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TECH CLUSTERS

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ABSTRACT

Tech clusters like Silicon Valley play a central role for modern innovation, business competitiveness, and economic performance. This paper reviews what constitutes a tech cluster, how they function internally, and the degree to which policy makers can purposefully foster them. We describe the growing influence of advanced technologies for businesses outside of traditional tech fields, the strains and backlash that tech clusters are experiencing, and emerging research questions for theory and empirical work.

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While Silicon Valley houses less than 0.1 percent of the world's population, its shadow looms large. Many cities aspire to be a tech cluster: for example, an astounding 238 US cities jumped through hoops in 2017-18 to enter Amazon's infamous "bidding" process for where it would establish a second headquarters. Wikipedia lists more than 25 efforts to brand a US location as "Silicon Something," along with many foreign ones (at https://en.wikipedia.org/wiki/List_of_technology_centers#United_States). Our personal favorite names are Silicon Peach (Atlanta) and Silicon Spuds (Idaho), whereas Silicon Prairie has at least four contenders. Other US examples include Silicon Anchor, Basin, Desert, Forest, Hill, Holler, Mountain, Shire and Surf.

This paper examines the tech cluster phenomenon by considering three only partially answered questions. We first ask how we might define a tech cluster—that is, what properties are required to be a tech cluster? This delineation is harder than it first looks and raises some key questions and issues. We start with the scale and density of local activity and then extend into the frontier nature of the work being undertaken and its ability to impact multiple sectors of the economy. We illustrate our definition through some common metrics like patents, venture capital funding, and employment in R&D intensive sectors or digital-connected occupations. We also note some interesting clues from emerging metrics (e.g., high-growth entrepreneurship, artificial intelligence researchers) and recent efforts to measure tech clusters globally.

We then ask how tech clusters function, with a focus on traits that extend beyond those associated with traditional industrial clusters. Not surprisingly, knowledge spillovers are a powerful force in tech clusters, and recent work explores how knowledge transmits across firms situated in a tech cluster and how density impacts the types of innovations created. Tech clusters facilitate powerful scaling for the best designs when they combine modular product structures with high-velocity labor markets. Universities, high-skilled immigration, and global production linkages also feature prominently in the functioning of leading US centers.

Finally, we turn to the roots of tech clusters and inquire into the mix of initial ingredients required for their formation. Leading tech clusters are far from permanent and have frequently emerged in new places following the advent of new general purpose technologies. Today, the rapid growth of Toronto as an artificial intelligence cluster suggests that there may be limits of Silicon Valley's grip on this frontier. Yet, despite the government having played an important role in this history of many tech clusters, top-down attempts to re-create Silicon Valley have mostly failed (Lerner 2009). Our historical examples suggest that local officials may instead want to facilitate the scaling of nascent industries that have taken root, even if due to random chance, rather than attempt to engineer a cluster from scratch.

We conclude with some thoughts on future research opportunities, including the question of whether tech clusters are at their high-water mark or are likely to strengthen further. The implications of the ongoing COVID-19 crisis for tech clusters could be profound. Our discussion focuses primarily on the US economy, but much of what we describe applies to other countries as well. We ground our discussion firmly within the economics and management disciplines, occasionally reaching out in incomplete ways to other social sciences as we go.

Defining Tech Clusters

While it is easy to point to high profile examples of tech clusters, such as Seattle or Austin, developing even a semi-formal definition is tricky. "Clusters" traditionally indicate an important overall scale of local activity, complemented by spatial density and linkages among local firms (e.g., Marshall 1890, Porter 1998). As discussed further below, the specific linked activities for tech clusters might include engineer mobility across employers, flows of technical knowledge, and reliance on shared local inputs like a research university. In addition to these traditional dimensions, we define "tech" clusters to be locations where new products (be they goods or services) and production processes are created that impact multiple parts of the economy. That is, a tech cluster must have a frontier edge to it, and it must extend beyond refinements to a single industry.

These criteria suggest that tech clusters are not a new phenomenon nor a permanent fixture. US economic history shows a continual movement of leading tech centers: for example, Lowell, Massachusetts, for textile mills reliant on water power in the 1800s; Cleveland, Ohio, for electricity and then steel in the early 1900s; and Detroit, Michigan, for automobiles in the early-mid 1900s (Lee and Nicholas 2012; Lamoreaux et al. 2004). Our definition puts early 19th century technology advances for engines in Detroit on par with the cluster of artificial intelligence firms in the Toronto area today, which seems conceptually useful.

An historical perspective also suggests that tech clusters may cease to be. For example, Detroit was the Silicon Valley of the first half of the 20th century. At some point, the auto industry matured and Detroit with it, and we would have taken away Detroit's tech cluster badge. Should Detroit's mojo return with electric or autonomous vehicles, perhaps in 2030 we will declare Detroit a tech cluster again. Over its relatively short history, Silicon Valley has also experienced doldrums after technology waves crested before the next major path emerged.

Our definition also suggests drawing a line between specific industries which make heavy use of technology (which include traditional industrial districts), and a true tech cluster with a broader impact across the economy. For example, should Wall Street and the surrounding area of lower Manhattan be considered a tech cluster? After all, Goldman Sachs in 2020 employs more engineers than the total combined workforces of LinkedIn and Twitter. The iconic bank has even been recently shedding traditional practices like dress codes to attract technical workers. Frontier quantitative hedge funds are at the bleeding edge of artificial intelligence, and fintech advances may reshape commerce. So maybe the Wall Street of the 1980s was not a tech cluster, but the Wall Street of 2030 might be. Using the framework of Duranton and Puga (2005), perhaps Wall Street is evolving from being a cluster specialized in a sector—financial services—into a cluster specializing in a function—(fin)tech?

These definitional challenges reflect how advanced technology and its leading firms are entering many parts of the economy in a variety of ways. Technology is becoming less of a segmented industry—for example, less focused on manufacturers of personal computers or shrink-wrapped software—and more ubiquitous and general purpose. There also exists a blurring of industry boundaries, especially as incumbent firms seek to move out of stagnating industries and towards new profitable opportunities. As robotics and cognitive automation advance, this ambiguity will grow. Technology is becoming so pervasive that one can be tempted to resort to phrasings like "talent clusters" to focus on frontier activity by sector in human-capital focused industries (for example, Kerr 2019).

Data to Measure US Tech Clusters

Empirically studying tech clusters requires making choices about what to measure and the appropriate scale of activity. Most analyses use patents, high-growth entrepreneurship supported by venture capital firms, and/or employment in R&D-intensive industries or occupations. In choosing a geographic unit, most empirical analyses of the US economy analyze the full distribution of states or cities, which is helpful for getting a workable sample size (for example, Acs et al., 2002; Delgado et al. 2010; Glaeser et al. 2015). An alternative method is to conduct case studies or sub-city empirical analyses of a recognized tech cluster like Silicon Valley (for example, Saxenian 1994, Kenny 2000, Bresnahan and Gambardella 2001). These choices should follow the type of economic linkage under study: for example, focusing on very short-distance knowledge spillovers in the area around Kendall Square near MIT vs. the labor mobility of engineers across the entire Boston metropolitan area.

Patents and venture capital data are popular with researchers due to the existence of detailed micro-data regarding individual inventions and funding transactions. Thus, in addition to measuring spatial concentration, researchers can use the same data to learn how the clusters operate by, for example, following the careers of inventors or entrepreneurs over time, modeling local networks and spillovers, etc. These data also offer a foothold for assessing whether the innovative work of the city touches multiple aspects of the economy. The central liability with both approaches is that many forms of innovative activity are not captured; moreover, the intellectual property and financing environment changes over time (e.g., greater recognition of software or business method patents). Researchers must carefully consider limits to comparability across industries (and therefore across cities, too) and longitudinally (see literature in Feldman and Kogler 2010 and Carlino and Kerr 2015).

With some exceptions, such as Carrincazeaux et al. (2001) and Carlino et al. (2012), location-specific R&D data are difficult to acquire. Industry- and occupation-level employment data offer another tactic. As an example, we use below micro-data from the 2014-2018 American Community Survey that records for individuals their metropolitan area, industry of employment, salary, education level, and so forth. We map R&D intensity by industry, as documented by the National Science Foundation (2017), to measure how much of a city's employment base is in R&D-intensive fields. This approach avoids some of the liabilities noted for patenting and venture data but also sacrifices many of the advantages that micro-data provided.

Table 1 documents several measures for cities using data from around 2015-2018 (the notes to the table provide details on sources and preparation). We list the top 15 MSAs in terms of venture capital investment, in descending rank, and then provide two aggregate categories for the other 266 MSAs and for rural areas. In this table and the figures to follow, we use consolidated MSAs, such that the San Francisco/San Jose/Oakland area is just referred to as San Francisco.

Table 1: Spatial concentration of US tech activity

Consolidated metro area	Venture capital investment	Granted patents	Employment in top 10 R&D industries, high-skilled	Employment in top 20 R&D industries, all workers	Employment in computer- and digital-connected occupations, high-skilled	Employment in STEM-connected occupations, all workers	Population
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
San Francisco	48.1%	18.4%	11.7%	4.9%	8.6%	5.5%	2.5%
New York	15.3%	6.0%	6.3%	5.1%	8.0%	6.0%	6.4%
Boston	10.5%	4.5%	5.5%	2.4%	3.4%	2.7%	1.6%
Los Angeles	6.5%	5.3%	5.6%	5.7%	3.9%	3.9%	5.8%
Seattle	2.1%	4.0%	4.2%	2.4%	3.5%	2.5%	1.2%
San Diego	1.9%	3.6%	3.2%	1.6%	1.5%	1.5%	1.0%
Chicago	1.7%	2.5%	3.2%	3.2%	3.9%	3.2%	2.9%
Washington DC	1.5%	1.7%	4.4%	1.8%	6.6%	4.6%	1.8%
Miami	1.5%	0.7%	0.9%	1.1%	1.0%	1.2%	1.4%
Denver	1.1%	1.5%	1.5%	0.9%	1.7%	1.5%	1.0%
Austin	1.0%	2.1%	1.8%	1.0%	1.5%	1.2%	0.6%
Philadelphia	0.8%	1.8%	3.3%	2.1%	2.4%	2.2%	2.0%
Atlanta	0.7%	1.5%	1.4%	1.6%	2.8%	2.3%	1.7%
Minneapolis-St. Paul	0.7%	2.0%	1.3%	1.7%	2.0%	1.9%	1.0%
Raleigh-Durham	0.5%	1.4%	1.7%	0.8%	1.2%	1.0%	0.5%
Share in top 15 VC MSAs	93.8%	57.0%	55.9%	36.0%	52.1%	41.2%	31.3%
Share in other MSAs	5.9%	37.3%	38.3%	49.3%	41.8%	47.9%	48.0%
Share in non-metro areas	0.3%	5.7%	5.9%	14.8%	6.1%	10.9%	20.7%
Correlation to VC share		0.98	0.91	0.63	0.73	0.66	0.31
Correlation to patent share	0.98		0.93	0.67	0.71	0.65	0.32

Notes: Table lists the top 15 (consolidated) MSAs in terms of venture capital investment in descending rank. Venture capital investments are for 2015-2018 based upon location of new investments in ventures and are taken from Thomson One. Patents are for 2015-2018 based upon the most frequent location of inventors and application date of utility patents and are taken from patents granted by the USPTO through end of 2019. Employment columns are for 2014-2018 using the combined American Community Survey 1% files. ACS sample includes those aged 18-65 who are working and with positive wage earnings, not in group quarters, with usual hours worked greater than 30 per week, and with usual weeks worked per year greater than 40. High-skilled workers are those with college-degrees or higher in education and earning $50,000 or more. The 10 industries with the highest R&D per worker as listed by NSF (2017) are Software publishers; Pharmaceuticals and medicines; Other computer and electronic products; Data processing, hosting, and related services; Communications equipment; Semiconductor and other electronic components; Navigational, measuring, electromedical, and control instruments; Pesticide, fertilizer, and other agricultural chemicals; Aerospace products and parts; Scientific research and development services. These industries in some cases map into more than one NAICS industry in the ACS for employment data. Population data are 2015-2018 based upon counties that comprise MSAs and are taken from the Census Bureau. There are 281 MSAs identified in the venture capital, patent, and population data and 261 identified in the ACS data. Population distributions in the ACS are very similar, with the one noticeable difference of LA being a 4.2% share.

This table speaks best to the scale of tech activity across cities and, through a comparison to the population share in Column 7, the implied density of tech efforts. The top 15 MSAs as ranked by venture capital investment hold 94 percent of venture capital activity in Column 1 and 57 percent of patenting in Column 2, compared to just 31 percent of population. If we instead rank on patents, Detroit, Portland, Dallas-Ft. Worth, and Houston feature in the 15 largest centers, with Washington, Miami, Atlanta, and Raleigh-Durham dropping out. Either way, patenting and especially venture capital investment are under-represented outside of leading tech centers. Looking across MSAs listed in Table 1, shares for venture capital and patent have a 0.98 correlation, while shares for venture capital and population have a 0.31 correlation.

Columns 3 and 4 of Table 1 next provide two measures of local employment in leading industries for R&D investment as measured by National Science Foundation (2017). We first show a restrictive definition, where we identify college-educated workers earning more than $50,000 (short-hand labelled as "high-skilled") and working in a top 10 R&D-intensive sector—11.7% of such individuals work in the San Francisco area, compared to 5.9% of them being outside metropolitan areas. The second measure broadens to any full-time employee (no education or salary restriction) among the 20 most R&D-intensive sectors. This makes a noticeable difference, with San Francisco's share now 4.9% and much smaller than the 14.8% in non-metro locations. Column 5 similarly looks at high-skilled workers in occupations in computer- and digital-connected work, and Column 6 expands to all full-time workers in a broader class of STEM-connected occupations.

This table shows the potential and challenges of defining tech clusters using the scale and density of local tech activity. Six cities appear to qualify under any aggregation scheme: San Francisco, Boston, Seattle, San Diego, Denver, and Austin all rank among top 15 locations for venture capital and for patents (scale) and hold shares for venture capital, patents, employment in R&D-intensive sectors, and employment in digital-connected occupations that exceed their population shares (density). They also pass the highly rigorous "sniff test" that they make sense! Washington, Minneapolis-St. Paul, and Raleigh-Durham would join the list if relaxing the expectation that that share of venture investment exceed population share (which is hard due to the very high concentration in San Francisco).

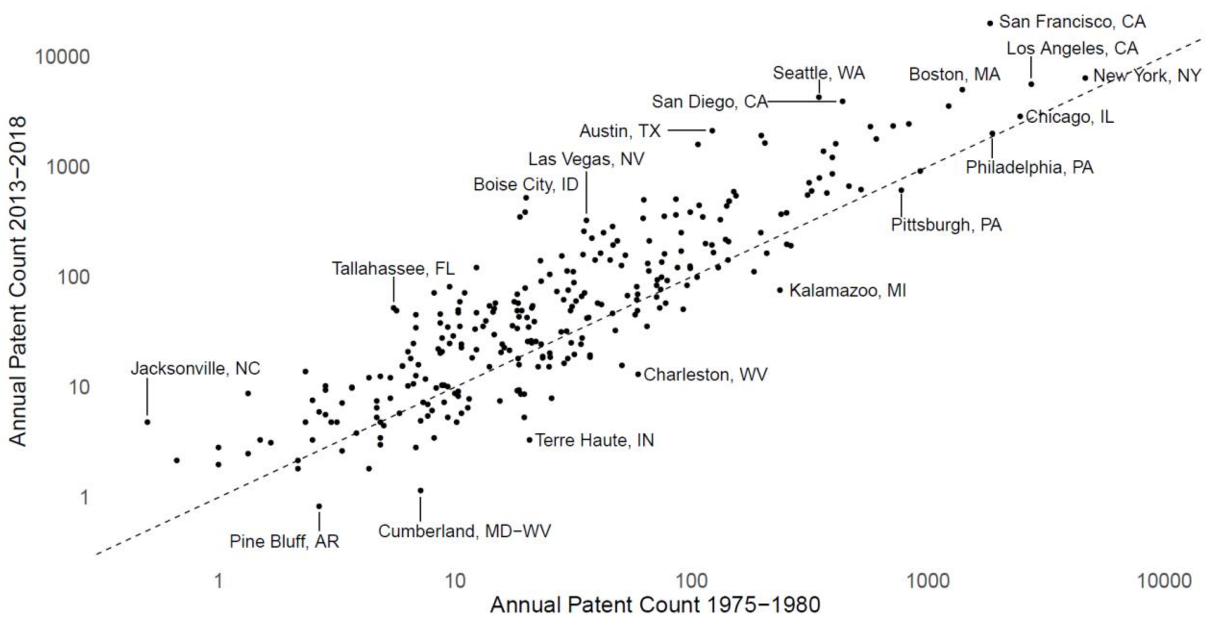
New York and Los Angeles are more ambiguous: they hold large venture capital markets (and venture investors frequently declare them leading tech clusters), but their patents and employment shares in key industries and fields are somewhat less than their population shares. Were we to disaggregate these huge metro areas, we would likely identify a sub-region that would independently make this short list by still holding sufficient scale and yet having more achieved a more recognizable density. Said differently, there is surely a part of New York and LA that would be stand-alone equal to or greater than Austin (e.g., Egan et al. 2017). Chicago's activity is mostly equal to its population share or less.

At the other end of the city size distribution, it is hard to be a robust-yet-small tech cluster on both venture investment and patent metrics due to the concentration of innovation. If one only requires that a tech cluster achieve a venture capital and patent share that is 1.5x the local population share, the one new city would be Provo, UT, with Denver dropping out. In summary, San Francisco and Boston are extreme cases, and we are probably looking at 5-10 additional leading centers across the country depending upon definition of scale and density.

At the start of this section, we conceptualized tech clusters as being positioned in frontier sectors and having a broad-based impact. Patents provide a preliminary example of these traits. We first consider new technology areas by isolating patent technology classes that the USPTO introduced in 1995 and afterwards. On average, cities have 7.8 percent of their patents during 2015-2018 in the newest classes, while the average for San Francisco, Boston, Seattle, San Diego, Denver, and Austin is 27.8 percent. When looking at patent classes introduced after 1980, these shares are 29.8 percent and 60.2 percent, respectively. Patents in these six cities also display higher forward and backward citations, with a greater measure of generality to the work (Hall et al. 2001). We return below to recent research describing differences in the type of innovation across clusters.

How is this picture changing over time? For the most part, the rich are getting richer. Figure 1 shows city patenting (presented in annual terms) from 1975-1980 to 2013-2018. The axes are in log format and a 45-degree line is included. There has been an overall increase in patent grants since the late 1970s, visible in the figure with more cities being above the 45-degree line than below. Cities that are farthest above the 45-degree line have the biggest percentage gains, and big patenting centers in the late 1970s show the most consistent increases. Consequentially, an Ellison and Glaeser (1997) index of patenting concentration relative to population distribution grows over ten-fold from an index value of 0.002 in the late 1970s to 0.028 in 2018.

Figure 1: Growth in Annual Patenting by Metropolitan Statistical Area



Notes: Figure presents for metropolitan areas the average annual patent count for 1975-1980 and 2013-2018. Patents are grouped by application year and all patents granted by the USPTO through end of 2019 are used. Axes are in log format and a 45-degree line is included. Some cities are labelled for illustrative purposes only.

Researchers have recently developed new empirical methods to measure tech clusters, as well. One approach focuses on measuring high-growth entrepreneurship independent of venture capital data. Guzman and Stern (2019) use state-level business registration data and develop techniques to identify whether new firms are targeting rapid growth, such as how the venture is named (e.g., Infinity Global Technologies vs. Fred’s Bicycle Repair) and its legal form of incorporation. The most intense areas for entrepreneurial potential are places like Silicon Valley, Boston, and Austin, where they also measure booms in local high-growth activity through 2019.

In another approach, using LinkedIn data on employment, Gagne (2019) estimates that more than a third of artificial intelligence researchers are located in the San Francisco Bay Area—a fact due in part to the presence of tech giants like Microsoft, IBM, and Google in that area.

Global Tech Clusters

An emerging frontier is to map out global tech clusters. This combination of data across borders gets complicated fast, and Table 2 shows metrics do not always point in the same way. For venture capital investment, the last decade shows the remarkable rise of Chinese tech clusters. The top 10 global cities include Beijing, Shanghai and Shenzhen, plus London, in addition to six cities from the United States. Looking instead at the post 2009 formation of unicorn start-ups (valued at $1 billion or more), the four non-US cities are similarly Beijing, Shanghai, and Hangzhou, plus London (Kerr 2018).

Table 2: Global Tech Clusters as Measured by Total Size

Venture Capital Investment (Thomson One, 2009-2018)	Unicorn Startup Companies (CB Insights, 2009-2018)	Patent Cooperation Treaty Filings (WIPO, 2010-2015)
San Francisco	San Francisco	Tokyo-Yokohama
Beijing	Beijing	Shenzhen-Hong Kong
Shanghai	New York	San Francisco
New York	Los Angeles	Seoul
Boston	Shanghai	Osaka-Kobe-Kyoto
Los Angeles	Boston	San Diego
London	London	Beijing
Shenzhen	Seattle	Boston
San Diego	Hangzhou	Nagoya
Seattle	Chicago	Paris

Notes: Table lists the 10 largest global tech clusters in terms of various metrics in descending rank. Venture capital investments are for 2009-2018 based upon location of new investments in ventures and are taken from Thomson One. Unicorn startup companies are counts of new ventures exceeding a billion dollars in valuation during 2009-2018 and are taken from CB Insights. Patent Cooperation Treaty filings are for 2010-2015 and are taken from the World Intellectual Property Organization. Geographic boundaries of clusters are defined by each data source and differ to some extent across columns.

While measures of tech clusters using venture capital and patents provide mostly similar pictures across US cities, globally this is not the case. In a World Intellectual Property Organization report (Bergquist et al. 2017) that aggregates over many patent offices, Tokyo-Yokohama holds twice the patent count to second place, Shenzhen-Hong Kong; the San Francisco Bay Area is third and Seoul is fourth. Moreover, the top 10 cities span three in Japan, three in America, two in China, and one each in Korea and France. For more specific frontiers like research in artificial intelligence, the leading roles of America and China are clear, but relative shares depend substantially on the yardstick employed and data source.

Building a stronger foundation for these comparisons is an important ongoing task. So far, we are only tackling the scale of local tech activity, but not the extra nuances about density, frontier status, and so forth. International settings also raise the interesting question of whether measures of a tech center should be context specific. Many speak of Bangalore as a "tech cluster," but while it is technologically advanced when compared to other locations in India, much of its activity is substantially lower tech and labor intensive relative to tech clusters in advanced economies.

Is a Tech Cluster Different from Other Clusters?

Industry clusters arise due to the production advantages of local specialization combined with subsequent trade across locations. Marshall (1890) famously described three forces of what we now call agglomeration economies: knowledge spillovers, labor market pooling, and customer-supplier interactions. Economic research over the last two decades has shown all three forces, along with natural advantages of areas for certain industries (e.g., harbors, coal mines), are important for explaining industrial clusters, with the most recent research quantifying the heterogeneity across industries and co-agglomeration dynamics over time (for example, Ellison et al. 2010; Faggio et al. 2017). While most studies of the Marshallian forces have focused on industrial settings, they also apply to tech clusters, if often in distinctive ways.[1]

Knowledge Spillovers and Forms of Innovation

Our definition of tech clusters emphasized settings with a frontier edge, and many companies seek insights on emerging possibilities, either through first access to codified knowledge or to tacit knowledge that cannot be so easily written down. Marshall famously described knowledge diffusion inside an industrial cluster in poetic terms: "The mysteries of the trade become no mysteries; but are as it were in the air, and children learn many of them unconsciously."

Researchers have since catalogued these knowledge transfers in many settings, such as Switzerland's watchmaking industry, and they appear particularly important for tech clusters (Audretsch and Feldman, 1996). Olson and Olson (2003) document very tight bands for collaborative interactions. In an ethnographic study of Silicon Valley, Saxenian (1994, p. 33) describes many formal and informal channels facilitating knowledge transfer, including a depiction of Wagon Wheel, a Mountain View bar that novelist Tom Wolfe dubbed the "fountainhead of the semiconductor industry":

> [M]embers of an 'esoteric fraternity'—the young men and women of the semiconductor industry—would head after work to have a drink and gossip and brag and trade war stories about phase jitters, phantom circuits, bubble memories, pulse trains, bounceless contracts, burst modes, leapfrog tests, p-n junctions, sleeping sickness modes, slow-death episodes, RAMs, NAKs, MOSes, PCMs, PROMs, PROM blowers, PROM blasters, and teramagnitudes, meaning multiples of a million millions.

More recently, then-CEO Jeff Immelt described in 2016 why General Electric was moving its headquarters from Fairfield, Connecticut, to Boston: "To look out the window [in Connecticut]

[1] Duranton and Puga (2004) recast Marshall's forces to emphasize higher-order functions like sharing and matching that occur within clusters. See Markusen (1996) and Porter (1998) for complementary approaches.

and see deer running across, I don't care about that. I want some 29-year-old [graduate of] MIT to punch me right in the nose and say all of GE's technologies are wrong and you're about to lose. That's the challenge." (as reported in Singer 2016; Kerr 2018 discusses the subsequent ups and downs of General Electric's move).

More formally, economists since Jaffe et al. (1993) have most frequently used patent citations to quantify the higher rate of knowledge flow within cities versus across them (for example, see Murata et al. 2014, and the references cited therein). The use of patent citations is only an imperfect proxy for knoweldge flows (e.g., Jaffe et al. 2000), and many of the captured information flows are due to inventor networks, licensing agreements, and so forth (e.g., Almeida and Kogut 1999; Breschi and Lissoni 2009). These citation metrics thus aggregate unpriced knowledge spillovers that are "in the air" alongside regular forms of economic activity. Citation patterns have been confirmed with co-authorship networks among inventors, and Fleming and Marx (2006) identify that leading tech clusters became more connected during the 1990s.

Recent applications focus on using patent data to open the black box of how clusters operate. Kerr and Kominers (2015) model localized spillovers within tech clusters. Firms interact with their closest neighbors, but the costs of interaction prevent direct spillover benefits from more distant members of the cluster. For example, a firm in Oakland may have useful information for a startup in East Palo Alto, but the search and acquisition costs for that information prevent it from diffusing directly, requiring instead indirect transfer via other firms. These conditions lead to overlapping zones of interaction, such that nearby interactions are direct, while those farther away happen through the underlying network of the cluster. (Arzaghi and Henderson (2008) document a similar phenomenon in a study of advertising agencies in Manhattan.)

In their empirical work using patent citations, Kerr and Kominers (2015) show that firms are more likely to directly cite the work of their closest neighbors but indirectly cite those farther away in the cluster. Consequently, econometricians can compare the shapes and sizes of clusters to learn about the technologies that sit behind them. Technologies with tight spillover lengths produce smaller and denser clusters. In this study, as well as other research using broader sources of variation (for example, Rosenthal and Strange 2001, 2003), knowledge spillovers are the most localized of agglomeration forces.[2]

Another promising line of work quantifies how the level and type of inventions varies within a broader metro area. For example, Carlino et al. (2007) and Berkes and Gaetani (2019) measure that patenting per capita across US cities mostly rises with higher density, with a 10 percent increase in density correlating with a 2 percent increase in intensity. At a more fine-grained level, however, patenting per capita peaks in areas with high but not too high density—for example, being higher in Silicon Valley or the Route 128 area surrounding Boston compared to downtown San Francisco and Boston, respectively.

[2] Even controlling for distance, political boundaries still matter for knowledge flows (Singh and Marx 2013). Similarly, local economic conditions (low commuting costs, skilled labor abundance) and technology features (localized knowledge spillovers, high startup costs) shape the decentralized emergence of science parks (Liang et al. 2019). By contrast, some studies do not find co-location to be essential (e.g., Waldinger 2012).

Berkes and Gaetani (2019) further show that the very densest districts instead foster atypical combinations of technologies that combine core elements seen in prior work with distinctly novel elements (Uzzi et al. 2013). These innovation advantages for developing the most novel forms of new work are often credited to a diverse range of local inputs (for example, Jacobs 1969; Glaeser et al. 1992; Henderson et al. 1995; Lin 2011). In contrast, "company towns" where a single large firm dominates the local tech activity, like Eastman Kodak in Rochester, New York, during the 20th century, are more likely to have internally focused innovation (Agrawal et al. 2010).

Continued investigation into how the technologies developed in frontier clusters differ from other settings is important. It would be also interesting to identify cases and situations in which tech clusters can become too isolated from a potential customer group to understand latent needs. Michael Bloomberg is a very rich tech entrepreneur because he knew what kinds of desktop terminals his former colleagues on Wall Street were missing, which someone in California may have had a hard time figuring out.

Specialized Labor and High Velocity Labor Markets

A distinctive feature of tech clusters is the specialized skillsets of many local workers, which becomes a powerful magnet to the area. As noted in Section 1, leading tech clusters hold a large share of the nation's college-educated workforce engaged in computer and digitally connected fields, and the concentrations become even more skewed when looking at extreme skills like specialization in artificial intelligence (e.g., Gagne 2019). Clusters provide several advantages for workers with specialized skills: insurance against the shocks befalling any one employer, deeper labor markets for better matching of particular skillsets with the best jobs, and often superior environments for investments in training by talented individuals without fear of later employer hold-up (for an entry point to this literature, see Overman and Puga 2010, and the citations therein). Studies examining labor pooling in the tech arena often emphasize its role for employee-firm matching and input sharing (e.g., Helsley and Strange, 1990, 2002).

Beyond these bread-and-butter features, the literature on tech clusters most emphasizes the high velocity turnover of its labor markets. Saxenian provides an early depiction of this rapid mobility, quoting an engineer on the ease of transitioning employers in Silicon Valley: "Out here, it wasn't that big of a catastrophe to quit your job on Friday and have another job on Monday and this was true for company executives. You didn't necessarily even have to tell your wife. You just drove off in a different direction on Monday morning. You didn't have to sell your house, and your kids didn't have to change schools." Another local executive notes: "People change jobs out here without changing car pools" (Saxenian, 1994, p. 35).

High profile executive moves are common within tech clusters, such as Sheryl Sandberg's move from Google to become Chief Operating Officer of Facebook in 2008 and Marissa Mayer's similar departure to become CEO of Yahoo! in 2012. These moves often spark legal challenges. In 2017, Alphabet's Waymo sued Uber, alleging that one of Waymo's former engineers, Anthony Levandowski, took confidential files with trade secrets related to self-driving cars with him when leaving to form his own self-driving startup, Otto, that Uber later acquired. The suit was settled in 2018 with Uber paying 0.34% of its equity (then valued at $245 million) to Waymo. (https://www.wired.com/story/uber-waymo-lawsuit-settlement/)

While frequently discussed, this labor velocity has been less studied empirically compared to the localization of knowledge flows. Fallick et al. (2006) is an important exception that further links the flexible labor markets of tech clusters to an industrial organization that emphasizes modular production.[3] They model how modularity allows for winner-take-all competition, with labor rapidly reallocating to the firm with the best design in order to scale it up for production. This benefit helps the cluster to overcome potential underinvestment in worker training due to rapid turnover in high-velocity labor markets. Related, Gerlach et al. (2009) connect labor pooling to greater risk taking with R&D activities inside tech clusters, and Fairlee and Chatterji (2013) document how rapid scaling of winning firms can ironically reduce start-up rates inside tech clusters during exceptional growth periods like the late 1990s.

This rapid labor mobility hints at the dual-edge nature of tech clusters: while they provide strong advantages, they impose real costs on firms, too. Despite the relative abundance of sought-after skills within tech clusters, these labor markets were exceptionally tight in the late 2010s and exhibited very low unemployment rates. Thus, many businesses located in these talent clusters struggled to get the workers they wanted especially if they lacked a brand name like Apple or Netflix that attracts employees.

Firms also need to be aware that company doors operate in both directions. While bosses get excited about the top-notch employees and knowledge stocks at neighboring companies that they might be able to lure away, they also become more likely to have their employees depart to rival organizations. Combes and Duranton (2006) model this tension, showing that single-minded pursuit of a position in the cluster is not always the best strategy. Building on Rotemberg and Saloner (2000), Matouschek and Robert-Nicoud (2005) and Almazan et al. (2007) highlight the role of firm-sponsored investments and firm-specific skills in investigating why employers should think twice before jumping into the hot spot of their sector. Alcacer and Chung (2007, 2014) and Groysberg (2010) consider these themes in the management literature.

These tensions stress how clusters are an outcome of an equilibrium process. Thus, places with great spillover benefits usually bring very high prices for real estate and talent. This market pricing is true across cities and across small zones inside prominent clusters. Not only is Boston more expensive as whole than Providence, the real estate around Kendall Square and MIT is the priciest. Indeed, abstracting from moving costs, escalating real estate prices can enhance the fidelity of the cluster, as only those who most benefit from the location are willing to pay astronomical rates (e.g., Malmberg and Power 2006, Bathelt and Li 2014). Few studies have explicitly modelled these tradeoffs and tensions, and yet they are critical for our understanding.

[3] Modularity is the method of making complex products or creating processes from smaller subsystems developed by a network of independent firms. Although different suppliers are responsible for separate modules, they follow "design rules" that ensure the modules work together (Baldwin and Clark 1997). This approach decentralizes innovation and may accelerate technical progress, since independent firms can focus on innovation to their specific components compared with the divided attention of vertically integrated firms. Saxenian (1991), Sturgeon (2002), and Berger (2005) provide case examples.

These labor tensions extend into employment law. Non-compete clauses in employment contracts limit the ability of a person to leave their employer and immediately compete in the same segment. Gilson (1999) proposed that Silicon Valley's dynamism should be attributed to the inability of local firms to enforce non-compete clauses. While non-compete clauses may encourage employers to invest more in training workers, as they are less likely to be poached by rivals, the labor rigidities can also stifle the flow of ideas and the optimal matching of workers and firms. Subsequent empirical analyses by Marx et al. (2009, 2015), and Hausman (2019) have shown to the latter to be particularly troublesome for inventors and technical diffusion.[4]

Immigration, Diversity, and Tech Talent

Immigration and talent diversity, two factors not discussed by Marshall (1890), are also critical for the understanding of US tech clusters. Classic early accounts of tech clusters by Saxenian (1994, 2002) and Florida (2005) emphasize how openness and tolerance in the community undergird the innovative productivity of the cluster. These authors, along with Falck et al. (2009), further consider how urban amenities and high quality of like are necessary to attract the highly skilled people central for tech clusters.

US tech clusters are high-skilled immigration hubs, in most cases building strong past waves of immigration to large coastal cities. More than 60 percent of Silicon Valley's entrepreneurs are immigrants to America (Kerr and Kerr 2020), and the chief executive officers of Alphabet, Microsoft, SpaceX/Tesla, and Uber are all foreign-born. Much of the large innovative workforce of tech clusters comes from abroad. Immigrants accounted for an astounding two-thirds of San Jose's college-educated workforce in the American Community Survey for information and communications technologies. While San Jose is an outlier, immigrants as a share of the college-educated workforce in these fields still exceed 40 percent in many tech clusters.

Kerr (2019) describes factors behind this reliance: talent for science, technology, engineering, and mathematics is quite transportable across countries, and the ranks of foreign talent looking for education and subsequent work opportunities in America in tech fields has been growing, especially from China and India. Part of America's immigration system is employer-driven (as a prominent example, the H-1B temporary visa program for those in "specialty occupations"), which also offers technology firms a substantial lever for using foreign talent. Not surprisingly, a literature has quantified how growth in US immigration can benefit tech clusters and their major employer firms (for example, see Kerr and Lincoln 2010; Peri et al. 2015). Nathan (2014, 2015) provides similar evidence with a European focus.

A distinguishing feature of tech clusters is their cultural celebration of innovation that has the potential to change the world. But other common cultural forces are counterproductive. Contrary to the growing evidence of a diversity premium for generating ideas, tech clusters have been frequently plagued by a "bro" culture that disadvantages women and minorities. Despite high-profile tech leaders like Mayer and Sandberg, women are under-represented and sometimes dramatically so (e.g., only 2-3 percent of venture funding goes to women entrepreneurs). African

[4] Firms can also seek extra-legal maneuvers. In the late 2000s, major tech employers entered into anti-poaching agreements with each other, later paying large fines to settle the cases (as reported in Roberts 2015; Mehrota 2016).

American participation is also terribly low, with recent gains in professional occupations like management consulting and investment banking not occurring in tech work (Gompers and Wang 2017). A separate concern is that tech companies may still operate with the "move fast and break things" spirit, but broader public concerns regarding privacy, data security breaches, and propagation of "fake news" via social media loom large.

Customer-Supplier Interactions, Firm Organization, and Global Networks

Returning to the last of Marshall's forces, the benefits that firms in tech industries gain from co-locating depend upon local production techniques and, perhaps less obviously, global integration and production chains. Taking the local perspective first, many case examples point to the critical nature of local supply (Saxenian 1991). An early Apple executive described the desire for regional proximity: "Our purchasing strategy is that our vendor base is close to where we're doing business… We like them to be next door. If they can't, they need to be able to project an image like they are next door." Even where manufacturing was to be ultimately off-shored, contract manufacturer Flextronics emphasized local integration: "In the early stage of any project, we live with our customers and they live with us. Excellent communication is needed between design engineers, marketing people, and the production people, which is Flextronics."

Agrawal and Cockburn (2003) and Feldman (2003) developed concepts of anchor firms for clusters, which all those cities hoped to achieve by luring Amazon's HQ2 to their area, and Glaeser and Kerr (2009) considered optimal industrial composition. Markusen (1996) and Agrawal et al. (2014) emphasize the importance of firm size diversity. Large local firms anchor the cluster and produce ideas that do not fit well internally and thus get spun-out. Lots of small firms are also vital to lower entry barriers and to stimulate specialized support services. This local diversity was present in Detroit in the early 1900s and Silicon Valley in the 1960s (for example, Klepper 2010), and Agrawal et al. (2014) find evidence for their model when looking at the innovative output of US cities during the 1975-2000 period.

Hellmann and Perotti (2011) alternatively conceptualize how tech clusters facilitate the generation, circulation, and completion of new ideas. They model an important tradeoff of seeking to circulate and complete novel ideas within firms (where they are more protected) vs. in local clusters (where they are more likely to find best matches). Their model predicts diverse organizational forms—internal ventures, spin-offs, and start-ups—coexisting and mutually reinforcing each other. An empirical analysis of these features, along with the acquisition of ideas into firms, is very promising for future research.

While the economics literature mostly studies the local properties of tech clusters, they must also be embedded in the larger value chain of an industry (Coe and Bunnell 2003, Humphrey and Schmidt 2002). While Apple and Google race to design the next features of the smart phone, the phones themselves are produced in much lower cost locations and sold in retail shops globally. The geography literature discusses how tech clusters achieve their scale by integrating the local "buzz" into regional, national, or global production networks (e.g., Storper and Venables 2004, Bathelt et al. 2004, Bathelt and Li 2014). Indeed, in addition to allowing rapid local scaling, modular production design makes it easier for supply chains to extend across multiple locations and over borders.

The linkages between global tech centers are also important and growing. In addition to constituting a large share of the local innovative workforce, high-skilled migrants facilitate many exchanges between tech centers (Saxenian et al. 2002; Saxenian 2006), and a substantial share of patent inventor teams are now cross-border (Miguelez 2014; Branstetter et al. 2015; Kerr and Kerr 2018). Venture capital firms are especially well connected internationally (Balachandran and Hernandez 2019), and leading corporations maintain a string of labs and move workers between facilities (Choudhury 2016, 2017). Nanda and Khanna (2012) also emphasize the degree to which time abroad can aid entrepreneurs when they return to less well-connected parts of their home country.

Preconditions and Dynamics of Tech Clusters

An emerging frontier of research focuses on whether tech clusters can be created, and the necessary preconditions in doing so, with a persistent meta-finding that it is very difficult to predict where leading clusters will take root. Krugman (1991) emphasizes the role of historical accidents in explaining *where* clusters form, and local efforts to “become the next Silicon Valley” have a poor track record (see discussions and references in Lerner 2009, Duranton 2011, and Chatterji et al. 2014). Though history provides multiple examples of the development of a new tech cluster, predicting or purposefully creating the location of the next cluster might be impossible.

For example, in a portrait of the origins of Silicon Valley, Lee and Nicholas (2012) note that San Mateo County was a technological backwater for several decades from the 1890s. It was not until the 1930s that the area began to be noticed for its work on transistors, vacuum tubes and microwaves, which helped draw in larger firms and enabled startups. The government’s huge demand for electronics in World War II brought critical mass to the region, as the local population of tech engineers surged ten-fold in a few years. When Silicon Valley went through its inflection point, many other cities would have looked much better prepared in terms of industry composition and talent base to be the next leading center. Indeed, accounts of the formation of Silicon Valley like Saxenian (1994) emphasize how the region’s “blank slate” allowed for new forms of work to emerge, versus some pre-existing factor that destined the region for success. Being a “blank slate” may have worked for Silicon Valley, but it is not a strategy that consistently guarantees success!

In most accounts of the origin of tech clusters, such as Klepper’s (2010, 2016) comparisons of Detroit and Silicon Valley, emphasis is given to the initial placement of a few important firms and the spinoff companies they subsequently generate. This outsized influence for anchor firms generates ample room for random influences on the early location decisions vital to a future cluster. For example, William Shockley, who shared a Nobel Prize in Physics for his work on semiconductors and transistors, moved to the San Francisco area to be near his ailing mother; the spinoffs from his firm Shockley Semiconductors included Intel and AMD.

Moretti (2012) also describes how personal factors led Bill Gates and Paul Allen to move Microsoft from Albuquerque to Seattle, their hometown. At the time, Albuquerque was considered the better place to live, favored by most of Microsoft's early employees, and the location of many early clients. Yet, proximity to family won out, and this decision has reverberated well beyond Microsoft's direct employment. The agglomeration advantages sparked by Microsoft have attracted countless other tech firms to Seattle, including Jeff Bezos relocating from New York City to Seattle when he founded Amazon. Had Gates and Allen not moved home, Albuquerque might be home to two of America's three most valued companies in 2020.

A similar and related randomness arises due to the often-serendipitous nature of breakthrough discoveries and their outsized subsequent importance. Zucker et al. (1998) show that the location of biotech industry follows the positioning of the star scientists in the nascent field, and the surging prominence of Toronto for artificial intelligence traces to the choice of some key early researchers to locate there, well before the field became so prominent. Duranton (2007) formalizes how random breakthroughs could lead to shifts in the leadership of cities for a tech field or industry, such as the migration of semiconductors from Boston to Silicon Valley, and Kerr (2010) quantifies this pattern of reallocation across 36 patenting sectors since the 1970s.

While random sparks play a role, the same breakthroughs often occur contemporaneously in two or more locations (Ganguli et al. 2019). Accordingly, a new line of work considers the factors that shape which location emerges the winner. Duran and Nanda (2019), for example, study the widespread experimentation during the late 1890s and early 1900s as local automobile assemblers learned about the fit between this emerging industry and their city. Despite having fewer entrants initially, activity coalesced in smaller cities – Cleveland, Indianapolis, St. Louis, and Detroit – with Detroit being the ultimate winner by the late 1920s. The smaller city advantage may have been due to the higher physical proximity of relevant stakeholders, allowing for easier experimentation, prototyping, and circulation of ideas. So long as they had sufficient local input supplies, smaller cities may have provided more attention and financial support to the new technology compared to larger markets and fostered relational contracts.

This stream of research yields some tentative conclusions for policy makers. Lerner (2009) documents the poor past performance of public efforts to engineer a cluster from scratch, and Ferrary and Granovetter (2009) blame the widespread failure of policymakers to replicate the success of Silicon Valley to their misunderstanding of complex innovation networks and to the shallowness of venture capital markets. The unique origin of each existing tech cluster suggests future efforts to seed from scratch are likely to be similarly frustrating.

Instead, a better return is likely to come from efforts to reduce the local costs to experimentation with ideas (Kerr et al. 2014), alongside the provision of a good quality of life. There is likely also a role for cities that have developed a position in an emerging sector, even if by random accident due to family ties, to increase the odds they are favored in the shakeout process. Such support is more likely to work if it is broad-based to a sector and avoids attempting to "pick winners" by targeting individual companies. Other cities can take the strategy of increasing their connectivity to leading centers via remote work. Tulsa Remote pays qualified workers with remote jobs $10,000 to move to Tulsa, Oklahoma, and similar programs are popping up elsewhere. Rather than seeking to "become the next Silicon Valley," these effort focus on connecting into the existing hotspots and being an attractive alternative with a lower cost of living.

Beyond anchor firms, universities also feature prominently in the history of tech clusters, both for the United States and globally (Markusen 1996, Dittmar and Meisenzahl 2020). Under Dean Fred Terman's guidance, Stanford University fostered a strong relationship with the growing tech community, such as the 1948 creation of the Stanford Industrial Park that would house 11,000 workers from leading tech firms by the 1960s. Famed venture capitalist Arthur Rock summed up the university's driving role around this time: "All of the energetic scientists were forming around Stanford." (Lee and Nicholas 2012). Similarly, the placement of a Carnegie-funded library into a city in the decades around 1900 corresponded to a substantial growth in patenting relative to peer cities for the next 20 years (Berkes and Nencka 2019).

Hausman (2012) documents how university innovation fosters local industry growth, and these spillovers can attenuate rapidly (see also Andersson et al. 2009; Kantor and Whalley 2014). With the increase in university patenting following the 1980 Bayh-Dole Act that provided universities greater ownership of intellectual property resulting from government-funded research, these intellectual sparks are growing in number. Universities are also a vibrant source of young, smart workers with frontier skillsets. Marshall (1890) emphasized the benefits of natural advantages like deep harbors and coal mines; strong research universities, along with government-sponsored laboratories, are likely to be key (man-made) natural advantages for new tech clusters. While Silicon Valley was a blank slate, it did possess from the start a powerful asset with Stanford.

These historical examples are starting to provide insight that will advance our theory on tech clusters. Duranton and Puga (2001) model a system of cities in which new industries emerging in large and diverse "nursery" cities. As industries mature and move from experimentation to scale, they no longer value the cross-fertilization enabled by industrial diversity and seek instead to maximize within-sector productivity. The model portrays mature industries as then relocating to less expensive and more specialized cities.

The nursery city model provides a powerful tool for thinking about systems of cities (Henderson 1974). It also fits many industrial experiences, such as the exodus of large-scale apparel manufacturing out of Manhattan over the last century (leaving the Garment District's name and some key fashion designers behind). The nearby "Silicon Alley" in Manhattan's Flatiron district also previously held names "Toy District" and "Photo District" reflecting the local cluster of previous eras. Yet, autos went from cradle to old age in Detroit, and other places like Lowell and Cleveland failed to renew themselves the way New York did. Boston has reinvented itself three times since its colonial days (Glaeser 2005).

What explains these differing fates? One promising hypothesis starts by thinking about the specialization of cities on function vs. industry lines (Duranton and Puga 2005). Many models keep industry size much smaller than city size, so that reallocation is more likely to happen at the industry level (Duranton and Puga 2001; Duranton 2007). The competitive framework by Porter (1998) emphasizes these radical upheavals that happen at the industry level. By contrast, the historical examples also suggest a fast-growing industry may come to dominate a nursery city so quickly that the city ceases to specialize on a function (like the breeding of new ideas) and instead specializes on an industry (like autos), thereby pushing out the local industry diversity to other locations.[5] The sociology and geography literatures also emphasize local threats to the growth of clusters, such as emerging endogenous barriers to entry (e.g., Granovetter 1973).

A richer depiction of these interacting forces connects to many interesting literature strands. Helsley and Strange (2014) model that cities hold a (non-optimal) mix of co-agglomerated industries due to legacy location choices and persistence. Perhaps the larger city size of a London or Tokyo protects it from becoming too hyper-specialized around any one fast-growing industry. Other work focuses on superstar cities and power couples seeking dual careers (for example, Gyourko et al. 2013, Costa and Kahn 2000). Maybe New York's greatest lever for long-term economic sustainability is that a high-income couple can be a daring fintech entrepreneur and conservative healthcare CEO, so long as they can also afford to pay $40,000 for their kid's pre-school.

Future Directions for Research

There are many open questions regarding tech clusters, and we conclude with some promising areas of inquiry. Just as tech clusters lead to spillovers across technological and industrial boundaries in the real economy, we expect that research on tech clusters will also spill over into and across other fields of economic inquiry.

New employer-employee datasets will allow researchers to quantify the creation and scaling of enterprises inside tech clusters. This step can build upon administrative data, such as the Census Bureau's Longitudinal Employer Household Survey, combined via external links to patenting and venture capital data. Others will take advantage of private datasets like LinkedIn, which is almost a pseudo-Census of the tech industry. For example, these analyses will help differentiate among the many theoretical channels for labor market pooling, ranging from greater matching to insuring workers against the risk of job separation.

Fine-tuned establishment data also facilitate new inquiries. Relatively few studies explore the internal choices within firms for how to locate their many activities, a decision that often involves a tradeoff between proximity to sources of external insight and internal communication and alignment (for recent examples, see Alcacer and Delgado 2016; Lychagin et al. 2017; Kerr 2018). As technology grows in importance, companies appear to be placing more key decision-makers and innovation personnel into tech clusters. Researchers need to develop a better understanding of these location decisions and their global consequences. For example, Landier et al. (2009) quantify the greater likelihood of business leaders to close plants farther away from the corporate headquarters.

These types of data further will refine our understanding of local spillovers in tech clusters from knowledge work to other industries. Moretti (2012) calculates that knowledge work creates five non-technical jobs for each knowledge worker, a local multiplier that is substantially higher than

[5] The spatial equilibrium model also struggles with aspects of the distribution of entrepreneurship across cities (for example, Glaeser 2008; Glaeser et al. 2010). Recent contributions to the underpinning of a system of cities model include Behrens et al. (2014) and Davis and Dingel (2019), which provide further references.

manufacturing. These generated jobs also pay better than similar work in other cities. Samila and Sorenson (2011) quantify how venture capital similarly creates new jobs in local areas beyond the start-ups directly supported, and that these tend to be well-paid positions, but that the magnitude is overall modest in nature. The resulting escalation of real estate rents, however, also crowds out lower income individuals (Gyourko et al. 2013), and a more complete portrait of the benefits and strains for local areas from blossoming tech work is needed.

Emerging research is also exploring how tech clusters shape the careers of individuals and the early stages of companies. Gompers et al. (2005) document how many venture capital-backed entrepreneurs cut their teeth through prior work in startups, and Moretti (2019) estimates that inventors moving to a larger tech cluster experience increases in their patenting outcomes. Future work can extend this person-level perspective to see how cities shape the types of work created by inventors. In a similar way, Guzman (2019) documents the migration of startups from their founding city to Silicon Valley. Higher-quality firms are more likely to migrate to the Valley, where they appear to receive better knowledge spillovers.

In closing, will the existing tech clusters strengthen going forward? A simple extrapolation of trend lines suggests greater spatial concentration for tech clusters looms on the horizon. Indeed, many policy proposals ranging from pushing massive basic R&D stimulus into the heartland (Gruber and Johnson 2019) to creating regionally capped visa allocations for skilled immigrants start with the premise that, because tech clusters are becoming more concentrated, policymakers need to step in. Due to lower agglomeration benefits outside of tech clusters, these proposals to push activity into other cities and regions are typically based upon achieving regional equity and political buy-in, perhaps coming with a reduced aggregate economic output. Moretti (2019) estimates, for example, that the special concentration of inventors into leading tech centers boosts innovation by 11 percent, compared to a scenario where all inventors spread out evenly over cities. Additional research to quantify the particular role of tech clusters and their innovations (both in total number and their traits like atypical combinations) into economic growth will be very valuable.

Yet, many factors may naturally limit further spatial inequality. Doubling Silicon Valley's size—which is impossible on many geographic and political levels—would still only make it 2 percent of the US population. We are witnessing a major transformation of business to achieve appropriate positions in powerful tech hubs, but most workers and consumers will always be far away. Large companies will only pay the hefty prices of tech clusters for some key workers, instead investing to ensure that the firm transmits the important information effectively to others in the company. At the local level, political pressures to limit housing construction will make it costly for certain tech centers to expand: for example, Hsieh and Moretti (2019) estimate that housing constraints that limited the spatial reallocation of workers towards the most productive cities of New York and the San Francisco Bay area lowered US growth by 36 percent since the 1960s. Political tensions and spatial disparities across US regions may also limit how big tech clusters can become.

These factors were already in play in early 2020 when the COVID-19 crisis added yet more complexity to the future of tech clusters. On one hand, the acceleration in technology adoption brought about by the pandemic (for example, to shift activity towards e-commerce or contactless stores) is likely to increase the near-term importance of tech clusters. Efforts by tech companies to provide assistance in the crisis have also helped repair some of the reputation hits they recently incurred. Yet, these clusters thrive on proximity, which can unfortunately transmit viruses as easily as ideas, and on global talent and trade. These benefits may be dampened in years ahead due to the virus itself and the follow-on business and political changes it produces. Catalysts like venture funding may also be in shorter supply in years ahead. The man-made nature of tech clusters leaves them more malleable than those built around harbors or coal mines, and future research will shed more light on tech clusters through the adjustments that lie ahead.

REFERENCES

- Acs, Z., Anselin, L., Varga, A. (2002). “Patents and innovation counts as measures of regional production of new knowledge.” Research Policy, 3, 1069-85.
- Agrawal, A., Cockburn, I. (2003). “The anchor tenant hypothesis: exploring the role of large, local, R&D-intensive firms in regional innovation systems.” International Journal of Industrial Organization, 21 (9), 1217-53.
- Agrawal, A., Cockburn, I., Galasso, A., Oettl, A. (2014). “Why are some regions more innovative than others? The role of firm size diversity.” Journal of Urban Economics, 81 (1), 149-65.
- Agrawal, A., Cockburn, I., Rosell, C. (2010). “Not invented here? Innovation in company towns.” Journal of Urban Economics, 67 (1), 78-89.
- Alcacer, J., Chung, W. (2007). “Location strategies and knowledge spillovers.” Management Science, 53 (5), 760-76.
- Alcacer, J., Chung, W. (2014). “Location strategies for agglomeration economies.” Strategic Management Journal, 35, 1749-61.
- Alcacer, J., Delgado, M. (2016). “Spatial organization of firms and location choices through the value chain.” Management Science, 62 (11), 3213-34.
- Almazan, A., De Motta, A., Titman, S. (2007). “Firm location and the creation and utilization of human capital.” Review of Economic Studies, 74 (4), 1305-27.
- Almeida, P., Kogut, B. (1999). “Localization of knowledge and the mobility of engineers in regional networks.” Management Science, 45 (7), 905-17.
- Andersson, R., Quigley, J., Wilhelmsson, M. (2009). “Higher education, localization and innovation: evidence from a natural experiment.” Journal of Urban Economics, 66 (1), 2-15.
- Arzaghi, M., Henderson, J.V. (2008). “Networking off Madison Avenue.” Review of Economic Studies, 75, 1011-38.
- Audretsch, D., Feldman, M. (1996). “R&D spillovers and the geography of innovation and production.” American Economic Review, 86, 630-40.
- Balachandran, S., Hernandez, E. (2019). “Mi Casa Es Tu Casa: immigrant entrepreneurs as pathways to foreign venture capital investments.” Wharton Working Paper.
- Baldwin, C., Clark, K. (1997). “Managing in an age of modularity.” Harvard Business Review (September-October).
- Bathelt, H., Li, P.F. (2014). “Global cluster networks—foreign direct investment flows from Canada to China.” Journal of Economic Geography, 14 (1), 45-71.
- Bathelt, H., Malmberg, A., Maskell, P. (2004). “Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation.” Progress in Human Geography, 28 (1), 31-56.
- Behrens, K., Duranton, G., Robert-Nicoud, F. (2014). “Productive cities: sorting, selection, and agglomeration.” Journal of Political Economy, 122 (3), 507-53.

- Berger. S. (2005). How We Compete: What Companies Around the World Are Doing to Make it in Today's Global Economy, New York, Doubleday.
- Bergquist, K., Fink, C., Raffo, J. (2017). “Identifying and ranking the world’s largest clusters of inventive activity.” WIPO Working Paper 34.
- Berkes, E., Gaetani, R. (2019). “The geography of unconventional innovation”, Working Paper.
- Berkes, E., Nencka, P. (2019). “‘Novel’ ideas: the effects of Carnegie libraries on innovative activities”, Working Paper.
- Branstetter, L., Li, G., Veloso, F. (2015). “The rise of international coinvention.” In: Jaffe, A., Jones, B. (Eds.) The Changing Frontier: Rethinking Science and Innovation Policy, University of Chicago Press, 135-68.
- Breschi, S., Lissoni, F. (2009). “Mobility of skilled workers and co-invention networks: an anatomy of localized knowledge flows.” Journal of Economic Geography, 9 (4), 439-68.
- Bresnahan, T, Gambardella, A. (Eds.) (2001). Building High-Tech Clusters: Silicon Valley and Beyond, Cambridge University Press, Cambridge.
- Carlino, G., Carr, J., Hunt, R., Smith, T. (2012). “The agglomeration of R&D labs.” Federal Reserve Bank of Philadelphia Working Paper 12-22.
- Carlino, G., Chatterjee, S., Hunt, R. (2007). “Urban density and the rate of invention.” Journal of Urban Economics, 61 (3), 389-419.
- Carlino, G., Kerr, W. (2015). “Agglomeration and innovation.” In: Duranton, G., Henderson, J.V., Strange, W. (Eds.) Handbook of Regional and Urban Economics Volume 5, 349-404.
- Carrincazeaux, C., Lunga, Y., Rallet, A. (2001). “Proximity and localisation of corporate R&D activities.” Research Policy, 30, 777-89.
- Chatterji, A., Glaeser, E., Kerr, W. (2014). “Clusters of entrepreneurship and innovation.” In: Lerner, J., Stern, S. (Eds.), Innovation Policy and the Economy, Vol. 14, University of Chicago Press, Chicago, IL.
- Choudhury, P. (2017). “Innovation outcomes in a distributed organization: intrafirm mobility and access to resources.” Organization Science, 28 (2), 339-54.
- Choudhury, P. (2016). “Return migration and geography of innovation in MNEs: a natural experiment of knowledge production by local workers reporting to return migrants.” Journal of Economic Geography, 16 (3), 585-610.
- Coe, N.M., Bunnell, T.G. (2003). “‘Spatializing’ knowledge communities: towards a conceptualization of transnational innovation networks.” Global Networks, 3, 437-56.
- Combes, P., Duranton, G. (2006). “Labour pooling, labour poaching and spatial clustering.” Regional Science and Urban Economics, 36 (1), 1-28.
- Costa, D., Kahn, M. (2000). “Power couples: changes in the locational choice of the college educated, 1940-1990.” Quarterly Journal of Economics, 115 (4), 1287-315.
- Davis, D., Dingel, J. (2019). “A spatial knowledge economy.” American Economic Review, 109 (1), 153-70.
- Delgado, M., Porter, M., Stern, S. (2010). “Clusters and entrepreneurship.” Journal of Economic Geography, 10 (4), 495-518.
- Dittmar, J., Meisenzahl, R. (2020). “Public goods institutions, human capital, and growth: evidence from German history.” The Review of Economic Studies, 87 (2), 959-96.
- Duran, X., and Nanda, R. (2019). “Experimentation in the early U.S. automobile industry.” Working Paper.
- Duranton, G. (2007). “Urban evolutions: the fast, the slow, and the still.” American Economic Review, 97, 197-221.
- Duranton, G. (2011). “California dreamin’: the feeble case for cluster policies.” Review of Economic Analysis, 3, 3-45.

- Duranton, G., Puga, D. (2001). “Nursery cities: urban diversity, process innovation, and the life cycle of products.” American Economic Review, 91, 1454-77.
- Duranton, G., Puga, D. (2004). “Micro-foundations of urban agglomeration economies.” In: Henderson, J.V., Thisse, J.-F. (Eds.), Handbook of Urban and Regional Economics, Vol. 4, North-Holland, Amsterdam.
- Duranton, G., Puga, D. (2005). “From sectoral to functional urban specialisation.” Journal of Urban Economics, 57, 343-70.
- Egan, E., Dayton, A., Carranza D. (2017). The Top 100 U.S. Startup Cities in 2016. Rice University Report. tophttp://www.edegan.com/wiki/US_Startup_City_Ranking.
- Ellison, G., Glaeser, E. (1997). “Geographic concentration in U.S. manufacturing industries: a dartboard approach.” Journal of Political Economy, 105 (5), 889-927.
- Ellison, G., Glaeser, E., Kerr, W. (2010). “What causes industry agglomeration? Evidence from coagglomeration patterns.” American Economic Review, 100 (3), 1195-213.
- Faggio, G., Silva, O., Strange, W. (2017). “Heterogeneous agglomeration.” Review of Economics and Statistics, 99 (1), 80-94.
- Fairlee, R., Chatterji, A. (2013). “High tech entrepreneurship in Silicon Valley: opportunities and opportunity costs.” Journal of Economics and Management Strategy, 22 (2), 365-89.
- Falck, O., Fritsch, M., Heblich, S. (2009). “Bohemians, human capital, and regional economic growth.” Jena Economic Research Papers 2009-049.
- Fallick, B., Fleischman, C., Rebitzer, J. (2006). “Job-hopping in Silicon Valley: some evidence concerning the microfoundations of a high-technology cluster.” Review of Economics and Statistics, 88 (3), 472-81.
- Feldman, M. (2003). “The locational dynamics of the US biotech industry: knowledge externalities and the anchor hypothesis.” Industry and Innovation 10 (3), 311-29.
- Feldman, M., Kogler, D. (2010). “Stylized facts in the geography of innovation.” In: Hall, B., Rosenberg, N. (Eds.), Handbook of the Economics of Innovation, Vol. 1. Elsevier, Oxford, 381-410.
- Ferrary, M., Granovetter, M. (2009). “The role of venture capital firms in Silicon Valley’s complex innovation network.” Economy and Society, 18, 326-59.
- Fleming, L., Marx, M. (2006). “Managing creativity in small worlds.” California Management Review, 48 (4), 6-27.
- Florida, R. (2005). Cities and the Creative Class, Routledge, New York.
- Gagne, J.-F. (2019). “Global AI talent report 2019.” jfgagne.ai/talent-2019.
- Ganguli, I., Lin, J., Reynolds, N. (2019). “The paper trail of knowledge spillovers: evidence from patent interferences.” American Economic Journal: Applied Economics, forthcoming.
- Gerlach, H., Ronde, T., Stahl, K. (2009). “Labor pooling in R&D intensive industries.” Journal of Urban Economics, 65 (1), 99-111.
- Gilson, R. (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.
- Glaeser, E. (2008). Cities, Agglomeration and Spatial Equilibrium, Oxford University Press, Oxford.
- Glaeser, E. (2005). “Reinventing Boston: 1630-2003.” Journal of Economic Geography, 5 (2), 119-153.
- Glaeser, E.L., Kallal, H.D., Scheinkman, J.A., Shleifer, A. (1992). “Growth in cities.” Journal of Political Economy, 100, 1126-52.
- Glaeser, E., Kerr, W. (2009). “Local industrial conditions and entrepreneurship: how much of the spatial distribution can we explain?” Journal of Economics and Management Strategy, 18 (3), 623-63.
- Glaeser, E., Kerr, S., Kerr, W. (2015). “Entrepreneurship and urban growth: an empirical assessment with historical mines.” Review of Economics and Statistics, 97 (2), 498-520.
- Glaeser, E., Kerr, W., Ponzetto, G. (2010). “Clusters of entrepreneurship.” Journal of Urban Economics, 67 (1), 150-68.

- Gompers, P., Lerner, J., Scharfstein, D. (2005). "Entrepreneurial spawning: public corporations and the genesis of new ventures, 1986 to 1999." Journal of Finance, 60 (2), 577-614.
- Gompers, P., Wang, S. (2017). "Diversity in innovation." Harvard Business School Working Paper, No. 17-067.
- Granovetter, M. (1973). "The strength of weak ties." American Journal of Sociology, 78 (6), 1360-80.
- Groysberg, B. (2010). Chasing Stars: The Myth of Talent and the Portability of Performance, Princeton University Press, New Jersey.
- Gruber, J., Johnson, S. (2019). Jump-Starting America: How Breakthrough Science Can Revive Economic Growth and the American Dream. Public Affairs.
- Guzman, J., Stern, S. "The state of American entrepreneurship: new estimates of the quantity and quality of entrepreneurship for 15 US states, 1988–2014." National Bureau of Economic Research Working Paper No. 22095.
- Gyourko, J., Mayer, C., Sinai, T. (2013). "Superstar cities." American Economic Journal: Economic Policy, 5 (4), 167-99.
- Hall, B., Jaffe, A., Trajtenberg, M. (2001). "The NBER patent citation data file: Lessons, insights and methodological tools." National Bureau of Economic Research Working Paper No. 8498.
- Hausman, N. (2012). "University innovation, local economic growth, and entrepreneurship." US Census Bureau Center for Economic Studies Paper No. CES-WP- 12-10.
- Hausman, N. (2019). "Non-compete law, labor mobility, and entrepreneurship." Working paper.
- Hellmann, T., Perotti, E. (2011). "The circulation of ideas in firms and markets." Management Science, 57 (10), 1813-26.
- Helsley, R., Strange W. (1990). "Matching and agglomeration economies in a system of cities." Regional Science and Urban Economics, 20 (2), 189-212.
- Helsley, R., Strange, W. (2002). "Innovation and input sharing." Journal of Urban Economics, 51, 25-45.
- Helsley, R., Strange, W. (2014). "Coagglomeration, clusters, and the scale and composition of cities." Journal of Political Economy, 122 (5), 1064-1093.
- Henderson, J.V. (1974). "The size and types of cities." American Economic Review, 61, 640-56.
- Henderson, V., Kuncoro, A., Turner, M. (1995) "Industrial development in cities." Journal of Political Economy, 103, 1067-90.
- Hsieh, C.-T., Moretti, E. (2019). "Housing constraints and spatial misallocation?" American Economic Journal: Macroeconomics, 11 (2), 1-39.
- Humphrey, J., Schmitz, H. (2002). "How does insertion in global value chains affect upgrading in industrial clusters?" Regional Studies, 36 (9), 1017-102.
- Jacobs, J. (1969). The Economy of Cities, Vintage Books, New York.
- Jaffe, A., Trajtenberg, M., Fogarty, M. (2000). "Knowledge spillovers and patent citations: evidence from a survey of inventors." American Economic Review, 90 (2), 215-8.
- Jaffe, A., Trajtenberg, M., Henderson, R. (1993). "Geographic localization of knowledge spillovers as evidenced by patent citations." Quarterly Journal of Economics, 108, 577-98.
- Kantor, S., Whalley, A. (2014). "Knowledge spillovers from research universities: evidence from endowment value shocks." Review of Economics and Statistics, 96 (1), 171-88.
- Kenny, M, (2000). Understanding Silicon Valley: The Anatomy of an Entrepreneurial Region, Stanford University Press.
- Kerr, S., Kerr, W. (2018). "Global collaborative patents." The Economic Journal, 128, F235-72.
- Kerr, S., Kerr, W. (2020). "Immigrant entrepreneurship in America: evidence from the survey of business owners 2007 & 2012." Research Policy, 49 (3), 103918.
- Kerr, W. (2010). "Breakthrough inventions and migrating clusters of innovation." Journal of Urban Economics, 67 (1), 46-60.
- Kerr, W. (2018). "Navigating talent hot spots." Harvard Business Review.

- Kerr, W. (2019). The Gift of Global Talent, Stanford University Press.
- Kerr, W., Kominers, S. (2015). "Agglomerative forces and cluster shapes." Review of Economics and Statistics, 97 (4), 877-99.
- Kerr, W., Lincoln, W. (2010). "The supply side of innovation: H-1B visa reforms and U.S. ethnic invention." Journal of Labor Economics, 28 (3), 473-508.
- Kerr, W., Nanda, R., Rhodes-Kropf, M. (2014). "Entrepreneurship as experimentation." Journal of Economic Perspectives, 28 (3), 25-48.
- Klepper, S. (2010). "The origin and growth of industry clusters: the making of Silicon Valley and Detroit." Journal of Urban Economics, 67, 15-32.
- Klepper, S. (2016). Experimental Capitalism, Princeton University Press.
- Krugman, P. (1991). Geography and Trade, MIT Press.
- Lamoreaux, N., Levenstein, M., Sokoloff, K. (2004). "Financing invention during the second industrial revolution: Cleveland, Ohio, 1870-1920." NBER Working Paper 10923.
- Landier, A., Nair, V., Wulf, J. (2009). "Trade-offs in staying close: corporate decision making and geographic dispersion." Review of Financial Studies, 22 (3), 1119-48.
- Lee, J., Nicholas, T. (2012). "The origins and development of Silicon Valley." Harvard Business School Case 813-098.
- Lerner, J. (2009). Boulevard of Broken Dreams: Why Public Efforts to Boost Entrepreneurship and Venture Capital Have Failed-and What to Do about It. Princeton University Press.
- Liang, W.-J., Mai, C.-C., Thisse, J.-F., Wang, P. (2019). "On the economics of science parks." NBER Working Paper 225595.
- Lin, J. (2011). "Technological adaptation, cities, and new work." Review of Economics and Statistics, 93 (2), 554-74.
- Lychagin, S., Pinkse, J., Slade, M., Van Reenen, J. (2017). "Spillovers in space: does geography matter?" Journal of Industrial Economics, 64 (2), 295-335.
- Malmberg, A., Power, D. (2005). "(How) Do (Firms in) Clusters Create Knowledge?" Industry and Innovation, 12 (4), 409-31.
- Markusen, A. (1996). "Sticky places in slippery space: a typology of industrial districts." Economic Geography, 72 (3), 293-313.
- Marshall, A. (1890). Principles of Economics. Macmillan, London.
- Marx, M., Strumsky, D., Fleming, L. (2009). "Mobility, skills, and the Michigan non-compete experiment." Management Science, 55 (6), 875-89.
- Marx, M., Singh, J., Fleming, L. (2015). "Regional disadvantage? Employee non-compete agreements and brain drain." Research Policy, 44, 394-404.
- Matouschek, N., Robert-Nicoud, F. (2005). "The role of human capital investments in the location decision of firms." Regional Science and Urban Economics, 35 (5), 570-83.
- Mehrohta, Kartikay. 2016. "Samsung, LG Accused of Silicon Valley Anti-Poaching Deal," Bloomberg, September 12, https://www.bloomberg.com/news/articles/2016-09-12/samsung-lg-accused-of-silicon-valley-anti-poaching-agreement.
- Miguelez, E. (2014). "Inventor diasporas and the internationalization of technology." Discussion Paper Series No. 25/14, Centre for Research & Analysis of Migration.
- Moretti, E. (2012). The New Geography of Jobs. Houghton Mifflin Harcourt, New York.
- Moretti, E. (2019). "The effect of high-tech clusters on the productivity of top inventors." Discussion Paper 13992, Center for Economic Policy Research.
- Murata, Y., Nakajima, R., Okamoto, R., Tamura, R. (2014). "Localized knowledge spillovers and patent citations: a distance-based approach." Review of Economics and Statistics, 96 (5), 967-85.
- Nanda, R., Khanna, T. (2012). "Diasporas and domestic entrepreneurs: evidence from the Indian software industry." Journal of Economics and Management Strategy, 19 (4), 991-1012.

- Nathan, M. (2014). “The wider economic impacts of high-skilled migrants: a survey of the literature for receiving countries.” IZA Journal of Migration, 3 (4).
- Nathan, M. (2015). “Same difference? Minority ethnic inventors, diversity and innovation in the UK.” Journal of Economic Geography, 15 (1), 129-68.
- National Science Foundation. (2017). National Center for Science and Engineering Statistics | NSF 20-311.
- Olson, G., Olson, J. (2003). “Mitigating the effects of distance on collaborative intellectual work.” Economics of Innovation and New Technology, 12 (1), 27-42.
- Overman, H.G., Puga, D. (2010) “Labour pooling as a source of agglomeration: an empirical investigation.” In Glaeser, E.L. (Ed.) Agglomeration Economics. Chicago, IL: University of Chicago Press, 133-50.
- Peri, G., Shih, K., Sparber, S. (2015). “STEM workers, H-1B visas and productivity in U.S. cities.” Journal of Labor Economics, 33 (S1), S225-55.
- Porter, M. (1998). “Clusters and the new economics of competition.” Harvard Business Review.
- Roberts, Jeff John. 2015. “Tech Workers Will Get Average of $5,770 Under Final Anti-Poaching Settlement,” Fortune, September 3, , http://fortune.com/2015/09/03/koh-anti-poach-order.
- Rosenthal, S., Strange, W. (2001). “The determinants of agglomeration.” Journal of Urban Economics, 50, 191-229.
- Rosenthal, S., Strange, W. (2003). “Geography, industrial organization, and agglomeration.” Review of Economics and Statistics, 85 (2), 377-93.
- Rotemberg, J., Saloner, G. (2000). “Competition and human capital accumulation: a theory of interregional specialization and trade.” Regional Science and Urban Economics, 30, 373-404.
- Samila, S., Sorenson, O. (2011). “Venture capital, entrepreneurship and economic growth.” Review of Economics and Statistics, 93 (1), 338-49.
- Saxenian, A. (1991). “The origins and dynamics of production networks in Silicon Valley.” Research Policy, 20 (1), 423-37.
- Saxenian, A. (1994). Regional Advantage: Culture and Competition in Silicon Valley and Route 128, Harvard University Press, Cambridge, MA.
- Saxenian, A. (2006). The New Argonauts, Harvard University Press, Cambridge, MA.
- Saxenian, A., Motoyama, Y., Quan, X. (2002). Local and Global Networks of Immigrant Professionals in Silicon Valley, Public Policy Institute of California, San Francisco, CA.
- Singer, S. (2016). “General Electric CEO lauds Boston as new site.” Hartford Courant, https://www.courant.com/business/hc-immelt-ge-boston-connecticut-20160324-story.html.
- Singh, J., Marx, M. (2013). “Geographic constraints on knowledge spillovers: political borders vs. spatial proximity.” Management Science, 59 (9), 2056-78.
- Storper, M., Venables, A.J. (2004). “Buzz: face-to-face contact and the urban economy.” Journal of Economic Geography, 4 (4), 351-70.
- Sturgeon, T. (2002). “Modular production networks: a new American model of industrial organization.” Industrial and Corporate Change, 11 (3), 451-96.
- Uzzi, B., Mukherjee, S., Stringer, M., Jones, B. (2013). “Atypical combinations and scientific impact.” Science, 342 (6157), 468-72.
- Waldinger, F. (2012). “Peer effects in science – evidence from the dismissal of scientists in Nazi German.” The Review of Economic Studies, 79 (2), 838-861.
- World Intellectual Property Organization. (2017). The Global Innovation Index 2017: Innovation Feeding the World.
- Zucker, L., Darby, M., Brewer, M. (1998). “Intellectual human capital and the birth of U.S. biotechnology enterprises.” American Economic Review, 88 (1), 290-306.