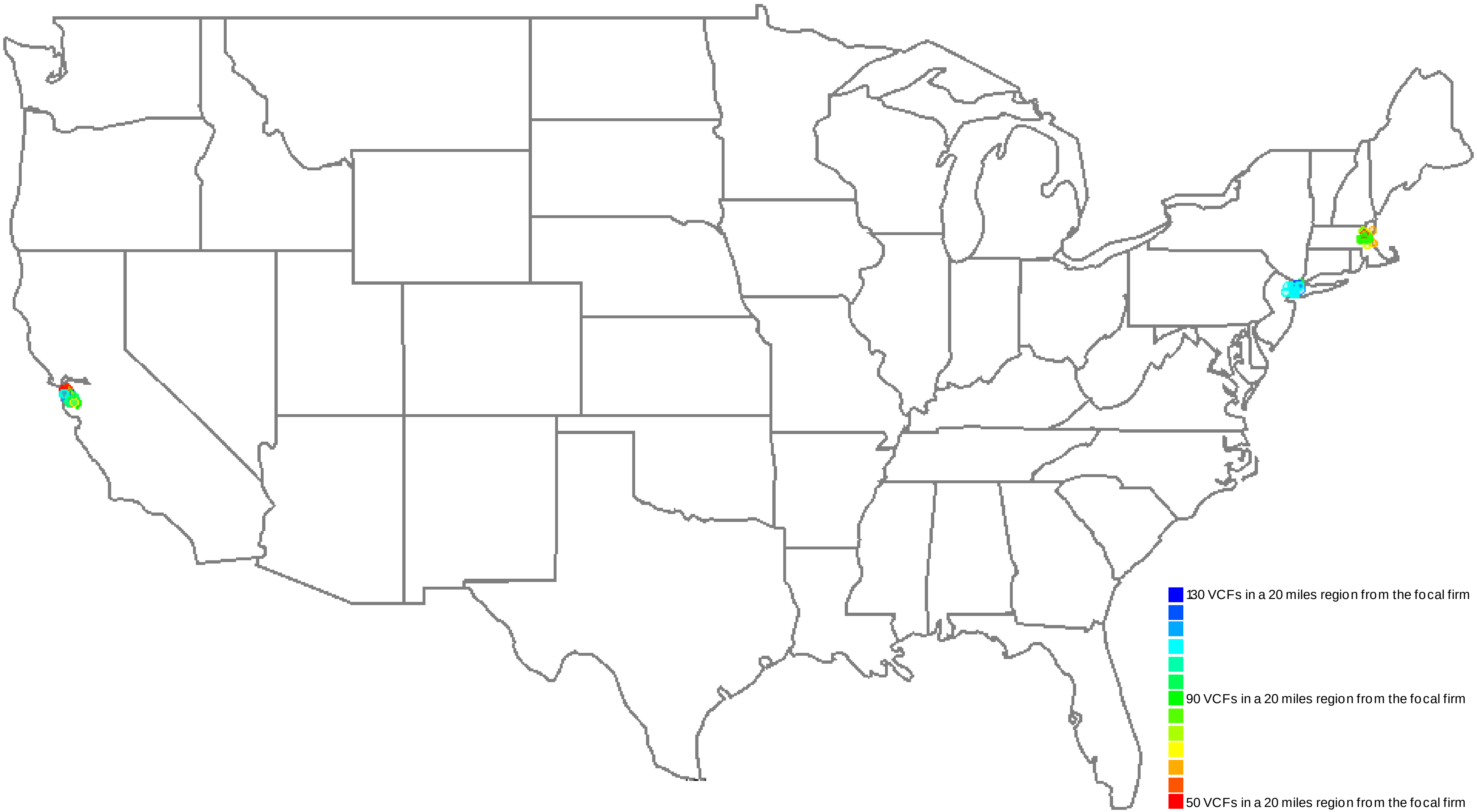

Figure 2c. Density of VCFs surrounding the focal biotechnology firm in a 0 to 20 miles radius.

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

	Variable name	Observations	Mean	St. Dev	Median	Mode
Total amount of venture capital funded to a biotechnology firm for the first round of investment ($1,000,000)	VCF_Investment_1	1,584	5.65	14.50	2.15	1.00
The total amount of venture capital funded to a biotechnology firm for the second round of investment ($1,000,000)	VCF_Investment_2	1,173	6.92	10.10	3.50	2.00
Number of patent applications filed by a biotechnology firm from foundation to the first round of investment	PATENTApp_1	1,326	0.53	10.57	0.00	0.00
Number of patent applications filed by a biotechnology firm from the first round of investment to the second round of investment	PATENTApp_2	1,092	0.38	1.78	0.00	0.00
Number of patents granted to a biotechnology firm from firm foundation to the first round of investment	PATENTGrant_1	1,327	0.42	7.70	0.00	0.00
Number of patents granted to a biotechnology firm from the first round of investment to the second round of investment	PATENTGrant_2	1,092	0.45	2.79	0.00	0.00
Average number of forward patent citations per year of patents granted between firm foundation and the first round of investment	PATENTCiteYear_1	1,523	0.06	0.46	0.00	0.00
Average number of forward patent citations per year of patents granted between the first round of investment and the second round of investment	PATENTCiteYear_2	1,523	0.11	0.74	0.00	0.00
An index that is increasing with the average reputation score of the participating venture capital firms in the previous investment round [1]	VCFreputation_1	1,762	0.31	0.43	0.00	0.00
Dummy variable which takes the value of 1 if a biotechnology firm founder holds a distinguished and/or named professorship and/or is a member of the Academy of Sciences and/or Nobel Prize and/or had previously founded other firms [2]	FounderSignal	101				
Average sum the funding venture capital firms had raised prior to investing in the focal firm for the first round of investment ($1,000,000)	SyndicateSize_1	1,762	295.24	430.67	80.29	0.00
Average sum the funding venture capital firms had raised prior to investing in the focal firm for the second round of investment ($1,000,000)	SyndicateSize_2	1,762	329.93	403.20	118.00	0.00
Number of venture capital firms participating in the first round of investment	SyndicateInvestors_1	1,762	2.28	1.74	2.00	1.00
Number of venture capital firms participating in the second round of investment	SyndicateInvestors_2	1,275	2.99	2.54	2.00	1.00
Distance of the focal firm to the closest funding participating venture capital firm (miles)	DistanceClosestVCF	1,424	390.01	707.36	26.61	0.04
Total number of universities located in the focal firm's Metropolitan Statistical Area	UniversitiesInMSA	1,762	9.60	9.02	6.00	1.00
Total number of venture capital firms located within 0 to 10 miles from the focal firm founded before the first round of investment	VCFarea_0010_1	1,762	16.05	24.07	5.00	0.00
Total number of venture capital firms located within 10 to 20 miles from the focal firm founded before the first round of investment	VCFarea_1020_1	1,762	10.72	20.47	2.00	0.00
Total number of venture capital firms located within 0 to 10 miles from the focal firm founded before the second round of investment	VCFarea_0010_2	1,762	17.98	26.36	5.00	0.00
Total number of venture capital firms located within 10 to 20 miles from the focal firm founded before the second round of investment	VCFarea_1020_2	1,762	11.80	22.01	3.00	0.00
Total number of patents held by biotechnology firms located within 0 to 10 miles from the focal firm before the first round of investment	PATENTArea_0010_1	1,762	89.46	137.83	23.00	0.00
Total number of patents held by biotechnology firms located within 10 to 20 miles from the focal firm before the first round of investment	PATENTArea_1020_1	1,762	51.18	98.49	9.00	0.00
Total number of patents held by biotechnology firms located within 0 to 10 miles from the focal firm before the second round of investment	PATENTArea_0010_2	1,762	94.34	140.87	26.00	0.00
Total number of patents held by biotechnology firms located within 10 to 20 miles from the focal firm before the second round of investment	PATENTArea_1020_2	1,762	54.39	102.87	11.00	0.00
Age of a biotechnology firm from foundation to the first round of investment (years)	Age_1	1,548	3.33	7.34	1.00	0.00
Age of a biotechnology firm from foundation to the second round of investment (years)	Age_2	1,187	4.36	8.75	2.42	1.00

[1]The index takes the value of 0 if the participating VCFs are unranked. When participating VCFs are ranked in the the Lee-Pollock-Jin VC Reputation index (Lee, Pollock et al. 2011), the value lies between 1 (when the VCF is rank 1) and 0.001 (when the VCF is the lowest ranked VCF in the list).

[2]In case of the FounderSignal variable the figure measures the number biotechnology firms with the founder matching the said characteristics

Figures 1a to 1c display the density of patents within a 20 miles radius from the firms in our dataset. Regions at the East and the West Coast tend to have the most dense areas in terms of patents; an observation that most likely reflects the intense spatial clustering of DBFs in the US (Kolympiris et al. 2011; Powell et al. 2002). As a case in point, the most intense 20 miles radius in our sample was observed Redwood City, California. Biotechnology firms within this 20 miles radius hold 644 patents in total. Further, the Figures illustrate that our dataset draws from both urban and rural areas, which suggests that our results are not limited to DBFs located only at a certain region. In a similar vein, the density of VCFs in our dataset, as shown in Figures 2a to 2c, roughly overlaps with the density of patents presented in Figures 1a to 1c. Given that the density of patents roughly resembles the density of DBFs in our sample, we observe that VCFs tend to share the same locations with the DBFs; an observation that likely emanates from the common strategy of VCFs to situate themselves close to their target firms.

Table 1 presents descriptive statistics of the variables used in the empirical models. Most DBFs in the dataset received 1 million for the first round of financing and 2 million for the second round of financing. Note that the standard deviation is significantly larger than the mean observed value which indicates the wide array of venture capital funds invested to different firms. Most firms did not have any patent activity before the focal round of financing, but similarly to the venture capital investments the standard deviation of the observed patenting activity surpasses the average of the observed values and suggest that some firms had a large number of patents and patent application before the focal round of financing. Along the same lines, most of the patents granted to a given firm did not receive any citations per year.

Most of the firms in the dataset were more than 3 and more than 4 years old when they received first and second round of financing respectively from mostly unranked VCFs in terms of reputation; the average reputation score for the highest ranked funding VCF was 0.313 which translates to a yearly ranking of 687[13]. More than 100 firms in the dataset had a founder that was coded as conveying a signal of quality, while most firms were receiving funds from VCFs located within a 0.04 miles distance. DBFs received funds mostly by 1 VCF regardless of round

[13] 1-(687/1000)=0.313

of financing while the average value for first round of financing was 2.2 investors and for the second round of financing the corresponding value was close to 3. With regard to the size of the investors, on average they had invested around 300 million before providing finance to the firm in question.

With regard to the variables that characterize the regional environment of each focal firm, around 10 universities were located in the same MSA, roughly 16 VCFs in a 0 to 10 miles radius and approximately 11 VCFs in a 10 to 20 miles radius. Note that the modal value for these variables is either 0 or 1, which is in line with Figures 2a to 2c that demonstrate that a large number of VCFs in the dataset are located in relatively isolated regions of the country. Finally, the average DBF in our sample was surrounded by DBFs that in sum had produced around 140 patents before the focal DBF received funds (approximately 90 patents originate from firms in a 0 to 10 miles distance and roughly 50 patents from firms in a 10 to 20 miles distance).

5. Empirical results

Tables 2 and 3 display the estimated coefficients for the models described in section 3. As discussed in section 3, often, there are difficult to observe regional factors that span beyond a 10 or a 20 miles radius that can affect the performance of a given firm and the subsequent size of the venture capital investments it attracts. Such factors include the efficacy of state Small Business Administration offices or the quality of services provided mostly to firms in the same state by private consulting organizations. Collectively, factors of these sorts can induce DBFs of a given state to overperform or underperform jointly. If such proposition holds, the assumption of independence across observations from firms in the same state may be violated (Nichols and Schaffer 2007; Stimson 1985). To address this possibility we estimate (1) and (2) with standard errors of firms in the same state modeled as correlated (i.e. clustered at the state level)[14] and report those errors and the associated statistical significance in the last two columns of Tables 2

[14] The parameters and the standard errors are estimated with generalized estimating equations which is a method of calculating the standard errors by first estimating the variability within the defined cluster (in our application the state) and then sums across all clusters (Zorn 2006).

and 3. The heteroskedasticity test reported in Tables 2 and 3 indicates strong evidence of heteroskedasticty and we use White's standard errors to account for this feature of the estimated models.

When estimating the two aforementioned types of standard errors the estimated coefficients remain intact by definition but the standard errors change. Nevertheless, the statistical inference from the two sets of standard errors we employed is nearly identical. Accordingly, the robustness of our findings strengthens and allows our discussion of the estimated results to make specific reference in one set of standard errors only in the few cases where there is a divergence between the findings.

The fit statistics reported at the bottom of Tables 2 and 3 indicate the joint significance of the included variables and suggest that the fitted models have explanatory power. Finally, the multicollinearity condition index (20.12 and 24 for each model) is within limits that alleviate inference concerns associated with high degrees of multicollinearity.

Table 2. Estimated coefficients for model of the first round of financing. The Dependent Variable is the natural log of the amount of venture capital funds raised by a biotechnology firm for the first round of financing.

Variable Description	Variable code	Coefficient	Heteroskedasticity robust standard errors	Standard errors clustered at the state level
	Intercept	11.5473	0.2679 ***	0.4349 ***
Number of patent applications filed by a biotechnology firm from foundation to the first round of investment	PATENTApp_1	0.1129	0.0371 ***	0.0359 ***
Number of patents granted to a biotechnology firm from firm foundation to the first round of investment	PATENTGrant_1	-0.0155	0.0466	0.0472
Average number of forward patent citations per year of patents granted between firm foundation and the first round of investment	PATENTCiteYear_1	0.1701	0.0639 ***	0.0603 ***
Dummy variable which takes the value of 1 if a biotechnology firm founder holds a distinguished and/or named professorship and/or is a member of the Academy of Sciences and/or Nobel Prize and/or had previously founded other firms	FounderSignal	0.4336	0.1338 ***	0.1353 ***
Average sum the funding venture capital firms had raised prior to investing in the focal firm for the first round of investment ($1,000,000)	SyndicateSize_1	0.0003	0.0001 ***	0.0002
Number of venture capital firms participating in the first round of investment	SyndicateInvestors_1	0.3790	0.0260 ***	0.0353 ***
Distance of the focal firm to the closest funding participating venture capital firm (miles)	DistanceClosestVCF	0.0003	0.0001 ***	0.0001 **
Total number of universities located in the focal firm's Metropolitan Statistical Area	UniversitiesInMSA	0.0016	0.0056	0.0045
Total number of venture capital firms located within 0 to 10 miles from the focal firm founded before the first round of investment	VCFarea_0010_1	0.0073	0.0020 ***	0.0026 ***
Total number of venture capital firms located within 10 to 20 miles from the focal firm founded before the first round of investment	VCFarea_1020_1	0.0021	0.0025	0.0026
Total number of patents held by biotechnology firms located within 0 to 10 miles from the focal firm before the first round of investment	PATENTArea_0010_1	0.0005	0.0003	0.0002 **
Total number of patents held by biotechnology firms located within 10 to 20 miles from the focal firm before the first round of investment	PATENTArea_1020_1	-0.0002	0.0006	0.0005
Age of a biotechnology firm from foundation to the first round of investment (years)	Age_1	0.0438	0.0108 ***	0.0118 ***
Trend variable that takes the value of 1 for first round investments in 1974 and increases by one unit for every additional year	Trend_1	0.0357	0.0068 ***	0.0162 **
	R^2	0.3259		
	Adjusted R^2	0.3165		
	F-test for overall model significance		36.17 ***	266.76 ***
	Multicollinearity Condition Number	20.125		
	X^2 for Breusch-Pagan test for heteroskedasticity	9.27 ***		
	Number of observations	1020		

*** .01 significance, ** .05 significance

Table 3. Estimated coefficients for model of the second round of financing. The Dependent Variable is the natural log of the amount of venture capital funds raised by a biotechnology firm for the second round of financing.

Variable Description	Variable code	Coefficient	Heteroskedasticity robust standard errors	Standard errors clustered at the state level
	Intercept	12.3852	0.2893 ***	0.2883 ***
Number of patent applications filed by a biotechnology firm from the first round of investment to the second round of investment	PATENTApp_2	0.0289	0.0339	0.0307
Number of patent applications filed by a biotechnology firm from foundation to the first round of investment	PATENTApp_1	0.0353	0.0338	0.0387
Number of patents granted to a biotechnology firm from the first round of investment to the second round of investment	PATENTGrant_2	0.0157	0.0183	0.0159
Number of patents granted to a biotechnology firm from firm foundation to the first round of investment	PATENTGrant_1	0.0234	0.0330	0.0333
Average number of forward patent citations per year of patents granted between the first round of investment and the second round of investment	PATENTCiteYear_2	0.0266	0.0291	0.0336
Average number of forward patent citations per year of patents granted between firm foundation and the first round of investment	PATENTCiteYear_1	0.0116	0.1051	0.1059
Total amount of venture capital funded to a biotechnology firm for the first round of investment ($1,000,000)	VCF_Investment_1	0.0263	0.0054 ***	0.0043 ***
An index that is increasing with the average reputation score of the participating venture capital firms in the previous investment round [1]	VCFreputation_1	-0.0426	0.0957	0.0871
Dummy variable which takes the value of 1 if a biotechnology firm founder holds a distinguished and/or named professorship and/or is a member of the Academy of Sciences and/or Nobel Prize and/or had previously founded other firms	FounderSignal	0.2441	0.1482	0.1469
Average sum the funding venture capital firms had raised prior to investing in the focal firm for the second round of investment ($1,000,000)	SyndicateSize_2	0.0004	0.0001 ***	0.0001 ***
Number of venture capital firms participating in the second round of investment	SyndicateInvestors_2	0.2470	0.0171 ***	0.0191 ***
Distance of the focal firm to the closest funding participating venture capital firm (miles)	DistanceClosestVCF	0.0002	0.0001 ***	0.0001 ***
Total number of universities located in the focal firm's Metropolitan Statistical Area	UniversitiesInMSA	0.0105	0.0055	0.0034 ***
Total number of venture capital firms located within 0 to 10 miles from the focal firm founded before the second round of investment	VCFarea_0010_2	0.0019	0.0020	0.0015
Total number of venture capital firms located within 10 to 20 miles from the focal firm founded before the second round of investment	VCFarea_1020_2	0.0033	0.0022	0.0031
Total number of patents held by biotechnology firms located within 0 to 10 miles from the focal firm before the second round of investment	PATENTArea_0010_2	0.0001	0.0003	0.0002
Total number of patents held by biotechnology firms located within 10 to 20 miles from the focal firm before the second round of investment	PATENTArea_1020_2	0.0005	0.0005	0.0006
Age of a biotechnology firm from foundation to the second round of investment (years)	Age_2	0.0003	0.0107	0.0110
Trend variable that takes the value of 1 for second round investments in 1974 and increases by one unit for every additional year	Trend_2	0.0296	0.0070 ***	0.0097 ***
	R^2	0.3596		
	Adjusted R^2	0.3449		
	F-test for overall model significance		25.04 ***	271.43 ***
	Multicollinearity Condition Nu	24.000		
	X^2 for Breusch-Pagan test for heteroskedasticity	19.28 ***		
	Number of observations	845		

[1]The index takes the value of 0 if the participating VCFs are unranked. When participating VCFs are ranked in the the Lee-Pollock-Jin VC Reputation index (Lee, Pollock et al. 2011), the value lies between 1 (when the VCF is rank 1) and 0.001 (when the VCF is the lowest ranked VCF in the list).

*** .01 significance, ** .05 significance

Because the dependent variable is in logarithmic form, the estimated coefficients can be interpreted as semielasticities. In line with our theoretical expectations, patent activity appears to serve as a signal that attracts venture capital investments but the attractiveness of that signal dies off once investors and target firms are more familiar with each other. In particular, one additional pending patent application before the first round of financing increases the amount of funds raised by the focal firm for that round by 11.2 percent. This is a considerable increase especially when considering the 0 modal value for the *PATENTApp_1* variable as it suggests that firms without patent activity generally receive less funds from VCFs. To put the magnitude of the estimated coefficient in perspective, when evaluated at the average amount of first round funds reported in Table 1 it indicates that one additional pending patent application increases venture capital investments by more than $632,000[15] when the modal value of the variable at hand is $1,000,000. Further, when compared with the direct costs of obtaining a patent that range between $10,000 and $38,000 (Graham et al. 2009; Lemley 2000), the $632,000 figure indicates that these direct costs are well compensated by the signaling value of a patent. Nevertheless, to have a fuller assessment of the cost-benefit ratio of patents, we need an estimate of the research and development (R&D) costs that accrue before a patent is granted. But, because the existing estimates of the research and development (R&D) costs that accrue before a patent is granted (e.g. Hall and Ziedonis 2001; Henderson and Cockburn 1996; Lanjouw and Schankerman 2004) do not distinguish between the costs that accrue specifically for the purposes of a patent and those costs that accrue as part of the overall research process, such assessment is difficult to make.

Pending patent applications do not appear to attract higher amounts of second round venture capital investments, implying that a reduction of information asymmetries between investors and target firms render patent activity irrelevant in that respect. It is important to note that contrary to pending patent applications, the granted patents of a focal firm do not appear to attract additional funds neither in the first nor in the second round of financing. This result is in line with previous findings (Baum and Silverman 2004; Häussler et al. 2009) and it likely

[15] 0.112*5.65M=632,800

emanates from the fact that unlike granted patents, pending patent applications allow room for changes that can potentially accommodate competing patent applications or preempt competitors that can arise from the fast pace that technological process occurs in high technology sectors such as biotechnology.

Along the same lines, the estimated coefficient of the forward citations variable may also qualify for explaining the insignificance of the patents variable. Our result suggest that VCFs have developed skills to identify patents of high quality and subsequent market value and are attracted to firms that possess such patents. Therefore, VCFs appear to invest larger amounts to firms with patents of higher quality instead of firms with large number of patents. Interestingly, the quality of patents generated after the first round of investment does not exhibit a significant impact on the growth of funds at the second round of investment. This might be observed perhaps because once VCFs are acquainted with the focal firm, its potential in generating future cash flow is generally assessed by the funding investors through day-to-day interaction and not through patent quality.

Moving to remaining signals that a focal firm can employ, we note that generally they follow the same trend with the signaling function of patent activity under which they matter before the involvement of VCFs in the target firm and not after. In line with the argument that a reduction of information asymmetries decreases the effectiveness of signals, we discover that firms that were founded by a serial entrepreneur or/and academic scientist received 43 percent larger amounts of first round financing but they did not enjoy a similar advantage in the second round of financing. In the same vein, the reputation of the investors of the first round did not explain a significant portion of the variation in the level of funding in the second round of investment. Note that as seen in Table 1 most of the firms received funds from a single investor, which in most cases it was the same investor in both rounds; hence the finding at hand may reflect the popularity of such funding structure in our sample.

The results that pertain to the syndication of investors are in line with our theoretical expectations and recent relevant findings (Tian 2011) that large groups of wealthy co-investors tend to boost the growth of capital funds of a given firm. One additional VCF in the first round of financing raised the total venture capital amount of that round for the origin firm by 37 percent; the corresponding coefficient for the second round of financing was close to 25 percent. Similar findings hold for the size of the funding VCFs. Finally, in contrast with our theoretical expectations we find that firms that receive funds from closely located VCFs receive less per round of financing. One additional mile in the distance between the target firm and the closest investor increases the total amount of financing by 0.03 percent. However, as seen in Table 1, most of the firms in our sample source funds from VCFs located within walking distance and half of the firms receive funds from VCFs located less than 27 miles away. Therefore, in this case, the average distance between target firms and investors reported in Table 1 (390 miles) is somewhat inflated by a few observations where East/West coast VCFs funded West/East coast DBFs. Therefore, while statistically significant, the effect of the *DistanceClosestVCF* is expected to have a small economic effect for the majority of firms in our sample.

For the variables that describe the regional environment around the focal firm, we find that generally the density of universities in the same MSA does not appear to influence the accumulation of venture capital funds neither in the first nor in the second round of financing[16]. On the other hand, the density of VCFs in a 10 miles radius from the origin firm (and not in a 10 to 20 miles radius) appears conducive to the growth of venture capital funds for the first round of financing but not for the second round of financing. Firms that have not attracted any investors may be in greater need to accumulate knowledge from nearby institutions because they lack guidance and consulting; thus the finding that the density of VCFs matters only for the first round of financing may reflect that proposition. Similar to the density of VCFs in the spatial units we consider in the empirical analyses, the coefficients that measure the effect of patent density in the region are statistically insignificant for the second round of financing and statistically significant for the *PATENTArea_0010_1* variable when the errors are clustered at the state level. Overall, the estimates of the variables that describe the regional environment indicate that the strength of proximity effects is sensitive to the actor that such effects originate

[16] The *UniversitiesInMSA* variable is statistically significant only in one case where the standard errors are clustered at the state level.

from, with VCFs appearing the most relevant in affecting the growth of venture capital funds for a given firm. What we find particularly interesting is that such proximity effects appear to matter only before the first round of financing where firms have not been involved with any investors. By extension, the case may be that agglomeration effects (partly) fill in for the lack of consulting and guidance provided by VCFs.

Finally, our control variables indicate that older firms receive more funds at the first round of financing and that over time the investments of both the first and the second round of financing become larger.

6. Conclusion and discussion

A long stream of research has documented the positive effects that patents bring about to firms. The general consensus is that patents contribute to firm growth because they confer monopolistic market rights, offer protection from competitors, increase the survival rate of patent holders and other benefits. What has received relatively less attention in this literature is whether patents can act as a signal that attracts investors. This inquiry is particularly relevant for firms in knowledge intensive industries where long research cycles, scientific complexities and strict regulatory regimes make the development of a track record for a given firm difficult and subsequently prompt firms to convey their potential via signals. Indeed, a handful of studies empirically reveal that knowledge intensive firms that either hold granted patents or have pending patent applications tend to receive larger venture capital investments faster. However, these studies have not examined whether the signaling function of patents reduces over time despite strong theoretical arguments that support such proposition.

Employing data from more than 1500 U.S.-based biotechnology firms, in this study we examined whether the patent activity (granted patents and pending patent applications) of a focal firm increases the sum of venture capital funds raised by a given firm during its first and second round of financing. Our empirical estimates strongly corroborate our theoretical expectations that patent activity before the first round of financing increases the growth of funds for that round. However, once investors and target firms decrease the information asymmetries between them, patent activity ceases to serve as a signal that increase the level of funds raised at the second round of financing. Interestingly, we discover that only pending patent applications act as a signal and not granted patents; a finding that potentially reflects the preference of VCFs to the opportunity that pending patent applications offer in terms of allowing the applicant to alter the contents of the application. Further, we reveal that the growth of venture capital funds for a given firm is influenced by the number and the size of the investors as well as from regional characteristics that allow firms to source knowledge from nearby institutions.

The present study has a number of policy and scholarly implications and can offer managerial prescriptions. For instance, our empirical estimates can inform managers of biotechnology firms on the benefits that arise from patent activity. We estimated that, on average, an additional pending patent application can increase the amount of venture capital funds raised in the first round of financing by more than $630,000. This figure clearly surpasses the existing estimates for the direct costs of being granted a patent (which ranges from $10,000 to $38,000). Nevertheless a fuller assessment requires an estimation of the R&D costs directly attributable to the patent. Such assessment is difficult to find in the existing literature, which indicates a fruitful avenue for further research. Moreover, in line with previous research, our estimates strongly point managers of biotechnology firms towards patents of higher quality since investors appear to be able to detect patents of higher value and invest in the firms that possess them instead of investing in firms that are granted a large number of patents (Häussler et al. 2009). Finally, our findings that patent activity matters only for the first round of financing imply that after the attraction of venture capital alternative protection mechanisms such as licensing may not be suboptimal in terms of venture capital attraction. Assessing the strength of alternative protection mechanisms in attracting venture capital investments is a potential avenue for further research that can complement the present work.

From a policy perspective, a number of concerns have been raised about the current status of the patenting system and the degree that it hinders innovation. The $630,000 figure we presented above can be informative towards that end if the federal costs per patent are discernible and if, as expected, higher investments eventually translate to higher innovation measures via the strengthening of firms with potential to innovate.

While the main focus of our work is not on the impact of regional features on the growth of venture capital funds realized by a given firm, we note that our findings yielded an interesting insight. Agglomeration economies appeared to matter for the growth of venture capital funds only for the first round of financing where the focal firm had not received any guidance from investors. Therefore, the case might be that agglomeration economies compensate for this lack of guidance as firms benefit from external sources of knowledge and pecuniary effects only when they do not receive the managerial services of the investors. This finding is a first step towards a deeper understanding on the sources of agglomeration economies and follow-up work can address the issue further.

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Appendix Table 1. Estimated coefficients for model of the first round of financing. The Dependent Variable is the natural log of the amount of venture capital funds raised by a biotechnology firm for the first round of financing. Compared to Table 2, the number of patent applications before 2001 is calculated with a linear trend.

Variable Description	Variable code	Coefficient	Heteroskedasticity robust standard errors	Standard errors clustered at the state level
	Intercept	11.2299	0.2777 ***	0.4253 ***
Number of patent applications filed by a biotechnology firm from foundation to the first round of investment	PATENTApp_1	0.0953	0.0336 ***	0.0313 ***
Number of patents granted to a biotechnology firm from firm foundation to the first round of investment	PATENTGrant_1	0.0016	0.0504	0.0512
Average number of forward patent citations per year of patents granted between firm foundation and the first round of investment	PATENTCiteYear_1	0.1852	0.0673 ***	0.0622 ***
Dummy variable which takes the value of 1 if a biotechnology firm founder holds a distinguished and/or named professorship and/or is a member of the Academy of Sciences and/or Nobel Prize and/or had previously founded other firms	FounderSignal	0.4455	0.1341 ***	0.1375 ***
Average sum the funding venture capital firms had raised prior to investing in the focal firm for the first round of investment ($1,000,000)	SyndicateSize_1	0.0003	0.0001 ***	0.0002
Number of venture capital firms participating in the first round of investment	SyndicateInvestors_1	0.3795	0.0260 ***	0.0351 ***
Distance of the focal firm to the closest funding participating venture capital firm (miles)	DistanceClosestVCF	0.0003	0.0001 ***	0.0001 **
Total number of universities located in the focal firm's Metropolitan Statistical Area	UniversitiesInMSA	0.0022	0.0056	0.0045
Total number of venture capital firms located within 0 to 10 miles from the focal firm founded before the first round of investment	VCFarea_0010_1	0.0073	0.0020 ***	0.0026 ***
Total number of venture capital firms located within 10 to 20 miles from the focal firm founded before the first round of investment	VCFarea_1020_1	0.0022	0.0025	0.0026
Total number of patents held by biotechnology firms located within 0 to 10 miles from the focal firm before the first round of investment	PATENTArea_0010_1	0.0005	0.0003	0.0002 **
Total number of patents held by biotechnology firms located within 10 to 20 miles from the focal firm before the first round of investment	PATENTArea_1020_1	-0.0002	0.0006	0.0005
Age of a biotechnology firm from foundation to the first round of investment (years)	Age_1	0.0446	0.0112 ***	0.0122 ***
Trend variable that takes the value of 1 for first round investments in 1974 and increases by one unit for every additional year	Trend_1	0.0422	0.0069 ***	0.0156 ***
	R^2	0.3247		
	Adjusted R^2	0.3152		
	F-test for overall model significance		36.28 ***	281.1 ***
	Multicollinearity Condition N	20.300		
	X^2 for Breusch-Pagan test for heteroskedasticity	8.66 ***		
	Number of observations	1020		

*** .01 significance, ** .05 significance

Appendix Table 2. Estimated coefficients for model of the second round of financing. The Dependent Variable is the natural log of the amount of venture capital funds raised by a biotechnology firm for the second round of financing. Compared to Table 3, the number of patent applications before 2001 is calculated with a linear trend.

Variable Description	Variable code	Coefficient	Heteroskedasticity robust standard errors	Standard errors clustered at the state level
	Intercept	12.1299	0.2945 ***	0.3295 ***
Number of patent applications filed by a biotechnology firm from the first round of investment to the second round of investment	PATENTApp_2	0.0037	0.0268	0.0199
Number of patent applications filed by a biotechnology firm from foundation to the first round of investment	PATENTApp_1	0.0760	0.0366 **	0.0416
Number of patents granted to a biotechnology firm from the first round of investment to the second round of investment	PATENTGrant_2	0.0243	0.0247	0.0238
Number of patents granted to a biotechnology firm from firm foundation to the first round of investment	PATENTGrant_1	0.0205	0.0349	0.0359
Average number of forward patent citations per year of patents granted between the first round of investment and the second round of investment	PATENTCiteYear_2	0.0289	0.0280	0.0325
Average number of forward patent citations per year of patents granted between firm foundation and the first round of investment	PATENTCiteYear_1	0.0009	0.0986	0.0917
Total amount of venture capital funded to a biotechnology firm for the first round of investment ($1,000,000)	VCF_Investment_1	0.0265	0.0053 ***	0.0046 ***
An index that is increasing with the average reputation score of the participating venture capital firms in the previous investment round [1]	VCFreputation_1	-0.0390	0.0956	0.0898
Dummy variable which takes the value of 1 if a biotechnology firm founder holds a distinguished and/or named professorship and/or is a member of the Academy of Sciences and/or Nobel Prize and/or had previously founded other firms	FounderSignal	0.2426	0.1484	0.1557
Average sum the funding venture capital firms had raised prior to investing in the focal firm for the second round of investment ($1,000,000)	SyndicateSize_2	0.0004	0.0001 ***	0.0001 ***
Number of venture capital firms participating in the second round of investment	SyndicateInvestors_2	0.2477	0.0171 ***	0.0196 ***
Distance of the focal firm to the closest funding participating venture capital firm (miles)	DistanceClosestVCF	0.0002	0.0001 ***	0.0001 ***
Total number of universities located in the focal firm's Metropolitan Statistical Area	UniversitiesInMSA	0.0103	0.0056	0.0034 ***
Total number of venture capital firms located within 0 to 10 miles from the focal firm founded before the second round of investment	VCFarea_0010_2	0.0020	0.0020	0.0015
Total number of venture capital firms located within 10 to 20 miles from the focal firm founded before the second round of investment	VCFarea_1020_2	0.0033	0.0022	0.0031
Total number of patents held by biotechnology firms located within 0 to 10 miles from the focal firm before the second round of investment	PATENTArea_0010_2	0.0001	0.0003	0.0002
Total number of patents held by biotechnology firms located within 10 to 20 miles from the focal firm before the second round of investment	PATENTArea_1020_2	0.0005	0.0005	0.0006
Age of a biotechnology firm from foundation to the second round of investment (years)	Age_2	0.0003	0.0106	0.0115
Trend variable that takes the value of 1 for second round investments in 1974 and increases by one unit for every additional year	Trend_2	0.0348	0.0070 ***	0.0103 ***
	R^2	0.3603		
	Adjusted R^2	0.3455		
	F-test for overall model significance		25.32 ***	241.21 ***
	Multicollinearity Condition Number	27.189		
	X^2 for Breusch-Pagan test for heteroskedasticity	19.79 ***		
	Number of observations	845		

[1]The index takes the value of 0 if the participating VCFs are unranked. When participating VCFs are ranked in the the Lee-Pollock-Jin VC Reputation index (Lee, Pollock et al. 2011), the value lies between 1 (when the VCF is rank 1) and 0.001 (when the VCF is the

*** .01 significance, ** .05 significance