Intercluster Innovation Differentials: The Role of Research Universities

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***Abstract*—We explore the role of research universities in explaining intercluster innovation differentials. Drawing on the knowledge production function, our baseline hypothesis is that cluster innovative performance is determined by the cluster's endowment with financial, intellectual, and human capital. Leveraging fine-grained, longitudinal panel data tracking the population of medical device clusters in the USA over a 12-year time period (1990–2001), we demonstrate strong support for the notion of spatial heterogeneity in cluster innovative performance. In particular, research universities, which play a critical role by serving as a source of knowledge spillovers and producing graduates who disseminate tacit knowledge within a cluster, are a critical ingredient for innovative performance in a regional technology cluster.**

***Index Terms*—Innovation, intercluster performance differentials, medical device industry, regional technology clusters, research universities, spatial heterogeneity, technology transfer.**

I. Introduction

THE GEOGRAPHIC concentration of economic activity has been of interest to scholars ever since Marshall [50], alluding to collectively held industry knowledge, remarked that there was "steel in the air" in Sheffield while documenting industrial districts, now commonly referred to as technology clusters. Globalization, the emergence of the Internet, and other advancements in communications technology and transportation logistics, however, have led some scholars to proclaim that firm location has become increasingly less important [9]. Because firms are now more than ever in a position to source inputs globally, location must be diminishing in importance when attempting to explain firm-level competitive advantage. Proponents of this theory suggest that this line of reasoning is especially salient in high-technology sectors like semiconductors, medical devices, or biotechnology, where the critical production inputs are financial, intellectual, and human capital. Some of the key production inputs for these high-technology industries tend to be either intangible (e.g., intellectual capital) or have the ability to cross spatial distance without incurring significant transaction costs (e.g., financial capital). Even human capital, particularly scientists and engineers, has exhibited significant geographic mobility in recent decades [13]. For these reasons, spatial agglomeration should have become less important, especially for high-technology industries.

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While these arguments are persuasive prima facie, a closer look at the economic geography at the beginning of the twenty-first century reveals a prevalence of regional technology clusters. If globalization and drastic advancements in technology reduce the importance of firm location, what accounts for the thriving clusters of semiconductor firms in Silicon Valley, medical device firms in the Chicago area, and biotechnology firms in Boston? Spatial concentration and heterogeneity are clearly evident here and appear to be especially salient in high-technology industries [3]. In contrast to the spatial homogeneity hypothesis, other scholars argue that technology clusters have become even more important in light of globalization and the emergence of the Internet [42], [43]. Porter captures this phenomenon appropriately, "Paradoxically, the enduring competitive advantages in a global economy lie increasingly in local things—knowledge, relationships, and motivation that distant rivals cannot match" [55, p. 77].

It is clear that understanding the performance of regional technology clusters is imperative to a wide set of constituencies including economic development agencies, university administrations, corporate managers, economists, and strategy scholars. Public entities such as cities, states, regions, and nations strive to become world leaders in specific industries [54]. University administrators increasingly explore the economic potential of their institutions' research for the local economy, an important topic in times of reduced public funding for research [47], [48], [53], [73]. Managers have to make critical location choices when deciding where to base startups or corporate R&D laboratories [6], [20]. Economists have a keen interest in potential knowledge spillovers within technology clusters [41]. Finally, strategy scholars attempt to understand whether location in a regional technology cluster might aid a group of firms in gaining and sustaining a competitive advantage [4], [55], [56]. Some even advocate that the context within which firm-level competitive advantage can be understood should be shifted from strategic groups or industries to regional clusters [55], [56], [66].

While prior research has produced compelling evidence that regional technology clusters provide benefits for companies, universities, and governments (see [56] for a review), the question of what determines intercluster innovation differentials remains. While understanding that regional technology clusters can offer substantial advantages is an important first step, one must also realize that not all clusters perform at the same level. Saxenian [66], for example, makes this point when comparing computer manufacturers in the Silicon Valley cluster to the Boston Route 128 cluster. While both regions are prominent computer technology clusters, Silicon Valley outperforms Boston's Route 128 in recent history, as demonstrated by Saxenian's insightful account based on qualitative research, highlighting factors such as informal information exchange, interfirm mobility of key personnel, and networking. Rothaermel *et al.* [60] documents that biotechnology startups located in top regional clusters are more likely to be chosen as alliance partners by large pharmaceutical companies, an endorsement that plays a critical role in helping new ventures accomplish an initial public offering [70]. Empirical evidence therefore, suggests, that spatial heterogeneity along several performance dimensions exists among clusters within the same industry.

The literature on intercluster performance differentials is noticeably lacking in large-scale quantitative studies, likely due to the difficulty of obtaining fine-grained data across a large number of clusters over time. The absence of studies allowing for more rigorous hypotheses testing through formal econometric analyses has hampered empirical progress in this field. This study attempts to close the gap by testing a model that highlights key capital endowments and their effects on intercluster innovation differentials.

We advance herein a theoretical model in which we predict that intercluster innovation differentials are a function of the clusters' endowments in financial, intellectual, and human capital. We highlight research universities as a critical ingredient to innovation within technology clusters, as they are a source of knowledge spillovers and produce graduates through which knowledge disseminates throughout a cluster. More specifically, we investigate the role of different academic disciplines in generating innovation in medical devices such as heart valves, vascular stents, total knee implants, and spinal disk replacements, all of which demand a high degree of innovation and engineering.

It is important to identify the sources of such ideas, whether from universities or industry, to better understand the production of new products in this important economic sector. To test the proposed model of intercluster innovation differentials, we leverage fine-grained, longitudinal panel data collected for the population of medical device clusters in the USA. We test this model on a sample of all 248 medical device locations during the 12-year time span between 1990 and 2001, enabling us to draw on a sample of close to 3000 observations.

II. Capital Endowments and Intercluster Innovation Differentials

Porter defines a regional technology cluster as a "geographically proximate group of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities" [56, p. 4]. Firms, public institutions like research universities, and trade and regional associations are interconnected through formal and informal networks. Firms in clusters are characterized by simultaneous competition and cooperation, because these relationships take place on different dimensions and stages along the industry value chain. Regional technology clusters present a hybrid spatial organizational form, located between the endpoints of a continuum beginning with arm-length transactions in markets and ending with vertical integration through hierarchies [55]. On the one hand, geographic proximity and close interactions among cluster firms, over time, contribute to the development of trust, and thus, enhance interorganizational exchange [21]. Clusters tend to provide a context of stronger social embeddedness than market transactions [27], and thereby, facilitate effective exchange. On the other hand, clusters provide more flexibility than do vertical integrated hierarchies or networks of formalized alliances because firms within clusters are generally linked through informal ties.

Firms located in a technology cluster can avail themselves of several benefits, frequently the result of externalities emerging within the geographically constrained space of that cluster [55]. According to the theory of localized knowledge spillovers, cluster firms benefit from local research universities because universities generate knowledge spillovers, which tend to be regionally constrained [3], [41]. Moreover, the cost of transferring and absorbing knowledge spillovers is a positive function of geographic distance to the knowledge hubs, frequently research universities [45], [46], [67]. Not only are research universities a source of knowledge spillovers, they also educate and train people in fields critical to innovation in technology industries like the sciences and engineering; this explicit and tacit knowledge then travels from the research laboratories to the companies [3], [5], [6]. One can, therefore, postulate that a prominent semiconductor cluster emerged in the Silicon Valley area because firms were able to benefit from intellectual and human capital generated at Stanford University and the University of California-Berkeley, among other research institutions in the immediate vicinity. In a similar fashion, one can argue that a leading biotechnology cluster emerged in Boston because biotechnology startups were able to benefit directly and indirectly from the research and teaching conducted at Massachusetts Institute of Technology (MIT), Harvard, and other institutions in the Boston metropolitan area.

In addition, firms in a cluster often have privileged access to venture capital (VC) because venture capitalists tend to colocate near premier research universities in order to evaluate and fund commercially viable research [25]. This benefit is particularly salient for new venture creation because venture capitalists not only provide capital but also strategic and technical assistance, often in the form of a monitoring role on the new venture's board of directors. Venture capitalists, moreover, tend to actively recruit managers, lawyers, suppliers, and customers for their portfolio companies. Because relationships between venture capitalists and their portfolio companies tend to be deep and extensive, venture capitalists generally prefer to fund spatially proximate ventures [68].

Taken together, most of a cluster's benefits are an outflow of its capital endowments in three critical areas: financial, intellectual, and human capital. Financial capital describes the monetary resources necessary to fund innovation. Here, venture capital and grants from public institutions like the National Science Foundation (NSF) or National Institutes of Health (NIH) play a critical role, especially in high-tech, science intensive research areas. VC is a direct source of capital for entrepreneurial ventures, whereas NSF and NIH grants apply more indirectly. While venture capitalists frequently fund university startups, NSF and NIH grants are given predominantly to research universities to fund basic and applied research. Intellectual capital captures basic and applied knowledge generated by research universities, which, in turn, spill over for entrepreneurs and startups to leverage without internalizing the costs related to research [40], [64]. Finally, human capital concerns the training of the labor force, in particular the necessary specialized training in the sciences and engineering; both fields are critical ingredients to commercially viable university inventions, and should contribute directly to the innovative productivity of technology clusters.

Porter [54] provides evidence for the notion that the competitiveness of a cluster depends, to some extent, on its capital endowments. The resource-based view is an important framework in strategic management research used to evaluate differential performance. Barney [8, pp. 105–106] elaborates on this view, positing that for a resource to have the potential to be the basis of a competitive advantage, "(a) it must be valuable, in the sense that it exploits opportunities and/or neutralizes threats in a firm's environment, (b) it must be rare among a firm's current and potential competitors, (c) it must be imperfectly imitable, and (d) there cannot be strategically equivalent substitutes for this resource that are valuable but are neither rare or imperfectly imitable." This framework is termed VRIN (valuable, rare, inimitable, and nonsubstitutable).

If we apply the VRIN framework to the cluster rather than the firm as the unit of analysis, we note that the three capital endowments (financial, intellectual, and human) are valuable, rare, unique, and nonsubstitutable because they tend to be geographically constrained, and therefore, imperfectly mobile [52], [69]. Intellectual capital is the basis for knowledge generation and knowledge spillovers, yet these spillovers tend to be locally constrained [41]. Clearly, university graduates move out of clusters, and with that movement, valuable knowledge travels away. Nonetheless, the knowledge transfer may be "sticky" [71], that is, the knowledge may not be transferred completely away. Stickiness happens particularly if a significant amount of knowledge is tacit in nature, which is frequently the case in science-intensive industries. Agrawal *et al.* [1], for example, demonstrate that knowledge flows tend to be localized because of social relationships, which are more likely to be developed and maintained in geographically constrained spaces. Stuart and Sorenson [69] provide evidence for the notion that important resources for new ventures are embedded in social relationships that tend to be spatially constrained. These findings provide indirect evidence that complex knowledge tends to travel poorly.

We also suggest that financial resources based on venture capital and grants from national agencies tend to be locally bound within regional clusters because venture capitalists tend to colocate near premier research universities, and the majority of grants are awarded to these same universities [25]. Therefore, we posit that financial, intellectual, and human capital endowments are resources that adhere to the VRIN attributes, and thus, may be employed to predict intercluster performance differentials.

III. Empirical Model

Taken together, our overarching hypothesis is that *a cluster's innovative output is a function of its endowments in financial, intellectual, and human capital.* Following the application of knowledge production functions to explain innovation [18], [29], we hypothesize that a cluster's innovative output is generated by the knowledge production function

$$Y = f(F, I, H; Z) \tag{1}$$

where Y is the measure of innovative output, F is the cluster's financial capital endowment, I is the cluster's intellectual capital endowment, H is the cluster's human capital endowment, and Z is the vector of control parameters. Taking a closer look at this knowledge production function, it becomes apparent that the role of research universities is a critical determinant in the innovation production function of clusters: not only are they the source of the intellectual capital, a result of ongoing basic and applied research, but they also produce the human capital necessary for innovation. Moreover, venture capitalists, as the major source of financial capital, tend to colocate near research universities [25]. Finally, the vast majority of federal research grants are given to leading research universities. Taken together, the research university determines, directly or indirectly, the levels of capital endowments in a regional technology cluster to a significant extent.

It is important to note that we do not advance a model of one-time capital endowments in terms of stocks, but rather a model in which a cluster's capital endowment is evaluated each year over time, making it more akin to a flow model of endowments over time [17], [29], [30]. A consistently higher flow of endowments over time should explain why one cluster outperforms another.

IV. Methodology

A. Research Setting

The research setting for this study is the USA medical device industry, a subset of the healthcare industry. The overall healthcare industry in the USA is approximately \$1.3 trillion, amounting to over 12% of the Gross National Product (GNP) [75]. The spending on healthcare products is a direct function of age demographics and is relatively insensitive to race, socioeconomic class, and gender. The growth in this sector is likely to dominate the USA economy as the baby boomers reach 60+ years, estimated to balloon to \$3.6 trillion by 2017. Within the healthcare industry, medical device technology, though a relatively young sector, is nonetheless quite important. In 2002, expenditure on medical devices totaled approximately \$220 billion, whereas expenditures on all pharmaceuticals and biotechnology products combined amounted to only \$176 billion [2].

The medical device industry is a vibrant high-technology industry that comprises the commercial activity related to the invention, development, manufacture, and sale of medical device implants and other external products such as braces, crutches, and bandages. The development of pacemakers, vascular grafts, heart valves, and joint replacements in the 1950s spearheaded the advancement of this industry. Pacemakers were pursued by Earl Bakken, an inventor and engineer in Minneapolis, and a cofounder of Medtronics in 1957. Joint replacements were developed in the metalworking environment of Warsaw, IN. Others [12] have identified important milestones such as the creation of advanced cardiovascular systems (ACS) in 1978 by Stanford-trained physician John Simpson, who successfully commercialized the invention of the balloon catheter to clear blocked coronary arteries in order to prevent cardiac arrest (i.e., angioplasty). Given his training at Stanford University, a worldwide leading research university, it was not surprising that Simpson based ACS in Santa Clara, CA, and thus, helped to initiate the formation of a medical device cluster (today, the San Jose, CA, cluster) through several entrepreneurial spin-outs from ACS [12].

Medical devices can approximately be divided into six major subdivisions [2]: biological products (7%), dental (5%), diagnostic (12%), medical equipment (16%), ophthalmic (7%), and surgical device implants, instruments, and supplies (53%). The dollar value for these subdivisions is weighted heavily toward surgical device implants such as pacemakers, heart valves, and total knee and hip replacements.

The distribution of medical devices companies is quite bipolar: 11 companies have market caps greater than $3 billion, while 105 are currently valued at under $200 million [2]. Typically, small startups produce most of the new products, with larger companies following with the acquisition of these successful smaller companies after market validation [36], [62]. Thus, large incumbent firms such as General Electric, Medtronic, or Johnson & Johnson focus mainly on incremental innovations. In contrast, more radical innovations tend to frequently emerge from university research or are user-led by physicians and clinicians [57]. However, it is also important to note that innovation in medical devices does not progress along a linear and unidirectional line, where basic knowledge and scientific breakthroughs emerge from research universities before they are refined and developed along the industry innovation value chain. Rather, innovation in medical devices depends on complex and extensive interactions between universities and industry, where knowledge and technology are exchanged in a bidirectional fashion [16], [22], [24].

It is noteworthy that medical device firms generally do not make significant investments in basic science, a fact that deepens their dependence on basic scientific research conducted at universities and leading company laboratories such as Bell Laboratories, which are often not directly related to the medical device industry. To illustrate this point, Gelijns and Thier [23] recall the history of the laser (short for light amplification by stimulated emission of radiation), an important scientific breakthrough underlying many medical devices today (see also [58]). Foundational work was accomplished by Charles Townes at Columbia University in the early 1950s, who invented the maser, "a device that creates a focused microwave beam using stimulated emission. Townes then collaborated with Schawlow of Bell Laboratories on a theory of how stimulated emission might work at the wavelength of visible light—from maser to laser" [23, p. 73]. The collaborative work by Arthur Schawlow and Charles Townes was published in 1958 in the *Physical Review*, and Bell Laboratories was granted a patent for the laser in 1960.

Gelijns *et al.* [22] describe the laser as "one most powerful and versatile advances in technology in the 20th century. The widening range of applications in the 35 years since the laser was patented at Bell Laboratories is breathtaking . . . The possibility of using the laser for eye and skin disorders became apparent soon after its introduction. However, fundamental research questions about the properties of light, transmission, scatter, reflection, and absorption needed to be answered before the laser could be used for clinical conditions such as refractory angina pectoris, which involve more complex tissue structures." This example, in turn, echoes the importance of basic science conducted at research universities, without which the laser's many subsequent medical applications would not have been possible. More recently, scientific breakthroughs in biotechnology, computing, and nanotechnology have opened up vast opportunities for continued innovation in medical devices.

Finally, the medical device industry is generally a clean one, requiring both skilled and unskilled labor. Growth is spurred mostly by innovation in technological development. As such, the outsourcing of early stage product development to overseas locations has generally not occurred, and it appears that this economic sector, like biotechnology, is likely to remain within the USA.

B. Data

To test our research model detailed in the knowledge production function before, we collected annual data on all regional technology clusters in the USA medical device industry over a lengthy time period. Cluster innovation data were drawn from the Cluster Mapping Project at the Institute for Strategy and Competitiveness (ISC), Harvard Business School [39]. The ISC is led by Professor Michael Porter, and operationalizes regional clusters as follows: "Clusters are defined initially using [USA] state-level data ($n = 50$). The robustness of cluster composition is verified using Economic Area as the geographical unit. Clusters are constructed using two approaches, which are then reconciled. First, select a prominent 'core' industry in a field or part of the economy [here: medical devices]. Calculate the locational correlations of all other industries with the core. Those industries with statistically significant correlations with the core define the extent of the cluster. Second, calculate locational correlations between all pairs of industries in a general field and potentially related fields. Those set of industries with statistically significant and substantial intercorrelations among each other define the cluster. In both cases some industries may have spurious correlations to a cluster because of the co-location of several strong clusters in the same geographical area. Spurious correlation is eliminated using Input–Output tables, industry definitions, and industry knowledge [39]."

Following this operationalization of the cluster concept, we included all metropolitan statistical areas with nonzero medical device employment over the study period. This approach is prudent to avoid sampling on the dependent variable, a frequently observed problem of cluster studies relying on small samples. The medical device companies are geographically dispersed throughout the USA, with 248 distinct locations. Because we are investigating intercluster performance differentials over time, it is important to note that medical device companies tend to stay in their place of birth. The profit margins for these companies are typically quite high because of regulatory entry barriers and strong intellectual property protection, and thus, most companies have not been forced to relocate to low-wage geographies. States with high numbers of medical device companies have enjoyed a dynamic but balanced growth from this sector, which has not been beset by the fluctuations of other markets such as information technology. We followed the 248 medical device clusters over the 12-year period between 1990 and 2001, and were able to draw on 2976 cluster-year (=248 × 12) observations.

C. Measures

1) Intercluster Innovation Differentials: We attempt to explain intercluster innovation differentials. A cluster's propensity to innovate is especially salient because of its importance to the dynamism of advanced economies [51]. We proxied a cluster's innovativeness through the number of medical device patents assigned to each cluster by the USA Patent and Trademark Office. Patenting in medical devices is a critical competitive element in this industry because growth and firm performance is determined by continued innovation [12]. In addition, protecting intellectual property through patents appears to be quite effective in medical devices; as Cohen *et al.* [15] found, based on a survey of 1478 laboratories in the USA manufacturing sector, medical equipment (SIC 3311) was the sector with the strongest patent effectiveness score among all 34 manufacturing sectors surveyed. Given the strong intellectual property protection that patents in the medical device industry enjoy, it is not surprising that close to 30 000 patents had been issued by the end of our study period [39]. The reliability of patent count data as a measure for innovation has been established empirically [31]. Moreover, prior research demonstrates that patent count data are highly correlated with citation-weighted patent measures, thus proxying the same underlying theoretical construct [32].

At the end of our study period in 2001, the Boston–Worcester–Lawrence–Lowell–Brockton, MA–NH, medical device cluster was the most innovative one in absolute terms, generating 243 medical device patents. This lead is followed by the Minneapolis–St. Paul, MN–WI, cluster with 133 patents, and the San Francisco, CA, cluster with 119 patents. Over the study period, however, the San Francisco cluster's patenting rate increased by a cumulative of almost 400%, followed by a 270% increase for the Minneapolis–St. Paul cluster, and a close to 250% increase for the Boston cluster. Fig. 1 and Table I document the spatial distribution, development, and heterogeneity of medical device patents in the USA at the beginning of the study period in 1990, and at the end of the study period in 2001.

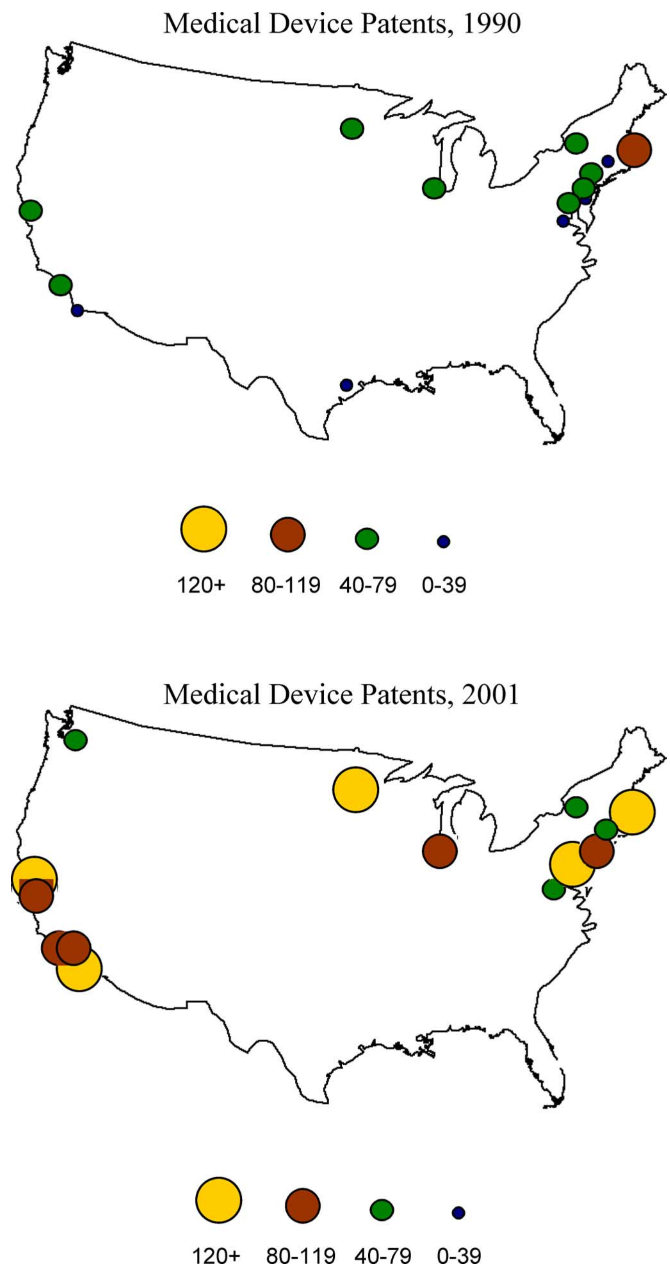

Fig. 1. Top 15 medical device clusters by patents, 1990 and 2001.

D. Independent Variables

1) Financial Capital: We used two proxies to assess a cluster's financial capital endowment: venture capital and grants from the NIH. VC plays a critical role in converting university inventions into commercially viable innovations [25], one of the assumed drivers in the medical device industry. The proxy we used was the amount of VC invested in the medical and health sector per cluster for each year during our study period. These data were collected from the SDC Platinum V database, which Thomson Financial publishes under the name VentureXpert. This database contains detailed information on VC transactions in the USA and abroad spanning several decades. To avoid unnecessary heterogeneity in the venture capital funding data, we limited venture capital transactions to the medical and health

TABLE I
TOP 15 MEDICAL DEVICE CLUSTERS BY PATENTS, 1990 AND 2001

Medical Device Patents, 1990	
Boston-Worcester-Lawrence-Lowell-Brockton, MA-NH	94
Los Angeles-Long Beach, CA	69
Chicago, IL	66
New York, NY	60
Philadelphia, PA-NJ	57
Minneapolis-St. Paul, MN-WI	48
Rochester, NY	45
San Jose, CA	42
Newark, NJ	41
Orange County, CA	39
Middlesex-Somerset-Hunterdon, NJ	36
Washington, DC-MD-VA-WV	36
Houston, TX	33
New Haven-Bridgeport-Stamford-Danbury-Waterbury, CT	33
San Diego, CA	32
Medical Device Patents, 2001	
Boston-Worcester-Lawrence-Lowell-Brockton, MA-NH	233
San Jose, CA	175
Philadelphia, PA-NJ	141
Minneapolis-St. Paul, MN-WI	130
San Diego, CA	123
San Francisco, CA	123
Los Angeles-Long Beach, CA	118
Chicago, IL	107
New York, NY	93
Oakland, CA	89
Orange County, CA	81
Washington, DC-MD-VA-WV	77
Rochester, NY	67
Seattle-Bellevue-Everett, WA	62
New Haven-Bridgeport-Stamford-Danbury-Waterbury, CT	56

sector. The clusters with the highest annual investments of venture capital in the medical and health sector were San Jose, CA, with over \$1.4 billion, followed by Orange County, CA, with close to \$850 million, and San Diego, CA, with about \$840 million. To alleviate any estimation biases caused by inflation, we converted all financial data into 2001 constant dollars.

The second proxy for a cluster's endowment of financial capital was the total amount of NIH research grants awarded annually to the research universities within the cluster. We obtained these data from the Office of Extramural Research at the NIH. The NIH budget amounts to approximately \$27.3 billion and funds most of the primary research in the area of human medicine. In contrast, the NSF budget for biological sciences and bioengineering amounts to approximately \$650 million, or about 2.4% of the NIH budget.

The products of publicly funded research discovered and developed at universities are required to be patented and made commercially available under the Bayh-Dole Act of 1980. Some of the new developments eventually become pharmaceuticals, while others become medical devices. Given that there are approximately 90 000 Food and Drug Administration (FDA)-approved medical devices versus approximately 1400 FDA-approved prescription drugs, it is much more likely that newly applied research will find its way into the medical device arena [2]. Clearly, research grants appear to be a critical driver for research productivity at research universities, and are directly related to knowledge spillovers, one of the important benefits of spatial agglomeration. The medical device clusters that obtained the largest annual grants from the National Institutes of Health were San Diego, CA, with close to \$250 million, followed by the Boston, MA, area with over \$200 million, and the Seattle, WA, cluster with close to \$180 million, again, in constant 2001 dollars.

2) Intellectual Capital: Intellectual capital emerges from research universities through engagement in basic and applied research, and provides the basis for complex tacit knowledge to develop within a cluster. We proxied a cluster's intellectual capital by the number of doctoral/research universities (extensive) within a cluster. This definition is based on the classification by the Carnegie Foundation [11, p. 1], which describes the leading research universities in the USA as follows: "Doctoral/Research Universities—Extensive: These institutions typically offer a wide range of baccalaureate programs, and they are committed to graduate education through the doctorate. . . . they awarded 50 or more doctoral degrees per year across at least 15 disciplines." As of 2000, 151 (3.8%) universities in the USA fell into this elite category. The highest concentration of premier research universities was found in the Boston cluster (8), followed by the Los Angeles, New York, and Washington, DC, clusters (six each).

Moreover, as evidenced by the founding of ACS, the medical device industry is an example where user-led innovation appears to be prevalent [12], [22]. In user-led innovations, "it is typically the product user, not the product manufacturer, who recognizes the need, solves the problem through an invention, builds a prototype, and proves the prototype's value in use" [37, p. 25]. Given the importance of the physician-led innovation in medical devices [44], we used the number of medical schools as a second proxy of a cluster's intellectual capital. Medical schools, as well as their attached teaching hospitals, are integral parts of the innovation system in medical devices, where physicians engage in cutting-edge research, instruction, and practice of medicine [23].

We obtained the names and locations of all 125 accredited M.D.-granting medical schools in the USA from the Association of American Medical Colleges (AAMC), and mapped the medical schools onto the medical device clusters based on their geographic locations. All but four medical schools were located in 1 of the 248 medical device clusters.[1] The greatest density of medical schools was found in the New York, NY, cluster (eight medical schools), followed by the Boston–Worcester–Lawrence–Lowell–Brockton, MA–NH, Philadelphia, PA–NJ, and

[1]The four medical schools not located in a medical device cluster are Dartmouth Medical School in Hanover, NH, and three medical schools in Puerto Rico. Moreover, with the exception of the Florida State University's College of Medicine, which was founded in 2000, all other medical schools were founded prior to the beginning of the study in 1990.

Washington, DC–MD–VA–WV clusters (four medical schools each).

3) Human Capital: Research universities produce the human capital necessary for innovation. When proxying the human capital endowment of a cluster, therefore, we focused on graduates in engineering, biomedical, and medical sciences as the relevant disciplines for innovation in medical devices. University graduates, especially from premier research universities like the ones included in Carnegie Foundation's top research category, are endowed with a high level of specific human capital that functions as a mechanism by which knowledge is transmitted. Both upstream training in the basic sciences and downstream complementary training in the more applied engineering disciplines are required to successfully convert inventions into viable innovations.

We collected annual data on the number of science and engineering graduates. The latter are considered to be critical in translating scientific inventions into commercially viable innovations, because "innovation in medical devices is by and large engineering-based problem solving by primarily individuals or small firms ..." [57, p. 5]. Thus, we obtained fine-grained data for several different fields in the sciences relevant to advancements in medical devices: chemical engineering, electrical engineering, mechanical engineering, biomedical engineering, and medical sciences.

New devices are frequently invented as a direct response to a clinical need [22]. Medical science graduates are potentially important drivers for these new treatments and devices, which, in turn, need to be made into practical products that can be manufactured at a large scale. Such devices are often in the form of glucose, biochemical sensors, and actuators, which are the main purview of chemical engineers. Cardiac rhythm management and controllers often depend on electrical circuits and controls, best addressed by electrical engineers. The domain of mechanical engineers includes the largest group of medical devices, which is structural in function (e.g., artificial hips and knees). All of these products must be manufactured under the standard of "Good Manufacturing Procedures." In recent years, a newer area of biomedical engineering has also emerged. Some programs emphasize medical device development and innovation, while others focus on biological quantitative behavior. New devices are most often proposed and developed by practicing surgeons (e.g., in the case of implants) and by internists (e.g., in the cases of efficiency instruments). After an idea is proposed, engineers typically create prototypes and develop manufacturing techniques. Thus, a wide variety of engineering disciplines from chemical, electrical, mechanical, and biomedical areas are expected to contribute to, but not dominate, the medical device arena. Medical sciences are more fundamental in nature than the engineering sciences, and tend to span these specific disciplines. Because engineering Ph.D.s are critical for converting inventions into economically viable products, we also collected data on Ph.D. degrees awarded in chemical engineering, electrical engineering, mechanical engineering, biomedical engineering, and the medical sciences. Annual data on university graduates were obtained from the NSF, and then, mapped onto each medical device cluster.

A fine-grained look at the distribution of the science graduates revealed that the Boston, MA, cluster produced the highest annual number of graduates in four out of the five science areas included in this study: chemical engineering (324), electrical engineering (1355), mechanical engineering (680), and medical sciences (1689). The highest annual number of biomedical graduates was produced by the Baltimore, MD, cluster (148). When considering science Ph.D. degrees only, we found that the Boston, MA, cluster produced the highest annual number of all Ph.D. degrees in the sciences (357), again leading in four out of five areas: chemical engineering (69), mechanical engineering (67), biomedical engineering (18), and medical sciences (52). The Los Angeles, CA, cluster graduated the highest annual number of electrical engineering Ph.D.s from 1990–2001 (123).

E. Control Variables

1) Cluster Size: When assessing intercluster innovation differentials, it is important to control for the size of each cluster. We used the annual number of *medical device employees* as a proxy for the size of a medical device cluster. Proxying firm size and aggregate cluster size by the number of employees is a common practice in high-technology industries [62], because the most critical assets in these science-driven industries tend to be intangible.

At the end of the study period in 2001, the largest medical device clusters in terms of employment were found in the Chicago cluster (28 211 employees), followed by the Boston cluster (23 238 employees), and the Minneapolis–St. Paul cluster (20 396 employees). Over the 12-year study period, the Chicago cluster's employment increased by a cumulative of more than 290%, followed by a 190% increase for the Minneapolis–St. Paul cluster, and a 125% increase for the Boston cluster. The employment growth numbers clearly reflect the dynamic growth of the medical device industry over these 12 years. Fig. 2 and Table II document the spatial distribution, development, and heterogeneity of medical device employment in the USA in 1990 and 2001.

2) Cluster Density: It is also prudent to control for the number of *medical device firms* in each cluster. We included this proxy to control for cluster density. Moreover, including the number of medical device firms in the regression equations allows us to test the baseline assumption that spatial agglomeration is indeed beneficial. The most densely populated medical device cluster was found in the Boston area with close to 300 firms, followed by the Chicago cluster with 226 firms, and the Los Angeles cluster with 222 firms.

3) Year Fixed Effects: Since we investigated a 12-year time period, it is prudent to control for time-varying factors that affect all firms, including macroeconomic conditions. We, therefore, inserted annual time dummies for each year, with 1990 being the omitted year, and thus, serving as the reference year. Such year fixed effects also capture secular movements in the dependent variable. Inserting year dummies is useful, because it addresses concerns that underlying secular trends could potentially influence our inference by introducing a simultaneity bias in the relationship between the dependent variable, medical

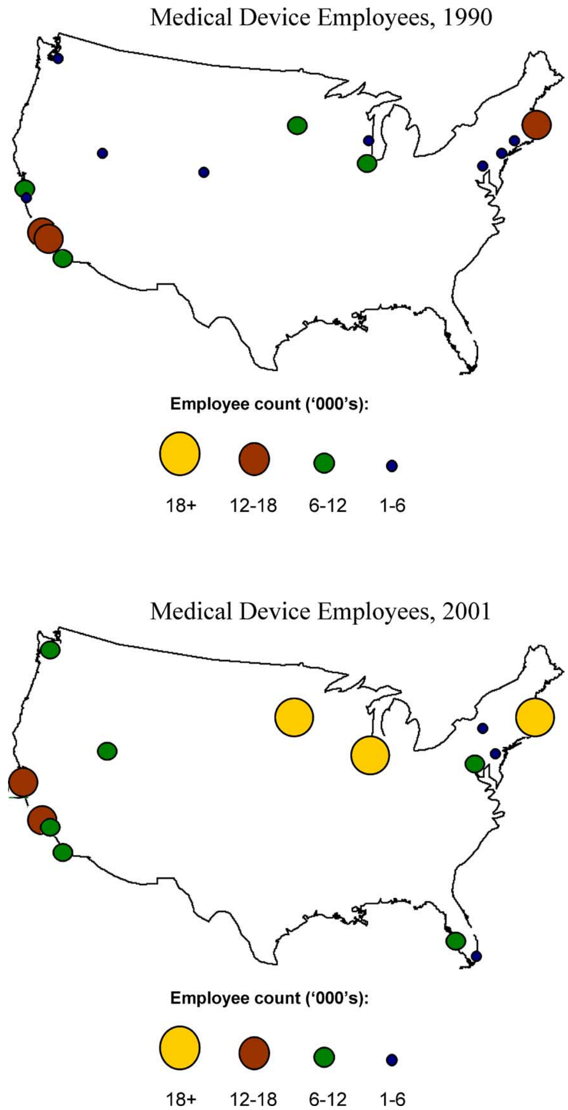

Fig. 2. Top 15 medical device clusters by employment, 1990 and 2001.

TABLE II
TOP 15 MEDICAL DEVICE CLUSTERS BY EMPLOYMENT, 1990 AND 2001

Medical Device Employees, 1990	
Boston-Worcester-Lawrence-Lowell-Brockton, MA-NH	18,461
Los Angeles-Long Beach, CA	12,796
Orange County, CA	11,006
Minneapolis-St. Paul, MN-WI	10,535
Chicago, IL	9,699
San Diego, CA	9,610
San Jose, CA	6,022
Nassau-Suffolk, NY	5,730
Denver, CO	5,580
Philadelphia, PA-NJ	5,371
New Haven-Bridgeport-Stamford-Danbury-Waterbury, CT	5,317
Oakland, CA	5,185
Seattle-Bellevue-Everett, WA	4,994
Milwaukee-Waukesha, WI	4,877
Salt Lake City-Ogden, UT	4,665
Medical Device Employees, 2001	
Chicago, IL	28,211
Boston-Worcester-Lawrence-Lowell-Brockton, MA-NH	23,238
Minneapolis-St. Paul, MN-WI	20,065
Los Angeles-Long Beach, CA	12,855
San Jose, CA	12,536
Orange County, CA	10,624
Salt Lake City-Ogden, UT	9,812
Oakland, CA	9,566
San Diego, CA	9,448
Philadelphia, PA-NJ	8,163
Tampa-St. Petersburg-Clearwater, FL	7,712
Seattle-Bellevue-Everett, WA	6,018
Middlesex-Somerset-Hunterdon, NJ	4,993
Rochester, NY	4,977
Miami, FL	4,976

device patents, and the main regressors of interest. In addition, year fixed effects also attenuate any right truncation effect.

F. Estimation Procedures

The dependent variable of this study, a medical device cluster's patents, is a nonnegative, integer count variable. Verified by a statistical test for overdispersion [26], the negative binomial estimation provides a significantly better fit for the data than the more restrictive Poisson model. Negative binomial regression accounts for an omitted variable bias, while simultaneously estimating heterogeneity [10], [34].

In theory, either fixed- or random-effects specification can be used to control for unobserved heterogeneity [28]. We applied a Hausman [35] specification test, and the result revealed that a fixed-effects estimation is indicated.[2] We, therefore, applied the following fixed-effects negative binomial model:

$$P(n_{it}/\varepsilon) = \frac{\lambda_i^{n_{it}-1\,\exp(\varepsilon)}\lambda_i^{n_{it}-1}}{n_{it}-1!} \tag{2}$$

where *n* is a nonnegative integer count variable, representing each cluster's patents in medical devices. Thus, $P(n_{it}/\varepsilon)$ indicates the probability that cluster *i* is granted *n* medical device patents in year *t*. To interpret the results in a meaningful manner and to reduce potential collinearity, we standardized all independent variables before entering them into the various regression models. Estimating all variance inflation factors (VIFs) revealed that none of the variables exceeded the cutoff point of 10 [14], with a maximum average VIF of 4.93. Further, to compensate for a potential simultaneity bias and to enhance any causality claims, we lagged the independent variables by one year. We submit that through the application of the Hausman specification test and the resulting fixed-effects specification, in combination with a set of rigorous control variables, including cluster size, cluster density, and year effects, we have effectively addressed any potential endogeneity [33].

[2] To assess how sensitive our results are to the reported fixed-effects specification, we additionally applied a random-effects estimation. The results remained robust, with the fixed-effects estimation producing the more conservative results.

TABLE III
DESCRIPTIVE STATISTICS AND BIVARIATE CORRELATIONS

	Mean	Std. Dev.	Min	Max	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.
1. Medical Device Patents	9.86	21.71	0	243																		
2. Year	1,995.50	3.45	1990	2001	0.12																	
3. Medical Device Employees	1,339.73	2,965.41	0	29,278	0.80	0.03																
4. Medical Device Firms	19.26	34.48	0	286	0.86	0.04	0.91															
5. Venture Capital	14,400	72,100	0	1,440,000	0.68	0.09	0.54	0.52														
6. NIH Grants	3,707	17,500	0	246,000	0.59	0.00	0.44	0.57	0.33													
7. Research Universities	0.51	1.05	0	8	0.62	0.00	0.57	0.66	0.22	0.60												
8. Medical Schools	0.48	0.92	0	8	0.60	0.00	0.53	0.63	0.23	0.52	0.73											
9. Science Graduates (total)	247.78	465.67	0	3,940	0.62	0.01	0.61	0.65	0.29	0.51	0.75	0.61										
10. Chem Eng Graduates	21.62	42.99	0	324	0.45	0.04	0.43	0.44	0.22	0.31	0.52	0.37	0.86									
11. Elec Eng Graduates	68.11	135.70	0	1,355	0.53	0.00	0.54	0.56	0.28	0.45	0.68	0.46	0.93	0.85								
12. Mech Eng Graduates	45.81	87.41	0	680	0.46	-0.01	0.46	0.47	0.23	0.37	0.58	0.40	0.91	0.90	0.92							
13. BioMed Eng Graduates	5.00	15.97	0	148	0.46	0.03	0.49	0.49	0.25	0.40	0.53	0.49	0.55	0.40	0.46	0.41						
14. Med Sciences Graduates	86.50	196.69	0	1,689	0.65	0.02	0.63	0.68	0.27	0.54	0.76	0.71	0.91	0.64	0.72	0.68	0.53					
15. Chem Eng PhDs	2.46	6.02	0	69	0.52	0.00	0.51	0.52	0.27	0.37	0.54	0.36	0.78	0.83	0.78	0.77	0.40	0.62				
16. Elec Eng PhDs	5.46	13.46	0	123	0.54	0.01	0.47	0.53	0.29	0.44	0.60	0.38	0.79	0.74	0.84	0.78	0.39	0.61	0.78			
17. Mech Eng PhDs	3.34	7.76	0	67	0.52	-0.01	0.50	0.51	0.29	0.37	0.55	0.40	0.82	0.78	0.81	0.84	0.42	0.65	0.79	0.85		
18. BioMed PhDs	0.54	1.88	0	18	0.43	0.03	0.46	0.46	0.24	0.35	0.34	0.37	0.48	0.38	0.37	0.38	0.74	0.48	0.36	0.32	0.38	
19. Med Sciences PhDs	1.77	5.20	0	52	0.50	0.04	0.50	0.51	0.25	0.39	0.52	0.45	0.74	0.62	0.63	0.61	0.45	0.74	0.62	0.64	0.66	0.43

N = 2,976.

V. RESULTS

Table III depicts the descriptive statistics and bivariate correlation matrix, while Table IV presents the regression results for predicting innovation differentials among medical device clusters. Recall that our estimation technique is a negative binomial regression, and thus, a nonlinear, exponential estimation technique, as explicated in (2). To interpret the effects captured by the beta coefficients, one needs to exponentiate the respective beta value [$\exp(\beta)$ or e^{β}] to obtain an incidence rate ratio (IRR) (see [49, pp. 228–229], and for a recent application, see [38]).[3] To enhance the interpretability of the results, we display incident rate ratios instead of beta values. An IRR >1 increases the probability that the cluster will be assigned the expected number of medical device patents, whereas an IRR <1 is reflective of a reduced probability.

Model 1 presents the results for the control variables, including the proxies for financial capital. We find that larger clusters in terms of medical device employees tend to be less innovative. In particular, each time a cluster grows in terms of total medical device employees by one standard deviation (2965 employees), its probability to obtain the expected number of medical device patents is reduced by about 1.8% ($1 - \text{IRR}$ or $1 - 0.9824 = 0.0176 =$ factor change).

The results in model 1 also reveal that the number of medical device firms is positive and statistically significant when predicting innovative output. This suggests that, *ceteris paribus*, the greater the number of medical device firms that are located in a geographic area, the greater the cluster's innovative performance. This finding provides some evidence for performance-enhancing benefits to agglomeration [19]. The factor change for the number of medical device firms is almost 10%.

Taking the results for the number of medical device employees and the number of medical device firms together implies that innovation in the medical device industry, at least in terms of generating patents, is driven by a large number of small, entrepreneurial ventures (with the average medical device firm in the sample having 63 employees and the median firm having 40 employees), rather than by a few large firms like Medtronic or Johnson & Johnson. This result is consistent through all subsequent estimations presented in models 2–5.

It is common in the medical device industry to find that a successful product introduced by one company will spawn several other local entrepreneurial ventures as the original members of the first company split to create parallel products [12]. This outgrowth occurs when employees of existing firms gain experience and develop connections to important doctors and financial networks within the regional cluster. Our results, therefore, resonate

[3] A negative beta value translates into an incidence rate ratio of less than 1, while a positive beta value translates into an incidence rate ratio of greater than 1.

TABLE IV
NEGATIVE BINOMIAL REGRESSION PREDICTING INTERCLUSTER INNOVATION DIFFERENTIALS IN THE USA MEDICAL DEVICE INDUSTRY

	Model 1		Model 2		Model 3		Model 4		Model 5	
	IRR	s.e.	IRR	s.e.	IRR	s.e.	IRR	s.e.	IRR	s.e.
Fixed Effects	*included*		*included*		*included*		*included*		*included*	
Year is 1991	0.5885 ****	(0.0192)	0.5843 ****	(0.0193)	0.5843 ****	(0.0193)	0.5802 ****	(0.0195)	0.5848 ****	(0.0195)
Year is 1992	0.5889 ****	(0.0188)	0.5886 ****	(0.0188)	0.5886 ****	(0.0188)	0.5850 ****	(0.0190)	0.5892 ****	(0.0190)
Year is 1993	0.5968 ****	(0.0184)	0.5968 ****	(0.0184)	0.5967 ****	(0.0184)	0.5944 ****	(0.0187)	0.5960 ****	(0.0185)
Year is 1994	0.6362 ****	(0.0195)	0.6364 ****	(0.0195)	0.6365 ****	(0.0195)	0.6356 ****	(0.0198)	0.6363 ****	(0.0197)
Year is 1995	0.6519 ****	(0.0197)	0.6521 ****	(0.0197)	0.6520 ****	(0.0197)	0.6509 ****	(0.0199)	0.6531 ****	(0.0200)
Year is 1996	0.7373 ****	(0.0211)	0.7375 ****	(0.0211)	0.7373 ****	(0.0211)	0.7383 ****	(0.0213)	0.7402 ****	(0.0216)
Year is 1997	0.8084 ****	(0.0227)	0.8087 ****	(0.0227)	0.8091 ****	(0.0229)	0.8103 ****	(0.0231)	0.8095 ****	(0.0233)
Year is 1998	1.0158	(0.0277)	1.0166	(0.0278)	1.0167	(0.0278)	1.0168 *	(0.0280)	1.0152	(0.0279)
Year is 1999	1.0329	(0.0267)	1.0335	(0.0267)	1.0335	(0.0267)	1.0346	(0.0268)	1.0325	(0.0270)
Year is 2000	1.0036 *	(0.0256)	1.0041 *	(0.0256)	1.0043 *	(0.0256)	1.0010 *	(0.0287)	0.9983 *	(0.0274)
Cluster-Specific Controls:										
Medical Device Employees	0.9824 *	(0.0120)	0.9821 *	(0.0120)	0.9820 *	(0.0120)	0.9810 *	(0.0121)	0.9812 *	(0.0120)
Medical Device Firms	1.0986 ****	(0.0332)	1.0964 ****	(0.0332)	1.0963 ****	(0.0332)	1.1086 ****	(0.0347)	1.1098 ****	(0.0350)
Financial Capital:										
Venture Capital	1.0390 ****	(0.0055)	1.0392 ****	(0.0055)	1.0391 ****	(0.0055)	1.0386 ****	(0.0056)	1.0391 ****	(0.0055)
NIH Grants	0.9946	(0.0077)	0.9945	(0.0077)	0.9946	(0.0077)	0.9963	(0.0079)	0.9964	(0.0080)
Intellectual Capital:										
Research Universities			1.1165 *	(0.0802)	1.1166 *	(0.0802)	1.1131 *	(0.0801)	1.1130 *	(0.0800)
Medical Schools			1.3543	(0.9630)	1.3546	(0.9636)	1.3516	(0.9617)	1.3496	(0.9602)
Human Capital:										
Science Graduates (total)					1.0026	(0.0186)				
CE Graduates							0.9921	(0.0161)		
EE Graduates							1.0224 *	(0.0163)		
ME Graudates							0.9953	(0.0214)		
BioMed Eng Graudates							0.9975	(0.0072)		
Med Sci Graduates							0.9864	(0.0148)		
CE PhDs									1.0067	(0.0104)
EE PhDs									1.0030	(0.0159)
ME PhDs									0.9929	(0.0117)
BioMed Eng PhDs									0.9947	(0.0060)
Med Sci PhDs									0.9918	(0.0097)
Log likelihood	-3763.34 ****		-3762.14 ****		-3762.13 ****		-3760.75 ****		-3761.04 ****	

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$; **** $p < 0.001$; Standard errors are in parentheses.

with Chatterji's [12] notion that there can be strong knowledge inheritance between firms within a geographic cluster as employment at an incumbent firm provides a springboard for the creation of new innovative ventures, which are frequently located within the same technological cluster. It is also important to note that findings reported in Table IV are among the first to empirically demonstrate the entrepreneurial dynamism of the medical device industry.

When turning to the financial capital endowments of medical device clusters, we find that the amount of venture capital in a cluster is a positive predictor of innovative output, with a factor change of close to 4%. This finding holds robust across all estimations. The products of the medical device industry are highly regulated, and as such, an entrepreneurial startup is generally unable to market products and gain revenues in their early years, unless it receives significant amounts of venture capital [25] or enters into a cooperation with an established firm [59]. The development of a new, implantable medical device often requires between \$50 and \$75 million in investment capital over several years before profitability is reached. Without sufficient and experienced capital investment, inventions rarely translate into successful products. Further, it is common for venture capitalists to require geographic proximity before funding [25]. Once funded, the venture-backed firm will use patenting as a strategy to gain further competitive advantage while protecting their investment in a medical device. This strategy is pronounced in this field since patents on devices are often incremental rather than revolutionary. The number of patents in medical devices, therefore, tends to be partly dependent on the interest of the financial partners rather than the researcher. It is not surprising, then, that the number of patents in this particular sector is highly correlated with the amount of VC. In sum, venture capitalists seem to be attuned to funding high-performance companies that are innovative and geographically proximate, which is a direct reflection of most venture capitalists' strategy for selecting investment opportunities [25].

In model 2, we insert the proxies for intellectual capital: number of research universities and number of medical schools. We find that the number of research universities in a medical device cluster is positively related to innovative output.[4] The factor change remains significant, and is greater than 11% in all estimations, demonstrating that it has the strongest effect on patenting in medical device clusters among all independent variables. This finding clearly highlights the role of research universities in explaining intercluster innovation performance differentials. Moreover, it provides support for the knowledge spillover hypothesis [40], [63], where research universities generate basic knowledge that spills over for firms to exploit, which is ultimately manifested in the innovative activity in the regional technology cluster. On the other hand, we did not find the number of medical schools to be statistically significant, even though the factor change is high at 35%.[5] Taken together, research universities exert a significant positive effect on the innovative output of regional technology clusters in medical devices, above and beyond that of medical schools.

In model 3, we enter the total number of science graduates as the proxy for human capital, which does not reach significance.

In model 4, we split the total number of science graduates into different disciplines detailed before, and find that the number of electrical engineering graduates has positive and significant effect on cluster innovation, with a factor change of about 2.2%.

In model 5, we replace the total number of graduates in each discipline with the number of Ph.D.s granted. None of the variables, however, reach statistical significance. While one would expect that Ph.D.s are important mobility mechanisms facilitating knowledge spillovers, the low number of science Ph.D.s granted in each year results in a low variance of this variable, thus making it difficult to pick up any statistically significant effects.[6]

These results support the hypotheses by Chatterji [12] and Roberts [57] that the medical device industry is significantly different from the pharmaceutical industry. Roberts' [57] description of the importance of "lead users" (M.D.s) and individual entrepreneurs (usually not Ph.D.s) stands in strong contrast to the image of basic Ph.D. research leading to invention in the pharmacology area [61]. Chatterji [12] adds the insight that entrepreneurial ventures spawned from established firms are important for medical device performance, even without inherited technical knowledge. Thus, it is industry-specific knowledge, not general Ph.D. scientific knowledge, that appears to characterize and drive innovation for the medical device industry. The nonsignificance of NIH grants and human capital also reflects this conclusion.

[4]When inserting a dummy variable for the existence of a research university in the cluster (1 = at least one research university in cluster) instead of the count of research universities, the result is robust, with a factor of about 11%.

[5]Inserting a dummy variable for the existence of a medical school in the cluster (1 = at least one medical school in cluster) instead of the total number of medical schools also leads to a statistically nonsignificant result.

[6]Given the low values of VIFs discussed before, however, the nonsignificance of the variable for the total number of graduates and the Ph.D. graduates across the different disciplines cannot be attributed to multicollinearity.

VI. Discussion

With this contribution, we take a first step toward closing the gap in the literature concerning intercluster performance differentials, with a special emphasis on the role of research universities. We submit that this constitutes an important empirical contribution, because scholars like Porter [55], [56] and others have suggested that the critical environmental factor determining a firm's competitive advantage is no longer found at the industry or strategic group level, but rather at the level of the regional technology cluster (see also [3] and [66]). The overarching hypothesis in this study, therefore, is that a regional technology cluster's productivity in terms of innovation is a function of its endowments in financial, intellectual, and human capital, with the latter two being provided predominantly by research universities. We test this hypothesis on comprehensive and fine-grained panel data covering the USA medical device industry between 1990 and 2001.

We find support for the hypothesis that a cluster's innovative output is determined by its financial, intellectual, and human capital endowments. With regard to financial capital, we find that the availability of VC funding is a strong predictor of innovative output in medical device clusters. Venture capitalists provide the necessary funding for medical device firms to pursue innovative new product development. VC funding is especially critical in the medical device industry because it is an industry with a cost-intensive, fairly protracted regulatory approval process with uncertain outcomes; in such high-risk endeavors, venture capitalists are often the only funding source willing to provide capital. Further, VC funding partly drives the submission of patent applications in the area of medical devices. As Roberts [57] describes, innovation in medical devices is more engineering-based problem solving that seldom reflects fundamental new knowledge. Because small changes in design and process can trigger and lead to settlements in the $100 million to $1 billion range when patents are infringed upon [e.g., Palmaz-Schatz patent (U.S. Patent No. 4 641 653) and the Gary Michelson patent portfolio], venture capitalists often adopt a strategy of applying for multiple patents to create a "picket-fence" of intellectual property protection [76].

With respect to a technology cluster's endowment with intellectual capital, we find that the greater the number of leading research universities within the cluster (or even the mere existence of a research university), the greater the cluster's innovative output in terms of patents. This result highlights the fact that the availability of intellectual capital is a key driver of intercluster innovative performance, and that intellectual capital is available within clusters, but constrained to their geographic boundaries.

Roberts [57] asserts that with medical devices, the user plays a substantial role and is frequently the innovator. In this situation, the user and innovator is much more likely to be a medical doctor (M.D.), not the Ph.D. scientist. It is interesting to note that the factor change of medical schools is quite high, although the standard error is also high. A future avenue for study may be to relate M.D. numbers and medical school faculty numbers to medical device innovation.

Among the three capital endowments investigated in this study, the results for human capital are the weakest. We do however, find, that innovative output in medical device clusters is driven by the number of graduates in electrical engineering. This seems to indicate that most patent-protected innovations fall into the realm of more complex products for cardiac rhythm management and controls such as pacemakers, where electrical engineers play a critical role in innovation. A future study may corroborate this assertion more systematically through a detailed study of the patents granted in medical devices.

While the results for basic science graduates are not as strong, our findings may be among the first to address specific engineering and science disciplines most likely to actually impact innovation within an industrial sector, while explicitly controlling for research universities, medical schools, and other factors. Additionally, the medical device industry rarely contracts universities for product development, in comparison to more frequent investments in university research made by pharmaceutical companies.

Taken together, we find evidence for university knowledge spillovers when predicting intercluster innovation differentials, as the impact factor of research universities on innovative output is the absolute strongest among all factors considered. This finding is particularly significant when considered in the context of the drastically changed role of research universities in the USA [13], [61]. Prior to World War II, USA research universities modeled themselves after their European ancestors, steeped in the Humboldt tradition of scholarship as the unity of research and teaching. Research in this tradition was understood to be "pure science"; that is, scholars conducted basic research with little focus on or interest in development or commercialization. This prevailing attitude resulted in the notion that universities provided an ivory tower for scientists to pursue their research interests detached from any practical concerns of how their scientific breakthroughs may be tied to societal welfare. In addition, the role of government in organizing and funding R&D was limited during this time period.

Over the last few decades, this isolationist knowledge landscape has transformed dramatically. One important mechanism of change in the USA was the creation of state-funded universities within a highly decentralized structure (e.g., land-grant universities). This change allowed these startup universities to respond to regional economic needs, which, in turn, led to the embrace of more applied disciplines like engineering; as a result, we saw a rise in supply of scientists and engineers looking for industrial employment. Increased government funding provided another mechanism of change.

More recently, other factors have facilitated what Chesbrough [13] terms the shift from a "closed innovation system" to an "open innovation system" in the USA. These factors include, among others, the rise in venture capital, the passage of the Bayh-Dole Act (providing incentives for universities to patent scientific breakthroughs accomplished with federal funding, and subsequently market them), the rise in the pool, and thus, mobility of scientists and engineers, and important technological breakthroughs in computing (microprocessor), biotechnology (genetic engineering), and nanotechnology. All of these factors directly or indirectly impact innovation in the medical devices sector.

While we find empirical evidence that research universities are the source of important knowledge spillovers affecting the innovative performance of technology clusters, the exact mechanisms of the spillovers are not clear, because we do not find strong effects of graduates on innovative output. Perhaps it is research faculty, rather than graduates, who play a more critical role in facilitating knowledge flows that generate patentable innovation. This seems to be a fruitful avenue for future research, because survey evidence has found that the extent of faculty cooperation needed ranged from 40% of the inventions licensed by businesses, when estimated by the licensing directors of the businesses who licensed university inventions, to 71% of inventions transferred to businesses, when estimated by university technology transfer personnel [72], [74]. Recent empirical work also found that faculty involvement in university incubator firms prolonged their early survival [65], providing evidence of the importance of faculty–new venture linkages. In addition, empirical evidence shows that high-technology startups in the life sciences tend to colocate near research universities that are the home affiliations of top scientists [7], [77]. Thus, faculty involvement appears to be a knowledge spillover mechanism that clearly deserves more attention in future research.

We study one industry longitudinally, which allows us to control for industry idiosyncrasies. However, this approach necessarily limits the generalizability of the results across different industries. The medical device industry has received considerably less attention in the social science and engineering management literature than other high-technology industries like biotechnology or telecommunications. While we take a first step in moving away from small size, descriptive case studies, future research should attempt to test the theoretical model of capital endowments predicting intercluster innovation differentials across a larger number of high-tech industries to enhance the external validity of the research model presented here. We speculate that the role of the research university in driving innovation in a diverse set of high-technology sectors is likely to be corroborated.

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