Geographic Clusters and Firm Innovation

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GEOGRAPHIC CLUSTERS AND FIRM INNOVATION

by

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A dissertation submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy
in the Department of Management
in the College of Business Administration
at the University of Central Florida
Orlando, Florida

Summer Term
2011

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ABSTRACT

Scholars dating back to the early 1900s have been interested in the idea that organizations benefit from locating in close proximity to other similar organizations (Marshall, 1920). Largely, this research suggests that economies of agglomeration accrue to clustered organizations which create performance advantages when compared to more isolated organizations. Recently, agglomeration theory researchers have focused on high technology clusters where the primary benefit of collocation is argued to be access to knowledge spillovers from local organizations. This dissertation argues that in order to access local knowledge, firms must be active participants in the local research community. Furthermore, in clusters where inventive activity, measured using patent data, is highly concentrated in one or a few organizations, firms derive less benefit from their participation in local research. Clustering does not come without a price, however. Membership in local research networks, which initially provides an advantage for clustered organizations, ultimately drives a convergence of inventions in the cluster. That is, networks of organizations in clusters channel institutional pressures which ensure that firms' inventions come to resemble the inventions of other organizations in the cluster, over time.

ACKNOWLEDGMENTS

Certain data included herein are derived from Nanobank (Lynne G. Zucker and Michael R. Darby, Nanobank Data Description, release 2.0 (beta-test), Los Angeles, CA: UCLA Center for International Science, Technology, and Cultural Policy and Nanobank, January 17, 2007-February 2, 2009).

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This material is based upon work supported by an award to Lynne G. Zucker, Michael R.Darby, Jonathan Furner, Evelyn Hu, Carlo Montemagno, and Roy Doumani by the National Science Foundation under Grant No. SES-0304727; and awards to Zucker and Darby by the University of California's Industry-University Cooperative Research Programunder Grant Nos. PP99-02, P00-04, P01-02, and P03-01. Any opinions, findings, and conclusions or recommendations expresssed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation nor the Industry-University Cooperative Research Program.

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INTRODUCTION

The first chapter of this dissertation asserts that geographic clusters confer advantages upon collocated firms, where the primary benefit of clustering for high-technology firms is the access to locally held know-how embedded in local knowledge networks (Porter, 1998; Audretsch, 1996; Powell, Koput, and Smith-Doerr, 1996). Clusters vary in the benefits they confer to collocated firms, and scholars have examined the benefits firms derive from locating in clusters of greater fertility, or munificence (Coombs, Ireland, and Deeds, 2009; Decarolis and Deeds, 1999). They argue that the fertility of a cluster is a function of the number of similar firms located in the region, or the level of knowledge stocks in the region (McCann and Folta, 2009; Folta, Cooper, and Baik, 2006; Arthur, 1990). This chapter argues that cluster fertility is better described in terms of the degree to which inventions in a region are concentrated in one or a few firms. Innovative concentration affects the motivation of organizations in a cluster to share valuable know-how (Zucker and Darby, 1996). Motivation to share valuable know-how is argued to be a key factor in the transfer of tacit knowledge (Szulanski, 1996), and is not accounted for in current research. Addressing this gap in the literature, I test hypotheses on the effects of collaborations with local organizations in a geographic cluster on the rate and novelty of firm inventions. Furthermore, I show that inventive concentration negatively moderates the local collaboration to firm invention relationship, even after controlling for typical measures of cluster fertility.

In the second chapter I develop theory and propose hypotheses for a future empirical study. This chapter investigates the relationship between clustering and organizational innovations. I suggest that the relationship between clustering and innovation is more complex than previously considered. I argue that the benefits of clustering result from firms becoming locally embedded in their local knowledge networks. However, embeddedness comes at a price for clustered firms. I argue that embeddedness channels information on competitors and mimetic forces which encourage imitation. The result, I argue, is that embeddedness leads to a convergence of innovations in geographic clusters, over time (Pouder and St. John, 1996). That is, clustering increases firms' abilities to generate inventions, but their inventions come to resemble the inventions of other's in the cluster, and their inventions are also less impactful.

The third chapter of this dissertation is a compilation of five proposals for future research. Proposals 1 and 2 investigate how entrepreneur's knowledge and experience endowments affect the number and types of market opportunities they consider prior to market entry. Proposal 3 investigates the effect of firms' technological focus on the relationship between the geographic dispersion of research collaborations on the impact of firm inventions. Proposal 4 seeks to understand how inventions in a cluster converge upon an average invention in the cluster, and investigates cluster characteristics that speed the convergence process. Finally, proposal 5 examines how NSF and NIH research grants affect firm and regional inventiveness.

FIRM INVENTIONS IN GEOGRAPHIC CLUSTERS: THE MODERATING ROLE OF INVENTIVE CONCENTRATION

Introduction

It is widely accepted that organizations tend to cluster geographically, and scholars dating back to Marshall (1890/1920) have analyzed why similar firms might collocate. Scholars commonly agree that firms are motivated to cluster with similar firms because of economies of agglomeration that accrue to collocated firms (Porter, 1998; Saxenian, 1994; Krugman, 1991; Arthur, 1990). The benefits of collocation include access to specialized labor and inputs, greater access to customers, and access to locally shared know-how embedded in the relationships between similar firms and organizations (Powell, Koput, and Smith-Doerr, 1996; Almeida and Kogut, 1997; Jaffe et al., 1993; Saxenian, 1994). As such, researchers have found compelling evidence that knowledge-based firms located in a geographic cluster of similar or related firms are more inventive (McCann and Folta, 2009; Aharonson, Baum, and Feldman, 2008; Folta, Cooper, and Baik, 2006), introduce more new products (Coombs, Deeds, and Ireland, 2009), and have higher valuations at IPO (DeCarolis and Deeds, 1999).

Research on organizational learning suggests, however, that locally held know-how will not simply diffuse to collocated firms. Rather, firms must be active in the research process in order to appreciate its value (Powell, Koput, and Smith-Doerr, 1996; Cohen and Levinthal 1990). This locally-held know-how is tacit and complex in nature, and represents a shared understanding among firms in the region (Tallman, Jenkins, Henry, and Pinch, 2004). The tacit nature of locally-held know-how resists diffusion and its acquisition requires frequent interactions between motivated parties in the context of long-term relationships (Agarwal, Echambadi, Franco, and Sarkar, 2004; Szulanski, 1996; von Hippel 1988). Therefore, in order to access and appreciate local ideas, firms must become locally embedded practitioners, where one means of doing so is the collaboration with other local firms or institutions in the publication of research articles.

Given that firms benefit from embedding themselves in their local regions, researchers have sought to understand how these regions vary in the potential benefits embeddedness confers. For example, a central tenet of agglomeration theory suggests that as the number of collocated firms increases, so does the stock of locally held knowledge to which clustered firms have access (Arthur, 1990). This suggests that some geographic clusters may offer richer pools of locally-shared knowledge, and therefore, firms located in them should realize performance advantages. However, in her rich case study of the Silicon Valley and Route 128 high technology clusters, Saxenian (1994) provides compelling anecdotal evidence that high-technology clusters vary along dimensions other than those receiving attention in the extant literature. For instance, Saxenian asserts similarity in size of the firms in Silicon Valley created an open and entrepreneurial environment. Saxenian's work suggests that characteristics of geographic clusters that affect the open sharing of information among firms may mitigate any potential benefits typically associated with clustering.

Integrating insights from Saxenian's case study with the literature on tacit knowledge transfer, this dissertation argues that more important than the quantity of similar or related firms in a region are factors that characterize the motivation for collocated organizations to exchange knowledge (Szulanski, 1996). Moreover, research on individual scientists suggests that when firm- and team-level innovations are concentrated in one or a few individuals, these "stars" may lack the motivation to share their valuable know-how with others (Zucker and Darby, 2001). This research also espouses that the concentration of innovative productivity creates power hierarchies that can suppress effective communication (Tzabbar, 2009). This dissertation examines how the concentration of inventive activity, defined as the degree to which patents in a geographic cluster are concentrated in one or a few firms, affects the extent to which firms benefit from locating in a cluster. I posit that the benefits resultant of clustering decline with increasing concentration of inventive activity.

In particular, I argue that when innovative activity in a cluster is highly concentrated, both highly inventive and less inventive organizations will have decreased motivation to share valuable know-how. The result is an environment less fertile than what might otherwise be predicted by present measures of cluster fertility. Therefore, to fully understand the benefits firms derive from collocation, researchers should look beyond current measures of fertility and towards aspects of the cluster which enhance or impair the open exchange of know-how among clustered organizations. I develop hypotheses regarding the effects of local collaborations, defined as co-authorship on a research publication with an organization in the same cluster, on the rate and novelty of firm inventions, defined as the number of patents applied for in a given year and the number of new technologies embodied in firms' patents, respectively. To test my hypotheses, I developed a longitudinal data set of 1,908 firms engaged in research in the area of nanotechnology between the years 1981-2004.

This dissertation makes three contributions to the literature on agglomeration theory and economic geography. First, whereas prior research has characterized the fertility of geographic clusters in terms of the quantity of information available to clustered firms (i.e. level of knowledge stocks, number of similar firms, research universities, and scientists) (Aharonson, Baum, and Feldman, 2007; Folta, Cooper and Baik, 2006; Beaudry and Breschi, 2003), I characterize geographic clusters by the motivation that clustered firms have to engage in the knowledge transfer process. Doing so tightens the theoretical link between the sources of benefits of clustering (access to local knowledge networks) and the mechanisms thought to permit access to them. For example, if we agree that absorbing locally held know-how requires the transfer of tacit knowledge, then research describing the advantages local environments bestow upon local firms should focus more on factors that enhance or impair knowledge transfer, than on factors describing the size of local knowledge pools.

Second, understanding that absorbing locally-held knowledge requires repeated and frequent interactions among organizations motivated to share knowledge (Tallman, Jenkins, Henry, and Pinch, 2004; Brown and Duguid, 2001; Szulanski, 1996), this dissertation moves beyond assumptions made in prior research. Specifically, researchers have assumed that locally-held knowledge spills over to collocated firms via chance meetings that occur when firms are located in close proximity. By modeling the effects of firms' collaborations on published research articles, this study provides a more accurate test of theory regarding how firms are able to access locally-held know-how. Third, this dissertation extends Zucker and Darby's concept of the "star" scientist to the organizational level. Building on their individual level theory regarding the effects of the concentration of innovative activity on team and firm dynamics, I argue these effects also occur at the inter-organizational level.

Theoretical Background

Geographic Clustering and Innovation

As the geographic concentration of similar or related organizations increases, so does the access to specialized labor, input providers, customers, and knowledge spillovers (Folta, Cooper, and Baik, 2006; Arthur, 1990). As such, extant research in agglomeration theory suggests that firms are motivated to cluster in order to access externalities generated by collocated organizations (Marshall, 1920), and a compelling body of agglomeration theory research suggests firms cluster in order to access these externalities (see McCann and Folta, 2008 for a review). Prior research has found that firms in knowledge-based industries are more likely to cluster than firms in other industries (Coombs, Deeds, and Ireland, 2009; Audretsch and Feldman, 1996). Notwithstanding the breadth of accepted benefits of clustering, firms in knowledge-based industries are thought to benefit from clustering primarily through their access to locally-shared knowledge (Powell, Koput, and Smith-Doerr, 1996; Saxenian, 1994). Following this, researchers have argued that knowledge-intensive firms located in geographic clusters of similar firms enjoy performance advantages when compared to their more isolated counterparts. These scholars have argued that firms located in regions with a high concentration of similar firms will have access to knowledge not available to firms in more remote locations, and such access will positively affect firm performance (DeCarolis and Deeds, 1999). With more locally-available knowledge, densely collocated firms will benefit more from their attempts to access local knowledge networks (Coombs, Ireland, and Deeds, 2009). Supporting these claims, empirical evidence has shown a positive effect of geographic clustering on high-technology firms' innovative outcomes (Beaudry and Breschi, 2003; DeCarolis and Deeds, 1999; Hill and Naroff, 1984).

Research espousing the benefits of collocation largely assumes that collocating with similar organizations permits access to locally-held know-how. However, in high-technology domains where locally held knowledge is tacit and complex, locating in close geographic proximity to similar organizations is necessary but insufficient for realizing the benefits of collocation. Location in a region densely populated with similar organizations and specialized inputs, by itself, does not provide for the transfer of technological knowledge between organizations, rather firms must embed themselves in local networks of knowledge in order to benefit from collocation (Almeida and Kogut, 1997; Saxenian, 1994). When knowledge is complex and tacit in nature, its transfer requires frequent and repeated interactions between individuals motivated to engage in the transfer process (Brown and Duguid, 2001; Szulanski, 1996). Therefore, in knowledge-intensive industries, firms' abilities to learn about new opportunities are a function of their level of participation in their local networks (Powell, Koput, and Smith-Doerr, 1996). Moreover, in high-technology domains, a firm's inventive ability is largely a function of its collaborations with similar organizations and local research universities, rather than its financial investment in R&D (Aharonson, Baum, and Plunket, 2008).

Regional Differences in Inventive Potential

With growing interest from both scholars and public policy makers, researchers have sought to investigate which characteristics of geographic clusters confer an advantage to collocated firms. In other words, how can we describe geographic clusters in a way that indicates the benefits clusters bestow upon clustered firms? Such a question is of great interest to both regional- and national- level policy makers interested in growing the prosperity of their regions (McCann and Folta, 2008), as well as investors concerned with predicting the performance of high-technology ventures. To date, researchers have found evidence suggesting that not all clusters are equal in terms of the potential benefits they provide to clustered firms, and have identified aspects of geographic clusters presumed to be indicative of a region's fertility.

Grounded in agglomeration theory, which suggests increasing marginal returns as each new organization enters a region, scholars have largely focused on regional characteristics related to the number of similar organizations in a region (McCann and Folta, 2009; Folta, Cooper, and Baik, 2006; Shaver and Flyer, 2000). As the number of organizations in a region increases, so does the opportunity for chance meetings and interactions between collocated organizations. This, researchers argue, increases the likelihood that firms are able to access locally-held knowledge. Therefore, firms located in regions with a greater number of similar or related organizations should have an inherent advantage over more remote firms (McCann and Folta, 2009; Folta, Cooper, and Baik, 2006). Related research also suggests that in knowledge-based industries, levels of local knowledge stocks may be more reflective of the level of externalities generated by clustered organizations than the number of clustered organizations in a region (McCann and Folta, 2009). In other words, a count of the number of collocated organizations does not speak directly to the amount of locally held knowledge, whereas measuring local knowledge stocks does. Accordingly, researchers have found that local knowledge stock levels, measured using patent data, positively affect firm patenting (McCann and Folta, 2009; Beaudry and Breschi, 2003).

However, evidence from a case study on the genesis of Silicon Valley (Saxenian, 1985), suggests that supporting features in a region, such as venture capital firms and the quality of research universities, are important for understanding regional growth, and more importantly, how firms benefit from their location in specific regions. In the case of high technology industries, it is unlikely that any single firm possesses all of the requisite capabilities needed to be competitive over an extended period of time. In such domains, firms need access to an ecosystem of local university researchers and university research projects, as well as access to other firms and institutions doing similar research (DeCarolis and Deeds, 1999; Powell, Koput, and Smith-Doerr, 1996). Therefore, firms located in regions with a developed research ecosystem will have access to knowledge which may be unavailable to more isolated firms. Accordingly, other researchers in this vein have characterized regions in terms of munificence, which indicates the quality of related industries and support infrastructure in a geographic cluster (Coombs, Deeds, and Ireland, 2009; DeCarolis and Deeds, 1999). Empirical evidence on the topic supports claims that both the number of similar organizations in a geographic cluster, as well as the munificence of a geographic cluster have positive effects on firm innovative outcomes (Coombs, Ireland, and Deeds, 2009; McCann and Folta, 2009; Folta, Cooper, and Baik, 2006; DeCarolis and Deeds, 1999).

Hypotheses

The Positive Role of Local Collaborations on Firm Inventions

In what follows, I offer three reasons for the positive role of local cluster collaborations on firms' inventions: a fertile search environment, shared language among collaborators, and increased legitimacy.

First, fertile search environments result from the accrual of economies of agglomeration where potential collaborators are densely clustered which creates both an awareness of potential collaborators and an awareness of who does what in the cluster. High technology clusters are often home to large research universities and federal research laboratories, which in turn tend to attract private firms, as well. In high technology industries, the locus of innovation is thought to exist in the knowledge networks between universities, firms, and research laboratories (Powell, Koput, and Smith-Doerr, 1996). This suggests that geographies containing these elements should be especially rife with opportunities and clustered firms will have access to a stock of knowledge not available to more isolated firms. Chance meetings and impromptu discussions between closely located organizations allow for lower initial costs when searching for potential collaborators. This proximity therefore lowers the costs of collaborative attempts.

Second, in addition to the benefits associated with location in a fertile environment, clustered organizations will come to share a common technological language and understanding of the technological landscape which will facilitate knowledge transfer among organizations. Research on localization of knowledge and the specialization of regions suggests collocation fosters shared cognitions (Pouder and St. John, 1996), as well as common identities (Romanelli and Khessina, 2005) among clustered organizations. Repeated interactions among organizations sharing similar perspectives on their science will result in rich channels of communication through which complex know-how is easily transferred. This results in increased acquisition and absorption of knowledge beyond what an isolated firm could accomplish.

Third, more densely populated regions may also provide greater legitimacy for collocated firms, and therefore increase the likelihood of attracting key investors and employees (Folta, Cooper, and Baik, 2008; Pouder and St. John, 1996). This may be especially important for small firms by helping them to overcome the liabilities of newness (Gittelman, 2007). Local collaborations signal membership in the local technological community; which confers advantage through access to privileged information and greater visibility to labor and venture capital markets (Gittelman, 2007; Owen-Smith and Powell, 2004). Taken together, this suggests that clustered firms will benefit from their collaborations with other firms and institutions in a fertile local environment comprised of organizations with which they share a common language. Thus:

H1a: A firm's local cluster collaborations are positively related to the firm's rate of inventions

The previous discussion suggests collaborations with organizations in the same geographic cluster increases firms' abilities to produce inventions. However, in rapidly changing technological environments, expertise with current technologies becomes less useful, and firms must explore new technologies (Danneels and Sethi, 2010). As firms engage the network of research universities, firms, and suppliers in their geographic cluster, they gain new perspectives on their science and become aware of new opportunities (Powell, Koput, and Smith-Doerr, 1996). An informational diversity perspective suggests firms who collaborate with others in the cluster may increase the variety of information available to the firm to recombine with its existing knowledge. Conversely, isolated firms will have less access to the variety of unique information available to clustered firms, and with less novel information available, will be less likely to experiment (Phene, Fladmoe-Lindquist, and Marsch, 2006; Ahuja and Lampert, 2001). Also, collaborating with others in the cluster may ease some of the normative constraints that exist within their own firms. For instance, Burt (1992) argues that open networks allow firms freedom from the normative expectations of others in a more closed network. This suggests that collaborations with other organizations in a geographic cluster may expose the firm to unique information which will increase experimentation such that:

H1b: A firm's local cluster collaborations are positively related to the firm's novelty of inventions

The moderating role of cluster fertility

The above hypotheses rest on the premise that geographic clusters create an environment rich in opportunities that firms are able to exploit through their involvement in local-knowledge networks. Some environments, however, provide more opportunities than others, and a growing body of research suggests that richer environments enhance the innovative performance of firms located in them (Coombs, Ireland, and Deeds, 2009; DeCarolis and Deeds, 1999).

As I previously argued, firm collaborations with organizations in the local research community provide access to a fertile network of organizations and should increase firm inventiveness. Intuitively, firms collaborating in local-knowledge networks characterized as rich, or having larger pools of available knowledge, should benefit more from their local collaborations. Higher levels of locally-available knowledge increase the likelihood firms are able to access local know-how (McCann and Folta, 2009). The result is greater certainty that local collaborations will result in meaningful knowledge exchange, and a decrease in fruitless searches. Thus, firms collaborating in clusters with a larger amount of locally-available know-how should receive more inventive value from their local collaborations than equally collaborative firms in clusters with less locally-available know-how.

Empirical evidence also supports claims that clusters vary in the richness of their local knowledge networks. For example, in their study of 806 U.S. biotechnology firms, Folta, Cooper, and Baik (2006) found that the number of biotechnology firms in a metropolitan statistical area (MSA) is positively related to firm patenting, and firms' abilities to attract private equity. Similarly, McCann and Folta (2009) found that the level of knowledge stocks in the cluster, measured as the number of patents held by the firms in the cluster, was positively related to firm patenting. In their study of 98 biotechnology firms, DeCarolis and Deeds (1999) found that cluster munificence, indicative of cluster fertility, was directly related to firm valuation at initial public offering (IPO). Moreover, in their study of biotechnology firm new product development, Coombs, Deeds, and Ireland (2009) found that cluster munificence increased the positive effect of a balanced search strategy on new product introduction. Taken together, these studies provide evidence suggesting that regions vary in the advantages they provide. More specifically, regions with greater local-knowledge stock levels provide a richer search environment and firms collaborating in such regions should derive more inventive value from their local collaborations. In regions with lower levels of local knowledge stocks, local collaborations will still permit the acquisition of locally held knowledge, but with less knowledge available, local collaborations will provide less benefit. Hence:

> *H2a: Local knowledge stocks positively moderate the relationship between a firm's local collaborations and the firm's rate of inventions such that the relationship between a firm's local collaborations and the firm's rate of inventions is stronger when local knowledge stocks are high.*

H2b: Local knowledge stocks positively moderate the relationship between a firm's local collaborations and the firm's novelty of inventions such that the relationship between a firm's local collaborations and the firm's novelty of inventions is stronger when local knowledge stocks are high.

The moderating role of cluster innovative concentration

The above hypotheses suggest that local collaborations in clusters with higher levels of knowledge stocks will be positively related to firms' innovative outcomes. However, I argue that cluster fertility not only depends on the level of local knowledge stocks but also on the degree to which inventions in the cluster are concentrated. Access to tacit knowledge embedded in local networks (Audretsch, 1998; Audretsch and Feldman, 1996) requires parties motivated to exchange knowledge (Szulanski, 1996). Parties to the knowledge exchange may not be motivated to share their know-how for fear of loss of ownership or control. Additionally, they may be unwilling to dedicate resources to the transfer process if they perceive they will not be adequately rewarded. I argue that the concentration of inventive activity in a geographic cluster has negative implications for the transfer of tacit know-how among organizations, and as a result, firms located in such a region will derive less benefit from their local collaborations.

I extend the individual-level phenomenon of the "star" scientist to the level of organizations within a region. Researchers have found that highly productive scientists can suppress innovation at both the team and the organizational level (Zucker and Darby, 2001; Tzabbar, 2009). They argue that when productivity is concentrated in one or a few scientists, power hierarchies emerge which limit effective knowledge transfer (Eisenhardt, 1989; Pfeffer, 1981). Zucker and Darby (1996) found that highly prolific scientists were very protective of their ideas and techniques, and tended to collaborate more within their own organization than with scientists at other organizations. Similarly, I argue that the concentration of innovative activity in a cluster creates power hierarchies among firms and increases the likelihood that firms will be protective of their ideas. Thus, innovative concentration at the cluster level has a negative effect on knowledge transfer between clustered firms, and therefore negatively impacts firms' inventive outcomes.

In high-technology domains, highly productive organizations gain both expert and referent power relative to less productive organizations because they possess rare and difficult to imitate knowledge production resources (Pfeffer, 1981). These highly prolific organizations are in a position to acquire and control a disproportionate amount of the resources in a region, such as access to federal funding, critical research facilities, and relationships with local research universities. The power hierarchies that result increase political activity among other firms such that other organizations compete for access to more productive organizations rather than share information with each other (Eisenhardt and Bourgeois, 1988; Ibarra, 1992). Additionally, when inventive activity is highly concentrated, both highly inventive and less inventive organizations will have decreased motivation to share valuable know-how. Highly productive organizations have little incentive to pass valuable know-how on to less productive organizations in the cluster. Conversely, less productive organizations face a dilemma in their relationships with more prolific organizations. They need access to the knowledge that more productive organizations possess (Pfeffer and Salancik, 1978), but they also fear misappropriation by the higher status organizations (Katila, Rosenberger, and Eisenhardt, 2008). Therefore, in clusters in which productivity is highly concentrated organizations may withhold truly valuable know-how, such as potential breakthroughs and best practices. In sum, firms located in geographic clusters where inventions are highly concentrated should derive less value from their collaborations within those clusters. Hence:

H3a: Innovative concentration negatively moderates the relationship between a firm's local collaborations and a firm's rate of invention such that the relationship between a firm's local collaborations and a firm's rate of inventions is weaker when innovative concentration is high.

H3b: Innovative concentration negatively moderates the relationship between a firm's local collaborations and the novelty of a firm's inventions such that the relationship between a firm's local collaborations and the novelty of a firm's inventions is weaker when innovative concentration is high

Method

Data

To test the hypotheses, I explored the rate and novelty of patenting of firms engaged in research in the area of nanotechnology from 1981-2004. I used publicly available longitudinal data on organizations engaged in research in the area of nanotechnology which was made available through *Nanobank*. *Nanobank* is a digital library containing observations from various sources (scientific articles, patents and government grants), determined to be related to nanotechnology, either by probabilistic information retrieval (IR) methods or by declaration from a source authority. Nanobank contains data on 580,711scientific articles in peer reviewed journals; 240,437 patents from the U.S. Patenting and Trademark Office's on-line database; and 52,831 research grants issued by the National Science Foundation (NSF) and National Institutes of Health (NIH). The dataset contains bibliographic information, including titles, abstracts, publication years, author names, associated organizations, and geo-coding information. From these data, variables were coded to test the relationships of interest. Firm level data was coded indicating which organizations, if any, the focal firm had collaborated with on a published research article, and the geographic location of these organizations. Further, firm level patent data was gathered to identify the patents, if any, for which the focal firm had applied. Data on patent classes was also used to estimate the novelty of the focal firm's inventions.

Patents contain detailed information on the inventions they protect, and thus patents are widely accepted as a rich source of information for the study of inventions (Hall, Jaffe, and Trajtenberg, 2005). Patents contain detailed information about the invention, the inventor, and the technological foundation on which the invention is built, including citations to previous inventions upon which the focal invention is based. There are, however, limitations to the use of patent data. Specifically, not all inventions are patented. However, most firms in nanotechnology do not offer any products in the marketplace and instead consider patents and the technologies embodied in them as their main innovative output. Moreover, patents signal legitimacy to potential investors and to the broader scientific community, and therefore represent a desired outcome for firms engaged in nanotechnology research.

A criticism of prior agglomeration research has been the lack of a clear definition of what constitutes a cluster (McCann and Folta, 2008). A central tenet of agglomeration theory is that economies accrue to collocated organizations as the number of organizations in the cluster increases. However, prior research has been unclear with regards to how many organizations are required to collocate in order for these economies to begin to accrue. In order to avoid this uncertainty, I limit my sample to the nanotechnology clusters identified by the National Science Foundation's (NSF) nanotechnology initiative (NNI) and the Project on Emerging Nanotechnologies (PEN). The PEN identifies "nanometros" based on the number of private organizations engaged in nanotechnology research or commercialization. In 2005, the NSF, with the backing of the federal government, provided funding to sixteen different nanotechnology 'districts,' or clusters. The funding was awarded to regions that were deemed to have the most established research infrastructure in place to advance science in the area of nanotechnology. Limiting the sample to firms located in these recognized clusters addresses shortcomings of prior research which in some cases assumes that economies of agglomeration accrue with as few as two similar or related organizations in a region.

Variables

Dependent variables

This study examines the conditions in which local collaborations in a geographic cluster affect the rate and novelty of firm inventions. First, I define *rate of invention* as the frequency with which a focal firm applies for patents that are ultimately granted. Accordingly, I operationalize the rate of invention as the total number of patents that a firm applied for in a given year from 1981-2004. Second, *novelty of invention* refers to a firm's patenting activities in a technological area with which it has no prior experience (Ahuja and Lampert, 2001). Patenting in new technological areas is especially important in rapidly changing technological fields where current expertise can quickly become obsolete (Danneels and Sethi, 2010). Thus, novel inventions, which embody technologies that are new to the firm, are an important firm outcome in the area of nanotechnology.

I rely on the technological class information identified in the patent's citation as proxies for the underlying knowledge elements (Benner and Waldfogel, 2008). Following Ahuja and Lambert (2001), I based this on a firm's prior patenting history and operationalize *novelty* as the number of new technology classes the firm entered in the previous three years. Although most patents are classified into more than one three-digit class code, most prior research has only utilized patent class data for the first technological class identified on the patent and has ignored subsequent listed classes. This approach fails to give an accurate representation of the technologies with which the firm is experienced and can therefore provide misleading results (Benner and Waldfogel, 2008).

To overcome this limitation of prior research, I include all of the technological classes identified by the patents in my sample. The patents in my sample cite 422 different technological classes, which makes an accurate assessment of a firm's technological footprint problematic (Hall, Jaffe, Trajtenberg, 2001). Following Hall, Jaffe, and Trantenberg (2001), I aggregate the technological class data of the patents in my sample to 37 broader classifications. The aggregation method provided by these authors groups similar classifications into broader categories of related technologies. The result is that when using more coarse grained categories, patenting in a new technological class represents a greater technological leap than would patenting in a new class using finer grained classes. Thus, this provides a more conservative test of my hypotheses in that there is greater technological distance between the classes in my data.

Independent variables

I define *local collaborations* as a collaboration on a published research article with an organization (or other knowledge producing entity, i.e. a firm, university, research institution, hospital, etc.) within the focal firm's geographic cluster. *Local collaborations* was operationalized as a count of the number of collaborations in a given year. Data on firms' research publications and geographic locations were available through *Nanobank.*

Moderating Variables

I define *innovative concentration* as the extent to which the inventions in the cluster (measured as the number of patents applied for in the cluster) are concentrated in one or a few organizations. A cluster with a high degree of innovative concentration is one where a highly innovative organization is generating a large percentage of the total patents produced in the cluster. Conversely, a cluster with a low degree of innovative concentration is one where the total number of patents produced in the cluster is evenly distributed among the collocated organizations. I operationalize innovative concentration as the Herfindahl index of the nanotechnology patents applied for by firms and institutions in a cluster in a given year. A higher score indicates a cluster whose inventions are concentrated in one or a few organizations. I operationalize *local knowledge stocks* as the total number of nanotechnology patents generated in the cluster, as identified by Nanobank.

Control variables

Cluster level controls. Prior research suggests that firms located in larger clusters may be more innovative (McCann and Folta, 2009; Folta, Cooper, and Baik, 2006). To control for these effects I define *cluster size* as the number of organizations located in a particular bureau of economic activity (BEA). BEAs define the regions surrounding metropolitan or micropolitan statistical areas. They consist of one or more the metropolitan or micropolitan statistical areas that serve as the centers of economic activity and the surrounding counties that are economically related the center. Since data on organization inception and closure were not available, I used data on when organizations either published an article or applied for a patent, in the area of nanotechnology, as evidence that a organization was active in the cluster. I operationalized cluster size as the number of entities (firms, research universities, national labs, research institutions, federal government, and hospitals) that either published a research article or applied for a patent in a given year. I also control for the number of *cluster publications* which are research publications in the area of nanotechnology which I operationalize as the count of the number of publications in a cluster in a given year. *Cluster publications* reflect the research activity level in a region, independent of the number of patents generated. Prior research has argued that the number of federal research grants awarded to organizations in a cluster is indicative of the fertility of the cluster environment (DeCarolis and Deeds, 1999). As such, I control for the number of *cluster grants* which I operationalize as the number of National Institutes of Health (NIH), and National Science Foundation (NSF) grants awarded in the area of nanotechnology in a cluster, in a given year.

Firm-level controls. Prior research on organizational ecology suggests organizational age can influence the rate and types of inventions a firm produces (Sorensen and Stuart, 2000). For instance, older firms have been shown to have a greater likelihood of patenting, but these patents are more likely to cite the firm’s prior patents, and these patents are less likely to be cited by other firms. To account for these effects in my model, I control for *firm age*, operationalized as the number of years a firm has been either publishing research articles or applying for patents in the area of nanotechnology, in a focal cluster. Firms develop patenting capabilities which can affect their future rate of patenting. As such, I control for a firm's total stock of prior patents, *firm patent stock*, which I operationalize as the total number of prior nanotechnology patents for which a firm has applied in its history. The firms in my sample also engaged in research collaborations with firms in distant geographic clusters. The knowledge gained from these collaborations could affect both the rate and novelty of their inventions. As such, I controlled for *distant collaborations*, which I operationalized as a count of the number of nanotechnology research collaborations with research entities outside of the focal firm's cluster, in a given year. Some focal firm research publications did not involve collaborations with other firms, although they may have been authored by several scientists within the focal firm. To control for the knowledge accumulated through the publication of a nanotechnology research article that did not include co-authors from other firms, universities, etc., I control for *firm publications* which is operationalized as the total number of nanotechnology publications in a given year. I also control for *firm publications total* which I operationalize as the total number of prior nanotechnology publications in the firm's publishing history, in a given year.

Model specification and estimation

The study examines 24 years of time-varying panel data (i.e. cross-section, time series data). Over this time, some firms entered the sample while others left the sample, which resulted in an unbalanced panel (Sayres, 1989). Because the dependent variables were both count type variables, Poisson models would typically be appropriate. However, these data violate an assumption of Poisson models regarding the equality of mean and variance. The dependent variables exhibited overdispersion (variance is greater than the mean) therefore making negative binomial regression the preferred method (Hausman, Hall, and Griliches, 1984). I used a fixed-effects, rather than random-effects, negative binomial model which addresses the problem of unobserved heterogeneity, as well as overdispersion (Hausman, Hall, and Griliches, 1984). Fixed-effects models allow random firm-specific effects to be correlated with the regressors, which allows for a limited form of endogeneity (Cameron and Trevedi, 2009). Random-effects models assume that firm-specific effects are purely random, and not correlated with the regressors, a stricter assumption than the fixed-effects models. The results reported here are based on fixed-effects models, although results using random-effects modeling were nearly identical. Analyses were performed using the xtnbreg command in Stata IC11.

Results

Table 1 shows the means, standard deviations, and correlations for all variables. The average firm in the sample applied for 1.56 patents, and cited an average of 2.26 new to the firm technology classes in a given year. The sample firms had an average stock of 4.8 prior publications and 16.18 prior patents. The average firm in the sample had 0.23 local collaborations and 0.33 distant collaborations in a given year. The sample firms were located in clusters which on average had a prior stock of 5708.26 patents and a prior stock of 1613.46 NIH and NSF grants. The average cluster innovative concentration score which has a theoretical

Table 1: Means, standard deviations, and correlations

	Variables	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11
1.	Cluster size	309.27	242.72											
2.	Cluster publications	107.33	106.98	.79*										
3.	Cluster patents	5708.26	5144.63	.69*	.89*									
4.	Cluster grants	1613.46	1000.30	.54*	.51*	.64*								
5.	Innovative concentration	0.098	0.125	-.51*	-.38*	-.36*	-.49*							
6.	Firm age	8.13	6.62	.02*	.04*	.08*	.11*	-.01						
7.	Firm patent stock	16.18	78.01	-.04*	-.02*	-.01	-.05*	.05*	.40*					
8.	Firm publication stock	4.80	30.96	.04*	.06*	.05*	.03*	-.02*	.24*	.22*				
9.	Distant collaborations	0.33	1.66	.03*	.04*	.03*	.01	-.01	.16*	.25*	.68*			
10	Local collaborations	0.23	1.13	.02*	.04*	.03*	.00	-.01	.12*	.18*	.68*	.69*		
11	Firm patents	1.57	8.20	-.00	-.02*	-.04*	-.08*	.04*	.22*	.67*	.13*	.19*	.15*	
12	Novelty	2.26	6.94	-.02	-.05*	-.08*	-.09*	.03*	.00	.12*	.02	.03*	.03*	.23*

*p<.05

range from 0 to 1, is 0.10 with a standard deviation of 0.13. Lower concentration scores indicate that the inventive output of a region is more evenly dispersed among clustered organizations.

Table 2 presents the results of the negative binomial regression analyses with the rate of firm patenting as the dependent variable. Three models were run. In model 1, I assessed the effect of the control variables on firm patenting as well as the effect of local collaborations on firm patenting. The coefficient of local collaborations was significant and positive (0.102, p<.01). Model 2 examines the moderating effects of cluster knowledge stocks on the local collaboration to patenting relationship. Similar to findings in prior research (Coombs, Ireland, and Deeds, 2009), the coefficient of the interaction was positive and significant (0.000, p<.01), suggesting that local collaborations in clusters with greater stocks of local knowledge increase firm patenting. Model 3 is the full model. With all of the variables entered simultaneously, the results show that local collaborations have a positive and significant effect on firm patenting (0.103, p<.01). This suggests that as a clustered firm collaborates with other entities (universities, firms, etc.) in its local area, it gains access to valuable know-how which increases the firm's patenting activities. This finding provides support for Hypothesis H1a. With the local collaboration-local knowledge stocks and the local collaboration-innovative concentration interaction terms entered simultaneously, the results show that moderating effect of local collaborations and knowledge stocks is no longer significant, thus I fail to find support for Hypothesis H2a. However, the effect of innovative concentration on the local collaboration to firm patenting relationship remains highly significant (-0.410, p<.001), proving strong support for hypothesis 3a. This suggests that the benefits associated with locating in regions with higher levels of knowledge stocks are mitigated in instances where the knowledge stocks are concentrated in one or a few firms.

Table 3 presents the results of the negative binomial regression analyses predicting the novelty of firm inventions. In model 1 I assess the effects of my control variables and local collaborations on the novelty of firm inventions. The coefficient of local collaborations was significant and positive (0.082, $p<.01$). Model 2 analyzes the moderating effect of cluster knowledge stocks on the local collaboration to novelty relationship. The coefficient of this term was positive, but not significant. Model 3 analyzes all of the hypothesized relationships. The results show that local collaborations are positively related to the novelty of firms' inventions (0.097, $p<.01$), providing support for Hypothesis 1b. This result suggests that collaborating with locally-clustered entities (universities, firms, etc.) provides access to unique information and increases the likelihood that firms will experiment with new technologies. The joint effect of local collaborations and local knowledge stocks was not significantly related to the novelty of firms' inventions, thus I fail to find support for Hypothesis 2b. However, the local collaboration-innovative concentration interaction term is significant and negatively related to the novelty of firms' inventions (-0.482, $p<.05$), proving support for Hypothesis 3b. This finding provides evidence that the likelihood that firms will experiment with new technologies, as a result of their local collaborations, decreases in clusters where innovative activity is concentrated in one or a few organizations.

To ensure correct interpretation of the results, I plotted the significant interactions. The graphs provide support for the significant interactions. Figure 1 provides support for Hypothesis 3a;

Table 2: Negative binomial regression for rate of firm patenting[a]

Variables	Model 1	Model 2	Model 3
Hypotheses			
H1a: Local collaborations (LC)	.102***	.064***	.103***
	(.01)	(.02)	(.03)
H2a: LC x Cluster knowledge stocks		.000***	.000
		(.00)	(.00)
H3a: LC × Innovative concentration			-.410**
			(.18)
Main effect for interaction			
Cluster knowledge stocks	-.000***	-.000***	-.000***
	(.00)	(.00)	(.00)
Innovative concentration	-1.88***	-1.90***	-1.81***
	(.21)	(.21)	(.21)
Cluster controls			
Cluster size	.004***	.004***	.004***
	(.00)	(.00)	(.00)
Cluster publications	-.002***	-.002***	-.002***
	(.00)	(.00)	(.00)
Cluster grants	-.000***	-.000***	-.000***
	(.00)	(.00)	(.00)
Firm controls			
Firm age	-.004	-.003	-.002
	(.00)	(.00)	(.00)
Patent stocks	.001***	.001***	.001***
	(.00)	(.00)	(.00)
Publication stocks	-.005***	-.005***	-.005***
	(.00)	(.00)	(.00)
Distant collaborations	.012	.011	.010
	(.01)	(.01)	(.01)
Constant	.140**	.141**	.137**
	(.06)	(.06)	(.06)
Log likelihood	-10175.84	-10172.61	-10169.69
Wald chi^2	1205.70	1242.62	1261.15
N	8389	8389	8389
Df	10	11	12

[a]Standard errors are in parentheses

*p<.10

**p<.05

***p<.01

Table 3: Negative binomial regression for novelty of firm inventions[a]

Variables	Model 1	Model 2	Model 3
Hypotheses			
H1b: Local collaborations (LC)	.082***	.054*	.097***
	(.02)	(.03)	(.03)
H2b: LC x Cluster knowledge stocks		.000	.000
		(.00)	(.00)
H3b: LC × Innovative concentration			-.482**
			(.23)
Main effect for interaction			
Cluster knowledge stocks	-.000***	-.000***	-.000***
	(.00)	(.00)	(.00)
Innovative concentration	-.734***	-.739***	-.634**
	(.26)	(.26)	(.26)
Cluster controls			
Cluster size	.003***	.003***	.003***
	(.00)	(.00)	(.00)
Cluster publications	-.001*	-.001*	-.001*
	(.00)	(.00)	(.00)
Cluster grants	-.00***	-.000***	-.000***
	(.00)	(.00)	(.00)
Firm controls			
Firm age	.002	.003	.003
	(.00)	(.00)	(.00)
Patent stocks	.001***	.001***	.001***
	(.00)	(.00)	(.00)
Publication stocks	-.002*	-.002**	-.002**
	(.00)	(.00)	(.00)
Distant collaborations	.003	.005	.007
	(.01)	(.01)	(.01)
Constant	-1.55***	-1.55***	-1.55***
	(.08)	(.08)	(.08)
Log likelihood	-9714.05	-9712.83	-9710.53
Wald chi^2	525.15	525.54	531.95
N	8389	8389	8389
Df	10	11	12

[a]Standard errors are in parentheses

*p<.10

**p<.05

***p<.01

firms in clusters where innovations are highly concentrated benefit less from their local collaborations and patent less than firms collaborating in regions where innovative activity is more dispersed. Figure 2 provides support for Hypothesis 3b. That is, the relationship between local collaborations and the novelty of firms' inventions is weakened in geographic clusters where innovative activity is highly concentrated.

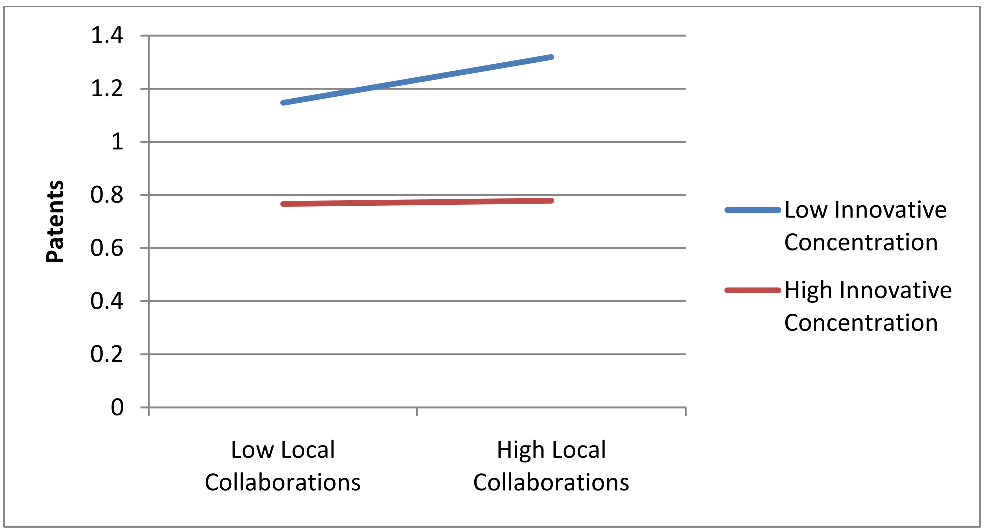

Figure 1: Effect of the interaction between local collaborations and innovative concentration on firms' rate of patenting

<u>Discussion</u>

The classic work by Marshall (1920) emphasized that firms of similar types will locate in close proximity of each other, and will realize performance advantages by doing so. In high-technology settings, the predominant benefit of collocation is access to knowledge embedded in local networks, and as a result, clustering is especially prevalent among high-technology firms

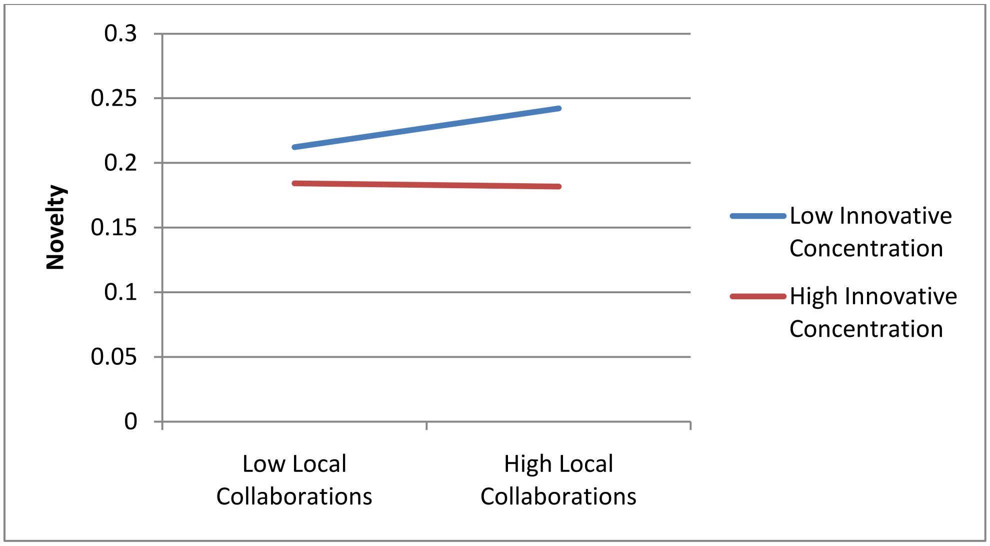

Figure 2: Effect of the interaction between local collaborations and innovative concentration on the novelty of firms' inventions

(Audretsch and Feldman, 1996). Recently, scholars have more thoroughly investigated the benefits of clustering by focusing on aspects of the region which confer an advantage to collocated firms. With this has come the understanding that clusters vary in terms of the potential benefits they bestow upon local firms. By focusing on quantities of collocated organizations or knowledge stocks, researchers have largely assumed that locally held knowledge spills over to clustered firms. Missing from our understanding of the benefits of locating in a geographic cluster is an account of factors that will impair firms' abilities to access locally held knowledge.

Motivated by lacunae in the literature, this dissertation argues that the tacit nature of locally held knowledge impedes its dissemination to clustered firms. As a result, collocation does not, by itself, confer advantage. Rather firms must actively engage their local knowledge networks in order to realize the benefits of collocation, and acquiring the tacit knowledge embedded in local networks requires repeated interactions between entities motivated to share their accumulated knowledge.

By accounting for the tacit nature of locally held knowledge, this dissertation makes three contributions to the existing agglomeration theory literature. First, I have developed a stronger theoretical link between the sources of benefits of clustering for high technology firms (access to knowledge networks) and the mechanisms by which benefits are conferred. Whereas prior research has argued that the benefits of clustering increase as the quantities of local knowledge stocks increase, this dissertation argues that the benefits of collocation result not from the size of local knowledge networks, but from the ability to access them. A more appropriate means of examining the benefits that regions bestow among clustered firms is to redirect our focus from the quantities of local knowledge stocks towards an approach of describing regional fertility in terms that are indicative of clustered firms' abilities to access and absorb the locally held knowledge. With literature on knowledge transfer as a basis, this dissertation argues that firms' abilities to acquire locally held knowledge will be largely determined by the extent to which firms, or other institutions, are motivated to share their know-how. Empirical evidence herein supports my arguments that regional aspects that limit sharing of know-how between clustered firms will decrease the benefits of clustering. I find strong support for hypotheses predicting that as regional innovative activity becomes increasingly concentrated, a phenomenon argued to limit knowledge sharing (Tzabbar, 2009; Zucker and Darby, 2001) clustered firms are decreasingly inventive in terms of both the rate and novelty of their inventions. Interestingly, although I do find a significant relationship between the interaction of local collaborations and local knowledge stocks on firm inventions, this relationship is no longer significant when examined simultaneously with the local collaboration – innovative concentration term. Put differently, the relationship between the interaction of local collaborations and innovative concentration remains is significant even after controlling for the interaction between local collaborations and local knowledge stocks. This finding has important implications for managers, investors, and policy makers alike. Research suggests that high-technology start-up location decisions are often determined by the location of the parent firm (Aharonson, Baum, and Feldman, 2007). The findings reported here should inform managers and investors that locating in a "hot spot" may not be as beneficial as prior research might indicate, especially for new firms which lack an established knowledge base. Moreover, policy makers hoping to spur growth in their regions have the ability to create fertile environments through the incentives they offer to lure firms to a region. My findings suggest that attracting numerous, equally, but not necessarily highly, productive firms would be far more beneficial for regional productivity than attracting one or two highly productive firms.

Second, this dissertation finds that higher levels of local collaborations are positively related to both the rate and novelty of firm inventions. This finding supports theoretical arguments regarding tacit knowledge transfer which would suggest that collocation is a necessary but insufficient condition for accessing locally held knowledge. Whereas prior research has modeled the benefits of clustering as a function of location in a cluster and thus assumes that informal interactions occur among clustered firms, this dissertation starts from the premise that accrued benefits will be determined by the extent to which firms engage their local networks, and thus provides a more stringent means of assessing firms' levels of local involvement. I find strong evidence that as firms collaborate more with local firms and institutions they are able to access the knowledge embedded in their local networks, and that doing so increases their inventiveness in terms of both rate and novelty of their inventions, even after controlling for their collaborations with firms and institutions in other geographic regions.

Third, this dissertation extends theory on Zucker and Darby's concept of the "star" scientists to the organizational level. Although Zucker and Darby find evidence that highly prolific scientists provide the "seeds" around which crystals grow, they also suggest that there is a potential downside associated with "stars." More specifically, they argue that "stars" may be protective of their secrets and also tend to collaborate less with outsiders, restricting their collaborations to known insiders. Empirical evidence also supports the idea that "stars" may be detrimental for innovation at the firm and team level (Tzabbar et al., working paper; Tzabbar, 2009). This research builds on the premise that when the innovative productivity of a firm, or a team, is highly concentrated in one or a few individuals, effective communication suffers at the expense of subsequent innovative performance. Herein, I argue that individual-level phenomenon of the "star" scientists can be extended to the inter-organizational level, with similar theoretical implications. Specifically, in an industry where innovative performance is dependent on the sharing of locally held knowledge, when one or a few organizations dominate the inventive output of the region, the open sharing of ideas and best practices will be negatively affected.

Analogous to the “star” scientists who lacks motivation to share know-how, highly innovative organizations will protect their trade secrets and stifle regional communication.

Despite the prevalence of research espousing that high-technology firms benefit most from locating in clusters with greater levels of knowledge stocks, this dissertation argues that theory regarding the transfer of tacit knowledge should redirect researchers toward aspects of clusters which enhance or impair effective knowledge transfer. I hypothesized that firms who collaborate more with local firms and institutions should be more inventive because increased collaborative activity provides the repeated interactions necessary for acquiring locally held knowledge. Furthermore, I hypothesized that collaborations in clusters where innovative activity is concentrated will yield less inventive potential for collaborating firms. These hypotheses were tested using panel data on nanotechnology firms, which allowed for causal inferences. In light of the robust findings regarding innovative concentration, a more thorough examination of regional characteristics that might enhance or impair knowledge sharing between clustered firms is warranted.

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CLUSTERS, CONVERGENCE, AND ORGANIZATIONAL INNOVATION

Introduction

The geographic concentration of similar organizations, sometimes referred to as clusters, are a dominant feature of nearly every advanced national, regional, and metropolitan economy (Porter, 1998). A few examples include high technology firms in Silicon Valley, the Hollywood movie industry, biotechnology in San Diego, and the automobile industry in Detroit. Clustering is argued to confer advantages to collocated firms through access to specialized labor and inputs, access to greater demand, and access to knowledge spillovers (Arthur, 1990). Extant research has argued that the clustering of similar firms creates an innovative environment which bestows advantages upon clustered firms (Coombs, Deeds, and Ireland, 2009; McCann and Folta, 2009; Aharonson, Baum, and Feldman, 2008; Folta, Cooper, and Baik, 2006; DeCarolis and Deeds, 1999; Romanelli and Khessina, 2005; Porter, 1998; Pouder and St. John, 1996; Powell, Koput, and Smith-Doerr, 1996; Saxenian, 1994). Yet there is striking evidence that firms in some of the largest and best-know clusters have experienced significant downturns in performance (e.g. Route 128 in Boston) (Saxenian, 1994); and recent theorizing suggests clusters may hinder firms' innovative efforts (Romanelli and Khessina, 2005; Pouder and St. John, 1996; Abrahamson and Fombrun, 1994).

Theory highlighting the downside of clustering suggest cognitive mechanisms underlie any potential negative effects of clustering. For instance, Abrahamson and Fombrun (1994) suggest that clustering may facilitate the growth of homogeneous macro-cultures where shared beliefs regarding strategy and competition impede the acceptance of new ideas generated outside of the cluster. Porter (1998:85) argues that clustered firms are susceptible to groupthink and insularity where the "whole cluster suffers from a collective inertia, making it harder for individual companies to embrace new ideas." In their research on the rise and fall of geographic clusters, Pouder and St. John (1996) posit that institutional forces drive a convergence of innovations in the cluster which makes clustered firms susceptible to radical technological changes. In this dissertation, I focus specifically on the convergence of innovations in geographic clusters.

Theorizing on the convergence of innovations in geographic clusters suggests that the availability of information on local competition and institutional pressures encourage imitation. The dense networks of interdependent organizations in clusters increases the knowledge of competitors' processes and capabilities (Abrahamson and Fombrun, 1993), which is argued to be a key determinant in the imitation of innovations (Zander and Kogut, 1995). Moreover, in addition to channeling technical information, local networks also provide a means by which organizations become socialized to accepted norms. From this perspective, linkages to local organizations encourage the mimetic adoption of accepted practices, sometimes regardless of their technical merit (Westphal, Seidel, and Stewart, 2001; Staw and Epstein, 2000; Pouder and St. John, 1996; DiMaggio and Powell, 1983).

This presents and interesting paradox for clustered firms. To benefit from collocation firms must embed themselves in their local knowledge networks (Aharonson, Baum, and Plunket, 2008;

Powell, Koput, and Smith-Doerr, 1996). However, local embeddedness transmits mimetic forces and information that restricts organizational action (Westphal, Seidel, and Stewart, 2001; Galaskiewicz, 1997; Burt, 1987; DiMaggio and Powell, 1983). Therefore, local embeddedness, which initially constitutes an advantage for clustered firms (Audretsch and Feldman, 1996; Powell, Koput, and Smith-Doerr, 1996; Saxenian, 1994), also has the potential to homogenize innovations such that over time firms' inventions come to resemble the inventions of other organizations in the cluster.

A consensus in the literature regarding effects of clustering on organizational innovation is lacking, suggesting that the relationship between clustering and innovation is complex. In this dissertation I focus on geographic clusters, and examine the multifaceted effects of clustering on organizational innovation. In so doing, I address an important unresolved issue in agglomeration theory research, namely, the nature of the relationship between clustering and innovation. This dissertation argues that clustering confers advantages to the extent firms become embedded in their local knowledge networks. I argue that local embeddedness permits access to valuable locally-shared knowledge which increases firms' inventive abilities. However, the very knowledge networks that increase firms' inventive capabilities ultimately work to narrow the innovative range of clustered firms. More specifically, the density of a firm's local interactions with clustered organizations increases firms' inventive abilities, but it also leads to an awareness of competitor capabilities and the mimetic adoption of accepted behaviors (Scott, 1995; DiMaggio and Powell, 1983), which causes a convergence of inventions in the region

(Romanelli and Khessina, 2005; Pouder and St. John, 1996; Abrahamson and Fombrun, 1994), and reduces the impact of firms' inventions.

I develop hypotheses regarding the effects of local embeddedness, defined as the frequency of collaborations in the publication of research articles with local organizations on the rate, convergence, and impact of firm inventions. For the purposes of this study I define rate of invention as the number of patents applied for in a given year; convergence of inventions as the decreasing technological distance between a firm's inventions and the average invention in the cluster; and impact of firm inventions as the number of times a firm's inventions are cited by future inventions. To test my hypotheses, I developed a longitudinal data set of 1,908 firms engaged in research in the area of nanotechnology between the years 1981-2004.

This dissertation makes two contributions to extant agglomeration theory and economic geography research. First, whereas prior research makes competing predictions regarding the relationship between clustering and organizational innovation, this dissertation attempts to reconcile these competing perspectives by unpacking the complex relationship between clustering and innovation. That is, in line with prior research, this dissertation argues that clustering does in fact increase firm inventiveness (McCann and Folta, 2009; Folta, Cooper, and Baik, 2006; DeCarolis and Deeds, 1999); however, clustering also drives a convergence of inventions in the cluster which ultimately reduces the impact of clustered firms' inventions (Pouder and St. John, 1996; Abrahamson and Fombrun, 1994).

Second, in contrast to the growing empirical evidence regarding the benefits of clustering for high-technology firms, scarce empirical evidence exists regarding the negative effects of clustering. Although several scholars have theorized that clustering leads to groupthink (Porter, 1998), homogeneous beliefs regarding competition and strategies (Abrahamson and Fombrun, 1994), and convergence of innovations (Pouder and St. John, 1996), empirical evidence to support or refute such claims is lacking. As such, this dissertation contributes to the dearth of empirical evidence regarding innovative convergence in clusters.

Theoretical Background and Hypotheses

Geographic clustering and innovation

Extant agglomeration research holds that as the geographic concentration of similar organizations increases, so does the access to specialized labor, customers, and knowledge spillovers (Folta, Cooper, and Baik, 2006; Arthur, 1990). As such, firms are motivated to cluster in order to access externalities generated by collocated organizations (Marshall, 1920). In spite of the breadth of benefits of clustering, firms in knowledge-based industries are thought to benefit from clustering primarily through their access to locally-shared knowledge (Powell, Koput, and Smith-Doerr, 1996; Saxenian, 1994). Following this, scholars have argued that firms located in regions with a high concentration of similar firms will have access to knowledge not available to firms in more remote locations, and such access will positively affect firm innovative outcomes (Coombs, Ireland, and Deeds, 2009; McCann and Folta, 2009; Beaudry and Breschi, 2003; DeCarolis and Deeds, 1999).

Research espousing the benefits of collocation largely assumes that collocating with similar organizations permits access to locally-held know-how. However, in high-technology domains where locally held knowledge is tacit and complex, locating in close geographic proximity to similar organizations is not sufficient for tapping locally-held knowledge. Rather, firms must embed themselves in local networks of knowledge in order to benefit from collocation (Powell, Koput, and Smith-Doerr, 1996; Saxenian, 1994). Local embeddedness describes the frequent and repeated interactions necessary for the transfer of tacit knowledge (Brown and Duguid, 2001; Szulanski, 1996). Consequently, researchers have argued that local embeddedness largely determines a firm's ability to learn about new opportunities in their field (Powell, Koput, and Smith-Doerr, 1996), and a firm's inventive ability is more a function of its embeddedness than its financial investment in R&D (Aharonson, Baum, and Plunket, 2008).

Innovation in geographic clusters is therefore governed by individual firms' embeddedness in their local knowledge networks. However, to understand the complex relationship between clustering and organizational innovation it is important to account for the distinct consequences of embeddedness. On one hand embeddedness facilitates the development of a shared language and access to timely and valuable know-how (Tallman, Jenkins, Henry, and Pinch, 2004). From this perspective, embeddedness ensures firms are able to appreciate and absorb rich local know-how, which should have positive implications for firm inventiveness. On the other hand, embeddedness provides channels through which information on competitor activities and cues regarding accepted behaviors are transmitted and received (Scott, 1995; DiMaggio and Powell, 1983). This alternative view suggests embeddedness may constrain organizational action as institutional pressures may restrict the range of normatively accepted innovations (Westphal, Seidel, and Stewart, 2001; Galaskiewicz, 1997; Burt, 1987; DiMaggio and Powell, 1983; Galaskiewicz, 1985). Combined, these competing views on embeddedness help unravel the complex nature of clustering and organizational innovation. That is, although embeddedness increases firms' inventive capabilities, it also works to restrict the range of firms' inventions.

Embeddedness and inventive ability

Understanding the role of local embeddedness in innovation requires an explanation of how embeddedness affects firms' abilities to innovate. In what follows, I offer three reasons why local embeddedness in geographic clusters increases firms' inventive abilities: a fertile search environment, shared language among collaborators, and increased legitimacy.

First, fertile search environments result from the accrual of economies of agglomeration where firms engaged in similar research are densely clustered which increases awareness of competitor practices and knowledge of who does what in the cluster. Also, high technology clusters are often home to large research universities and federal research laboratories, which in turn tend to attract private firms, as well. In high technology industries, the source of innovation is argued to exist in the knowledge networks between universities, firms, and research laboratories (Powell, Koput, and Smith-Doerr, 1996). This suggests that geographies containing these elements should be especially rife with opportunities and clustered firms will have access to a stock of knowledge not available to more isolated firms. Moreover, chance meetings and impromptu discussions between closely located organizations allow for lower initial costs when searching for solutions to the technological challenges facing the firm. Lower search costs in a fertile environment where firms understand who knows what facilitates the resolution of scientific challenges and the acquisition of key resources.

Second, clustered organizations will come to share a common technological language and a similar understanding of the technological landscape which will facilitate knowledge transfer among organizations in the region. Research on localization of knowledge and the specialization of regions suggests collocation fosters shared cognitions (Pouder and St. John, 1996), as well as common identities (Romanelli and Khessina, 2005) among clustered organizations. Repeated interactions among organizations sharing similar perspectives on their science will result in rich channels of communication through which complex know-how is easily transferred. The ability to trade know-how allows clustered organizations to access a potentially large number of solutions to their scientific challenges relative to what a more isolated firm could accomplish.

Third, more densely populated regions also provide greater legitimacy for collocated firms, increasing the likelihood of attracting key investors and employees (Folta, Cooper, and Baik, 2008; Pouder and St. John, 1996). This may be especially important for small firms by helping them to overcome liabilities of newness (Gittelman, 2007). Local embeddedness signals membership in the local technological community which confers advantage through access to privileged information and greater visibility to labor and venture capital markets (Gittelman, 2007; Owen-Smith and Powell, 2004). Access to capital markets and investors should increase a firm's ability to acquire other key resources such as personnel and equipment critical for innovative functioning. Taken together, this suggests that clustered firms will improve their inventive abilities as a result of their embeddedness with other organizations in a fertile local environment comprised of organizations with which they share a common language. Thus:

H1: A firm's local embeddedness is positively related to the firm's rate of inventions

Embeddedness and the convergence of innovations

The previous hypothesis argued that local embeddedness increases firms' inventive abilities. In what follows I argue that although local embeddedness increases firms' inventive abilities, it also limits the range of their possible inventions. It is generally accepted that interactions among organizations facilitate the transfer of practices and routines between them, a topic commonly studied by institutional theorists (Westphal, Seidel, and Stewart, 2001; Scott, 1995; DiMaggio and Powell, 1983) and social network scholars (Burt, 1987; Galaskiewicz and Burt, 1981). Research in institutional theory , which emphasizes the cognitive aspects of organizational action, holds that the adoption of routines and practices – referred to as mimetic isomorphism – occurs when routines and practices become taken for granted as normatively accepted (Scott, 1995). In this sense, organizational action can be characterized as the enactment of established norms, where mimetic processes provide the guidelines for accepted actions (Scott, 1995; Meyer, Scott, and Strang, 1987).

Interactions between organizations, as a result of their local embeddedness, constitute a means by which accepted norms are modeled and organizations become socialized to them (Scott, 1995; Galaskiewicz and Wasserman, 1989; DiMaggio and Powell, 1983). Socialization through modeling is a primary mechanism underlying mimetic isomorphism, and is one process by which organizations change over time to become more similar to other organizations in their environments (DiMaggio and Powell, 1983:151). Extant research suggests that socialization effects will be strongest among firms in the same geographic region (Porac et al., 2002; Hannan and Freeman, 1989).

Organizations will imitate others thought to be similar, as their will be more observable and salient (Haveman, 1993). Cognitive approaches to strategy assert that organizational action will be influenced by the way decision makers categorize others in their competitive environment (Daft and Weick, 1984; Porac and Thomas, 1990). Perceived categories focus the attention of decision makers to organizations in the same category, and this ensures that the actions of organizations within a focal firm's category will be more salient than the actions of organizations in other categories. Furthermore, once decision makers have defined their environment and categorized their competitors, strategies will be enacted to counter the actions of organizations within a focal firm's group. That is, a focal firm's strategies and actions will be reflective of the organizations within their perceived category, rather than in response to the actions of their actual competitors (Porac and Thomas, 1990: 233). One means of categorizing organizations is geographic proximity (Porac, Thomas, and Baden-Fuller, 1989). Cognitive limitations force decision makers to enact simplified representations of their environments (Porac, Thomas, and Emme, 1987). Local interactions, media coverage, and direct observation make information on local competitors important and salient. Thus, decision makers will categorize organizations based on geographic proximity (Pouder and St. John, 1996). In their study of Scottish knitwear firms, Porac Thomas, and Baden-Fuller (1989) found that although these firms sell their products all over the world, when asked, they defined their competitors mainly as those firms in the same town or in surrounding areas. Thus, embeddedness with organizations in the same geographic location will provide strong cues regarding received behavioral norms.

Research in network theory holds that organizational routines and practices are transferred among organizations through the direct sharing of information (Burt, 1987). As the frequency of interactions among organizations increases, so does the level of information sharing between them. Organizations closely tied to other organizations come to share close to full information about other organizations in the network (Abrahamson and Fombrun, 1994). Complementary to institutional theory perspectives, this research suggests that linkages among organizations can provide the means by which managers learn about normative behaviors (Westphal, Seidel, and Stewart, 2001; Galaskiewicz, 1997; Westphal, Gulati, and Shortell, 1997), and organizations will imitate the actions of other organizations with which they share network ties (DiMaggio and Powell, 1983; Galaskiewicz, 1985).

In geographic clusters, established relationships that result from frequent interactions among organizations combined with the amount of information available about local organizations that creates a mutual awareness of others give rise to what DiMaggio (1983) refers to as an organizational field. Once the field is created, uncertainties about markets and technologies and institutional pressures encourage adoption of accepted practices which makes the organizations in the field more alike. (DiMaggio and Powell, 1983). When faced with uncertain markets and technologies firms will economize on search costs (Cyert and March, 1963) and imitate the normatively accepted actions of others (Haveman, 1993). In the context of innovation, this suggests that locally embedded firms are exposed to institutional pressures to adopt widely accepted practices, possibly regardless of their technical merit (Westphal, Gulati, and Stewart, 1997). In high-technology clusters firms will offset the inherent uncertainty of their markets and technologies by imitating the actions of organizations with which they share ties. Taken together, firms' local embeddedness results in exposure to normatively accepted practices, which causes a focal firm's inventions to more closely resemble the inventions of other firms in the cluster, over time. Thus:

> *H2: Local embeddedness will be negatively related to the technological distance between a firm's inventions and the average invention in the cluster*

Embeddedness and the influence of firm inventions

The previous hypothesis suggests that local embeddedness works to restrict the variability of firm inventions such that over time a firm's inventions resemble the inventions of other organizations in the cluster. I now argue that similarity of inventions will reduce their importance, as well. Important inventions are those that influence subsequent inventions and have an impact on the broader technological community (Sorenson and Stuart, 2000).

Organizations embedded in the same local knowledge networks should come to resemble other organizations in the network. With a convergence of inventions clustered organizations come to work in proximate technological areas, and as firms' inventions converge the firms become more similar. Firms on similar technological paths are more likely make similar discoveries (Merton, 1972). Moreover, firms on similar technological paths will be quick to appreciate the distinguishing features of new inventions originating in the cluster. When a firm's inventions are similar to the inventions of other organizations in the region their technological proximity to others' inventions facilitates imitation by other organizations. The ease of imitation becomes manifest in imitative, rather than differentiation strategies (Nerkar, 2003) The convergence inventions that results from local embeddedness ensures that potentially important innovations are more easily and quickly copied or improved upon, reducing the time that any one invention stands as an influential invention. Thus inventions in clusters experiencing convergence will have only temporary importance due to the appearance of similar inventions.

In addition to imitation reducing the importance of clustered firms' inventions, the narrowing of managerial attention to local competitors creates a mismatch between firms' innovative strategies and the broader industry environment. Due to the ease of observation and the salience of information on local competition, decision makers in clustered firms will narrow their focus to local competition. Local focus will draw attention away from outside competitors and strategies will be reflective of the actions of local organizations (Pouder and St. John, 1996). Losing sight of distant competitors decreases decision makers' awareness of industry changes and trends. This creates a mismatch between the firms' inventions and the inventions in the overall industry. Consequently, when a firm's inventions become unrelated to the activities of other organizations in the technological community, their inventions will be less important (Sorensen and Stuart, 2000). Thus, local embeddedness will reduce the impact of firms' inventions such that:

H3: Local embeddedness will be negatively related to the impact of a firm's inventions

Method

Data

To test the hypotheses, I explored the rate and technological position of patents applied for, and ultimately granted, by firms engaged in research in the area of nanotechnology from 1981-2004. I used publicly available longitudinal data on organizations engaged in research in the area of nanotechnology which was made available through *Nanobank*. *Nanobank* is a digital library containing observations from various sources (scientific articles, patents and government grants), determined to be related to nanotechnology, either by probabilistic information retrieval (IR) methods or by declaration from a source authority. Nanobank contains data on 580,711scientific articles in peer reviewed journals; 240,437 patents from the U.S. Patenting and Trademark Office's on-line database; and 52,831 research grants issued by the National Science Foundation (NSF) and National Institutes of Health (NIH). The dataset contains bibliographic information, including titles, abstracts, publication years, author names, associated organizations, and geo-coding information. From these data, variables were coded to test the relationships of interest. Firm level data was coded indicating which organizations in the cluster, if any, the focal firm had collaborated with on a published research article. Further, firm level patent data was gathered to identify the patents, if any, for which the focal firm had applied. Finally, patent class data was used to determine the cluster's and the firm's position in technological space.

Patents contain detailed information on the inventions they protect, and thus patents are widely accepted as a rich source of information for the study of inventions (Hall, Jaffe, and Trajtenberg, 2005). Patents contain detailed information about the invention, the inventor, and the antecedents of the invention, including citations to previous inventions upon which the focal invention is based. There are, however, limitations to the use of patent data. Specifically, not all inventions are patented. However, most firms in nanotechnology do not offer any products in the marketplace and instead consider patents and the technologies embodied in them as their main innovative output. Moreover, patents signal legitimacy to potential investors and to the broader scientific community, and therefore represent a desired outcome for firms engaged in nanotechnology research.

A criticism of prior agglomeration research has been the lack of a clear definition of what constitutes a cluster (McCann and Folta, 2008). A central tenet of agglomeration theory is that economies accrue to collocated organizations as the number of organizations in the cluster increases. However, prior research has been unclear with regards to how many organizations are required to collocate in order for these economies to begin to accrue. In order to avoid this uncertainty, I limit my sample to the nanotechnology clusters identified by the National Science Foundation's (NSF) nanotechnology initiative (NNI) and the Project on Emerging Nanotechnologies (PEN). The PEN identifies "nanometros" based on the number of private organizations engaged in nanotechnology research or commercialization. In 2005, the NSF, with the backing of the federal government, provided funding to sixteen different nanotechnology 'districts,' or clusters. The funding was awarded to regions that were deemed to have the most established research infrastructure in place to advance science in the area of nanotechnology. Limiting the sample to firms located in these recognized clusters addresses shortcomings of prior research which in some cases assumes that economies of agglomeration accrue with as few as two similar or related organizations in a region.

Variables

Dependent variables

This study uses patent-based measures of innovation to test the relationships of interest. I examine the nature of the relationship between clustering and organizational innovations. I tested hypothesis 1, that local embeddedness produces a greater number of inventions by modeling the rate of invention as a function of local embeddedness and other covariates. *Rate of invention* is the frequency with which a focal firm applies for patents that are ultimately granted, which I operationalize as the total number of patents that a firm applied for in a given year from 1981-2004.

To test my hypothesis related to the convergence of innovations in a cluster, I first constructed measures reflecting the technological position of my focal firms and the technological position of the clusters in which the focal firms are located. I rely on the technological class information identified in the patent's citation as proxies for the underlying knowledge elements in the patent(Benner and Waldfogel, 2008). Although most patents are classified into more than one three-digit class code, most prior research has only utilized patent class data for the first technological class identified on the patent and has ignored subsequent listed classes. This approach fails to give an accurate representation of the technologies with which the firm is experienced and can therefore provide misleading results when assessing a firm's technological position (Benner and Waldfogel, 2008).

To overcome this limitation of prior research, I include all of the technological classes identified by the patents in my sample. The patents in my sample cite 422 different technological classes, which makes an accurate assessment of a firm's technological footprint problematic (Hall, Jaffe, Trajtenberg, 2001). Following Hall, Jaffe, and Trantenberg (2001), I aggregate the technological class data of the patents in my sample to 37 broader classifications. To determine a firm's technological positioning, I first considered the 37 technology class to be 37 orthogonal dimensions of technological knowledge. Each firm's patents could then be represented by a vector that counted the percentage of references (backward citations) in a given technological area. For example, if firm patent j has nine citations, of which two belong to technology area A, three to technology area B, and four to technology area C, the vector M (.22, .33, .44, 0, 0, . . . ,

0) describes the patent's component knowledge. By counting the proportion of citations in given technological areas, vector M represents the firm's technological position by combining the information on which classes the firm references and the frequency with which those classes are referenced. Finally, I aggregated all citations in a firm's existing patents (over the previous three years) and calculated the resulting vector. I updated this vector each year to reflect recent patent applications. The aggregated vector thus indicates the firm's technological position at a given time. To establish the firm's initial technological position, I used its aggregate vectors of the first two patents. In a similar manner, I calculated the technological position of each cluster in my sample by aggregating all of the patents applied for by organizations in that cluster in a given three year period. The result is two vectors, one representing the 37 dimensional technological position of my focal firms, and the other one representing the 37 dimensional technological position of the clusters in which the focal firms are located.

Using this approach, I compared each firm's technological position relative to their cluster's technological position. Specifically, I measured the angle between each of a focal firm's new patents (vector a) and the cluster's technological position (vector b). I then operationalize *innovative convergence* as the change in the angular distance between the two vectors. A decreasing angular distance between the firm and the cluster indicates the firm is converging on the average invention in the cluster. Conversely, an increasing angular distance score indicates the firm's inventions are diverging from the average invention in the cluster (see figure 3).

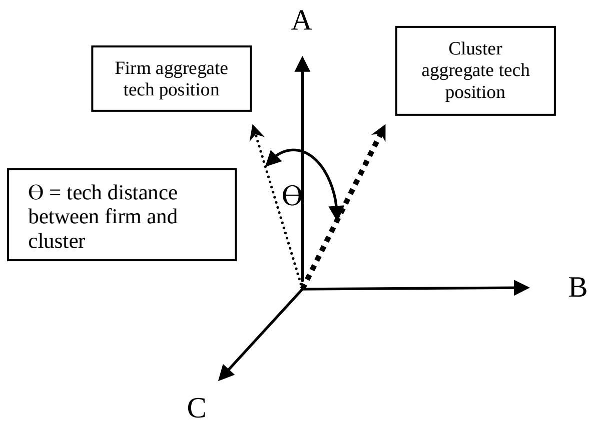

Figure 3: The angular technological distance between a firm and the cluster

Finally, to test the hypothesis related to the relationship between local embeddedness and the impact of firm inventions, I operationalized *impact of invention* as a count of the number of times a focal firm's inventions have been cited in a given year. Previous studies have suggested that highly cited patents are innovations that can be considered more important or influential than less cited patents (Sorenson and Stuart, 2000; Trajtenberg, 1990).

Independent variables

Following Reagan and Zuckerman's (2001) measure of network density, I define local embeddedness as the average level of collaboration frequency among local organizations with the focal firm in the publication of a research article in the area of nanotechnology. *Local embeddedness* was operationalized as a count of the number of collaborations in a given year. Data on firms' research publications and geographic locations were available through *Nanobank*.

Control variables

Cluster level controls. Prior research suggests that firms located in larger clusters may be more innovative (McCann and Folta, 2009; Folta, Cooper, and Baik, 2006). To control for these effects I define *cluster size* as the number of organizations located in a particular bureau of economic activity (BEA). BEAs define markets surrounding metropolitan or micropolitan statistical areas. They consist of one or more metropolitan or micropolitan statistical areas that serve as regional centers of economic activity and the surrounding counties that are economically related. Since data on organization inception and closure were not available, I used data on when organizations either published an article or applied for a patent, in the area of nanotechnology, as evidence that an organization was active in the cluster. I operationalized cluster size as the number of entities (firms, research universities, national labs, research institutions, federal government, and hospitals) that either published a research article or applied for a patent in a given year. I also control for the number of *cluster publications*, operationalized as the count of the number of research publications in the area of nanotechnology in a cluster in a given year. Cluster publications reflect the research activity level in a region, independent of the number of patents generated. Prior research has argued that the number of federal research grants awarded to organizations in a cluster is indicative of the fertility of the cluster environment (DeCarolis and Deeds, 1999). As such, I control for the number of *cluster grants* which I operationalize as the number of National Institutes of Health (NIH), and National Science Foundation (NSF) grants awarded in the area of nanotechnology in a cluster, in a given year.

Firm-level controls. Prior research on organizational ecology suggests organizational age can influence the rate and types of inventions a firm produces (Sorensen and Stuart, 2000). For instance, older firms have been shown to have a greater likelihood of patenting, but these patents are more likely to cite the firm's prior patents, and these patents are less likely to be cited by other firms. To account for these effects in my model, I control for *firm age*, operationalized as the number of years a firm has been either publishing research articles or applying for patents in the area of nanotechnology, in a focal cluster. Firms develop patenting capabilities which can affect their future rate of patenting. As such, I control for a firm's total stock of prior patents, *firm patent stock*, which I operationalize as the total number of prior nanotechnology patents for which a firm has applied. The firms in my sample also engaged in research collaborations with firms in distant geographic clusters. The knowledge gained from these collaborations could affect both the rate, technological position, and impact of their inventions. As such, I controlled for *distant collaborations*, which I operationalized as a count of the number of nanotechnology research collaborations with research entities outside of the focal firm's cluster, in a given year. Some focal firm research publications did not involve collaborations with other firms, although they may have been authored by several scientists within the focal firm. To control for the knowledge accumulated through the publication of a nanotechnology research article that did not include co-authors from other firms, universities, etc., I control for *firm publications* which is operationalized as the total number of nanotechnology publications in a given year. I also control for *firm publications total* which I operationalize as the total number of prior nanotechnology publications in the firm's publishing history, in a given year.

Model specification and estimation

The study examines 24 years of time-varying panel data (i.e. cross-section, time series data). Over this time, some firms entered the sample while others left the sample, which resulted in an unbalanced panel (Sayres, 1989). Because the dependent variables rate of invention and impact of invention were both count type variables, Poisson models would typically be appropriate. However, these data violate an assumption of Poisson models regarding the equality of mean and variance. The dependent variables exhibited overdispersion (variance is greater than the mean) therefore making negative binomial regression the preferred method (Hausman, Hall, and Griliches, 1984). I used a fixed-effects, rather than random-effects, negative binomial model which addresses the problem of unobserved heterogeneity, as well as overdispersion (Hausman, Hall, and Griliches, 1984). Fixed-effects models allow random firm-specific effects to be correlated with the regressors, which allows for a limited form of endogeneity (Cameron and Trevedi, 2009). Random-effects models assume that firm-specific effects are purely random, and not correlated with the regressors, a stricter assumption than the fixed-effects models. Analyses were performed using the xtnbreg command in Stata IC11. To test the hypotheses related to convergence, I used linear regression techniques using the xtreg command in Stata IC11.

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FUTURE WORK

Introduction

This chapter is a compilation of research proposals which lends insights into my future research. Each of the proposals herein will be studied in the context of nanotechnology either solely with existing data, or by supplementing current data with a proposed survey.

Proposals 1 and 2 investigate how entrepreneur's educational and functional backgrounds shape the types of market opportunities they pursue. Proposal 1 asks entrepreneurs how many opportunities they considered and what types of opportunities they considered prior to market entry. Building on this, proposal 2 uses archival data on the licensing of a breakthrough invention in nanotechnology to understand how educational and functional background shapes the way entrepreneurs commercialize breakthrough inventions.

Proposal 3 builds on a growing body of research which investigates the effect of the geographic dispersion of firm R&D activity on firm inventions. I argue the geographic dispersion of collaborative activity in the publication of research articles provides access to non-redundant information which firms combine with their existing to knowledge which increases the impact of firms' inventions. Furthermore, I argue that firms' technological focus increases the effect of geographic dispersion on impact of firms' inventions.

Proposal 4 empirically investigates the oft theorized phenomenon that institutional forces may drive a convergence of inventions in geographic clusters. Most notably, Pouder and St. John (1996) describe the rise and fall of geographic clusters and argue that clustered firms may lose sight of broader industry trends and are susceptible to normative pressures that reduce the inventiveness of clustered firms. I argue that the density of communications in the cluster increases the transmission of normatively accepted practices which causes organizations to become more similar. Moreover, clusters should vary in the strength of convergent forces. I assert that clusters home to highly prolific organizations, research universities, or venture capital firms will have convergent forces of greater magnitude and will therefore strengthen the density to convergence relationship.

Proposal 5 investigates how federal research grants affect firm and regional inventiveness. Nanotechnology is asserted to spark the next industrial revolution, a thought not lost on policy makers. As a result, more than half of the total investment in nanotechnology research in federally funded. Yet, despite the large investment in organizations and regions engaged in 'nano' research, we know little about the impact of federal funding on inventiveness. Building on a recent study which found an inverted U relationship between funding and inventive impact (Waldman, 2010), I plan to investigate the effect of federal research grants on the inventiveness of organizations and the regions in which they are located.

Proposal 1

TMT background and the identification of market opportunities

Research Question

How do founders' pre-entry knowledge and experience shape the number and types of market opportunities entrepreneurs consider prior to market entry?

Following Gruber, McMillan, and Thompson (2008, 2010), this research seeks to understand how founder's knowledge and experience affects the number and types of market opportunities considered prior to market entry. Research highlights the fact that before entrepreneurs can leverage their technological competences they need to identify at least one market in which their competences meet customer demand (Gruber, McMillan, and Thompson 2010, 2008; Shane 2004; Shane, 2000). Moreover, extant research suggests that although identifying multiple opportunities prior to entry has important advantages, most entrepreneurs only consider one opportunity (Shane, 2000).

When technological competences are fungible they may create benefits for end users in multiple markets (Penrose 1959, Prahalad and Hamel 1990, Danneels 2007). Such is the case in nanotechnology, which is considered a general purpose technology and is applicable across many different industries (Peters, 2010). The fungibility of technological competences in the area of nanotechnology makes nanotechnology an ideal setting to ask questions about the number and types of opportunities entrepreneurs consider prior to market entry.

I begin with a general assessment of how the founding team's knowledge and experience influences market opportunity identification. Following Gruber, McMillan, and Thompson (2008, 2010), I then discuss in more detail how four different types of pre-entry knowledge and experience endowments (in management, entrepreneurship, marketing, and technology) affect the identification of market opportunities. Existing research holds that teams with diverse backgrounds provide a heterogeneous set of knowledge, skills, and abilities, which provides a broader knowledge base which can be brought to bear on organizational problems. Therefore founding teams with higher functional background diversity should identify more opportunities, and the opportunities identified should be dissimilar relative to their current markets.

Educational specialization and level diversity. Education builds and influences the knowledge, skills, and abilities a person brings to a task (Gruber, McMillan, and Thompson 2008, 2010). In terms of educational specialization, a person's choice of curriculum not only reflects his or her cognitive style and personality, it also shapes this person's understandings and problem solving approaches (Wiersema & Bantel, 1992). Prior research has found evidence suggesting that diversity with respect to educational specialization has a positive effect on cognitive task performance (e.g., Bantel & Jackson, 1989). In the context of new market opportunities, founding teams with diverse educational backgrounds possess a broader set of knowledge, opinions, and perspectives.

In terms of education level, research holds that the attained level of formal education is reflective of an individual's cognitive ability (Gruber, McMillan, and Thompson, 2008, 2010; Pelled, 1996). That is, individuals who are more educated tend to be more receptive to innovation and ambiguity. However, individuals with lower levels of formal education may possess more applied knowledge and more practical intelligence (Sternberg, 2004) and may be more interested in solving practical problems. Identifying market opportunities for the emergent firm's technological competence is a complex task requiring a mix of theoretical and applied knowledge (Gruber, McMillan, and Thompson, 2008, 2010), therefore teams with diverse educational levels should have an advantage in identifying market opportunities. Moreover, the mix of basic and applied know-how will increase the likelihood that the opportunities identified serve markets which are dissimilar to the firm's existing markets.

Work experience. In addition to education, founding team members' work experiences can influence the amount and types of market opportunities these teams identify. Prior work experience is indicative of the set of learned routines that individuals bring to their current firms (Baron, Burton, & Hannan, 1999). With different work experiences people thus possess different problem-solving experiences and perspectives and are also subject to different blind spots (Gruber, McMillan, and Thompson, 2008, 2010; Finkelstein et al., 2009). Scholars have suggested that entrepreneurs with a marketing background will see opportunities differently that will entrepreneurs with an engineering background (Eisenhardt, Kahwajy, and Bourgeois, 1997). Following Gruber, McMillan, and Thompson (2008, 2010), I examine four types of pre-entry experience endowments that are likely to influence the number and types of market opportunities entrepreneurs identify: management experience, entrepreneurial experience, marketing experience, and technological (engineering) experience.

In short, I consider management and entrepreneurial experience to be general experience and technological and marketing experience to be specialized experience. I hypothesize that generalist will conceive of more opportunities than will specialists, and their opportunity set will be dissimilar to their current markets, compared to the opportunities identified by specialists.

Method

The hypothesized relationships will be tested using a survey to founders and top management team members of start-up nanotechnology firms. Respondents will provide demographic data to construct measures on team educational background and level heterogeneity as well as measures on dominant functional background experience. Further, following Gruber and colleagues (2008, 2010), respondents will be asked to indicate how many opportunities they considered prior to their first market entry. Also, respondents will be asked to indicate the types of markets that were considered.

<u>Proposal 2</u>

TMT background and the exploitation of breakthrough inventions

Research Question

How do entrepreneur's pre-entry knowledge and experience endowments influence firms' exploitation of breakthrough inventions?

Following Gruber, McMillan, and Thompson (2008, 2010) and Shane (2000), this research seeks to understand how founder's knowledge and experience affects the types of market opportunities emerging firms exploit. Using a significant breakthrough in the area of nanotechnology – the invention of the scanning tunneling microscope (STM), which allows manipulation of materials at the nano level – this study investigates how experience and knowledge endowments affect the ways firms commercialize breakthrough inventions. Before breakthrough technologies can be exploited, entrepreneurs must first discover opportunities in which to use the new technology. Because opportunities do not appear in a prepackaged form (Venkataraman 1997), this process of opportunity identification is far from trivial.

Building on the work of Shane (2000) and Gruber and colleagues (2010, 2008), this study argues that experience and knowledge endowments influence the types of commercial opportunities emerging firms pursue in licensing breakthrough inventions. Furthermore, experience and knowledge endowments should affect which opportunities are commercialized by new or existing firms. Taking an Austrian economics perspective, I argue that different people will exploit different opportunities in a given technological breakthrough because they possess different prior knowledge (Venkataraman 1997).

I draw on literature suggesting that diverse backgrounds provide a heterogeneous set of knowledge, cognitive abilities, skills, and information, which when combined provide a broader knowledge base from which to solve organizational problems. Therefore diversity in knowledge and expertise should lead to entry into markets which are distant from the firm's current markets

Educational specialization and level diversity. Education shapes the knowledge, skills, and perspectives a person brings to a task (Tsui, Egan, & Xin, 1995). Prior studies have shown that group diversity with respect to educational specialization has a positive effect on cognitive task performance (e.g., Bantel & Jackson, 1989). Working in a group with a diverse educational background exposes individuals to a broader set of knowledge, opinions, and perspectives (Harrison & Klein, 2007).

In terms of education level, extant work argues that the attained level of formal education is reflective of an individual's cognitive ability (Pelled, 1996). Whereas individuals who are more educated tend to be more receptive to innovation, have a higher capacity for information processing, and are more likely to engage in boundary spanning (Hambrick & Mason, 1984), individuals with lower levels of formal education yet on-the-job training may possess more applied knowledge and more practical intelligence (Sternberg, 2004) and may be more interested in solving practical problems. Identifying market opportunities for the start-up's technological resources is a complex task requiring a mix of theoretical and applied knowledge, so teams with diverse educational levels should have an advantage in market opportunity searches.

Work experience. Beyond education, prior work experience affects the exploitation of breakthrough inventions. Prior experience represents learned routines that individuals bring to emergent firms (Baron, Burton, & Hannan, 1999). Following Gruber, McMillan, and Thompson (2008, 2010), I examine four types of pre-exploitation experience endowments that are likely to influence the number and types of exploitation opportunities entrepreneurs identify: management experience, entrepreneurial experience, marketing experience, and technological (engineering) experience.

In short, I consider management and entrepreneurial experience to be general experience and technological and marketing experience to be specialized experience. I hypothesize that generalist will exploit breakthrough inventions by commercializing products that are distant from their current products. Conversely, specialists will exploit breakthrough inventions by commercializing products that are in close proximity to their current products. See figure 4 for my conceptual model.

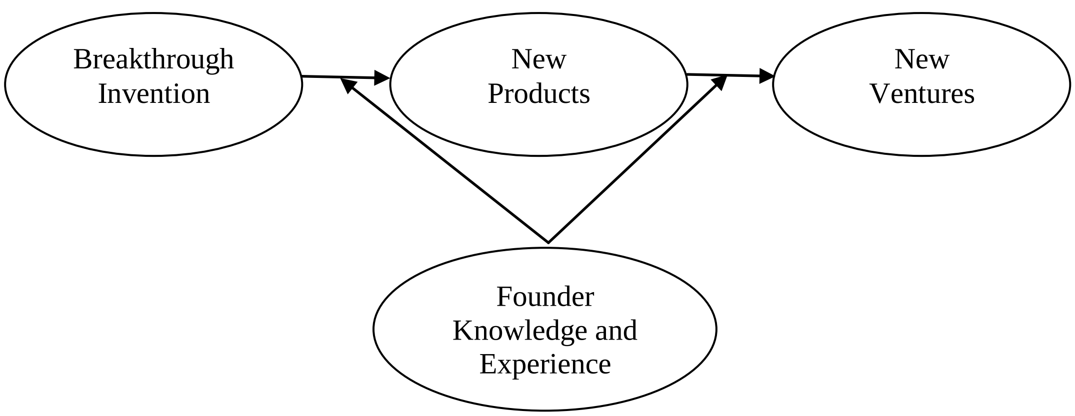

Figure 4: The influence of founder knowledge and experience on the exploitation of breakthrough inventions

Method

Following Shane (2000), I seek to investigate specific instances of the licensing of a breakthrough invention in the area of nanotechnology. Leveraging data available through the technology transfer office at the relevant universities; I plan to survey individuals or firms who have licensed the aforementioned breakthrough invention. I will survey participants regarding their demographic and background information to construct my independent variables related to educational and experiential diversity.

Proposal 3

Geographic dispersion of collaborative activity and impact of inventions: the moderating role of technological focus

Research Question

How does firms' technological focus shape the relationship between their geographic dispersion of collaborations and the impact of their inventions?

Recently, a growing body of research has begun to investigate the effects of geographically dispersed R&D and its affect on firms' innovative abilities. Largely, this research holds that geographic dispersion provides access to unique skills and information that may enable the firm to explore new opportunities. However, the distance and embeddedness of knowledge which makes is valuable, also makes its acquisition and absorption difficult. As such, research investigating the link between geographic dispersion and innovative outcomes reports mixed results (Leiponen and Helfat, forthcoming; Singh, 2008; Phene et al, 2006) Notwithstanding the mixed results, these researchers generally agree that a firm's ability to recognize and assimilate distant and unique knowledge hinges on its ability to assimilate new knowledge with existing knowledge bases. Whereas research on geographic dispersion and firm innovative outcomes largely examines cases of decentralized R&D (Singh, 2008), this study examines the effects of geographically dispersed collaborative activities on firm inventions. Noting the difficulties associated with integrating distant knowledge, I argue that greater technological breadth decreases firms' abilities to absorb and exploit distant knowledge (Cohen and Levinthal, 1990).

Consistent with theories of organizational learning, collaborations with organizations in many different locations offers key benefits. Literature on economic geography and national innovation systems suggests that countries and regions develop distinct areas of expertise, even within the same industry (Phene et al., 2006; Almeida and Kogut, 1999; Jaffe, Henderson, and Trajtenberg, 1993; Bartholomew, 1997). The specialization of knowledge and the tendency for knowledge to localize creates the potential for non-overlapping knowledge bases (Kogut, 1991). Therefore, collaborations with organizations in different geographic regions may provide the firm with access to novel information. This expanded knowledge increases the likelihood that firms gain new perspectives on existing technologies, experiment with the newly acquired knowledge, and explore new technologies.

Another school of thought emphasizes the difficulties of integrating distant knowledge. Increased complexity resulting from increased diversity of knowledge sources may reduce the ability to integrate new knowledge due to information overload (Haunschild and Beckman,

1998) which outweighs any potential benefits of accessing another unit of new information. Research on expertise diversity suggests greater diversity has a curvilinear effect on exploration, such that some initial diversity has more value than subsequent increments (Van der Vegt and Bunderson, 2005; Williams and O'Reilly, 1998). In light of this research and the mixed empirical evidence sited above, I argue that geographic dispersion of collaborative activity will have an inverted U relationship with the novelty of firm inventions. Initially, geographically dispersed collaborations will have a positive relationship with the novelty of inventions, but at a tipping point, additional geographically dispersed collaborations will be negatively related to the novelty of inventions. Thus:

H1: Geographically dispersed collaborations have an inverted U shape relationship with novelty of invention, such that the relationship is initially positive but decreases at high levels of geographic dispersion

Research in organizational learning suggests that firms may vary in the abilities to learn from their geographically dispersed collaborations. Specifically, some firms may be better suited for managing the complexity that arises with increasing levels of dispersed collaborations. To this end, organizational learning researchers have highlighted the importance knowledge breadth in recognizing and absorbing new knowledge (Kim and Finkelstein, 2009; Haunschild and Sullivan, 2002; Cohen and Levinthal, 1990). There is, however, conflicting theoretical guidance as to how technological breadth influences firms' integrative capabilities. For instance, research on absorptive capacity would suggest that technological breadth provides a cognitive foothold for the acquisition of new knowledge and firms with greater breadth will better appreciate increasing levels of unique information (Cohen and Levinthal, 1990). Conversely, technologically focused firms will be unable to recognize and absorb the complexity of information gleaned from geographically dispersed collaborations.

However, there is some suggestion in the literature that firms with broader technological bases deal with a larger set of technologies, have more variance in their resource requirements, and deal with a wider array of technological issues (Haunschild and Sullivan, 2002). These authors also suggest that firms with broader technological bases may be diversified and more hierarchical which increases the difficulty of knowledge integration. This organizational complexity magnifies the difficulties associated with integrating distant knowledge, as the complexity of a high degree of distant knowledge is less likely to be utilized effectively in complex systems as the organization is already overloaded with diverse information. Conversely, technologically focused firms have narrower resource requirements, deal with a smaller set of technologies, and are inherently less complex. As a result, they learn more effectively given complex information and are better able to manage the complexity of dispersed collaborations. Thus:

> *H2: The curvilinear relationship between geographically dispersed collaborations and novelty of invention is positively moderated by the firm's technological focus, such that it weakens the negative effect of high levels of geographic dispersion*

Method

Dependent variable. Geographically dispersed collaborations are argued to affect the *novelty of firm inventions,* which refers to a firm's patenting activities in a technological area with which it has no prior experience (Ahuja and Lampert, 2001). I operationalized this as the number of new technological classes entered in the previous three years.

Independent variables. The independent variable of interest is the *geographic dispersion of collaborative activity*. Using data from Nanobank.org, I identified firms' collaborations in the publication of research articles in the area of nanotechnology. Data was extracted to indicate the geographic locations of the organizations with which the focal firm had collaborated, if any. I then calculated the Herfindahl index of the different geographic locations in which a focal firm had collaborated. A lower score indicates a more geographically dispersed collaborative network that, I argue, provides access to a greater variety of unique information. The key moderating variable is firms' *technological focus,* which I operationalize, using patent class data, as the concentration of inventions in one or a few technological areas. A firm whose patents predominantly site one or a few technologies would have a high degree of technological focus as compared to a firm whose inventions are spread among many different technologies.

Proposal 4

The convergence of inventions in geographic clusters

Research Question

Do the inventions originating in geographic clusters converge over time? What causes this convergence?

Clustering is argued to confer advantages to collocated firms through access to specialized labor and inputs, access to greater demand, and access to knowledge spillovers (Arthur, 1990). Extant research has argued that the clustering of similar firms creates an innovative environment which bestows advantages upon clustered firms, and that clustered firms are more inventive (Coombs, Deeds, and Ireland, 2009; McCann and Folta, 2009; Aharonson, Baum, and Feldman, 2008; Folta, Cooper, and Baik, 2006; DeCarolis and Deeds, 1999; Romanelli and Khessina, 2005; Porter, 1998; Pouder and St. John, 1996; Powell, Koput, and Smith-Doerr, 1996; Saxenian, 1994). Yet there is striking evidence that firms in some of the largest and best-know clusters have experienced significant downturns in performance, and entire clusters have fallen into decline (e.g. Route 128 in Boston) (Saxenian, 1994); and recent theorizing suggests clusters may restrict innovative activity (Romanelli and Khessina, 2005; Pouder and St. John, 1996).

Researchers hold that the root of any downside associated with clustering may be a result of the broader cluster environment. For instance, Abrahamson and Fombrun (1994) suggest that clustering may facilitate the growth of homogeneous macro-cultures where shared beliefs regarding strategy and competition impede the acceptance of new ideas generated outside of the cluster. Porter (1998:85) argues that clustered firms are susceptible to groupthink and insularity where the "whole cluster suffers from a collective inertia, making it harder for individual companies to embrace new ideas." In their research on the rise and fall of geographic clusters, Pouder and St. John (1996) posit that institutional forces drive a convergence of innovations in the cluster which makes clustered firms susceptible to radical technological changes. In this dissertation, I focus specifically on the convergence of innovations in geographic clusters.

Theorizing on the convergence of innovations in geographic clusters suggests that the availability of information on local competition and institutional pressures encourage imitation. The dense networks of interdependent organizations in clusters increases the knowledge of competitors' processes and capabilities (Abrahamson and Fombrun, 1993), which is argued to be a key determinant in the imitation of innovations (Zander and Kogut, 1995). Moreover, in addition to channeling technical information, local networks also provide a means by which organizations become socialized to accepted norms. From this perspective, linkages to local organizations encourage the mimetic adoption of accepted practices, sometimes regardless of their technical merit (Westphal, Seidel, and Stewart, 2001; Staw and Epstein, 2000; Pouder and St. John, 1996; DiMaggio and Powell, 1983).

I contend that the local networks that attract firms to the region, also pass information and mimetic forces that ultimately drive a convergence of inventions in the cluster such that inventions in the region come to resemble one another. In spite of recent theorizing that suggests a convergence of inventions may occur, and in spite of the practical importance of such an occurrence, scant empirical evidence exists to support or refute such claims. In this dissertation I test hypotheses regarding the narrowing of focus, or convergence, of inventions in geographic clusters

H1: The density of collaborations among organizations in the cluster is positively related to the convergence of inventions in the cluster

In what follows, I suggest that Geographic clusters may be home to varying degrees of convergent forces, and extant research suggests that regional characteristics may enhance or weaken the forces driving the convergence of inventions in a cluster. For instance, recent research on regional identities (Romanelli and Khessina, 2005) suggests that the types of organizations in a cluster signal internal and external audiences alike the types of resources and investments the regions supports. Diversity in the types of organizations in a region may stave off inventive convergence in a cluster by attracting heterogeneous resources which increases the variability of normatively accepted routines and practices. In his classic work on organizational learning, March (1991) argued that individuals learn from a code, and that the rate of learning from the code is a function of the variability of knowledge embedded in the code. Therefore, greater variability in the sources of regional knowledge should decrease the rate of firm learning from the regional code. Finally, firms are more likely to imitate organizations perceived as achieving successful outcomes (Haunschild and Miner, 1997). In other words, highly successful organizations provide an attractive model for other organizations to imitate. Therefore, regions that are home to highly prolific organizations should be more susceptible to the forces driving convergence. In this study I conceptualize prolific organizations as premier research universities, highly productive private research firms, and highly reputable venture capital firms.

The presence of any of these organizations, singularly or in combination, will provide stronger modeling cues and thus will increase the convergence of inventions in their clusters.

H2: Variety in the types of organizations in the local network negatively moderates the relationship between local network density and cluster convergence, such that organization type variety softens the positive effect of network density on convergence.

H3: The presence of prolific organizations in the local network positively moderates the relationship between local network density and cluster convergence, such that prolific organizations increase the positive effect of network density on convergence.

Method

Dependent Variable. To test my hypothesis related to the convergence of innovations in a cluster, I constructed measures reflecting the technological position of my focal clusters as an aggregate measure of the patents generated by all organizations in the cluster. I rely on the technological class information identified in the patent's citation as proxies for the underlying knowledge elements in the patent(Benner and Waldfogel, 2008). Although most patents are classified into more than one three-digit class code, most prior research has only utilized patent class data for the first technological class identified on the patent and has ignored subsequent listed classes. This approach fails to give an accurate representation of the technologies with which the firm is experienced and can therefore provide misleading results when assessing a firm's technological position (Benner and Waldfogel, 2008).

To overcome this limitation of prior research, I include all of the technological classes identified by the patents in my sample. The patents in my sample cite 422 different technological classes, which makes an accurate assessment of a firm's technological footprint problematic (Hall, Jaffe, Trajtenberg, 2001). Following Hall, Jaffe, and Trantenberg (2001), I aggregate the technological class data of the patents in my sample to 37 broader classifications. To determine a cluster's technological positioning, I first considered the 37 technology class to be 37 orthogonal dimensions of technological knowledge. Each cluster's patents could then be represented by a vector that counted the percentage of references (backward citations) in a given technological area. For example, if patent j has nine citations, of which two belong to technology area A, three to technology area B, and four to technology area C, the vector M (.22, .33, .44, 0, 0, . . . , 0) describes the patent's component knowledge. By counting the proportion of citations in given technological areas, vector M represents the cluster's technological position by combining the information on which classes the patents in the cluster references and the frequency with which those classes are referenced. Finally, I aggregated all citations in a cluster's existing patents (over the previous three years) and calculated the resulting vector. I updated this vector each year to reflect recent patent applications. The aggregated vector thus indicates the cluster's technological position at a given time.

Using this approach, I compared each cluster's technological position relative to prior years. Specifically, I measured the angle between a focal cluster's position at time t (vector a) and the cluster's technological position at time t+1 (vector b). I then operationalize *innovative convergence* as the change in the angular distance between the two vectors. A decreasing angular distance between vectors A and B indicates the cluster is generating patents in fewer new technological areas. That is, the patents generated by organizations in the cluster are converging such that they are become more similar to the patents previously generated by organizations in the cluster (see figure 5).

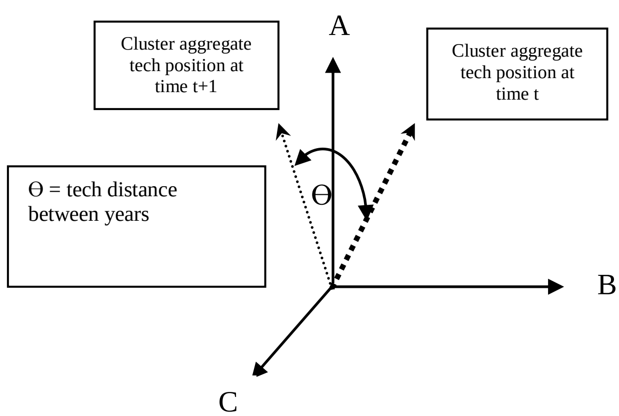

Figure 5: The angular technological distance in a cluster at time t and t+1

<u>Proposal 5</u>

The impact of NSF and NIH funding and scientific productivity

Research Question

How does NSF and NIH funding affect organizational and regional inventiveness in geographic clusters?

Nanotechnology is considered a general purpose technology (Palmberg, 2008) and it is largely assumed that nanotechnology has the potential to redefine many industries. Nanotechnology is defined as the study and manipulation of materials smaller than 100 nanometers which is at the level of atoms and molecules (Peters, 2010). Working at the nano level is of interest because the physical and chemical properties of materials at the nano-scale can be novel in ways that have economic potential. For instance, carbon nanotubes have a strength-to-weight ratio greater than diamonds, and 100 times greater than steel (Peters, 2010).

According to policy makers, the development of nanotechnology is the latest mega-trend in science and engineering and will enable fundamentally new means of production which could spark a new industrial revolution (ICON, 2008; Siegel, Hu, and Roco, 1999). The basis for such claims rests on predictions that nanotechnology will become the platform for inexpensive but remarkably more powerful computing, cost effective alternative energies, and fundamentally new medical technologies (Peters, 2008). This potential has not gone unnoticed. Worldwide funding in nanotechnology increased six-fold from $4B in 2001 to $25B in 2008. In the U.S. more than half of all funding is federal government funding, followed by corporate and venture capital funding. In 2010, the National Science Foundation (NSF) budgeted $422M to be awarded competitively to actors engaged in nanotechnology research. In spite of this substantial investment, scant research has been conducted to investigate the efficacy of these investments.

Furthermore, a recent study published by the director of the National Institutes of Health (NIH) found that medium levels of federal funding led to the highest impact research. In other words, federal grants increased the impact of scientists' research to a point after which more funding actually decreased the impact of their research. This finding suggests a gap in our understanding of how federal grants influence innovation.

I propose a study of NSF and NIH grants in the area of nanotechnology and their affect on innovation. Specifically, I'm interested in the relationship between funding level and impact of firm inventions, defined as the number of times future inventions cite a focal invention. Moreover, given the regional nature of nanotechnology funding (e.g. National Nanotechnoloy Iniative, NNI), I'm interested in the effect of regional level funding on regional inventions. Several questions emerge when examining funding at the regional level. For instance, should funding be concentrated in the large research universities whose mission it is to disseminate knowledge? Or, should regional funding be more dispersed among organizations to encourage diversity in the research avenues pursued?

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APPENDIX A: VARIABLE CODING DESCRIPTION

The following appendix outlines the process undertaken in the coding of the key variables in this study.

Local collaborations. Using the data available from Nanobank.org, I extracted all firms that published a research article in the area of nanotechnology. As a first step, I extracted firms publishing for the entire range of available dates (1956-2004). After becoming more knowledgeable regarding the development of nanotechnology as a field of science, I later limited the sample to firms publishing between 1981-2004 (1981was a breakthrough year in nanotechnology research and could be considered the birth of modern nanotechnology). Given my focus is on firm innovation in geographic clusters, I limited my sample to those firms located in one of the sixteen nanotechnology clusters identified by either the National Science Foundation (NSF), or the project on emerging nanotechnologies (PEN). The clusters used in this study are: Syracuse - Auburn, N.Y., Atlanta – Sandy Springs - Gainesville, GA-AL, Boston – Worcester-Manchester, MA-NH, Washington, D.C. – Baltimore – Northern Virginia, DC – MD – VA - WV, Raleigh-Durham – Cary, NC, State College, PA, San Jose – San Francisco – Oakland, CA, Los Angeles – Long Beach – Riverside, CA, Detroit – Warren – Flint, MI, Minneapolis – St. Paul – St. Cloud, MI-WI, Albuquerque, NM, Austin – Round Rock, TX, Seattle – Tacoma – Olympia, WA, Houston – Baytown – Huntsville, TX, Chicago – Naperville – Michigan City, IL-IN-WI, San Diego – Carlsbad – San Marcos, CA.

Having gathered any firm located in one of the sixteen focal clusters that published a research article in the area of nanotechnology, I then determined with whom the focal firms had collaborated with on these publications. While several focal firm publications had no co-authors from other organizations, many publications had several co-authors from organizations both in and out of the focal firm's geographic cluster. With the help of a research assistant, visual basic code was written for Microsoft excel to code the number of collaborations focal firms engaged in with other organizations in the focal firm's cluster in a given year. For example, if in a given year, a focal firm had three nanotechnology publications, the coding routine would count the total number of collaborators on those three publications that were in the focal firm's cluster. Data on collaborations with organizations in different geographic areas (not necessarily other clusters) was also captured for use as a control variable (distant collaborations). In this manner, each firm was given a count type score indicating their number of collaborations with local organizations in a given year. In the case that a focal firm collaborated with the same local organization on more than one publication, each collaboration was included in the score. However, when the same organization was listed more than once on the same publication (multiple authors in the same organization would cause such a scenario) it only counts as one collaboration.

Knowledge stocks. Using Nanobank.org, I aggregated nanotechnology patent data for the focal geographic clusters for each year of my sample (1981-2004). That, for each year I counted the total number of nanotechnology patents applied for by all organizations in a focal cluster. I then calculated a cumulative sum of the number of nanotechnology patents for each year going back to the first year in my sample.

Inventive concentration. Using Nanobank.org, I extracted the number of nanotechnology patents applied for by every organization in my focal clusters, in a given year. 'Every organization' indicates that my measure of concentration included the patents of more than just my sample firms. That is, universities, research labs, hospitals, non-profits, etc. were included in the calculation. Conceptually, this yielded an understanding of who was patenting and with what frequency. To assess inventive concentration, I calculated the Herfindahl index of patent applications in my focal clusters for each year of my sample.

Novelty of inventions refers to my sample firms' experimentation with new technologies. To determine which technologies a firm had experience with, I leveraged patent class data as reported on the patents applied for by my focal firms. Further, I used all of the technology classes cited on each patent rather than using only the first class cited. For instance, cited technologies are listed in order of position on a patent application. Some researchers have used only the patent class in the first position on the patent application, ignoring technology classes cited in other positions on the application. Doing so doesn't accurately capture the technologies with which the firm has experience (e.g. some cited technologies are ignored because they aren't in the first position). To improve on this, I include all cited technologies regardless of position on the application. I did not, however, include patent subclass data in my assessment of novelty. The focal firms in my sample cited 422 patent classes, or technologies. This large number makes assessing novelty problematic and would bias my results. To account for this, I followed Hall, Jaffe, and Trantenberg (2001), and aggregated the technological class data of the patents in my sample to 37 broader classifications.

With each firm's technological position mapped on to the 37 broad technological classifications, I determined which technologies each firm had experience with. I then had a research assistant write visual basic code to assess for each firm, and for each year, how many new technologies the firm cited in the previous three years. Conceptually, this was a rolling three-year window that for each year looked backwards three years to count how many times a new technology was cited by a firm's patents. This approach followed Ahuja and Lampert (2001).

APPENDIX B: NANOTECHNOLOGY INDUSTRY AND SAMPLE FIRM DESCRIPTION

Nanotechnology is a process innovation which refers to the manipulation of matter at the nano scale. The manipulation of matter at the nano scale is of interest because it can change the physical and chemical properties of materials. For instance, the position of single atom can determine whether a material acts as an insulator or a conductor. It has been suggested that nanotechnology represents the next great trend in science and could usher in the next industrial revolution. This remains to be seen, but it is difficult to ignore the growing interest in the field.

Nanotechnology is highly interdisciplinary and crosses the domains of chemistry, biology, molecular biology, quantum physics, biochemistry, materials science, electrical and chemical engineering, and others (Peters, 2010). The fact that nanotechnology is so highly interdisciplinary has implications regarding the complexity of the science, and makes nanotechnology an especially well-suited setting for the testing of my hypotheses. My hypotheses are built on arguments that the firms in my sample (1) do not possess all of the requisite knowledge to be innovative, and therefore must embed themselves in local networks of organizations, and (2) must be active in local research to appreciate and absorb local knowledge.

First, the interdisciplinary nature of nanotechnology dictates that organizations must access the expertise of others in their local communities. The fields of expertise which comprise nanotechnology make it unlikely that any single firm can be inventive in isolation. Second, the complexity of nanotechnology suggests that the knowledge transferred among organizations is tacit in nature. This fact has implications for what is required in order to absorb local knowledge. It is unlikely that organizations will absorb and be able to exploit local knowledge without being active in local research. This key point has been lost on previous agglomeration theory researchers who assume that location in a cluster automatically grants access to local knowledge.

The firms in my sample are engaged in research in the area of nanotechnology, as evidenced by the fact they published an article in the area of nanotechnology between 1981 and 2004. My sample firms may or may not be dedicated nanotechnology firms. In what follows I provide summary descriptions of a few of my sample firms.

Abbott Laboratories, headquartered in Chicago, Illinois, appeared in my sample every year (1981-2004). They did, however, have a nanotechnology patent in 1975 and therefore had a firm age of six years in 1981. By 1987 they had only three additional patents, but beginning in 1990 they began patenting at a much greater rate. During the years 1990-2000 they averaged 26.4 patents per year with a peak of 60 patents in 1995. During this time their patents cited an average of six new-to-the-firm technologies with a peak of sixteen new technologies cited in 1996. In addition to Abbott Laboratory's patenting, they were also engaged in research publications both on their own, and in collaboration with other organizations. Over the entire sample frame, Abbott Laboratories averaged 4.75 publications per year and they averaged nearly ten publications per year between 1990 and 2000. This indicates that Abbott Laboratories had a lower patent to publication ratio (2.64 = 26.4/10) than did the average firm in my sample across all years – approximately four times as many patents as publications. By 1992, Abbott Laboratories had sole authored all but two of their research publications. Moreover, these two collaborations were with organizations outside of the Chicago cluster. During the time frame between 1990 and 2000, they averaged 1.16 collaborations with organizations in the Chicago cluster and 2.0 collaborations with organizations outside of the Chicago cluster. In all but two years, Abbott Laboratories collaborated with more distant than local organizations.

3rd Tech is a graphics and imaging company that designs 2D and 3D visual crime scene reconstruction products. They are located in Durham, N.C. and are in the Raleigh, N.C. nanotechnology cluster. Information gathered on 3rd Tech's website indicates they have been in operation since 1999. However, they've only been active in nanotechnology research, based on my criteria, since 2002. During my sample time period, 3rd Tech published one research article, and that was in 2002. This article was coauthored with the University of North Carolina and an organization in distant geographic area (i.e. a non-local collaboration). The article was titled : "Controlled placement of an individual carbon nanotube onto a microelectromechanical structure" 3rd Tech did not apply for any patents that were subsequently granted, and therefore did not have a score for either of my dependent variables.

Advion Bioscience Incorporated is a contractor of bioanalytical services and infusion and chemistry products. They are located in the Syracuse, N.Y. nanotechnology cluster. Advion was founded in 1993 by a researcher at Cornell University. Advion does not show up in my sample until 2002 when they published two nanotechnology articles. Subsequently, they published five articles in 2003 and one article in 2004. In spite of their publishing productivity, Advion did not apply for a patent during my sample time period.