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The Evolution of Inventor Networks in the Silicon Valley and Boston Regions

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Abstract: While networks are widely thought to enhance regional innovative capability, there exist few longitudinal studies of their formation and evolution over time. Based on an analysis of all patenting inventors in the U.S. from 1975 to 2002, we observe dramatic aggregation of the regional inventor network in Silicon Valley around 1989. Based on network statistics, we argue that the sudden rise of giant networks in Silicon Valley can be understood as a phase transition during which small isolated networks form one giant component. By contrast, such a transition in Boston occurred much later and much less dramatically. We do not find convincing evidence that this marked difference between the two regions is due to regional differences in the propensity to collaborate or the involvement of universities in patenting. Interviews with key network players suggest that contingent labor mobility between established firms in Silicon Valley, in particular resulting from IBM's policy as a central player in patenting activity, promoted inter-organizational networking, leading to larger inventor networks.

1. Introduction

Knowledge production is a collective phenomenon and increasingly so (Guimera et al., 2005). In scientific knowledge production, for example, the share of papers coauthored by two or more scholars has risen from 10% at the start of the twentieth century to about 50% in the 1990s (Wagner-Doebler, 2001). Similarly, an increasing share of patents is authored by multiple inventors (Fleming et al., 2006). In both cases, the underlying phenomenon is one of increasing division of labor in the production of knowledge.

An interesting aspect of the collaborative nature of knowledge production is the increasing share of *inter-organizational collaborations*. For example, it has become increasingly common for employees from different companies to collaborate in knowledge production even though firms face the risk that commercially relevant knowledge leaks to other firms. Firms, though, recognize that the relevant community for their knowledge workers is not only, or even primarily, colleagues within the firm, but also their fellow researchers in specialized subdisciplines across different organizations. A related trend in collaborative knowledge production is the proliferation of university-industry collaborations. The societal functions traditionally “assigned” to industry (commercializing technology) and academia (producing scientific knowledge) have become blurred. Increasingly, both academia and firms have become engaged in profit-seeking activities, and both academia and firms are active in scientific research, both fundamental and applied (Rosenberg, 1990).

A second aspect of collaborative knowledge production is the role of geography or, more precisely, of *geographical proximity* in the establishment and endurance of research collaboration. In short, the probability of collaboration rapidly diminishes with geographical distance (Katz, 1994). One explanation for the existence of this “distance decay” holds that, even though communication can take place relatively easily at long distance, frequent face-to-face meetings are important in complex problem-solving activity. In R&D, the success of inter-organizational collaboration relies partly on complex formal contractual arrangements, partly on frequent face-to-face contacts, and partly on the exchange of personnel. These are facilitated when participants are geographically nearby and share an institutional environment.

A complementary explanation for increased inter-organizational collaboration is related to labor mobility (Almeida and Kogut, 1999; Breschi and Lissoni, 2003). On many occasions, collaborators from different organizations have shared the same organizational environment (a firm, a research institute, or a university) at a previous moment in time, for example, when researchers who had left an organization remained in contact with previous colleagues in their networks. Thereafter, they worked for different organizations but usually in the same region because labor mobility takes place primarily within regions rather than between regions.

From a scholarly point of view, the understanding of the evolution of inventor networks is both interesting and challenging. Particularly within the context of complexity theory and its applications to the static and dynamic analysis of networks, interest has been growing in explaining patterns of research collaboration (e.g., Newman, 2001, 2004; Barabasi et al., 2002). From a regional policy perspective, the understanding of the evolution of networks is also

important. Research networks are expected to be a crucial contributor to innovation and, therefore, to employment and economic growth.

A particularly illuminating case of collective knowledge production is the contrasting histories of Silicon Valley, which has witnessed dramatic growth in the last half century, and the Boston region, which has witnessed uneven growth. Saxenian (1994) argued that the different histories of the two regions can be explained, in part, by the differences in networking in the two regions. She proposed that the job hopping, interfirm relationships, and informal knowledge exchange prevalent in Silicon Valley gave it a decisive edge in competing against the more secretive and autarkic firms of Boston. This reasoning is in line with other research pointing to the importance of relaxed enforcement of legal proscription of noncompete covenants (Gilson, 1999) and increased labor mobility (Angel, 1989). However, these claims have not yet been scrutinized by extensive network analysis.

Our contribution consists of an attempt to understand some of the dynamics in regional innovator networks, making use of network analysis, in particular, to shed light on the surprisingly sudden emergence of a giant component in the Silicon Valley region. In the following we combine statistical network analysis of inventor network data taken from the U.S. Patent and Trademark Office (USPTO) with outcomes of interviews in some of the central nodes in the Silicon Valley and Boston networks. Our analysis shows that network analysis can bridge quantitative and qualitative methods, thus capitalizing on the comparative advantages of both types of research tools.

Our strategy will be inductive rather than deductive. We start by analyzing in Section 2 the phenomenon of the giant component emerging in Silicon Valley and only later, and on a smaller scale, in Boston. We then analyze in Section 3 whether differences between the two regions in terms of university research or the propensity to collaborate may explain the marked difference in network evolution (we find they do not). In Section 4 we turn to results from interviews with key network players in Silicon Valley and Boston, and, finally, in Section 5, we draw some conclusions.

2. Analysis of Coinventor Networks

We extracted source data on all U.S. patents granted from 1975 to 2002 inclusive from USPTO 2003 (see Fleming et al., 2006). The database includes 2,058,823 inventors and 2,862,967 patents. Every patent includes all inventors' last names (with varying degrees of first and middle names or initials), inventors' hometowns, detailed information about the patent's technology in subclass references (over 100,000 subclasses exist), and the owner or assignee of the patent (generally a firm, and less often a university, if not owned by the inventor).

As only patents are given a unique code and inventors are not, the problem is to clean the data for homonyms, as many inventors have the exact same name. Fleming et al. (2006) devised an inventor-matching algorithm to determine each inventor's patents and other inventors with whom the focal inventor had coauthored at least one patent. The matching algorithm refines previous approaches (Newman, 2001). If last names match, first initials and middle initials (if present) must then match. Whole first names and whole middle names (if present) are then compared. If

all comparisons are positive, the algorithm then requires one additional non-name similarity: home city and state, corporation (via assignee codes), or technology (via technology subclassifications). This creates the possibility that two inventors named Robert Smith in Boston might be assigned to the same person. To avoid such mistakes with common names, we stipulated that common names required two other field similarities (for example, home city and assignee) to match.

For 30 randomly selected inventors, the algorithm correctly assigned 215 of their 226 patents (as determined by resume searches and personal contact). The 11 incorrectly determined patents were assigned to four isolated nodes (that is, they did not create spurious cutpoints). Given the sensitivity of the measures to cutpoints, false negatives remain preferable to false positives or incorrectly matching two different inventors. There remains the possibility of two individuals with common names being falsely matched if they live in the same location. This would result in a false positive, though we did not observe any in our robustness test or interviews. To decrease false negatives, we implemented a common name parameter that ignored the additional match requirement if the last name applied to less than 0.05% of the U.S. population, as determined by the U.S. Census Bureau.

To construct inventor networks, we first have to define what constitutes a link between two inventors. A link exists if two inventors have coauthored any patent over a five-year moving window (alternative window sizes also demonstrated qualitatively similar dynamics). This relational definition results in many disconnected components the population of which generally demonstrates a skewed distribution, with most components of small size and fewer and fewer of larger sizes. We refer to the largest and right-most component of this distribution as the “largest component.”

We define a patent as being in a region if at least one inventor lives within that region, as determined by their hometown listed on the patent.¹ Hometowns are classified within metropolitan statistical areas (MSAs) by the U.S. Census Bureau (Ziplist5 MSA 2003). Though we found similar dynamics in all MSA regions, we focus on Silicon Valley and the Boston region for purposes of comparison.

Figure 1 illustrates the proportion of patenting inventors belonging to a region’s largest component. For example, if there were 10 inventors in a region and six of them coauthored any patents together in the prior five years such that they formed a network, then the proportion in that region would be 0.6. If four had coauthored patents and no other group of coauthors was bigger, then the proportion would be 0.4. Thus, if inventor A and B worked together on one patent and B and C on another, then A and C can trace an indirect co-authorship to each other and lie within the same component. The interesting feature of **Figure 1** is the sudden aggregation process in Silicon Valley that began in 1990 and culminated in almost 50% of the Valley’s inventors agglomerating into the largest component by 1998. Boston, by contrast, did not begin

¹ We included all inventors from patents that had at least one inventor from the region (with the exception of the inventor mobility data, which only considers inventors who live within each region). In essence, these analyses include inventors who live in the region and their collaborators who do not. Restriction of the analyses to inventors within MSA boundaries gave substantively similar results, though of course the graphs were smaller.

this process until 1995, and its largest component had only reached 25% of the region's inventors by 1998.

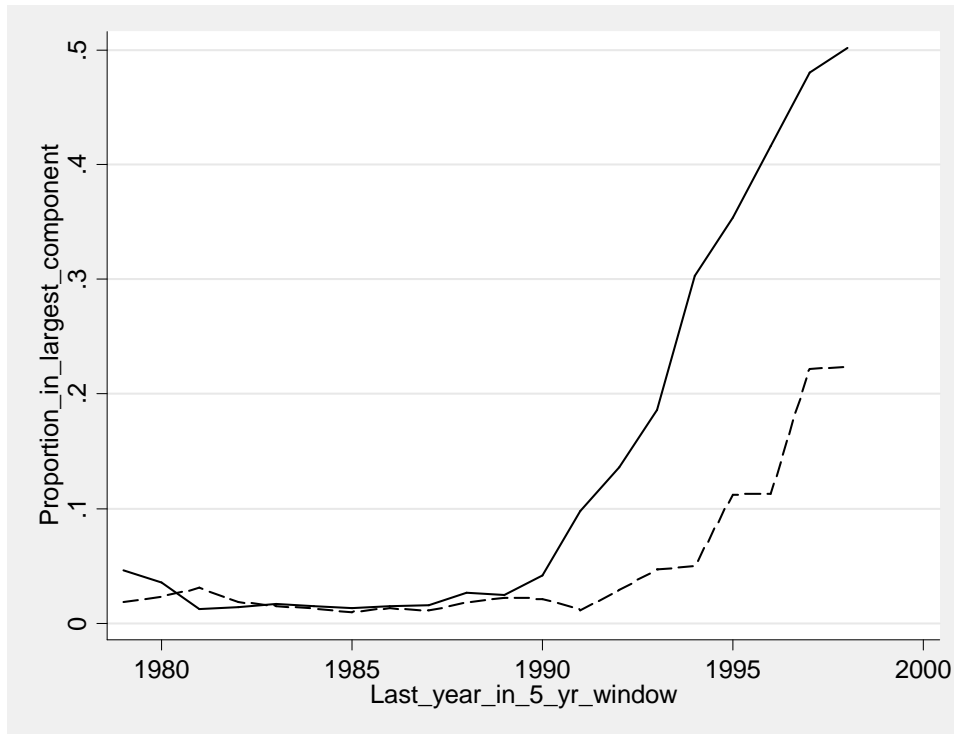


Figure 1: Proportional size of largest connected component to total number of inventors in Silicon Valley (solid line) and Boston (dotted line). The x axis indicates the last year in a five-year moving window.

Figure 2 illustrates how the largest component in Silicon Valley began to encompass an increasing number of smaller components around 1990. Up until 1990, the largest component in Boston absorbed a greater number of the previous year's components. After 1990, however, the Valley began to absorb a greater and greater number of components as it began a runaway process of aggregation. The sudden rise of giant networks in Silicon Valley can be understood as a phase transition during which small isolated networks form one giant component. By contrast, such a transition in Boston occurred much later and much less dramatically. To further support our reading, we also computed the ratio between the size of the first largest and the second largest component in **Figure 3**. One can observe the high ratio for Silicon Valley compared to Boston, which shows that the second largest component in Silicon Valley was more quickly absorbed into the first component than in Boston, which led the sizes of the first and second components to diverge more quickly in the Valley. **Figure 2** also reminds us of the many other unconnected components in each region; the largest component is only the far-right outlier of a highly skewed distribution of component sizes.

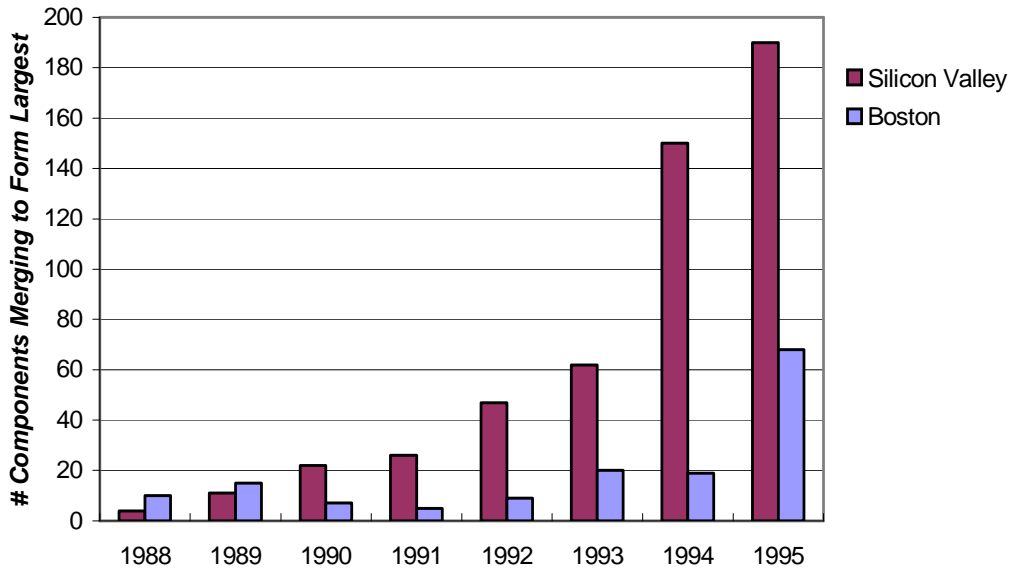


Figure 2: Illustration of how many components from the previous year merged into each year’s largest component. For example, in 1989, 13 components from Silicon Valley merged into the 1990 largest component, and 16 components from Boston merged into the 1990 largest component. The figure illustrates the runaway aggregation process that began in Silicon Valley in 1990.

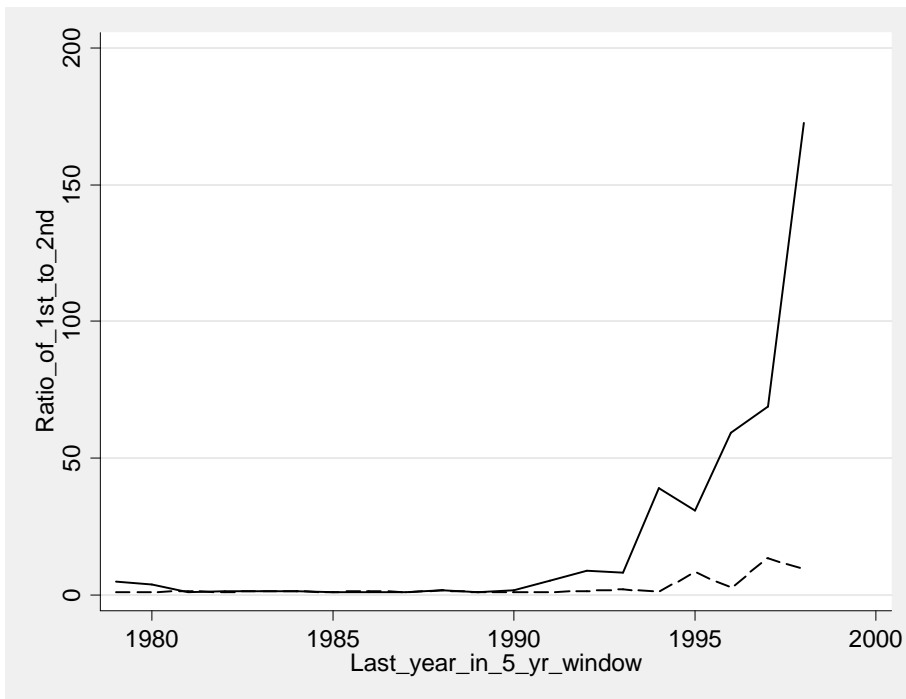


Figure 3: Ratio of the first largest component to the second largest component in Silicon Valley (solid line) and Boston (dotted line). The x axis indicates the last year in a five-year moving window. The spike in the Silicon Valley line illustrates how the Valley’s largest component reached a critical mass, such that it connected almost half the inventors in the Valley (as illustrated in Figure 1).

The rapid growth of the first component in Silicon Valley suggests that a different dynamic has been operating in Silicon Valley than in the Boston region. This dynamic may be partly responsible for the innovative success of the whole Silicon Valley region (as reflected in its higher growth in patenting than the Boston region). The growth of the largest component can be related to regional knowledge spillovers: larger networks provide more routes for knowledge to spill over between different firms. However, one should be careful about interpreting the size of the largest component as an indicator of the scope of knowledge spillovers, because a larger component may also imply a longer path between nodes in that component. The probability that knowledge is transmitted accurately quickly decays for longer paths (Cowan and Jonard, 2004; Singh, 2005). Interestingly, if we compare the average path length between any two inventors in Silicon Valley and in the Boston region (**Figure 4**), we find that, even though the largest component in Silicon Valley grew more rapidly, its average path length was roughly equal from the period 1991–1995 onwards. Thus, even though the first component grew much larger in Silicon Valley, this did not affect the social distance between inventors, and, indirectly, the probability of knowledge to spill over between any two people.

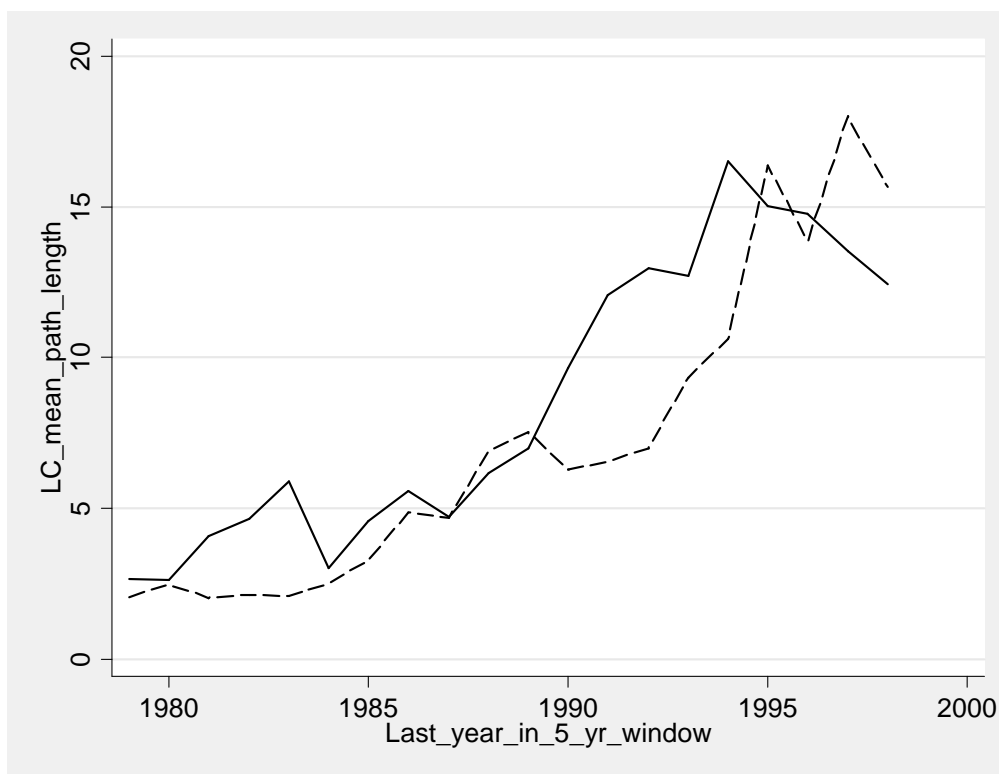


Figure 4: Mean path length for inventors to reach furthest node in Silicon Valley (solid line) and Boston (dotted line) largest component. The x axis indicates the last year in a five-year moving window.

Our interpretation of the evolution of the two networks, however, rests on the assumption that the network structures are robust, that is, rather insensitive to small changes in their nodes. To test the robustness of the network we chose to work with a two-mode network data representation (Wasserman and Faust, 1994). These data contain nodes representing both patents and inventors. The relation graphed is the authoring relationship, which means that inventors are tied to patents they have authored and tied to one another only indirectly through patents. Using these data we

examine the consequences for the connectivity of each component when individual patents are removed.

We focus on patents rather than inventors here because the inclusion of patents is more contingent than the inclusion of inventors. It also takes the strength of ties into account and enables a more nuanced comparison of the regions. Patents may fail to be included because the relevant innovation might fail to be invented. If researchers' undertakings are unsuccessful, then no patent will ever be filed. Since the invention process is highly contingent, one could easily imagine that any of the inventions currently included in the data might not have been successfully developed or, conversely, that unfruitful research conducted differently might have resulted in patents that never were. Although one could also easily imagine that particular inventors might fail to develop ideas successfully, their inclusion in the network is less contingent with a patent, rather than an inventor, analysis. Because most inventors are acting as employees of an organization, we can assume that even if a particular individual has chosen a different career path (and thus "never exists" as far as the network is concerned), the organization will still employ someone within that inventor's role and the alternative employee will have a similar pattern of inventions.

We limit our analyses to the six largest components from 1989, the key year immediately preceding the surge in connectivity in Silicon Valley. We chose 1990 because it is the first year of obvious divergence between the Valley and Boston (as revealed in **Figure 1**) and because the two regions were never close from this point onward. We chose the top six components because we observed the first, second, and sixth components in Silicon Valley agglomerating in that time frame into the following year's (1990) largest component. Since we did not observe *any* of the top six components merging in Boston, we chose these top six as a comparison set. For each of these components we examined the extent to which the component would be disconnected by the removal of each patent. We defined the extent to which a component was disconnected by the proportion of inventor dyads in that component that could no longer reach one another after the patent was removed. We found this measure by considering each of these components individually and then calculating for each patent:

$$\sum_{c=1}^K (n / N)^2$$

where n is the number of inventors in a component c existing after a patent is removed and N is the number of inventors in the original component, and K is the number of components in the post-removal network. This measure yields a high value when the removal of a patent results in the creation of many new components and the inventors are divided equally among components. For example, if the removal of a patent divides a component into 10 smaller components with a tenth of inventors in each component, this results in 90% of the dyads being disconnected. However, if the removal of a patent results in a similar number of components but with inventors less evenly spread among them, the value generated by this measure will be smaller. For example, given a component of 100 inventors, if the removal of a patent results in breaking the component into 10 components, with 9 of these being isolates and 91 inventors in the remaining component, 17.1% of the dyads are disconnected, indicating far less damage to the connectivity of the network. The maximum possible value would exist in a component where all inventors were

coauthors of one patent and no other co-authorships existed. In this case the removal of the one shared patent would result in the disconnection of all inventor dyads.

Component	Component Vulnerability	No. of Patents	Maximum
Boston 1st	.0212 (.0763)	208	.52
Boston 2nd	.0074 (.0231)	345	.20
Boston 3rd	.0301 (.0762)	123	.49
Boston 4th	.0179 (.0806)	182	.65
Boston 5th	.0226 (.0610)	116	.35
Boston 6th	.0451 (.0989)	45	.46
Silicon Valley 1st	.0311 (.0757)	159	.49
Silicon Valley 2nd	.0208 (.0552)	161	.45
Silicon Valley 3rd	.0209 (.0477)	107	.38
Silicon Valley 4th	.0330 (.0950)	131	.52
Silicon Valley 5th	.0338 (.0729)	60	.49
Silicon Valley 6th	.0237 (.0712)	78	.54

Table 1: Patent analysis of component robustness. Component vulnerability is the mean of the proportion of inventor dyads disconnected by the removal of each patent within a given component (higher values indicate more vulnerable components). Standard deviation is in parentheses.

We measure the vulnerability of each network by taking the mean proportion of inventor dyads disconnected by each patent. As stated earlier, the maximum value of this number is 1.0 for individual inventors; calculating the maximum value for the mean of patents in a component is considerably more complex and beyond the scope of this paper. However, since the maximum possible value will be related to the component size, caution should be exercised when comparing mean values across components of different sizes. **Table 1** illustrates robustness results. As the low numbers suggest, most patents within each component can do only minimal damage to the network. What is most striking is the lack of systematic difference across the two regions. The mean vulnerability over all the Boston components is 0.0241, and that over all Silicon Valley components 0.0272. The second component appears to be much more robust in Boston, relative to all other components—in both Boston and the Valley. This suggests that the Valley’s aggregation did not occur because its components were more robust and able to merge with other components.

Despite the similarities of robustness in the networks, these results suggest that different dynamics have been operating in the aggregation processes in Silicon Valley and Boston, since very similar starting points have resulted in very different sizes of the largest components. In particular, the mechanism at work in Silicon Valley has led to a continuous enlargement, with the largest component sucking in many components of all sizes in a number of successive years, whereas this mechanism did not occur in Boston until later, and then to a smaller extent..

3. Potential Explanatory Factors

To understand the different nature of the mechanisms at work in the two regions, we first compared Silicon Valley and Boston in terms of a number of general characteristics that could be expected to affect the degree of networking in the respective regions.

First, a potential factor affecting the emergence of large networks is the involvement of *universities*. Universities, compared to firms, have traditionally been less oriented towards profit making and thus less restricted in collaborating with other organizations. Regions with universities active in patenting may thus contribute to the emergence of large networks. In particular, in the case of the Silicon Valley phenomenon, the alleged exceptional role of Stanford in the commercialization of science is often mentioned as one of the driving forces of aggregation. **Figure 5** shows the number of university patents per region. It is clear that universities in the Boston area have been far more active in patenting during the whole period considered (though, it should be noted, Boston has more universities than Silicon Valley). Thus, the role of universities as an “open platform” for collaboration does not account for the Silicon Valley phenomenon, since the role of university research in patenting seems to be much more dominant in Boston than in Silicon Valley.²

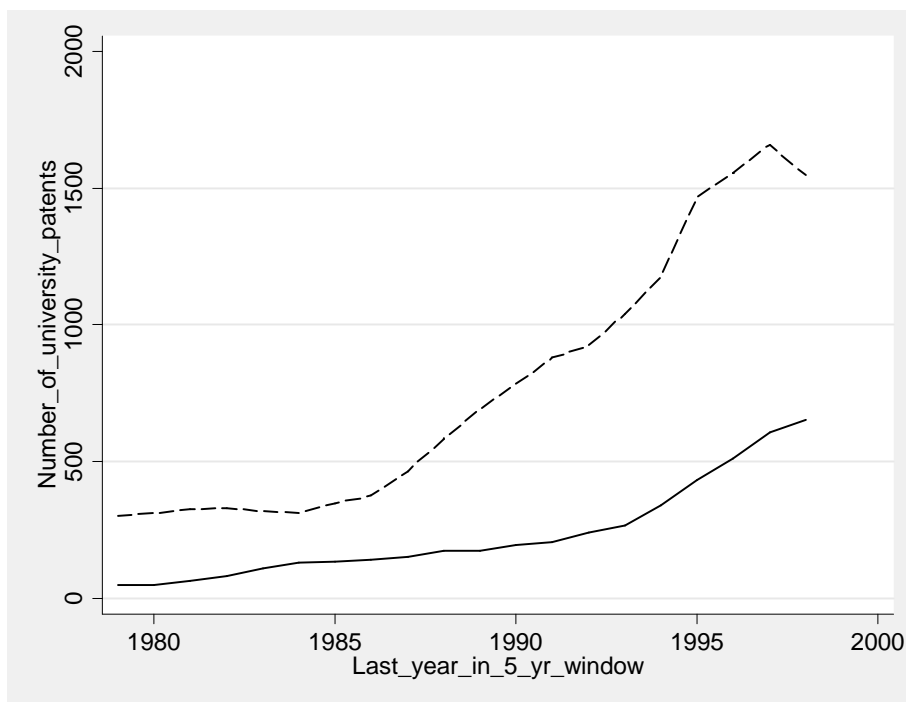


Figure 5: Number of patents assigned to universities in Silicon Valley (solid line) and Boston (dotted line). The x axis indicates the last year in a five-year moving window. The decline in the time series probably results from observation truncation.

Second, one may ask whether regional differences in the *propensity to collaborate* explain these different evolutionary paths. Obviously, if inventors in Silicon Valley started collaborating much more than inventors in Boston around the time the giant component emerged, this would render the emergence of a large component much more probable. **Figure 6** shows the average number of inventors per patent (or “patent degree”) for different regions. Two observations can be made. One can observe that the patents assigned to Silicon Valley indeed show a higher degree of collaboration compared to Boston. Yet, the difference is small and does not demonstrate an

² As noted by a reviewer, one may also interpret a greater involvement of universities as hampering inter-organizational networking, as private firms have less incentive to collaborate with universities.

abrupt transition around the time the giant component emerged. **Table 2**, which lists a variety of supporting statistics, also demonstrates that the Valley networks are slightly denser (that is, the number of actual ties divided by the number of possible ties between all the inventors in the region). While the Valley starts out more densely connected, its advantage falls steadily, such that Boston is denser by the end of the series. Hence, it does not appear that greater overall density can explain the aggregation in the 1990s.

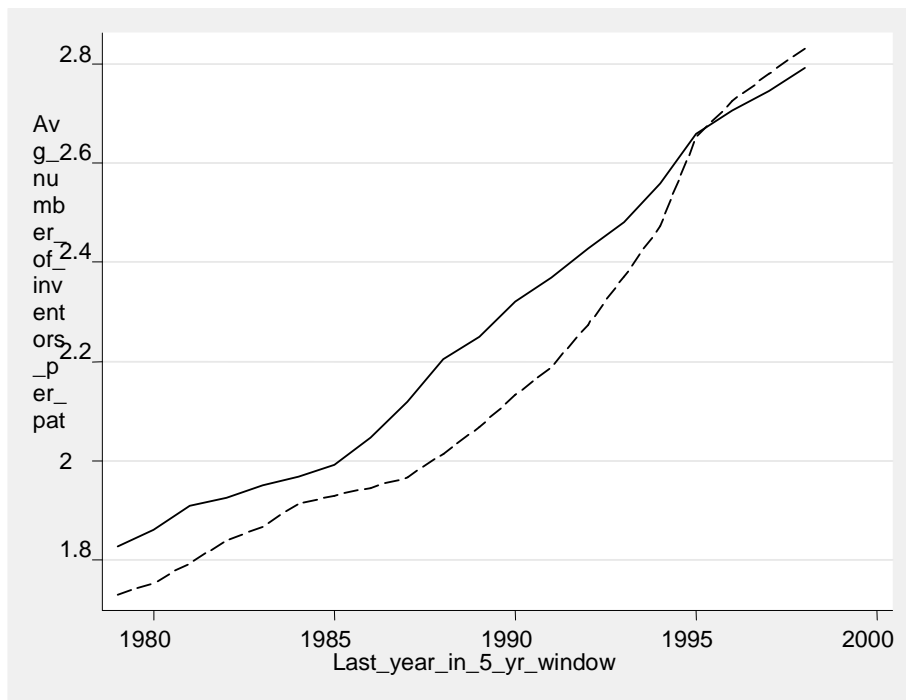


Figure 6: The average number of inventors per patent in Silicon Valley (solid line) and Boston (dotted line). The x axis indicates the last year in a five-year moving window.

Last year in 5 yr window	Number of inventors		Number of patents		Number of components		Density ($\times 10^{-4}$)	
	Boston	Silicon Valley	Boston	Silicon Valley	Boston	Silicon Valley	Boston	Silicon Valley
1979	6517	4850	7465	4809	2809	1986	2.91	4.05
1980	6655	5023	7552	4879	2770	1991	2.94	4.06
1981	6700	5178	7475	4938	2726	2005	3.02	4.18
1982	6824	5311	7338	4948	2694	2061	3.09	4.02
1983	6856	5378	7040	4960	2718	2068	3.12	4.03
1984	7126	5650	6898	5182	2784	2138	3.15	4.15
1985	7411	5960	6962	5368	2840	2241	3.09	4.00
1986	7787	6540	7057	5682	2935	2303	2.99	3.86
1987	8271	7123	7422	6058	3071	2396	2.82	3.75
1988	9004	8069	7951	6678	3202	2516	2.81	3.60
1989	9828	8883	8627	7335	3315	2646	2.79	3.35
1990	10930	10088	9408	8188	3523	2817	2.63	3.15
1991	12034	11392	10157	9337	3712	3005	2.47	2.90
1992	13214	13162	10770	10892	3821	3200	2.39	2.66
1993	14556	15195	11509	12579	3968	3418	2.32	2.43
1994	16568	17884	12725	15082	4174	3610	2.16	2.26
1995	18852	21220	15166	19347	4238	3881	2.07	2.04
1996	20470	25583	16477	24177	4297	4234	2.00	1.78
1997	22730	30746	18370	30904	4503	4546	1.89	1.55
1998	24988	35728	20198	36530	4643	4905	1.77	1.39

Table 2: Descriptive network statistics of Silicon Valley and Boston.

The sudden emergence of the large component in Silicon Valley may also be related to some institution specific to Silicon Valley, in that the collaboration behavior of researchers in Silicon Valley has been much more oriented towards establishing links between previously unconnected networks. One can safely assume that previously unconnected networks typically reflect different firms, within which collaboration is common but between which collaboration is uncommon. These “structural holes” (Burt, 1992) between firms are formed by *inter-organizational collaboration* and *labor mobility*. The question then becomes, why researchers in Silicon Valley have been more inclined to establish inter-organizational connections than those in Boston.

Figure 7 shows the number of assignees per patent, which indicates the degree of inter-organizational networking. As expected, we observe a rising trend reflecting the general pattern of increasing inter-organizational networking. Comparing Silicon Valley to Boston, we find, rather surprisingly, that inter-organizational networking between the two areas has been almost exactly equivalent until 1994 and thereafter slightly higher for Boston. The propensity to network between organizations is clearly not higher in Silicon Valley and does not explain the sudden rise of the large component.

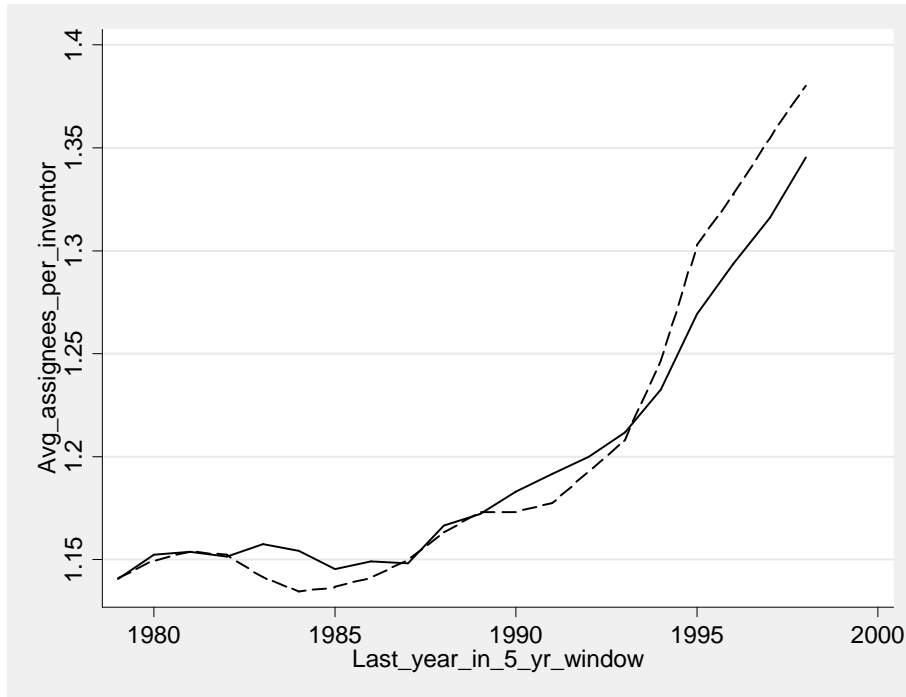


Figure 7: Number of assignees per inventor in Silicon Valley (solid line) and Boston (dotted line). The x axis indicates the last year in a five-year moving window.

Supporting these results for the number of assignees per patent, **Figure 8** illustrates inventor mobility in the two regions (the proportion of patent holders who are observed with a patent from a new assignee each year, divided by the number of unique inventors in the region).³ Supporting Almeida and Kogut's (1999) finding, we find that Silicon Valley demonstrates greater mobility until 1994. Surprisingly, however, we also find that Boston demonstrates greater mobility during and after 1994. While the greater mobility in Boston may have caused the component aggregation in that region, the increased mobility in California did not occur until after the aggregation had begun in Silicon Valley. In summary, while our analyses of collaborative structure raise a number of interesting hypotheses, they indicate that differences in collaborative structure cannot directly account for the 1990 aggregation in Silicon Valley.

³ We would like to thank the anonymous reviewers who suggested these analyses in their reviews. All of these hypotheses are the subject of current research efforts.

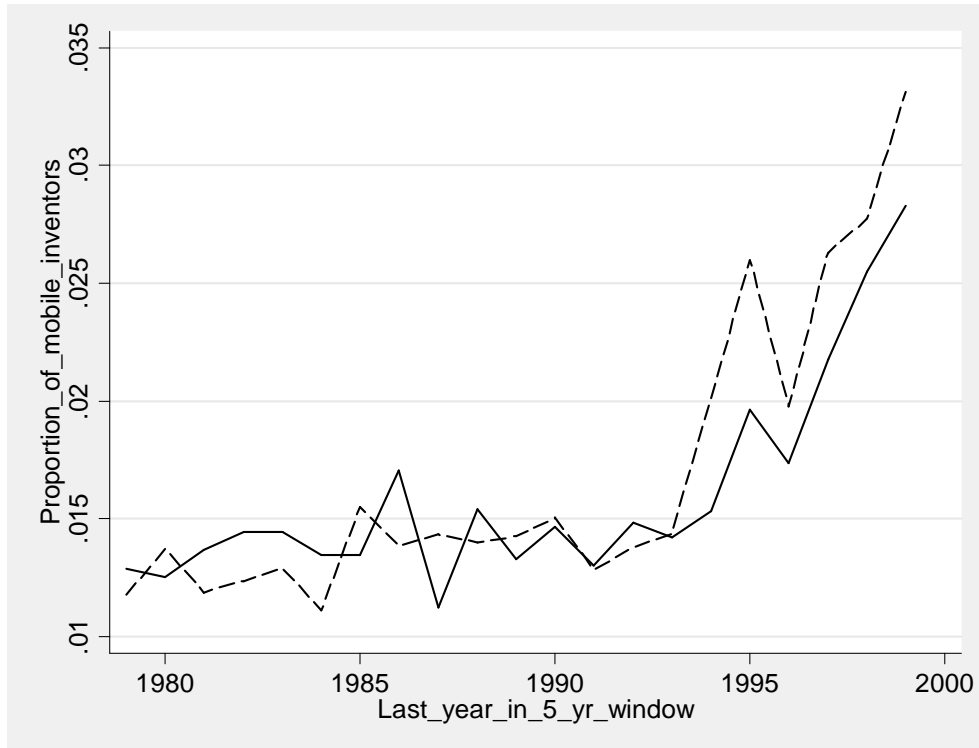


Figure 8: Proportion of inventors that lived within a region and changed assignee, in Silicon Valley (solid line) and Boston (dotted line) largest component. The mobility is low because it is conditional upon observing a second patent (by the same inventor, with a different assignee, in the same region).

The analysis thus far does not yet provide a satisfactory explanation for the emergence of a large first component in Silicon Valley. Even though by some measures inventors in Silicon Valley seem to be more inclined to networking than inventors in the Boston region, the differences between Silicon Valley and Boston remain small and do not demonstrate an abrupt transition around the time of the emergence of the large component in Silicon Valley. The degree of inter-organizational networking and labor mobility, as indicators of the presence of structural holes, is not higher in Silicon Valley than in Boston. Moreover, we found that the role of universities in patenting, in absolute terms, is much more dominant in Boston than in Silicon Valley. In so far as universities act as network intermediaries (since they are not-for-profit organizations), one would have expected Boston rather than Silicon Valley to have developed a large first component. Thus, all results obtained so far do not indicate any structural specificity that can differentiate between Silicon Valley and Boston.

4. Interview Results

An important advantage of network analysis, which is exploited in the current study, is that one can use the network to select the key players for interviews. In this way, one can have a more in-depth understanding of the motives and mechanisms driving the rapid aggregation process in one region (Silicon Valley) and the much slower aggregation process in the other region (Boston). As

described in Fleming et al. (2006), eight inventors were sampled from both regions.⁴ From the conversations, a number of conclusions could be drawn. First, it was found that institutions in the aggregation of regional inventor networks in Silicon Valley have indeed been important. Universities and private firm postdoctoral programs catalyzed the initial connections between components. Second, this institutional “glue” created opportunities for inventors to forge new ties across technologies and firms. These new ties increased innovation in the region that, if successfully commercialized, increased wealth. This wealth could then be cycled back into institutions (such as venture capital networks) that increased inventor mobility, leading to a virtuous co-evolution of aggregation and innovation. However, the interviews with inventors in Boston indicated that many of these institutions also operated in Boston. Indeed, given the greater reliance on scientific research and academic networks in Boston, also evident from **Figure 5**, one would expect an even greater openness than in the Valley.

One truly idiosyncratic story in Silicon Valley, though, deserves further analysis. Several interviewees pointed to the impact of IBM’s postdoctoral program that ran during the 1980s. During that time, IBM’s Almaden Lab hired postdocs straight from school—mainly from within the region and especially Stanford—with the intention that they would leave for employment with another private firm after one or two years. The program served three strategic purposes for IBM. First, the postdocs worked for low salaries. Second, there was the perception of value in new people with fresh ideas. Third, the firm assumed that such people would come in and then go away as ambassadors for the firm. It was the latter objective—to seed the technological community with more experienced, IBM-friendly scientists—that catalyzed the formation of large networks in Silicon Valley, as this process created many ties between IBM and many other firms. In other words, the postdoctoral program jump-started a process of network aggregation. Unlike the departure of senior inventors from large and established firms for start-ups (which does not create ties between large components), the postdocs found future employment across a variety of firms. Hence, the IBM postdoctoral program played a crucial role in the initial and continuing aggregation processes in the Valley because it linked large components to other large components.⁵

Two snapshots of the largest component in Silicon Valley in 1990 and 1995 (**Figures 9 and 10**) further support our reading (IBM inventors are the dark nodes in the graphs). **Figure 9** illustrates the network as it came together initially. IBM is the central core in the aggregation process. In **Figure 10**, IBM inventors remain heavily clustered in the lower right but are also distributed across the network, indicating their strong inter-organizational focus. The network position of IBM inventors remains dominant but no longer central to a much bigger largest component. Both phenomena can be related to the post-doctoral program, which led to less clustering and more centrality as former postdocs, after having left IBM, continued collaborating with IBM employees. The program led to the emergence of a giant component, but once in place, the component outlived the program (the program was discontinued as a result of IBM’s financial

⁴ The study sampled inventors responsible for connecting previously separate components as well as similar inventors who did not.

⁵ IBM has since cut the postdoctoral program back due to the firm’s financial problems in the early 1990s. Other firms, however, such as Hewlett-Packard, have begun similar programs. IBM modeled its program on Bell Labs’ postdoctoral program (which, with the breakup of AT&T, no longer exists) (Fleming et al., 2004).

difficulties in the early 1990s). Thus, our network data further support the thesis that IBM played a key role in the network dynamics in Silicon Valley.⁶

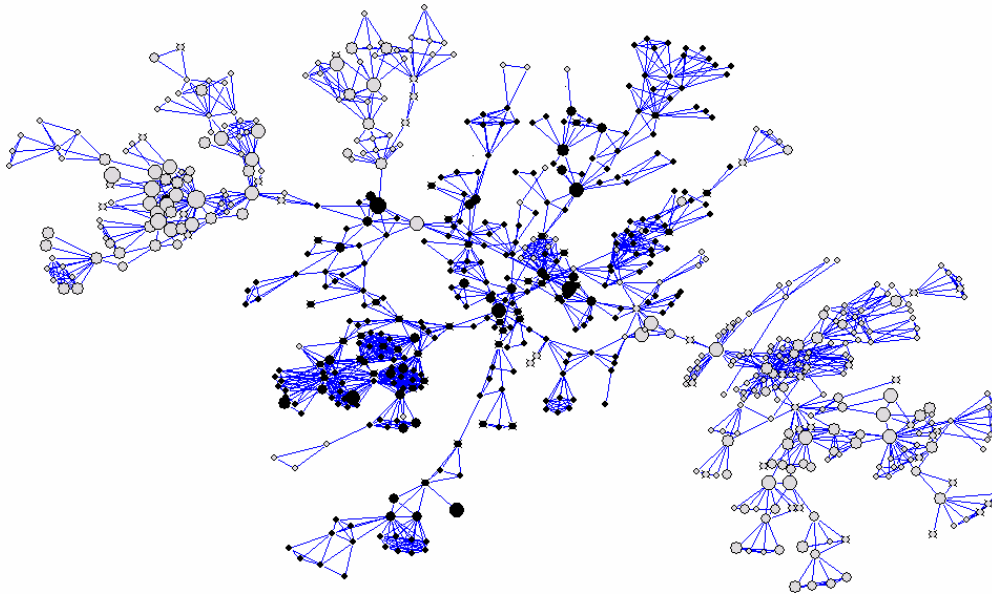


Figure 9: First largest component of Silicon Valley 1986–1990 by assignee and importance of inventions. Dark nodes are IBM Corporation; light nodes are all others (mainly Stanford in upper left and Syntex and pharmaceutical firms in lower right). Node sizes indicate the number of future prior art citations to an inventor, normalized by the number of collaborators. Graphed in Pajek with Kamada-Kawai/Free algorithm (Batagelj and Mrvar, 1998).

⁶ The role of IBM in Silicon Valley has also been highlighted by Kenney and Von Burg (1999).

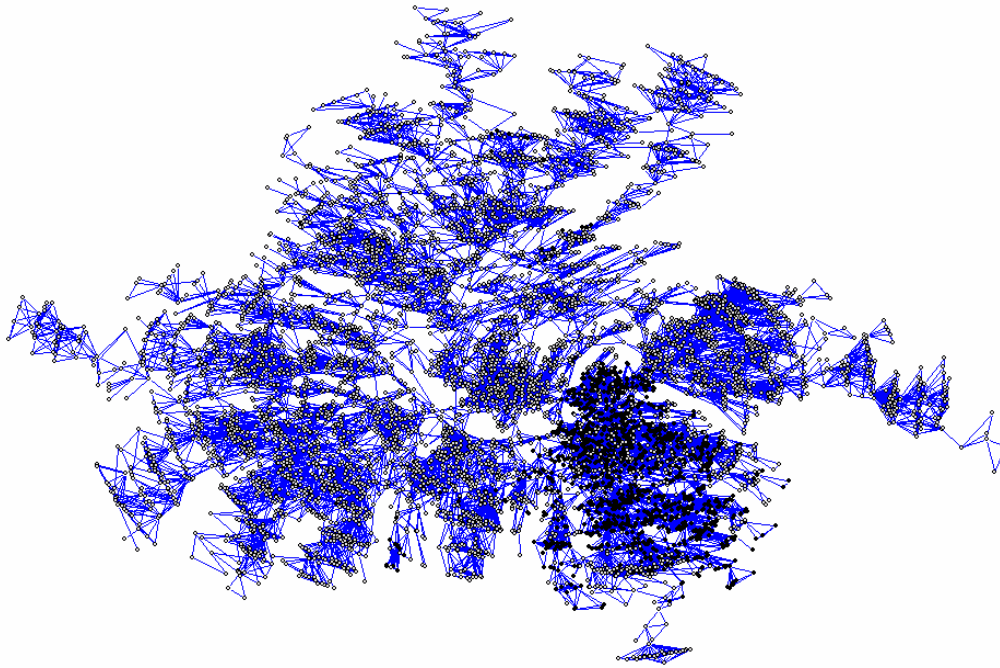


Figure 10: First largest component of Silicon Valley 1991–1995 by assignee and importance of inventions. Dark nodes are IBM Corporation; light nodes are all others. Node sizes indicate the number of future prior art citations to an inventor, normalized by the number of collaborators. Graphed in Pajek with Kamada-Kawai/Free algorithm (Batagelj and Mrvar, 1998).

From similar interviews with key inventors from the Boston region (Fleming et al., 2006), a different dynamic emerges. In Boston, the main player had been DEC, as evidenced by the fact that its inventor network constituted the first largest component in many years. Differently from IBM, however, DEC organized its labor market mainly internally by promoting job switches within the firm and intra-organizational networking. Job mobility to other firms was discouraged. Some interviewees even remarked that leaving was considered “kind of traitorous” and noted that DEC had an explicit policy that employees who left were not to be rehired. Further hampering aggregation in the Boston region was that MIT, as an elite institution, trained researchers for employment (both academic and private) on an international scale, which explains why many more researchers left the region at an early age compared to Silicon Valley. These inventors disappear from the network after five years and thus contribute to the disintegration of the network over time. Analysis of the largest component in Boston in 1990 revealed it to be almost entirely composed of inventors from Digital Equipment Corporation. Unlike in Silicon Valley, very few inventors had connections outside their firms.

5. Conclusion

We analyzed the dynamics in regional innovator networks descriptive statistics, graphical illustration, and qualitative interviews. Our results did not indicate general differences in the collaboration networks between Silicon Valley and Boston. Rather, the sudden emergence of a giant component in the Silicon Valley region may be more related to specific institutional dynamics driven by key players, in particular IBM.

Saxenian (1994) is right in stressing the greater degree of inter-organizational networking and labor mobility in Silicon Valley. However, we question the idea that Silicon Valley as a region is characterized by a different institutional regime that applies to all firms in the region. From our data analysis, we found no significant structural differences between Silicon Valley and Boston. Rather, we tend to favor a reading based on *contingent* events reflecting specific strategies of key players in the region, especially IBM recruiters, which drove the dynamics of networking in Silicon Valley. Much of the difference in aggregation can be traced to IBM's Valley postdoctoral program and Stanford doctoral students taking local employment, especially with IBM, while MIT students more often than not left the Boston region. Thus, the observed institutional differences between Silicon Valley and the Boston region were mainly caused by differences in firm strategies.

The next step is to develop a formal model of the network dynamics in the two different regions using percolation theory (Newman et al. 2001). This would allow us to further examine the nature of the dynamics that has given rise to the emergence of the sudden giant component in Silicon Valley and the later, and less pronounced, emergence of such a component in the Boston region. In particular, such a modelling exercise should try to determine in a more precise manner whether the percolation dynamics can be attributed to the exceptional behavior of certain specific organizations (like IBM) or whether the resulting dynamics can still be approximated as being essentially a random process.

Methodologically, our analysis has shown that network analysis can bridge quantitative and qualitative methods, thus capitalizing on the comparative advantages of both types of research tools. One can use the network to select the key central players for interviews. In this way, one can obtain an in-depth understanding of the motives and mechanisms driving dynamic networks.

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