The geography of opportunity: spatial heterogeneity in founding rates and the performance of biotechnology firms

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Abstract

One of the most commonly observed features of the organization of markets is that similar business enterprises cluster in physical space. In this paper, we develop an explanation for firm co-location in high-technology industries that draws upon a relational account of new venture creation. We argue that industries cluster because entrepreneurs find it difficult to leverage the social ties necessary to mobilize essential resources when they reside far from those resources. Therefore, opportunities for high tech entrepreneurship mirror the distribution of critical resources. The same factors that enable high tech entrepreneurship, however, do not necessary promote firm performance. In the empirical analyses, we investigate the effects of geographic proximity to established biotechnology firms, sources of biotechnology expertise (highly-skilled labor), and venture capitalists on the location-specific founding rates and performance of biotechnology firms. The paper finds that the local conditions that promote new venture creation differ from those that maximize the performance of recently established companies.
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1. Introduction

Industrial activity is concentrated in space. From the assembly of automobiles to the weaving of textiles, production in many industries occurs in geographically localized clusters. The tendency of firms to locate close to one another seems easy to explain in markets where the transportation of raw materials or the outputs of production entail substantial cost—in such instances, the basic economics of production and distribution dictate the location of industrial activity. The fact that production concentrates geographically in most high-technology industries, however,

eludes this simple explanation. The central production inputs in these industries—intellectual property, human and financial capital—weigh nothing and in principle should move quickly and inexpensively through space. The levity of these ingredients implies that the choice of where to locate a high-technology firm should be relatively unconstrained by the spatial distribution of inputs and end markets.

To address this conundrum, we develop an ecological and network-based account of spatial co-location in high-technology industries and then test this theory by analyzing spatial heterogeneity in founding rates and organizational performance in one high tech industry. We contend that firms concentrate in space for two reasons: the individuals most likely to start new companies of a particular type, as well as the social and professional ties of these would-be

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entrepreneurs to important resource providers, both tend to cluster in space. Building a new organization involves amassing a broad array of resources and commitments (Stinchcombe, 1965). To establish a high-technology firm, the entrepreneur must persuade investors to commit funds to an uncertain venture and individuals with specialized human capital to join the fledgling enterprise. Entrepreneurs must also convince established organizations to transact with their new ventures in the capacity of suppliers, buyers, strategic partners, and advisers. We assert that entrepreneurs' social relationships play an essential role in attracting the resources to create new organizations (Shane and Cable, 2002; Shane and Stuart, 2002); the potential to discover latent opportunities and the social capital to initiate the resource mobilization process reside in the existing (and potential) relationships of the entrepreneur.

These social networks also structure the geographic distribution of production. Sociologists have long asserted that spatial propinquity greatly facilitates relationship formation, and substantial empirical work now supports this view (e.g. Park, 1926; Bossard, 1932; Zipf, 1949; Festinger et al., 1950; Blau, 1977; Kono et al., 1998; Sorenson and Stuart, 2001). To the degree that entrepreneurial activity depends upon activating relationships that are anchored in space, the geographic distribution of resources will significantly influence the spatial distribution of industry (Sorenson and Audia, 2000). In particular, because would-be entrepreneurs in areas that lack important resources probably also lack connections to resource holders, they often cannot assemble the resources to start a new organization. For this reason, the distribution of resources across physical space plays a crucial role in determining where new businesses arise.

Our empirical analyses examine the biotechnology industry and establish three findings. First, we show that the physical locations of the holders of the resources necessary to create new biotechnology firms affects where new ventures appear. Second, we show that proximity effects dissipate as the industry evolves—a trend we ascribe to the emergence of industry-specific institutions that expand the geographic reach of individuals' networks. Third, we demonstrate that physical nearness to competing organizations and important resources influences the early-life performance of biotechnology firms.

Specifically, the results will show that the most fecund conditions for new venture creation often do not occur in the regions best suited for fostering the performance of these newly established ventures, although data limitations to some extent qualify this finding. We credit this discrepancy to the fact that a highly competitive environment arises as a byproduct of the relational processes that yield geographically concentrated industrial spaces.

In addition to its theoretical import, understanding the forces underlying high tech industrial clusters can also inform policy. Urban planners have shown keen interest in replicating the successes of established high-technology regions in new locales. With the loss of manufacturing jobs to countries with lower wages, policymakers increasingly look to technology entrepreneurship as a stimulus for regional development. For many urban planners, Silicon Valley and Boston's Route 128 represent blueprints for generating employment and economic growth in an increasingly knowledge-based economy. To lay the foundations for the emergence and growth of technology-intensive industries, state and local governments around the world have launched various incarnations of high-technology development (HTD) initiatives (OTA, 1984; Preer, 1992). Nevertheless, relatively few systematic empirical studies analyze spatial heterogeneity in new venture creation in high-technology industries, and even fewer document the effect of geographic location on organizational viability. As a result, although regional policies have been informed by a number of careful case studies of high-technology agglomerations (e.g. Saxenian, 1994), systematic empirical evidence upon which to ground policy initiatives is lacking (Galbraith, 1985).

2. Spatial proximity, local ties, and resource mobilization

A sizable, if largely theoretical, literature in economic geography addresses the spatial concentration of industry. Much of the recent work in this area has focused on agglomeration economies—a form of scale economy external to any one firm but internal to regions containing clusters of the same type of enterprises—in generating spatial concentration (e.g. Marshall, 1920; Arthur, 1990; Krugman, 1991).

Agglomeration economies imply positive returns to scale at the regional level, such that the advantage to an organization of locating in a particular region increases with the number of other firms in the area.

Several processes might generate agglomeration economies. One is the 'spillover' of knowledge between geographically proximate firms. If geographic propinquity facilitates the diffusion of technical knowledge, high-technology startups may choose to locate near to established organizations in their field to benefit from localized knowledge externalities (Jaffe et al., 1993). A second potential source of increasing returns in agglomerations is the emergence of specialized suppliers in areas with a high concentration of particular kinds of firms (Marshall, 1920). For instance, one finds silicon wafer producers and semiconductor equipment manufactures near the cluster of Silicon Valley chip producers. Similarly, suppliers of reagents, advanced laboratory equipment, biological materials, intellectual property law, and industry-specific consulting services have located near to the biotechnology clusters in California and Massachusetts. To the extent that high-technology firms benefit from proximity to these suppliers and service providers, the emergence of clusters of support organizations represents a second source of agglomeration economies.

Our emphasis in this paper differs from much of the work on industrial clusters in that we adopt a sociological perspective to explain the co-location of firms. Specifically, rather than examining heterogeneity in local founding rates as a function of differences between geographic areas in their capacities to support established businesses, we explore regional differences in the conditions that enable entrepreneurs to assemble the resources to start new companies as determinants of the local founding rate.

To do so, we introduce an explicit consideration of how social networks influence the resource mobilization process to a conventional ecological account of organizational foundings. Our argument in brief: organizational ecologists have observed that newly formed ventures often experience a 'liability of newness'. Because they lack committed workforces, slack resources, effective organizational designs, and relationships with customers and suppliers, early stage companies fail at a higher rate than do larger, more established organizations (Stinchcombe, 1965; Baron et al., 1996). As a result, potential employees, investors, customers, and collaborators (collectively, 'resource holders') inevitably assume some risk when they affiliate with a new organization. In turn, network theorists have argued that social capital—particularly in the form of pre-established relationships and reputations with resource holders—provides the mechanism that entrepreneurs use to overcome these uncertainties and to secure tangible commitments from skeptical resource holders (Zimmer and Aldrich, 1987; Portes and Sensenbrenner, 1993; Shane and Cable, 2002; Shane and Stuart, 2002). Thus, we contend that social capital crucially enables the organization building process. Because close social and professional relationships tend to localize geographically (Festinger et al., 1950), would-be entrepreneurs often can best leverage their existing connections to assemble and coordinate resources when they reside close to resource holders. Thus, we argue that entrepreneurs have difficulty starting new firms outside of areas abundant in the necessary resources. Consequently, some geographic areas afford more opportunities to create new ventures than do others.

To launch a technology-based startup, an entrepreneur requires at least three kinds of resources. All three types of resources exist in space in the sense that social actors who reside at particular locations control them. First, high-technology startups typically require a new idea or foundational technology. Hence, as likely sources of ideas for new ventures, we begin by considering the local density of experts in a particular field of technology as a determinant of where in space new ventures begin. Second, startups need capital; and given the risks associated with capital-intensive high-technology firms, this frequently comes in the form of venture capital (VC). Accordingly, we investigate whether the proximity of an area to sources of VC promotes organizational foundings. Third, new technology companies require employees with highly specialized human capital. Because existing enterprises provide sources of skilled technical and managerial labor and training grounds for prospective company founders, areas close to many enterprises in the focal population may experience higher rates of new venture founding. Treating these in turn, we argue that physical distance from people with technical expertise, sources of specialized labor, and suppliers of VC greatly hampers organization building.

Founding a new technology company begins with an idea. Researchers widely believe that information concerning new technologies diffuses *within* the confines of areas containing many individuals working on similar technical problems. When people with common professional interests cluster in physical space, informal social and professional networks emerge and serve to disseminate information (Piore and Sabel, 1984; Herrigel, 1983; Saxenian, 1994; Liebeskind et al., 1996; Hedström et al., 2000; Sorenson and Stuart, 2001). Hence, technologists in locations densely populated with other specialists in their fields often can form networks that contain many close, casual, and indirect ties with colleagues. These networks may convey information about new technological developments, important and unresolved technical puzzles, and emerging market opportunities.

Being situated in networks that provide exposure to diverse developments importantly influences technology-based entrepreneurship, because new inventions stem from novel combinations of existing ideas and technologies (Schumpeter, 1942; Fleming, 2001). Those positioned at the intersection of diverse information streams inhabit ideal locations for coming into contact with or creating the idea for a new venture (Hawley, 1986). Therefore, entrepreneurs in areas with a large population of technical experts tend to occupy positions in communication networks that lend themselves to idea generation, awareness of promising technical opportunities, and the ability to assess market opportunities. As a result, we anticipate, *the rate of founding of new high-technology companies increases in areas geographically proximate to the developers of the underlying technologies*.

A second crucial resource for new venture creation, closely related to the first, is specialized human capital. Prior to pitching an idea to potential investors and to starting operations, entrepreneurs must recruit the members of the founding team and document the interest of the key technologists and managers who will assume senior positions at the new organization. Thus, technology-based entrepreneurship requires the ability to recruit an initial staff of skilled technical and managerial workers.

Given the need for experienced managerial and technical labor, established high-technology firms often provide the largest source of labor to new ventures of like kind (Scott and Storper, 1987; Angel, 1991). To secure staff for a proposed company, entrepreneurs often leverage their networks to persuade potential cofounders and employees to leave their current employers to join their new organization (Sorenson and Audia, 2000). Because of the uncertain economic prospects of fledgling technology companies and questions about the capacity of these organizations to develop into operating companies, entrepreneurs often find it difficult to attract highly-skilled workers away from secure positions at established organizations. Without trust in the founder of a company and confidence in her ability and judgement, senior level managers and technologists will not likely leave secure positions to join a new firm. Trust flows through relationships. Assuming, as we have, that relationships concentrate spatially and that connections to workers at established firms play a large role in sourcing specialized labor, then proximity to existing firms should greatly expedite the recruitment of a workforce.

In addition to being a source of skilled labor, established firms also serve as training grounds for—and therefore sources of—entrepreneurs. Successful high-technology firms provide blueprints for the construction of organizations of their particular type (Meyer and Rowan, 1977; Hannan and Freeman, 1989; Aldrich and Wiedenmayer, 1993; Thornton, 1999). Insiders and close observers of established firms in the industry have access to knowledge about appropriate organizational structures, strategies, and systems for a new enterprise. Moreover, if starting the new venture requires highly tacit and difficult to transfer knowledge, then only individuals with direct technical experience will have the skills necessary to begin a new company. Similarly, past experience at a successful company allows potential entrepreneurs to establish the professional contacts and the reputations necessary to attract investors (Sorenson and Audia, 2000; Shane and Cable, 2002). In addition, employees of established firms often encounter unmet market opportunities and exciting technical possibilities in the course of their work. As laboratories for the observation of organizational practice and as developers of new technology, established high-technology firms thus provide a direct source of entrepreneurs (in addition to would-be employees), making areas in the vicinity of established enterprises fecund places for

new venture creation.[1] We predict: *the rate of founding of new high-technology companies rises in areas geographically proximate to established firms in a focal industry*.

In addition to a foundational idea, technological expertise, and a skilled labor supply, new technology-based startups require financial capital. Owing to the difficulty of evaluating early stage technology companies, the prohibitive cost of technology development, and the high chance of failure among technology-based startups, much of the funding for new, technology-based concerns comes from VC firms.

Though it might seem that investment capital should move easily across space, investors in early stage ventures often consider only geographically proximate opportunities. Venture investors actively monitor the firms in which they invest, and therefore insist upon close and frequent interactions with company leaders (Gompers, 1995). Venture capitalists also help portfolio companies recruit managers and customers, analyze markets, solve strategic, production, and organizational problems, identify new investors and strategic partners, and select lawyers, consultants, accountants and investment banks (Bygrave and Timmons, 1992). Because of the depth and intensity of the relationship between venture capitalists and the startups in which they invest, venture capitalists prefer to fund spatially proximate ventures (Sorenson and Stuart, 2001, present detailed evidence to this effect).

Venture capital firms also prefer to finance early stage companies when principals at the VC firm have pre-established, direct or indirect relationships with entrepreneurs (Sorenson and Stuart, 2001; Shane and

Cable, 2002; Shane and Stuart, 2002). The explanation for this pattern centers on the fact that the transactional risks imposed by information asymmetries between entrepreneurs and venture investors shrink when the financial investment takes place in the context of an embedded relationship between entrepreneur and investor. The presence of such a relationship may also provide an extra-contractual deterrent to opportunistic behavior when the financial contracts that govern the relationship do not deal with all possible contingencies that might arise. Again making the assumption that individuals' networks localize geographically, this argument—and the preference of VCs to invest in nearby companies—suggests that entrepreneurs may find it easier to secure funding for a new organization when they reside in the vicinity of venture capital firms. We anticipate: *the rate of founding of new high-technology companies is greatest in areas geographically close to VC firms*.

The role of entrepreneurs' networks in mobilizing resources offers only one of several possible reasons why proximity to technical experts, established firms, and venture investors accelerates new venture founding rates. Unfortunately, a retrospective, population-level study cannot identify the myriad relationships of previous company founders; indeed, even observing the connections of current-day entrepreneurs to all resource holders in a population-level study would not be possible. Therefore, we can only indirectly test how entrepreneurs' networks affect new venture formation.

Regardless, we believe that the hypothesis that the geographic distribution of network ties affects the spatial distribution of company formation implies a clear and unique expectation: the significance of geographic proximity to resource holders should wane as the industry evolves. This shift occurs because the geographic reach of individuals' networks expands over time as industry-centered conferences, industry associations, and the like facilitate the formation of ties among geographically disparate industry participants. Moreover, when an entirely new technological field emerges on the heels of a radical scientific advance, the pioneers of the technology typically reside at just a few firms or universities. Effectively, new scientific fields are for a time 'naturally excludable': they emerge from the labs of a few leading researchers, and proficiency in the new area requires the hands-on training from one of the technology's pioneers (Zucker

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[1] A great deal of case-based evidence suggests that many high-technology firms spawn from individuals who leave their current employers to establish new enterprises of the same type. For instance, Saxenian (1994) reports that former Raytheon employees started close to 150 companies. Similarly, she notes that virtually every Silicon Valley semiconductor firm began as an unofficial spin-off from a pre-existing chip producer. Phillips (2001) also finds that spin-offs account for most of the foundings in the population of Silicon Valley law firms. In the population of biotechnology firms, we identified 13 companies founded by former employees of Hybritech, a biotech firm located in San Diego. Haug's (1995) study of 33 Seattle area biotech firms similarly finds that employees of local biotech companies or members of Seattle area research institutions established all but four (12%) of the firms in his sample.

et al., 1998). As universities and firms invest in the new technology and as the scientific foundations and methods of production for a new area become incorporated in university curricula and corporate production processes, close proximity to the sources of technology may become less important and specialized labor should become less scarce. As researchers publish patent disclosures and academic papers, assemble at technical and investment conferences, join and found new firms and technology consulting companies, knowledge disseminates more widely (Almeida and Kogut, 1997; Zucker et al., 1998). With the growth of an industry and the emergence of events and organizations that disseminate information, knowledge of technical developments and job and market opportunities diffuse more broadly. We expect: *the effect of being near to resource holders on the rate of founding of new high-technology companies declines as the focal industry matures*.[2]

3. Local competition and the performance of new ventures

Our central assertion to this point is that the uncertainty regarding new venture success coupled with the spatial concentration of social and professional relationships debilitates the resource mobilization process in geographic areas scarce in the essential production inputs (capital, labor, and technology). We now shift our attention to consider how the spatial distribution of resources affects the performance of early stage ventures. We believe that the factors that promote new venture formation differ from those that enhance the post-entry performance of early stage companies. In particular, we argue that new ventures in geographically crowded areas, though benefiting from proximity to technical experts, suffer from the

competition generated by a heavy concentration of nearby competitors. Stated differently, we hypothesize that negative ecological externalities arising from intense competition among spatially proximate firms may unavoidably follow fecund founding conditions (Baum and Haveman, 1997).

Beginning with the positive dimension of geographic concentration, we expect that high-technology startups located near to many technical experts may perform well. First, engineers and scientists likely have extensive professional contacts when located close to many experts in their area of specialty. Presumably, they can leverage these contacts to obtain quick resolutions to specific technical dilemmas. To succeed, high-technology startups must also recruit individuals with strong technical skills. The presence of a large number of technologists in the vicinity of a firm surely facilitates the recruiting of key staff members and therefore benefits firms in areas with a rich supply of highly-skilled workers. For these reasons, we expect that *spatial proximity to scientific experts who work in the domain of high-technology startups improves new venture performance*.

Although proximity to technical experts will likely enhance firm performance, we expect that locating in a geographic area crowded with many competing firms adversely impacts startups. Despite the fact that high-technology firms typically face national or global product markets, firms will likely compete intensely at the local level for at least one of the key inputs to production: labor. It is widely understood that firms of like kind occupy structurally equivalent positions in buyer–supplier networks[3] (McPherson, 1983; Podolny et al., 1996; Sorenson and Audia, 2000), implying among other things that firms in the same industry segment demand similar types of skilled (technical and managerial) labor. This in turn implies high, local competition for one of the most important production inputs in knowledge-based industries, particularly if one assumes that the high transaction costs associated

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[2] In a study of geographic patterns of affiliation between academic scientists and biotechnology companies, Audretsch and Stephan (1996) develop a very similar prediction at the level of the individual scientist. This paper finds that older scientists and star scientists are much more likely than young scientists to have a formal affiliation (e.g. membership on the scientific advisory board) with a geographically distant biotech company. They ascribe this finding to the greater reach of the networks of established scientists, and thus their argument directly parallels our hypothesis that resource proximity effects will diminish over time as networks in the industry extend in reach.

[3] In the social networks literature, two actors are structurally equivalent in a network of relations when they have identical ties to identical actors. The concept has been generalized to operationalize organizational niches in networks of inter-firm transactions, and it has been extended in this context to refer to a situation in which two firms interact with the same *type* of alters, in addition to the exact same alters (see DiMaggio, 1986; Burt, 1992; Podolny et al., 1996).

with relocation preclude the rapid equilibration of labor supply and demand in professional labor markets.

This position stands in direct opposition to the claim of some researchers that open labor markets and rampant inter-firm mobility represent a distinctive advantage that accrues to firms in regional technology clusters (Angel, 1991; Scott and Storper, 1987; Saxenian, 1994). According to this work, recruiting managers and technologists from competitors benefits firms, because it enables them to integrate technologies and competencies imported with these itinerant workers (Baty et al., 1971; Granovetter, 1974; Aldrich and Pfeffer, 1976). Yet, in addition to the wage inflation generated by heavy competition for local labor and the fact that firms will lose technology from the mobility of their staff as often as they gain it from a competitor, open labor markets and very high rates of inter-firm mobility may also lead enterprises in a region to converge around particular technologies and strategies. Recruitment from the same managerial and technical pool can lead to a reduction in strategic diversity among the firms in a technology cluster. For example, Boeker (1997) found that recruiting a manager from a firm with a particular product portfolio increased the likelihood that the destination firm would enter the markets occupied by the firm from which the manager originated (Rao and Drazin, 2002, present similar evidence from the mutual fund industry). As a result of the strategic convergence and implicit competition created by sharing the same labor pool, Sørensen (1999) has demonstrated that organizational growth suffers when firms recruit managers from the same set of organizations.[4] Particularly when holding constant the overall supply of skilled labor in the vicinity of a focal firm—so as not to confound inter-firm mobility rates and the size of the supply of skilled labor—we anticipate that *spatial proximity to competing firms detracts from new venture performance*.

Lastly, we argue that locating in a region with many VC firms may also hinder new venture performance. We anticipate that the optimal situation for a given firm

is to receive venture financing, yet do so while locating in a region that contains few providers of VC. Venture capital firms, although obviously not direct competitors of high-technology startups, can adversely affect the performance of new ventures in two ways. First, VCs may recruit important managers and technologists away from a focal organization for the purpose of creating a new firm. Of course, encouraging workers to leave their employers to establish new companies need not be predatory; a significant pool of VC in a region presents a temptation for highly-skilled staff (potential entrepreneurs), who will find it easier to leave their current employers to start new companies. At a minimum, the departure of key managers and research personnel will delay technology development at a firm. These departures may also lead to the formation of new companies that compete directly with a focal organization in the technological areas in which it specializes. Second, VC firms can undermine the performance of established firms by providing funding to their competitors. To the extent that venture capitalists prefer to fund companies located near to them (cf. Sorenson and Stuart, 2001), then proximity to many VCs implies that a focal organization may compete against well-financed rivals in local factor markets. Particularly when taking the funding status of a focal organization into account, we predict that "spatial proximity to VC firms detracts from new venture performance".

In summary, we hypothesize that proximity to many of the resources anticipated to promote new venture creation in fact detracts from the performance of newly formed companies. The exception to this is proximity to technical experts, which we suspect will benefit startups.

4. Context and spatial measures

To test our ideas, we have gathered data on all US VC firms, all US biotechnology firms, all US research universities, and all US biotechnology patents. Thus, we situate our analyses of the effects of spatial proximity to resources on organizational creation and performance in the biotechnology industry. We selected the biotechnology industry to study because of its (relative) newness. Recentness concerns us because we need to trace important events back to the origin of the industry to avoid bias associated with left censoring. The analyses investigate location-specific founding

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[4] This implies that, even with geographically dispersed markets for technological end products, firms in dense industrial clusters still may experience more intense competition in *both* labor and product markets. The former occurs because they compete for the same local labor supply and the latter results from the strategic convergence that follows from the high rates of inter-firm personnel mobility and demographic similarity.

rates in the population of dedicated biotechnology firms (DBFs)—organizations founded to research, develop, and commercialize biotechnologies—and the impact of location on the early-life performance of a subset of the population.

As the three central biotechnology production inputs, we have argued that the proximity of a geographic region to experts in biotechnology, established biotechnology firms, and VC firms should affect founding rates in that region and the performance of startups in the region. We have identified technical experts in two ways. First, we have measured the continuous distance of each focal area (and each established firm) to universities with departments in biotech-relevant disciplines, including biochemistry, cellular and molecular biology, and microbiology. Second, we have identified approximately 30,000 biotechnology patents developed in the United States (filed between the early 1970s and the middle 1990s). These data come from the Micropatent Patent Abstract CD series, which contains basic information on all US patents from the mid-1970s to mid-1990s. From a different data source (the Center for Regional Economic Issues at Case Western Reserve University), we obtained the address of the lead inventor listed on each of these patents, which enables us to determine the distance of physical areas and firms to the locations of all lead inventors of patented biotechnologies. As we discuss below, we continuously updated the proximity measures as new patents 'arrive'.

Next, we acquired data on the locations of VC firms from the Securities Data Corporation's (SDC) New Ventures database. The SDC database covers the entire industry and reports the date when each VC organization began operations. It also includes the founding dates and locations of all VC firms.[5]

We acquired founding dates and the location of biotechnology firms from a number of sources. First, the SDC New Ventures database covers all venture-backed biotechnology firms. Much of the data on non-VC-backed firms came from Informagen, a biotechnology industry directory available on the

web (www.informagen.com). For additional information on the founding dates and locations of DBFs, we consulted the Bioscan and CorpTech directories, SEC filings, the Lexis/Nexis database, and Bioworld.

Because our analyses focus on the spatial determinants of firm foundings and performance, the reader may find it useful to have a sense of the geographic distribution of the biotechnology industry. Fig. 1a portrays the locations of all biotech firms established prior to 1983 and Fig. 1b illustrates the spatial configuration of the industry at the end of 1995. The figures demonstrate that the heaviest concentrations of biotechnology firms reside in the San Francisco Bay area, the greater San Diego area, and the eastern Seaboard, primarily in Massachusetts, New York, Pennsylvania and New Jersey. Only two of the contiguous states—Wyoming and West Virginia—had no biotechnology firms at the onset of 1996.

To test the effects on the location-specific founding rates and performance of biotechnology firms of being near to (1) other biotechnology companies; (2) the lead inventors of patented biotechnologies; (3) VC firms; and (4) universities with leading departments in the biological sciences, we constructed quarterly, distance-weighted measures of the local concentration of each of these four resource categories relative to every focal organization and geographic area. Because all measures follow the same method of construction, we limit our discussion of the computation to the creation of the 'patent concentration (PC)' variable—the measure of proximity to the lead inventors on biotechnology patents—with respect to focal biotech firms. We created this measure by weighting the contribution of each patent to each point in space by the inverse of the distance between the focal point in space and the lead inventor on the patent (see Sorenson and Audia, 2000, for more detail). We then summed these weighted contributions across all patents to yield a distance-weighted measure of the proximity of each point in space to all patent inventors. Suppose that a point in space corresponds to the location of a focal biotech firm, which we label i. The PC for biotech firm i at time t can be described by the equation:

$$PC_{it} = \Sigma_j \left\{ \frac{1}{[1 + d(ij)]} \right\} \tag{1}$$

where j indexes all patents that do not belong to organization i, and $d(ij)$ is the physical distance

Fig. 1. Distribution of biotechnology companies in (a) 1983 and (b) 1995.

between biotech firm i and the lead inventor on patent j.

To construct the data matrix to test our predictions, we repeat this process for each of the three other resource categories. Thus, in addition to patent inventors, the vector j in Eq. (1) indexes VC firms, universities, and other biotechnology firms. Eq. (1) thus yields the weighted distance of each point in space to the four categories of resources thought to influence biotech firm foundings and performance.

Because of the longitudinal nature of our analyses, we continuously update the weighted distance measures to account for entries and exits. For each of the resource categories, 'objects' (patents, firms, VC firms, and universities) enter the dataset when they 'arrive'.[6]

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[6] In the performance models, we update all covariates four times each year. In the founding rate models, we update the covariates once a year. Because we can only pinpoint many founding dates to the year, the latter models are annual.
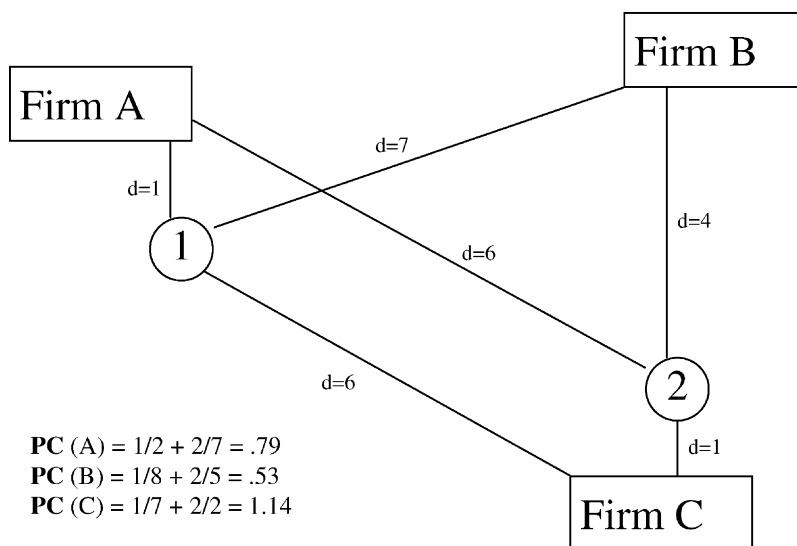
Fig. 2. Calculation of PC measures.

Universities create a complication here, because we cannot determine the entry date of universities into biotech-related scientific fields, we have chosen to code entry of universities into the dataset at the application date of the first biotechnology patent filed by the university.[7]

Fig. 2 demonstrates how we would construct the PC_{it} measure in a highly simplified scenario consisting of three organizations and three patents. One patent inventor resides at location 1 and two inventors reside at location 2. Consider firm A for the sake of illustration. Since firm A lies one unit distant from the patent at location 1, we increment its PC measure (PC_{At}) by 0.5 ($1/[1+1]$) for that patent. Firm A resides six units from the two patents at location 2, so we add 0.143

($1/[1+6]$) to PC_{At} for each of these patents. Thus, $PC_{At} = 1/2 + 2/7$, or 0.78. The same process can be used to calculate PCs for firm B (PC = 0.53) and firm C (PC = 1.14).

We calculate distance by representing objects in space according to their latitudes and longitudes. Biotechnology companies, lead inventors on patents, VC firms and universities can be linked (via zip codes) to latitude and longitude coordinates, available from the US Postal Service. We recorded the zip codes of all firms, universities, inventors, and VCs and the longitude and latitude coordinates for the center point of every zip code. Over small distances, Euclid's formula would yield accurate calculations of the distance between two locations; however, the curvature of the earth seriously affects these calculations over areas as large as the continental United States. Thus, we calculated distances using spherical geometry. The distance between two points, A and B, can be calculated by

$$d(A, B) = 687.56 \times \{arccos[\sin(\text{lat A}) \times \sin(\text{lat B}) + \cos(\text{lat A}) \times \cos(\text{lat B}) \times \cos(\Delta)]\} \quad (2)$$

where the units for latitude (lat) are measured in radians, and Δ is the absolute value of the difference between the longitude of A and the longitude of B in

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[7] We have experimented with several alternative options for measuring proximity to universities. For example, we estimated the models including just the 20 leading biotech research universities as identified in Zucker et al. (1998) (this list almost perfectly matches the list of the leading universities measured in terms of the number of biotech patents assigned to the university). We obtained weaker results using just the Zucker, Darby, and Brewer universities. As we discuss below, this might occur because we use a fixed effects estimator to model the data. The 20 leading universities specification contains no time varying component in the proximity-to-university covariate; thus, the fixed effects estimator has little power to identify the effect.

radians. The constant, 687.56, converts the distance into units of 5 miles.[8]

5. Methods and control variables

5.1. New venture creation

To investigate the new venture founding process, we analyzed the arrival rates of new biotechnology companies at the level of the zip code. The analysis of event counts has become the standard method for investigating founding rates in organizational sociology (Hannan and Freeman, 1989; Hannan and Carroll, 1992). Our analysis differs from others in that it allows for spatial heterogeneity in founding rates and does so at a very fine-grained level.

Most of the work on spatial heterogeneity in organizational founding and failure rates has used much larger regions, such as SMSA[9] or states, as the units of analysis (e.g. Carroll and Wade, 1991; Lomi, 1995; Zucker et al., 1998; Sorenson and Audia, 2000; for an exception, see Barnett and Sorenson, 2002). We have opted to use the smallest geographic units we can observe, zip codes, and to utilize continuous distances rather than binary density measures.[10] Looking at the spatial distribution of the firms in the industry (Fig. 1a and b), it seems clear that segmenting the population at city or state levels would result in highly arbitrary spatial boundaries, many of which would bisect technology clusters and yield inaccurate measures of the true levels of local resource concentrations. Defining density variables at the SMSA or state level creates a problem, because studies that have done this treat these units as self-contained populations. In these studies, density measures (such as firm density) have been incremented only for organizations inside the focal area (i.e. the density of object i in region j simply counts the number of i in each j). Local density counts ignore the presence of any objects that fall beyond the arbitrary geographic boundary, even if they lie very near to the borderline.

The weighted density measures employed in these analyses redress the problem of arbitrary boundaries. However, because of the computational intensity of the method for calculating inter-object distances, we cannot investigate entry rates in all zip codes in the country. Thus, in the founding rate models, we condition our analyses on the first arrival of a biotechnology company to a locale (i.e. we do not model the first founding of a biotechnology firm in a zip code; only subsequent founding events enter the analysis). In this sense, our models describe why some local areas gain additional firms while others do not, rather than why any particular zip code has a biotechnology firm (Barnett and Sorenson, 2002, adopt a similar approach in their study of Illinois banks); in other words, we examine the determinants of co-location of biotech firms.

With event count data such as organizational births, error distributions tend to be skewed, because zero bounds the lower end of the observed range. Researchers often estimate models on such data using Poisson regression. This procedure assumes that a Poisson process governs the occurrence of the observed events. Nevertheless, the Poisson process does not allow for unobserved heterogeneity (the independent variables must completely determine the rate) or variation in the base rate (King, 1989). Since we suspect that several factors that may influence the rate of founding do not appear in our models, Poisson regression does not seem appropriate for our data.

To cope with unobserved heterogeneity and time-dependence in the rate, researchers typically use negative binomial regression to analyze event counts. We employ a variant of the negative binomial estimator that accommodates interdependence among founding

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[8] The constant term we use implies that objects receive a weight of 0.5 when they lie 5 miles away from a focal point, and so on according to the concentration equation. The process of computing weighted distances consumes a great deal of time for a data matrix as large as ours, but we did recalculate all distance variables using 10-mile units (thus, an object 10 miles from a focal point receives a weight of 0.5). The bivariate correlations between 5- and 10-mile concentration measures all exceeded 0.985, and the results did not substantively change in models using 10-mile units.

[9] The US Office of Management and Budget defines and uses metropolitan statistical areas (MSA) and standard metropolitan statistical areas (SMSA) to report information on geographically contiguous regions. These regions typically include both a 'core' city as well as the suburbs and satellite communities that lay in close geographic proximity to the primary city; these regions presumably represent communities with a substantial degree of economic and social integration.

[10] On average, a zip code covers a considerably smaller geographic area than a MSA. In the data we analyze, the mean area of a zip code is 27.4 square miles (S.D. = 56.9 square miles). The mean area of an MSA is 10,515 square miles (S.D. = 154,443.1 square miles).

events that may arise because the data contain multiple observations within each geographic area. To account for the possibility that some unspecified factors, which vary systematically with location, may influence founding rates, we employ Hausman et al. (1984) fixed-effects version of the negative binomial model. This estimator conditions on the total number of events in a particular region. We report regressions that include the fixed effect at the state level.[11] States differ with respect to several of the institutional factors thought to influence entrepreneurial activity. First, corporate tax rates vary significantly across states. Second, the legality and the enforcement of non-compete contracts between employers and employees vary across states and may have a major impact on the propensity of would-be entrepreneurs to depart from established firms to begin new companies (Gilson, 1999; and see Stuart and Sorenson, 2002, for evidence). Hence, our models incorporate an implicit control for the total organizational fecundity of the state.

Finally, although we know the exact date of incorporation for a substantial number of biotechnology firms, we can identify only the year of founding for many of the firms in the population. As a result, we organize the data as annual panels of observations on the number of biotechnology foundings in each zip code (conditioned on there having been a previous biotechnology firm founding in the zip code), and we enter all covariates in the founding models as 1-year lags.

5.2. New venture performance

We follow a number of recent studies (e.g. Freeman, 1999; Stuart et al., 1999; Baron et al., 2001; Shane and Stuart, 2002) that examine the occurrence of an initial sale of securities on the public equity markets as a performance milestone for early stage technology companies. We have opted to analyze the hazard of IPO for two reasons. First, we can observe this metric for all firms in the sample. Alternative measures of organizational performance, such as accounting-based metrics and firm growth rates, would exclude the majority of firm-years in the dataset, because private companies

generally do not divulge this information. The second reason why we model IPOs is that it represents an extremely important milestone for high-technology firms in general, and biotechnology firms in particular. Biotechnology firms—especially companies developing human therapeutics—incur very high product development and commercialization costs. As a result, these firms depend critically upon the sale of equity to raise technology development funds.

To insure that the occurrence of an IPO provides a valid indicator of new venture performance, we have opted to limit the time-to-IPO analyses to the subset of firms that received venture financing. Three factors contributed to this decision, and in our view these considerations offset the disadvantage that limiting the performance analyses to VC funded companies reduces the generalizability of the results. First and foremost, we can be certain that all VC funded biotech companies aspire to go public. Although VC firms may vary in how quickly they push portfolio companies toward an IPO, VCs generally prefer a quick liquidity event so they can make cash distributions to the fund's investors (cf. Gompers and Lerner, 1999). Second, we possess information on the exact time of founding only for VC-backed firms. Third, VC-funded companies look more alike than the members of the biotechnology population as a whole. The population of biotech firms contains considerable diversity in the business models and market niches represented. Restricting the sample to VC-supported companies results in a substantial reduction in this heterogeneity. Since firm heterogeneity may affect the results, to the extent that differences in business models and market niches correlate with the weighted resource density measures, limiting this variance can dramatically improve the accuracy of estimation. Thus, the performance models only include venture-backed companies.

We estimate the transition to public status as an instantaneous hazard rate (Tuma and Hannan, 1984). The hazard rate $(h(t))$ is defined as follows:

$$h(t) = \lim_{\Delta t \to 0} \frac{P(\text{IPO between } t \text{ and } t + \Delta t | \text{private at } t)}{\Delta t}$$

(3)

where $P(.)$ is the probability of going public (an IPO) in the period running from t to $t + \Delta t$, conditional on the firm still being private at time t. To avoid mis-specification of age dependence, we employ

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[11] We also report the full model with the fixed effect included at the MSA level. We obtain very similar results using MSA-level fixed effects, but we concentrate on the state-level models, because 7.1% of the observations occur in zip codes that do not fall within any MSA.

a piece-wise specification following the procedure used in Barron et al. (1994). The piece-wise exponential model breaks time into several dummy variables representing mutually exclusive periods in the organization's life. Within each of these periods, the baseline rate does not change, but the rate varies freely across segments. This specification allows us to model age dependence without making strong assumptions regarding its functional form.

Our analysis covers the time period from 1 January 1978 to 31 December 1995. A relatively small number of biotechnology companies started before 1978, so we begin the analyses very shortly after the emergence of the industry. All covariates date back to the start of the industry, and we have no left-censored organizational or geographic histories.

The values for most of the covariates vary over the history of each organization. To account for this variation, we used 'spell-splitting', the standard procedure for incorporating time-varying covariates in event history analysis (Tuma and Hannan, 1984). We split organizational histories into quarter-year spells, which allowed us to update all covariates four times a year. The weighted density measures in the IPO models received quarterly updating using the same procedure as in the founding models. If the organization did not have an IPO prior to the end of a quarter, we coded its observation during that spell as right-censored. An IPO was an absorbing state in the performance analyses, so firms left the risk set at the time that they experienced IPOs.

5.3. Control variables

We controlled for three additional environmental characteristics that likely affect founding rates and firm performance. First, the analyses included an equity index representing changes in the valuation of public biotechnology stocks. The index, described by Lerner (1994), consists of equal dollar shares of thirteen publicly traded, DBFs. We included this variable because the ability of a company to go public and the incentive of entrepreneurs and VCs to start new firms may depend upon equity market conditions (Ritter, 1984). In the time-to-IPO models, the biotech equity index updates quarterly. In the founding models, the index enters as its average value during the lagged year.

We have also included in the models the national density of DBFs. We entered this variable to link the empirical analyses to the density dependent model of legitimation and competition, which has become the standard founding rate model in organizational analysis (Hannan and Carroll, 1992). We anticipate that density will have an inverted U-shaped effect on the rate of foundings and IPOs. The density dependence model predicts that rising legitimation increases the rates of founding and IPOs with initial increases in national biotech firm density, while the opposing force of competition will eventually decrease these rates as density continues to rise.

The human population of each zip code in 1990 also enters in the models. We included this variable because more populated areas contain a greater number of potential entrepreneurs and, in all likelihood, superior infrastructure for starting new companies. We also control for the age of the industry in each geographic area. This variable enters by itself and as an interaction term with the weighted density variables to determine if, as implied by the network-based account of new venture formation, the effects of proximity to resources become less important as the industry matures. To differentiate industry age from other developmental processes, we also include a control for the calendar year.

Finally, we included three firm-level control variables in the IPO models, each of which updated quarterly: a cumulating sum of the dollar amount of venture funding received by each firm; a time-changing count of the number of VC financing rounds experienced by each firm; and the number of patents granted to the firm, which also changes over time. Because all of the firms in the performance sample receive venture backing and all participate in the same industry, these three variables should control for quality differences between firms. Moreover, including all of these firm quality controls renders a more conservative test of the geographic proximity covariates.

6. Results

6.1. New venture creation

Table 1 reports means and standard deviations for the variables in the models. Table 2 presents the

Table 1
Descriptive statistics

Independent variables	Mean	S.D.	Minimum	Maximum
1990 zip code population (logged)	9.217	2.585	4.317	11.577
BT equity index	3.087	0.799	1.182	4.802
National BT density	828.772	354.665	35	1271
Total number of financing rounds	2.134	1.762	0	10
Total VC raised ($M)	8.984	13.570	0	123.937
BT firm concentration	21.239	17.794	1.168	111.092
BT patent concentration	343.316	285.779	1.207	1575.475
VC concentration	31.034	27.934	0.780	217.637
University concentration	1.926	2.561	0	16.704
Calendar year	16.325	4.232	5	22
Local industry age	7.005	4.767	1	35

Descriptive statistics from the founding rate dataset, with the exception of "total number of financing rounds" and "total VC raised". The latter two variables reflect their values in the time-to-IPO dataset.

fixed-effects negative binomial founding rate models. In the baseline model, the national biotech density variable depresses founding rates. We report specifications that include only a monotonic density effect, because adding the density-squared term did not improve model fit. In both the founding rate and time-to-IPO models, the national density effect is exclusively competitive. In the baseline model, neither the 1990 census population of the zip code nor the index of biotech equities had a statistically significant effect on the founding rate.

The age of the local biotech industry has a strong, positive effect in the baseline model. Two possible factors could explain this result. First, local industry age may proxy for the establishment of complementary businesses, such as specialized law firms and lab equipment suppliers that likely enter an area after biotech firms establish themselves, that could accelerate local founding rates. Second, local industry age may correlate positively with the size of biotech firms in a region. If larger firms produce more spin-offs, then industry age would have a positive effect on the founding rate (indeed, this variable continues to have a positive effect even after entering the weighted density of biotech firms).

We enter the local resource concentration variables separately in models 2–5. Proximity to the resource categories positively and significantly impacts founding in each of the four models; zip codes spatially proximate to other biotechnology firms (model 2), biotechnology patent inventors (model 3), VC firms

(model 4),[12] and leading universities (model 5) all experience accelerated founding rates.

Before discussing the full model, let us emphasize that our theory of the spatial determinants of new venture creation holds that resource mobilization involves leveraging relationships that we have assumed to be geographically concentrated. Unfortunately, we cannot directly measure the many ties between entrepreneurs (founders) and resource holders. We do, however, know the locations of all VC firms and all biotechnology startups. This permits us to be more specific about the extent to which funding relationships between VCs and startups localize geographically. With 399 venture-backed biotech startups and 1543 VC firms, we created a data set that consists of all potential VC firm-startup pairings (i.e. dyads consisting of each biotech startup paired with every VC firm). We then dummy coded all dyads by whether or not the VC firm in each pairing invested in the first-round funding of the biotech startup. A total of 1224 of these dyads were 'realized', meaning that the VC firm in the dyad participated in the target firm's first funding round. In the realized dyads, the 25th percentile of the distribution of distances between VC and biotech firms fell at 23 miles and the median

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[12] In the models in Table 2, we have computed the VC concentration variable using all VC firms. In unreported models, we computed the concentration variable by excluding all VC firms that had not made at least one previous investment in a biotech company. The two variables correlate very highly and the results do not change using the alternative specification.

Table 2
Fixed-effects negative binomial models of biotechnology company founding rates in zip codes, 1978–1996

Independent variables	Model						
	1	2	3	4	5	6	7
Biotech equity index	0.0563 (0.0630)	0.0679 (0.0628)	0.0656 (0.0631)	0.0624 (0.0630)	0.0456 (0.0630)	0.0576 (0.0624)	0.0348 (0.0662)
National BT density	−0.0032* (0.0016)	−0.0044** (0.0016)	−0.0040** (0.0016)	−0.0030 (0.0016)	−0.0027 (0.0017)	−0.0029 (0.0017)	−0.0040* (0.0018)
Population in 1990	0.0501 (0.0297)	0.0468 (0.0300)	0.0514 (0.0299)	0.0559 (0.0305)	0.0530 (0.0302)	0.0531 (0.0306)	0.0902* (0.0385)
Calendar year	0.1709 (0.1361)	0.1654 (0.1357)	0.1772 (0.1352)	0.1065 (0.1366)	0.1445 (0.1380)	0.0961 (0.1392)	0.1140 (0.1415)
Age of local BT industry	0.0693** (0.0087)	0.0620** (0.0086)	0.0658** (0.0087)	0.0654** (0.0086)	0.0453** (0.0127)	0.0457** (0.0128)	0.1000** (0.0152)
BT firm concentration		0.0225** (0.0029)				0.0289** (0.0048)	0.0377** (0.0068)
BT patent concentration			0.0008** (0.0002)	0.0115** (0.0020)			
VC concentration						0.0060** (0.0017)	0.0062* (0.0018)
University concentration					0.0610** (0.0233)	0.0442* (0.0223)	0.0790** (0.0262)
BT × age of local industry							−0.0005* (0.0002)
University × age of local industry							−0.0085** (0.0021)
Constant	−3.136** (0.9579)	−3.010** (0.9559)	−3.088** (0.9508)	−2.984** (0.962)	−3.034** (0.9708)	−2.892** (0.9734)	−2.222** (1.0469)
Fixed effects	State	State	State	State	State	State	State
log-likelihood	−1737.71	−1698.85	−1728.73	−1721.81	−1734.48	−1689.68	−1677.22
χ^2 (d.f.)		77.72 (1)	17.96 (1)	31.80 (1)	6.46 (1)	96.06 (4)	24.92 (2)

Observations on 6412 zip code years, 644 founding events. Models condition on one previous founding in a zip code.

at 304 miles. In contrast, the same descriptors of the distance distribution for the unrealized dyads were 356 miles (25th percentile) and 1057 miles (median). Thus, VC investments support to our assumption, localizing strongly in geographic space.[13]

Model 6 includes all four of the local concentration variables entered simultaneously. In this model, three of the four weighted density variables remain positive and statistically significant. The coefficient magnitudes indicate that proximity to other biotech firms has the strongest effect on the founding rate; a standard deviation increase in local firm concentration multiplies the founding rate by a factor of 1.67 ($\exp^{[0.0289 \times 17.79]}$). For comparison, a standard deviation increase in either the weighted VC or university density variables accelerates the founding rate by approximately 20%.[14]

Model 7 includes two interaction effects. One interacts the age of the local biotech industry and the weighted density of biotech firms. The second multiplies local industry age and the weighted density of

universities. We include these two interactions in the founding rate models to test the network-based theory of new venture formation. The prediction is that geographic proximity to resource holders will have the greatest impact on local founding rates in the early period of the industry when would-be entrepreneurs have few formal opportunities to meet members of the industry from geographically distant locales. We anticipate that the geographic effects will taper as industry participants establish trade associations, conferences and events that facilitate professional relationships between geographically disparate individuals.

Before reporting the findings, we first show that industry conferences and community-development organizations emerged gradually with the evolution of the organizational field. Table 3 reports the founding dates of many of the biotech industry's state and national trade associations, conferences for the scientific, business, and investment communities, government funding agencies, specialty consulting and law firms, and trade publications. The table illustrates that these social foci—work-related forums in which individuals in the industry convene to discuss ideas and further collective interests—developed in tandem with the industry. Technical specialists, experienced managers and consultants, and venture capitalists come into contact through the activities of these unifying events and organizations. We expect that a byproduct of the organizations and conferences in Table 3 is an expansion of the geographic reach of industry participants' professional contact networks, thereby reducing the impact of geography on population dynamics.

The results including the geography–age interactions appear in model 7 of Table 2.[15] The statistically significant and negative interaction effects on both

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[13] These differences are statistically significant. The geographic distance between realized and unrealized dyads becomes increasingly similar as we move beyond the median of the distributions of distances in the realized and unrealized dyads because of syndication: most VC investments include multiple VCs and often only the lead investor actively nurtures and monitors the startup. Syndication allows VC firms far from a focal venture to participate in that deal. If we could identify which of the VCs in a round led, we would almost surely find even stronger evidence of localization. We also estimated a probit model predicting the likelihood of a VC-startup investment as a function of physical proximity. This model included as covariates the distance between VC firms and startups and a count of the number of investments made by each VC firm in biotech startups. The latter variable controls for VC firm specialization, which may be correlated with location. The estimated coefficient for distance was negative, large, and highly significant ($P < 0.0001$). In short, geographic distance strongly influences the pairing of investors and new ventures (Sorenson and Stuart, 2001, present detailed evidence relating to geographic patterns in VC investing).

[14] Recall that the founding rate models condition on the first founding of a biotechnology firm in a focal zip code. Given the tacit nature of knowledge in biotechnology, the proximity to leading universities would likely have a stronger effect in models that do not condition on the existence of the first biotechnology firm, because academic researchers founded or transferred technology into many of the initial entrants into the industry (Audretsch and Stephan, 1996; Zucker et al., 1998). Unreported regressions confirm this speculation. In short, the way we created the sample attenuates the effect of proximity to universities on the founding rate.

[15] An identical pattern of results obtains if the overall age of the industry is used to create the interaction effects, rather than the age of the industry in a focal area. Conceptually, we prefer the latter specification. Using local industry age affords the possibility of a type of residual centrality effect: it allows for the (presumed) network effects to be stronger—and thus to more quickly dissipate the importance of local resource concentrations on local founding rates—in regions that entered the industry earlier. If one assumes random linkages within the industry-wide network of professional relationships and that some ties have durations of many years, then the individuals in the industry in older locales will on balance have more extensive networks than industry participants in recently formed agglomerations. These differences are assumed away when the interaction effects are specified with industry age.

Table 3

Date of establishment of biotechnology industry conferences and trade associations

Organizations and conferences	Founded
National- and state-level industry associations	
ASEE: Biomedical Engineering Division	1973
Industrial Biotech Association	1981
Massachusetts Biotechnology Council	1985
Pharma	1985
ASEE: Biological and Agricultural Engineering Division	1985
Association of Biotechnology Companies	1986
Georgia Biomedical Partnership	1989
Minnesota Biotechnology Association	1989
Washington Biotechnology and Biomedical Association	1989
The Chicago Biotech Network	1989
BIOCOM	1989
Connecticut United for Research Excellence	1990
Bay Area Bioscience Center	1990
New York Biotechnology Association	1991
Southern California BioMedical Council	1991
Biotechnology Industry Organization (BIO)	1993
Oregon Biosciences Association	1993
Arkansas Biotechnology Association	1994
Iowa Biotechnology Association	1994
Biotechnology Council of New Jersey	1994
Biotechnology Association of Maine	1996
Conferences: scientific	
The Asilomar Conference	1975
The Recombinant DNA Advisory Committee (RAC)	1987
International Genome Sequencing and Analysis Conference	1988
Conference on Research in Computational Molecular Biology (SKB sponsor)	1997
Conferences: business community	
ALLICENSE	1989
BIOCOM	1989
Ernst and Young/Oxford Ventures National Conference	1989
Recombinant Capital/Wilson Sonsini Goodrich and Rosati	1997
Conferences: investment community	
Annual Conference in Yeast Genetics and Molecular Biology	1971
The Hambrecht and Quist Investors Conference	1982
NationsBank/Montgomery Securities	1982
BancBoston/Robertson Stephens	1984
Gordon Conference 1984: Forefront Technology in Crop Protection/Productivity	1984
Pharma Tech (emerging technologies)	1989

Table 3 (*Continued*)

Organizations and conferences	Founded
Government-funded agencies	
Office of Medical Applications Research: OMAR (NIH)	1977
BERAC Report Recommends Creation of Genome CTRs	1987
DOE-NIH Collaboration	1987
National Human Genome Research Institute	1988
National Center for Biotechnology Information	1988
Establishment of Genome Research Centers	1989
Office of Recombinant DNA Activities	1990
Consulting firms	
Vitadata	1985
Recombinant Capital	1986
Synergistic Media Network	1988
BioScience Ventures	1991
Trade publications	
McGraw-Hill Biotechnology Watch	1982
Genetic Engineering News	1983
BioVenture View	1986
BioWorld	1989
Human Genome News	1989
Nature–Biotechnology (formerly Bio/Technology)	1990
Genomics Today	1996

variables indicate that local founding rates do indeed become less sensitive to the presence of spatially proximate firms and universities over time.[16] Although one could envision other social processes that lead to a decline over time in the influence of geographic proximity to resource categories on the local founding rate, we believe that the network-based explanation developed here is the most likely of the obvious candidates.

Finally, although we do not report the results, the coefficients in the regressions in Table 2 are consistently in the same direction and of similar

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[16] We do not run the industry age interaction with local VC density, because one explanation for why VCs invest in spatially proximate companies is that it is costly to monitor investments that are far away. Such costs obviously would not decline with industry age. Although Sorenson and Stuart (2001) present evidence that VCs extend the spatial reach of their investments when their networks expand, this effect proves to be contingent on the presence of syndicate partners nearby potential investment targets. As a result, we would not predict that the effect of local VC density would change over time, and unreported regressions support this view.

significance levels when the fixed effects are specified at the MSA (rather than state) level. Because slightly more than 7% of the zip code-year observations fall outside of the spatial boundaries of any MSA, these observations are lost when we include MSA-level intercepts. Given that the results are equivalent and we lose observations in the MSA-level regressions, we have opted not to report those results.

6.2. Time-to-IPO results

Table 4 reports the results from the IPO rate models. In the baseline model, the biotech equity index positively and strongly affects the rate of IPO. The total dollar amount of venture funding and the number of financing rounds also significantly increase the IPO rate, as does the number of patents assigned to the firm. The national density of biotechnology firms has a significant, negative effect on the rate.

Models 9–12 add the four local resource concentration variables. Among the four, only biotechnology inventor concentration has a statistically significant and positive effect (model 10), consistent with the notion that proximity to a highly-skilled technical workforce aids firm performance. Regardless, the geographic proximity effects appear more pronounced in the regression that includes all four weighted density variables together. In model 13, the local density of patent inventors remains positive and significant. The parameter estimate suggests that a standard deviation increase in a firm's proximity to biotech patent inventors raises the baseline IPO rate by a factor of 1.63 ($\exp^{[0.0017 \times 285.7]}$). In contrast, holding inventor concentration constant, firms located near to many competitors and those in the vicinity of many VC firms have lower predicted IPO rate multipliers. In the full model, the effect of proximity to universities with leading biotech-related departments does not differ significantly from zero.

Several factors might explain why proximity to biotechnology inventors enhances new venture performance. One possibility is that news of recent developments spreads through local networks, so that proximity to centers of innovation increases the likelihood of gaining early knowledge of technical developments. Also, dense local networks among technologists may facilitate the quick resolution of technical problems, as individuals embedded in these networks have many colleagues and friends who can contribute to the resolution of technical roadblocks (Saxenian, 1994; Liebeskind et al., 1996). Related to the two previous points, rumors concerning technical advances likely spread rapidly through dense, local networks. As ethnographic studies of the biotechnology industry suggest, rumors of advances at other research centers can prove highly motivating for an organization, particularly when they concern milestones at competing labs (Werth, 1994; Stuart, 1999, presents evidence from the chip industry).[17] This can accelerate the rate of technology development. Finally, spatial proximity to many biotechnology inventors suggests that a focal firm may have a large and diverse labor supply. Thus, firms residing near to many biotechnology patent holders probably find it easier and cheaper to build a strong technical staff.

Although proximity to biotechnology inventors positively affects performance, being close to many competing firms reduces the hazard of IPO. This finding coincides with those of other ecological studies that have empirically examined geographic competition (e.g. Baum and Mezias, 1992; Sorenson and Audia, 2000). In the models that do not control for the size of the local technical workforce, the negative impact of being close to competing biotech firms cannot be observed because of the correlation between firm and inventor concentration; however, after controlling for the local concentration of biotechnology inventors, proximity to firms appears to capture the intensity of local competition. Neighboring firms compete directly for two reasons. First, with the size of the technical labor force held constant, high firm concentration implies greater demand (and higher prices) for specialized labor with an adverse impact

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[17] One could draw a similar conclusion from studies of competition for priority in the sociology of science. Merton (1973, pp. 286–324) highlighted the motivating effect of concern about priority in discovery on scientists' productivity. A now classic illustration of the salience of priority concerns is Watson's (1968) chronicle of the discovery of the helical structure of DNA. When describing the year leading up to the discovery, Watson expressed concern that Linus Pauling would identify the structure of DNA before him. In their search, Watson and Crick were motivated not just by their belief in the scientific importance of the structure of DNA, but more immediately by rumors that Pauling was closing in on the structure. Werth (1994) provides a detailed history of priority contests in biotechnology (the commercialization of a family of immunosuppressive drugs).

Table 4
Piece-wise exponential estimates of time to public offering (IPO rates) in sample of VC-backed biotechnology companies, 1978–1996

Independent variables	Model						
	8	9	10	11	12	13	14
Age (year)							
0–3	−5.270** (0.5524)	−5.282** (0.5536)	−5.123** (0.5485)	−5.309** (0.5561)	−5.344** (0.5551)	−4.695** (0.5617)	−4.694** (0.5824)
3–7	−5.048** (0.5780)	−5.066** (0.5799)	−4.897** (0.5748)	−5.087** (0.5814)	−5.133** (0.5810)	−4.508** (0.5903)	−4.447** (0.6126)
7 or more	−5.687** (0.6153)	−5.720** (0.6207)	−5.489** (0.6127)	−5.714** (0.6172)	−5.759** (0.6174)	−5.185** (0.6276)	−5.109** (0.6523)
Biotech equity index	0.6261** (0.0691)	0.6254** (0.0692)	0.6364** (0.0693)	0.6284** (0.0692)	0.6268** (0.0692)	0.6387** (0.0695)	0.6405** (0.0697)
National BT density	−0.0077** (0.0027)	−0.0077** (0.0027)	−0.0076** (0.0027)	−0.0077** (0.0027)	−0.0076** (0.0027)	−0.0070** (0.0027)	−0.0069** (0.0027)
Calendar year	0.5621** (0.2364)	0.5648** (0.2367)	0.5040* (0.2352)	0.5604** (0.2366)	0.5654* (0.2364)	0.4219 (0.2330)	0.4173 (0.2322)
Local BT industry age	0.0473** (0.0172)	0.0506** (0.0188)	0.0408* (0.0172)	0.0461** (0.0172)	0.0350 (0.0192)	0.0591** (0.0224)	0.0472 (0.0270)
Total number of financing rounds	0.2311** (0.0383)	0.2319** (0.0383)	0.2384** (0.0387)	0.2318** (0.0383)	0.2364** (0.0385)	0.2532** (0.0390)	0.2541** (0.0392)
Total VC raised ($M)	0.0119** (0.0031)	0.0119** (0.0031)	0.0119** (0.0031)	0.0118** (0.0031)	0.0110** (0.0032)	0.0126** (0.0033)	0.0131** (0.0033)
Total number of firm patents					0.0181** (0.0019)	0.0188** (0.0020)	0.0189** (0.0020)
Total number of patents	0.0178** (0.0019)	0.0179** (0.0019)	0.0177** (0.0019)	0.0178** (0.0019)			
BT firm concentration		−0.0011 (0.0027)				−0.0075* (0.0036)	−0.0081* (0.0041)
BT patent concentration			0.0007** (0.0002)			0.0017** (0.0004)	0.0017** (0.0004)
VC concentration				0.0012 (0.0018)		−0.0081* (0.0034)	−0.0078* (0.0034)
University concentration					0.0327 (0.0228)	−0.0004 (0.0302)	−0.0233 (0.0507)
BT × age of local industry							0.0003 (0.0005)
University × age of local industry							0.0016 (0.0032)
log-likelihood	−687.02	−687.01	−682.55	−686.88	−686.13	−675.13	−674.45
χ^2 (d.f.)		0.02 (1)	8.92 (1)	0.28 (1)	1.78 (1)	23.78 (4)	1.36 (2)

6462 organization quarters, 199 IPOs.

on focal firm performance. Second, a certain degree of strategic convergence likely occurs in areas with a heavy concentration of structurally equivalent firms and rampant migration of personnel between firms (Boeker, 1997; Sørensen, 1999), suggesting that firms in technology clusters may also experience intense competition in factor and product markets.

Model 13 also shows that biotechnology startups located close to many VC firms experienced lower IPO rates relative to otherwise comparable firms. When interpreting this result, it is important to recall that the sample analyzed in the performance regressions consists exclusively of venture-backed companies. Because the models also control for the total amount of VC funds raised by the firms in the sample, the coefficient on the local density of VCs reflects the residual performance effects of being near to VC firms (i.e. it omits the potentially countervailing influence of local density of VC firms on the amount of VC support that the firms in the sample received in the first place).[18] With this caveat in mind, we believe that the negative effect of proximity to venture capitalist firms reflects the consequences of a relatively high availability of funding for an organization's nearby, privately-held competitors. In addition, the weighted VC density variable likely covaries with the attractiveness of the opportunities for a firm's key managers and technologists to leave their current employers to start a new company.

The last regression we report in Table 4 parallels the final model in the founding rate analysis: we include interactions between the age of the local biotech industry and the local concentration of biotechnology firms, and between age and university concentration. In model 14, neither of these interaction effects reaches the level of statistical significance. The insignificant coefficients on these interaction effects lends further credence to the view that different processes underlie high local founding rates and strong early-life performance—the explanation for why resource proximities impact new venture creation relates to the spatial concentration of relationships;

by contrast, the weighted density variables in the performance models relate to the spatial ecology of competitors. The explanation for the spatial effects pertaining to new venture creation loses force as networks among industry participants expand nationally, while the ecological rationales for spatial effects in the new venture performance should be, and is, unaffected by time. The strong interaction effects in the founding models and the null results in the performance regressions therefore fit the theory.

Because we know the locations of universities, VC firms, biotechnology firms and patent inventors, the models of the determinants of new venture founding rates and early-life performance allow us to identify the areas of the country most likely to spawn new biotechnology ventures and the areas in which startups will likely perform best. From the model 6 estimates, one would expect zip code 02154, on route 128 north of Boston, not far from Harvard, MIT and Mass General, to be the most fecund area of the country for new biotechnology foundings. Palo Alto (94303)—the home of Stanford University and near to the headquarters of Genentech, one of the biotechnology industry pioneers and also the source of a number of spin-off companies came in as a close second.

By contrast, the performance models predict that the Bay area offers the worst location for new venture performance (conditional on the covariates in the regressions, VC-backed startups in Palo Alto have the lowest predicted IPO rates of all VC-funded firms in the sample). The estimates from Table 4 (model 14) suggest that firms should perform best in the tri-state area, where New Jersey, Pennsylvania, and New York come together. The advantage of the tri-state area stems from the fact that it lies at the center of the pharmaceutical cluster in the US; among many other companies, Merck, Johnson and Johnson, American Home Products, Pfizer, and Bristol–Meyers all reside in this area. As a result, the tri-state area has a large pool of technically skilled workers. Perhaps of even greater importance, this area offers an ample supply of seasoned executives (individuals with years of leadership experience in pharmaceutical companies) that could be recruited into the senior ranks of startup biotech companies. At the same time, the tri-state area does not contain that many rival biotechnology firms. The details of the predicted rates aside, the fundamental point is that our findings suggest that

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[18] It is almost certainly the case that the firms in the performance sample had a better chance of receiving venture funding—and thus meeting the screen that determined entry into the sample—because of their proximity to venture capital firms. The results must be interpreted cautiously because of sample selection.
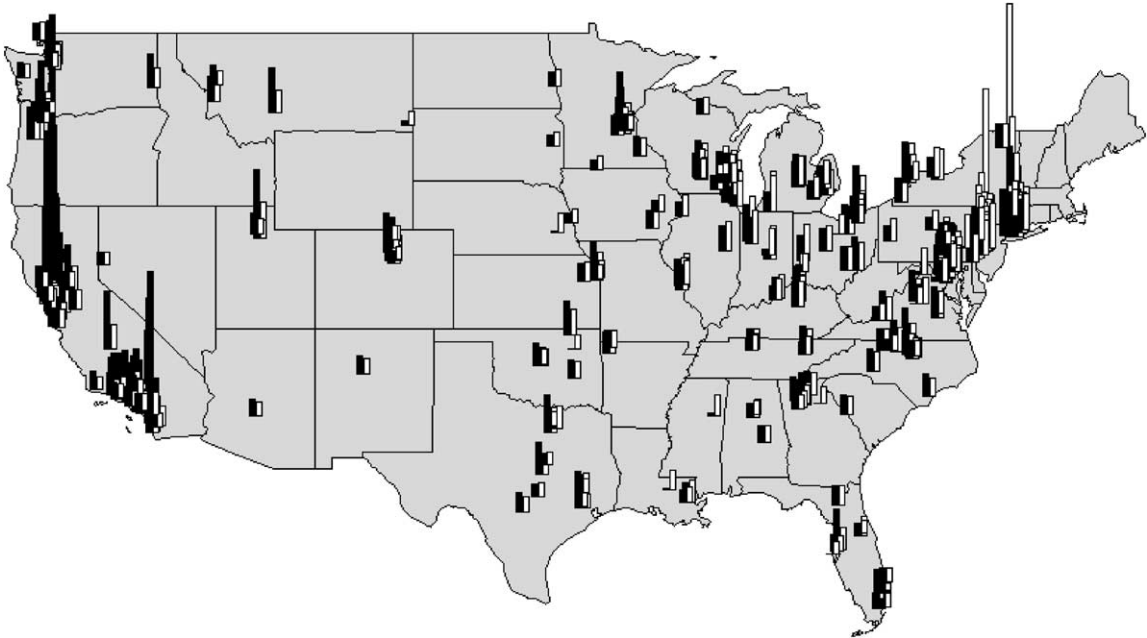
Fig. 3. Predicted entry (shaded) and IPO rates (unshaded) in 1995.

the regions in which entrepreneurs most frequently began new firms were not the ones in which newly created organizations performed exceptionally well. Taken together, these results draw into question the argument that agglomeration economies drive the location of technology-based entrepreneurship.[19]

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[19] One might counter that sample selection explains the founding rate/performance contradiction. The selection explanation contends that because starting a biotech firm in resource-rich geographies is cheaper, these areas require entrepreneurs to pass a lower quality threshold; thus, performance should be lower. For example, new companies not located in the vicinity of venture capital firms may need to be of higher quality to attract VC funding (because VC firms prefer to transact with companies nearby). Ideally, one would rule out this explanation by estimating two-stage performance models with a sample selection correction. Estimating the selection equation, however, requires knowledge of the risk set of all potential entrepreneurs in each zip code, which we do not possess. Instead, we performed analyses to determine whether the quality of the companies in the performance sample actually varied across geographies. We estimated a series of probit models to determine if the resource concentration variables predicted whether or not a biotech firm had a patent at various ages (3-month-old, 6-month-old, 1-year-old). We found no effect of any of the resource concentration variables on the likelihood of a patent, which we consider evidence that the quality of firms does not vary much across geographic areas.

To illustrate this point systematically, Fig. 3 presents a map of the US biotechnology industry at the end of 1995 (a reproduction of Fig. 1b). However, in Fig. 3 we weight each zip code by its predicted rate of IPO (the unshaded bars) and its rate of new venture creation (the shaded bars). Large bars represent high predicted rates; short bars indicate low predicted rates. The figure clearly shows that our models predict the highest founding rates in southern California, northern California, and Boston, while IPO rates peak in eastern Pennsylvania, New Jersey, and Maryland.

7. Discussion and conclusions

In a nutshell, we argue that the spatial distribution of relationships and resources limits potential entrepreneurs' ability to create new organizations. People almost always have more, more diverse, and stronger ties to contacts in the geographic region in which they reside. This suggests that the form of social capital most valuable in the resource mobilization process is to a large extent a geographically localized currency. If, as we believe, founders must leverage many strong and weak relationships to mobilize the

resources to create a new firm, then the local nature of social capital suggests that new ventures will more likely begin in regions that offer ample supplies of the necessary resources. Although relationships exist virtually everywhere in space, specialized resources such as technical experts and VC firms do not. Thus, regions with dense resource concentrations afford the greatest opportunities for would-be entrepreneurs to mobilize the necessary inputs to establish a high-technology venture. For this reason, we conclude that opportunities to create new firms vary across space.

Viewed as a whole, our results show that areas with large populations of biotech and VC firms do enjoy a 'regional advantage'; such areas experience the highest rates of biotechnology entrepreneurship. Although we do not possess data to confirm this, these areas also quite likely attract specialized service providers, such as biotechnology consultancies and patent law firms, and suppliers of industry-specific goods, such as reagents and biological materials. In fact, the positive effect of local industry age in both the founding rate and new venture performance regressions may occur for this reason. Thus, the emergence of ancillary industries provides an additional boost to the regional economies of areas with a high concentration of technology firms. Nevertheless, the findings in the IPO rate models suggest that this regional advantage belies a firm-level disadvantage; (venture-backed); startups in close proximity to dense clusters of structurally equivalent high-technology firms perform worse than otherwise comparable organizations in less concentrated areas. To be clear, however, the results do not suggest that remote areas offer the best locations for new biotech startups. Biotech firms depend upon a highly educated workforce with industry-specific experience that is difficult to find in remote areas. According to our results, the most advantageous locations for new biotech firms provide access to an extensive technical workforce, but do not present intense local competition from nearby biotech firms. The results do, however, suggest that the interests of entrepreneurs may not align with those of regional planners hoping to develop high-technology districts.

Before concluding, we wish to highlight a limitation of the paper and a few extensions to the reported analyses. The salient shortcoming of this endeavor is our inability to generate direct measures of the network positions of potential entrepreneurs 'at risk' of establishing biotechnology companies. The ideal situation would be to know who every potential entrepreneur is, whom they know, when they met those people, and how the strength of their relationships changed over time. Unfortunately, one can probably only collect such data prospectively with any accuracy (and even then it would be a monumental undertaking to identify all potential entrepreneurs in an industry). The founding rate analysis therefore rests on the assumption of a correlation between the physical location of the holders of knowledge-based and financial resources and the spatial concentration of the professional relationships in which resource holders are embedded. It also depends on the assumption that social capital is a necessary impetus to the resource mobilization process in technology-based, resource-intensive new venture formation. Although a wealth of anecdotal data and some systematic evidence support both assumptions, we would be the first to acknowledge that ruling out alternative mechanisms that might yield the effects observed in the founding rate analysis would require more direct measures of founders' networks. In this regard, the waning effect of resource proximities in the founding rate models as the industry matures encourages us, but we still fall short of being able to claim that the findings definitively support the importance of social networks.

Finally, we wish to discuss some extensions of the reported analyses and a few theoretical implications of our findings. First, we tested for the presence of two interaction effects not reported or discussed above. In the founding rate models, we observed a large, statistically significant, negative interaction between the local concentrations of universities and of biotechnology firms. This result suggests that the faculties of leading universities in the biotech-related sciences establish more new biotechnology firms when only a few biotech companies operate in the immediate vicinity of their universities. Perhaps the negative interaction occurs because leading academic scientists find it less tempting to create their own firms when they can establish lucrative consulting contracts with local firms, when they are able to join the scientific advisory boards of nearby firms, and when they can conveniently choose to work in the industry on a part-time basis.

In the performance models, we found a large, statistically significant, and positive interaction between

the total dollars of VC funding received by a focal organization in private financing rounds and local biotechnology firm concentration. When coupled with the negative main effect of local firm concentration, the interaction suggests that the competitive effect of being located in a densely populated biotechnology cluster impacts poorly funded startups most strongly. The coefficient estimates suggest that the negative effect of local biotech firm concentration disappears above the 90th percentile of the total cash raised distribution. We believe that the most cogent explanation for this interaction effect is that well-funded firms can recruit top talent away from nearby competitors, perhaps because they have the resources to pay higher salaries and because they anticipate successful IPOs. Thus, the effect of being close to many structurally equivalent firms depends on the financial strength of the focal firm; local competition has the severest consequences for poorly financed startups.

The findings this paper demonstrate will hopefully convince readers of the utility of a sociological perspective on the location of high-technology entrepreneurship in particular and industrial activity in general. We believe that the relational intensity of the new venture creation stands as a compelling explanation for the strong effect of the spatial distribution of resources on the location of new ventures. Despite the apparent ability to transport the ethereal resources necessary for entrepreneurial activity in high-technology markets, spatial propinquity greatly facilitates the formation of the social, employment, and interorganizational relationships necessary to erect new organizations. Given the importance of social and professional relationships in technology-based entrepreneurship, sociology would appear to have ample opportunity to make a strong contribution to the study of high-technology entrepreneurship.

Acknowledgements

References

Aldrich, H.E., Pfeffer, J., 1976. Environments and organizations. Annual Review of Sociology 2, 79–105.

Aldrich, H.E., Wiedenmayer, G., 1993. From traits to rates: an ecological perspective on organizational foundings. Advances in Entrepreneurship, Firm Emergence, and Growth 1, 145–195.

Almeida, P., Kogut, B., 1997. The exploration of technological diversity and the geographic localization of innovation. Small Business Economics 9, 21–31.

Angel, D.P., 1991. High-technology agglomeration and the labor market: the case of Silicon Valley. Environment and Planning A 23, 1501–1516.

Arthur, B., 1990. Positive feedback in the economy. Scientific American. February 92–99.

Audretsch, D.B., Stephan, P.E., 1996. Company–scientist locational links: the case of biotechnology. American Economic Review 86, 641–652.

Barnett, W.P., Sorenson, O., 2002. The red queen in organizational creation and development. Industrial and Corporate Change 11, 289–325.

Baron, J.N., Hannan, M.T., Burton, M.D., 1996. The road taken: origins and early evolution of employment systems in emerging companies. Industrial and Corporate Change 5, 503–536.

Baron, J.N., Hannan, M.T., Burton, M.D., 2001. Labor pains: organizational change and employee turnover in young, high-tech firms. American Journal of Sociology 106, 960–1012.

Barron, D.N., West, E., Michael, T.H., 1994. A time to grow and a time to die: growth and mortality of credit unions in New York, 1914–1990. American Journal of Sociology 100, 381–422.

Baty, G.B., Evan, W.M., Rothermel, T.W., 1971. Personnel flows as interorganizational relations. Administrative Science Quarterly 16, 430–443.

Baum, J.A.C., Mezias, S.J., 1992. Localized competition and organizational failure in the Manhattan hotel industry, 1898–1990. Administrative Science Quarterly 37, 580–603.

Baum, J.A.C., Haveman, H.A., 1997. Love thy neighbor? Differentiation and agglomeration in the Manhattan hotel industry, 1898–1990. Administrative Science Quarterly 42, 304–338.

Blau, P., 1977. Inequality and Heterogeneity. Free Press, New York.

Boeker, W., 1997. Executive migration and strategic change: the effect of top manager movement on product-market entry. Administrative Science Quarterly 42, 213–236.

Bossard, J.S., 1932. Residential propinquity as a factor in marriage selection. American Journal of Sociology 38, 219–224.

Burt, R.S., 1992. Structural Holes: The Social Structure of Competition. Harvard University Press, Cambridge, MA.

Bygrave, W.D., Timmons, J.A., 1992. Venture Capital at the Crossroads. Harvard Business School Press, Boston.

Carroll, G.R., Wade, J., 1991. Density dependence in the organizational evolution of the American brewing industry across different levels of analysis. Social Science Research 20, 217–302.

DiMaggio, P., 1986. Structural analysis of organizational fields: a blockmodel approach. In: Staw, B.M., Cummings, L.L. (Eds.), Research in Organizational Behavior. JAI Press, Greenwich, CT, pp. 335–370.

Festinger, L., Schachter, S., Back, K.W., 1950. Social Pressure in Informal Groups. Harper & Row, New York.

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

Freeman, J., 1999. Venture capital as an economy of time. In: Leenders, R., Gabbay, S. (Eds.), Corporate Social Capital and Liability. Kluwer Academic Publishers, Boston, pp. 460–482.

Galbraith, C.S., 1985. High technology location and development: the case of Orange County. California Management Review 28, 99–109.

Gilson, R.J., 1999. The legal infrastructure of high technology industrial districts: Silicon Valley, Route 128, and covenants not to compete. New York University Law Review 74, 575–629.

Gompers, P.A., 1995. Optimal investment, monitoring, and the staging of venture capital. Journal of Finance 50, 1461–1489.

Gompers, P.A., Lerner, J., 1999. The Venture Capital Cycle. MIT Press, Cambridge, MA.

Granovetter, M.S., 1974. Getting a Job. Harvard University Press, Cambridge, MA.

Hannan, M.T., Freeman, J.H., 1989. Organizational Ecology. Harvard University Press, Cambridge, MA.

Hannan, M.T., Carroll, G.R., 1992. Dynamics of Organizational Populations. Oxford University Press, New York.

Haug, P., 1995. Formation of biotechnology firms in the greater Seattle region: an empirical investigation of entrepreneurial, financial, educational perspectives. Environment and Planning A 27, 249–267.

Hausman, J., Hall, B.H., Griliches, Z., 1984. Econometric models for count data with an application to the patents—R&D relationship. Econometrica 52, 909–938.

Hawley, A., 1986. Human Ecology. University of Chicago Press, Chicago.

Hedström, P., Sandell, R., Stern, C., 2000. Mesolevel networks and the diffusion of social movements: the case of the Swedish Social Democratic Party. American Journal of Sociology 106, 145–172.

Herrigel, G., 1983. Democracy at work: changing world markets and the future of labor unions. Industrial and Labor Relations Review 46, 742–744.

Jaffe, A., Trajtenberg, M., Henderson, R., 1993. Geographic localization of knowledge spillovers, as evidenced by patent citations. Quarterly Journal of Economics 108, 577–598.

King, G., 1989. Unifying Political Methodology: The Likelihood Theory of Statistical Inference. Cambridge University Press, Cambridge.

Kono, C., Palmer, D., Friedland, R., Zafonte, M., 1998. Lost in space: the geography of corporate interlocking directorates. American Journal of Sociology 103, 863–911.

Krugman, P., 1991. Increasing returns and economic geography. Journal of Political Economy 99, 483–499.

Lerner, J., 1994. Venture capitalists and the decision to go public. Journal of Financial Economics 35, 293–316.

Liebeskind, J.P., Oliver, A.L., Zucker, L., Brewer, M., 1996. Social networks, learning, and flexibility: sourcing scientific knowledge in new biotechnology firms. Organization Science 7, 428–443.

Lomi, A., 1995. The population ecology of organizational founding: location dependence and unobserved heterogeneity. Administrative Science Quarterly 40, 111–144.

Marshall, A., 1920. Principles of Economics, 7th ed. Macmillan, London.

McPherson, J.M., 1983. An ecology of affiliation. American Sociological Review 48, 519–532.

Merton, R.C., 1973. In: Storer, N.W. (Ed.), The Sociology of Science. University of Chicago Press, Chicago.

Meyer, J.W., Rowan, M., 1977. Institutionalized organizations: formal structures as myth and ceremony. American Journal of Sociology 83, 340–363.

OTA (Office of Technology Assessment), 1984. Technology, Innovation, and Regional Economic Development. USGPO, Washington, DC.

Park, R.E., 1926. The urban community as a spatial pattern and a moral order. In: Burgess, E.W. (Ed.), The Urban Community. University of Chicago Press, Chicago, IL, pp. 21–31.

Phillips, D.J., 2001. The parent-progeny transfer and organizational mortality: the case of Silicon Valley law firms, 1946–1996. Working Paper, University of Chicago.

Piore, M.L., Sabel, C.F., 1984. The Second Industrial Divide: Possibilities for Prosperity. Basic Books, New York.

Podolny, J.M., Stuart, T.E., Hannan, M.T., 1996. Networks, knowledge, and niches: competition in the worldwide semiconductor industry, 1984–1991. American Journal of Sociology 102, 659–689.

Portes, A., Sensenbrenner, J., 1993. Embeddedness and immigration: notes on the social determinants of economics action. American Journal of Sociology 98, 1320–1350.

Preer, R., 1992. The Emergence of Technopolis: Knowledge Intensive Technologies and Regional Development. Praeger, New York.

Rao, H., Drazin, R., 2002. Overcoming resource constraints on product innovation by recruiting talent from rivals: a study of the mutual fund industry, 1986–1994. Academy of Management Journal, June 2002, 45, 491–508.

Ritter, J.R., 1984. The hot issue market of 1980. Journal of Business 57, 215–240.

Saxenian, A., 1994. Regional Advantage: Culture and Competition in Silicon Valley and Route 128. Harvard University Press, Cambridge, MA.

Schumpeter, J.A., 1942. Capitalism, Socialism and Democracy. Harper & Row, New York.

Scott, A.J., Storper, M., 1987. High technology industry and regional development: a theoretical critique and reconstruction. International Social Science Journal 34, 215–232.

Shane, S., Cable, D., 2002. Social relationships and the financing of new ventures. Management Science 48, 364–381.

Shane, S., Stuart, T.E., 2002. Organizational endowments and the performance of university start-ups. Management Science 48, 154–170.

Sorenson, O., Audia, P.G., 2000. The social structure of entrepreneurial activity: geographic concentration of footwear production in the United States, 1940–1989. American Journal of Sociology 106, 424–462.

Sorenson, O., Stuart, T.E., 2001. Syndication networks and the spatial distribution of venture capital investments. American Journal of Sociology 106, 1546–1588.

Sørensen, J.B., 1999. Executive migration and interorganizational competition. Social Science Research 28, 289–315.

Stinchcombe, A.L., 1965. Social structure and organizations. In: March, J.G. (Ed.), Handbook of Organizations. Rand McNally, Chicago, pp. 142–193.

Stuart, T.E., 1999. A structural perspective on organizational innovation. Industrial and Corporate Change 8, 745–775.

Stuart, T.E., Sorenson, O., 2002. Liquidity events and the geographic distribution of organizational foundings. Mimeo, University of Chicago GSB.

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

Thornton, P.H., 1999. The sociology of entrepreneurship. Annual Review of Sociology 25, 19–46.

Tuma, N.B., Hannan, M.T., 1984. Social Dynamics: Models and Methods. Academic Press, Orlando, FL.

Watson, J.D., 1968. The Double Helix: A Personal Account of the Discovery of the Structure of DNA. Atheneum, New York.

Werth, B., 1994. The Billion-Dollar Molecule. Touchstone, New York.

Zimmer, C., Aldrich, H.E., 1987. Resource mobilization through ethnic networks: kinship and friendship ties of shopkeepers in England. Sociological Perspectives 30, 422–455.

Zipf, G.K., 1949. Human Behavior and the Principle of Least Effort. Addison-Wesley, Reading, MA.

Zucker, L.G., Darby, M.R., Brewer, M.B., 1998. Intellectual human capital and the birth of US biotechnology enterprises. American Economic Review 88, 290–306.