Distribution Agreement

Local Community Structures and the Novelty and Generality of Innovations

By

Scott D. Hayward
Doctor of Philosophy

Business

Dr. Peter W. Roberts
Advisor

Dr. Russell W. Coff
Committee Member

Dr. Kira R. Fabrizio
Committee Member

Dr. Robert K. Kazanjian
Committee Member

Accepted:

Lisa A. Tedesco, Ph.D.
Dean of the James T. Laney School of Graduate Studies

Date

Local Community Structures and the Novelty and Generality of Innovations

By

Scott D. Hayward
M.B.A., Emory University, 2003
B.S.B.A., University of Florida, 1993

Advisor: Peter W. Roberts, PhD

An abstract of
A dissertation submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy
in Business
2010

Abstract

Local Community Structures and the Novelty and Generality of Innovations
By: Scott D. Hayward

Location has become a key factor in explaining innovation and technological change. Local inventors form communities around particular technologies and industries, facilitating the flow of knowledge. Local knowledge flows drive inventor productivity and give innovations a local flavor. Yet every given region houses many communities, and a current debate pits the advantages of knowledge flowing within a local industry against those of knowledge flowing across local industries within the same region. While location matters for innovation, is it deep pools or diverse selections of local knowledge which matter more? This dissertation addresses this debate by focusing on whether an inventor's place within a broad structure of regional communities shapes the types of innovations they create. Combining patent data with employment and establishment data for the years 1977 through 1997, I locate inventors in technical and industrial communities housed within different U.S. metropolitan areas. Results suggest that local knowledge spillovers shape innovation novelty, while innovation generality follows a different process. While prior investigations focus on local counts of innovations, these findings advance the field by testing the logic of local knowledge spillovers to understand the antecedents of innovation novelty and generality. Furthermore, I introduce technical communities as a more direct measure than local industries, providing evidence to suggest they are different concepts and should be considered in future examinations of local innovation. This dissertation drives a broader understanding of how location matters for innovation, with subsequent implications for regional growth and technological development.

Local Community Structures and the Novelty and Generality of Innovations

By

Scott D. Hayward
M.B.A., Emory University, 2003
B.B.A., University of Florida, 1993

Advisor: Peter W. Roberts, PhD

A dissertation submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy
in Business
2010

ACKNOWLEDGEMENTS

I am deeply humbled when I think about the number of people who supported me through the writing of this dissertation. First, I am indebted to Peter Roberts for his guidance. From the first day of the doctoral program Peter impressed the importance of doing good work, and the care and effort it takes to do it. His respect for high quality research is contagious, and I see it currently afflicting not only me, but the other doctoral students coming through the program. Of course, I also thank Peter for his patience, a side of him I tested more than he may have liked, but for which I'm eternally grateful.

Thank you also to the other members of my committee. Kira Fabrizio, who provided feedback that both gives me confidence and shows me how to make the work better. She has a gift for searching through my jungle of ideas to find just the right ones to nurture further. I am indebted to Rob Kazanjian for his professionalism and willingness to help with the dissertation and job market. His MBA class made me want to teach Strategic Management. With great gusto, I have adopted Rob's teaching style as my own; I've asked myself more than once "what would Rob do here?" Rob, I think my students thank you too. Finally, I thank Russ Coff, who provided my first foray into doctoral student research and later pinch hit on my committee. His flexibility and insights were the final push needed to complete this dissertation.

Many of the present and past faculty members at Emory University provided the foundation for this dissertation. Tom Thomas took an MBA student under his guidance for a summer, and showed him how interesting research can be. Mary Ann Glynn, Bob Drazin and Diana Robertson, encouraged me to join academia and helped make a smooth transition into it. Even as I added two infants to my life, they convinced me that the sleepless nights and hectic days of a doctoral student and new father were worth it. Finally, Monica Worline deserves special mention for her time, devotion, and care for doctoral students; she kept us (mostly) sane. From her I learned that we all are a wellspring of exciting ideas waiting to be tapped.

Of course, many of my fondest memories I owe to my colleagues in the PhD program. Sascha Vitzthum, I could never ask for a better friend. David Tan provided a never ending source of remarkable questions and ideas. The late nights around the dry erase board taught me more than any class; I look forward to following his research throughout the rest of my career. I have long admired Chad Navis' ability to roll up his sleeves and get things done; thanks also for reminding me of life outside of research. Laura McClelland, Adina Sterling, and David Kryscynski all have and continue to be great friends with their support and a spirit of camaraderie. Watching them struggle with ideas, and seeing how those ideas have blossomed into interesting dissertations makes me happier than I can say without sounding silly. Jung Lee and Chirag Kasbekar show me the O&M department continues to turn really nice, really intelligent people into really nice, really intelligent academics. I am proud to have gone through this program with you all.

When I was applying to PhD programs, a student told me "Whatever you do, don't get a dog. You won't have time for it." When I replied, "OK. But my wife is pregnant… how does that work?" she looked at me with sad, pitying eyes. Here I am eternally grateful to Tex and Gemma Crane for all the support they provided Jen and me. They were always willing to lend a hand or a place to stay throughout the writing of this

dissertation. I am lucky to have wonderful in-laws; they make us a stronger family. Further, there are no words to describe my love, gratitude and appreciation for Allison, and my Mom and Dad. You are my role-models in parenting and in life. Your love and faith in me is secret supply of confidence and energy, always with me to tap into when I most need it. Thank you for that gift, and for having that same love and faith for Jen and the boys. I am so happy that the boys are growing up knowing you so well; I see you giving them that same secret supply of esteem and energy that you gave me.

While they may not yet know it, Griffin and Everett proved that pitying doctoral student right and wrong. They were a never ending source of distraction, sometimes greatly needed and sometime not. Yet they are also a never ending source of inspiration. Griffin, the "King of Questions", re-ignites my wonderment about the world and reminds me why I want to be an academic in the first place. I never get tired of talking with him. Everett shows me a world of creative imagination that shakes me to life when I get stuck in heavy logic. Getting cozy on the couch with him always brings me comfort. Watching them grow up is my greatest joy.

Of course, all of my life is better with my wife, Jen. Her love, faith and tremendous sacrifice made everything possible, and makes everything worthwhile. She weathered my storms, earned an income, loved our sons, and kept some sense of normalcy. I continue to be amazed at how blessed I am to have her in my life. This dissertation is as much her accomplishment as it is mine - and for that reason I dedicate it to her with all my love.

TABLE OF CONTENTS

LIST OF TABLES

1 INTRODUCTION

George Washington Carver has been credited with inventing three hundred uses for peanuts and hundreds more for soybeans, sweet potatoes and Alabama clay while teaching in Tuskegee, Alabama. From these products he developed a broad set of uses: adhesives, axle grease, linoleum and mayonnaise to name a few. Would Carver had found a similarly broad utility if he had worked in New Jersey? Johannes Gutenberg brought together knowledge of printing, metal working, and winemaking to create a new printing machine that fostered future science, arts and religion. Would Gutenberg have sparked the modern world had he not lived in the mining town of Mainz in southern Germany?

Inventors are often influenced by their local communities, and they have often influenced the fates of those communities. This observation finds its way into some of the canonical works in economics. In discussing differences among nations, Adam Smith proposed in 1776 that larger local markets drive technological progress as a consequence of specialization (Smith, 1981). Schumpeter described technological possibilities as “uncharted seas”, but suggested that progress depends on current market structures, supplies of entrepreneurs, and social forces (Schumpeter, 1934, 1942). Marshall laid the foundation for subsequent studies by noting how knowledge and innovation diffuses between co-located actors driving further local innovation and economic development (Marshall, 1936). The extent to which these factors differ across locations may help explain the extent to which innovation differs as well.

Outside of economics, urbanist such as Jane Jacobs and AnnaLee Saxenian also recognize the local roots of innovation. Like Marshall, Jacobs (1968) observed how co-location spurs innovation as economic actors observe and use the products and ideas of others. In the words of Jacobs, “one kind of work leads to another” and thus the make-up of a city’s economy molds the innovations that emerge from it. Saxenan (1996) raised location as a source of organizational competitive advantage and a determinant of industry evolution. In her comparison of Silicon Valley and Boston’s Route-128, she illustrated how local market structure and local culture leads to differences in the flow of ideas across economic actors. Part of the success of Silicon Valley computer firms, she described, rose from their ability to continually innovate as knowledge flowed more freely there than in Boston.

Motivated in part by Silicon Valley’s rise, scholars have rediscovered the insights of Marshall and Jacobs, combining them with new data sets like the County Business Pattern Data, allowing us to move beyond small-N case studies in search of systematic patterns linking location and innovation. Three lines of inquiry have grown simultaneously to provide important tools and insights allowing for a renewed focus on location and innovation. First, new economic growth models sought to understand differences in economic development across locations. Models by Romer (1986) and Lucas (1988) featured technology and knowledge spillovers. As Glaeser (2000) noted "knowledge spillovers solved the technical problem in economic theory of reconciling increasing returns (which are generally needed to generate endogenous growth) with competitive markets (p.83)." This work relies on innovation and local knowledge flows as the intermediate between local context and local growth. It suggests that knowledge does not flow freely across borders, but that geography - and in particular the city (Lucas, 1988) - matters. In cities, proximity enables workers to imitate plentiful role models and learn by seeing. The flow of ideas increases the rate of technical innovation leading to faster rates of new product introductions (Glaeser, 2000).

Empirical testing for knowledge spillovers first employed localized knowledge production functions. Jaffe (1986) found that states with higher public university and private research were associated with higher patenting among local firms. This he interpreted as evidence of within-state knowledge spillovers. Subsequent examinations showed this result held for new product innovations (Acs, Audretsch, & Feldman, 1992) and with patents at the metropolitan statistical area (Anselin, Varga, & Acs, 1997). The co-location of innovative activity occurs even beyond the co-location of production, and is particularly evident in industries where we would expect knowledge spillovers to play a particularly crucial role (Audretsch & Feldman, 1996).

While this literature provided an account of the uneven distribution of inventive active, patent citations analyses provide systematic evidence of local knowledge spillovers. Using citations as direct measures of knowledge flowing from one inventor to another, Jaffe et al. (1993) explored the reach of knowledge spillovers across time and distance. Patents in their sample tended to cite other patents from the same city more frequently, particularly in the cited patent's first year. Furthermore, two studies of within-patent variations in citation rates found that inventors are far more likely to cite other local state and metropolitan area patents than examiners who serve as an external control (Alcácer & Gittelman, 2006; Thompson 2006).

In a parallel approach, Glaeser et. al (1992) sought to understand if the impact of knowledge spillovers differed depending on whether those spillovers come from others with similar knowledge or others with different knowledge. Drawing from the insights of Jacobs and Marshall, they tested local industry employment data from the County Business Pattern data to examine two sets of spillovers which may lead to local growth, with innovation as the key (albeit unmeasured) mechanism. Within a local industry, concentration within a given city facilitates the "spying, imitation, and rapid interfirm movement of highly skilled labor" that disseminates ideas among neighboring firms (Glaeser et al., 1992: 1127). Across local industries, a diversity of local knowledge flows provides fodder for Schumpeterian recombination that leads to innovation and growth. Inter-industry knowledge flows may, in fact, be more important for innovation than intra-industry knowledge, as Jacobs (1968) explains. Examining a cross section of employment in city-industries, Glaeser et. al (1992) found evidence in favor of inter-industry knowledge spillover and against intra-industry spillovers. Henderson et. al (1995) followed by suggesting that both types of spillover matter, depending on the level of industry maturity. Thus, the local composition of economic activity seems to matter, although the exact nature of its impact remains an open question.

Building on Glaeser et al.'s path breaking work, other scholars provide evidence of local community composition's impact on innovation and inventiveness itself. In a study of new product introductions, Feldman and Audretsch (1999) found evidence that local industrial diversity within a shared science-base promotes innovation. Duranton and Puga (2001) presented and tested a model of co-existing diversified and specialized cities, where diversified cities as "nurseries" for innovation and entrepreneurship. With an eye on local rates of patenting, Paci and Usai (1999) and Gruenz (2004) estimated positive effects of both diversity and specialization in local European patenting.

While we begin to understand that innovations are shaped by their communities of origin, most studies linking location and innovation focus specifically on local counts of innovations. Yet innovations differ in important ways. Nelson and Winter (1982) and others explored the degree to which an innovation refines and extends an existing technological field versus changing the entire direction of technological development (see also Dewar & Dutton, 1986). Fleming (2001) described innovations according to their novelty, as some innovations employ well-known combinations of technical knowledge while others break from the familiar. Bresnahan and Trajtenberg (1995) coined the phrase "general purpose technologies," depicting differences in an invention's utility in a wide range of sectors. Differences among innovations link to their impact on firms, industries and economies. Thus, it behooves us to understand the antecedents of such differences.

Extending the work of Glaeser et al. (1992) and others, this dissertation seeks to understand local patterns of innovation novelty and generality. Chapters 2 and 4 use an alternative measure of communities. Rather than focusing on local industry employment, I employ the number of patent inventors active in each technical field and each metropolitan area. This variable gets to key knowledge flows, as one inventor's proximity with another is likely to have a more direct influence on subsequent innovation than proximity between line-workers. I find evidence that large technical communities focus inventors on familiar technical combinations, while diversity supports novelty. The breadth of an innovation's impact seems more shaped by diffusion rather than inventor's selecting more general problems.

Chapter 3 uses local industry employment, linking the County Business Pattern data with USPTO patent data to identify local industry innovations. Estimating at the patent level, the chapter differs from prior work not only by focusing on the novelty and generality of patents but also by using fixed effect to control for unobserved time, industry and metropolitan area factors. Innovation novelty differs across cities rather than changing with local industry structures. The degree to which the locale supports given industry and the diversity that surrounds the industry both focus the innovations subsequent impact.

The studies in this dissertation contribute to our understanding of the dynamics of location and innovation. Yet research is still just beginning to understand key topics in this vein. Our ability to model and estimate the creative sparks of Carver and Gutenberg remains limited. In conclusion, I lay out some of the most important open questions.

First, what is the impact of novelty and generality at the local level? As discussed in the following chapters, it is exceedingly difficult to identify exogenous variation in innovation that is independent of other sources of economic growth, and vice versa. In favor of the approach used here, relative city sizes tend to be stable over time, but there may be a relatively high degree of industrial churn as industries migrate across locales (Duranton, 2007; Findeisen & Südekum, 2008). Variation at the local industry level, rather than city-level change, may have identifiable impacts on innovation. Yet Kerr (2010) suggested that breakthrough innovations attract future inventors from other locales. Thus, local community characteristics may follow the nature of local innovations as well as driving them. More generally, while economic development models assume local structures drive innovations leading to economic growth, we still lack compelling evidence of the link at the level of cities and regions.

Second, current studies provide evidence that innovation increases with the availability of relevant inputs. University research, corporate research and industrial production are local sources of knowledge corresponding with local innovation (e.g., Jaffe, 1989). As this dissertation suggests, these inputs may be captured within local inventor communities. Still, there is much work to do to determine which of these are more important and to what extent and where. University and corporate research may impact innovation differently depending on the nature of the technology, the characteristics of the organization, or in the local networks connecting them.

Inventors themselves are not isolated actors, but are a part of networks of friends, relatives and colleagues that together offer information, norms and opportunities (e.g., Granovetter, 1985). Social interactions channel and spread innovation knowledge (Rogers, 2003). Clearly, we should seek to better understand how the sources of knowledge and the density of social interactions work in tandem to shape local innovation. In this sense, social interactions serve as a local multiplier of innovation, giving more impact to local inputs. So while we know the supply curve of innovation slopes up, how might this supply curve differ across inventors, organizations, and metropolitan areas?

Of course, inventive activity may also be governed by the expected value of the solution to technical problems. Inventors produce innovations for which they believe they will be rewarded (Schmookler, 1966). The rewards may be pecuniary, as inventors sell the new ideas or products. However, rewards may be social: a culture of creativity, opportunities for professional advancement, status among one's peers, etc. In the extreme, some locations may offer a New Atlantis-type paradise: a great hall housing statues of inventors in wood, marble, silver and gold (depending on the innovations importance) (Bacon, 1974). Rewards may be social and organizational in nature, and are perhaps tied to geographic space in ways monetary incentives aren't. Thus, while we measure and test local inputs to the innovation process, variation in innovation across regions may result from variation in community norms and opportunities amplified by local social interactions.

Innovation is rooted in a place. Few people would doubt that Silicon Valley and Nashville have special characteristics that help make them centers of innovation in information technology and music respectively. Few people would also doubt that innovation plays a major role in building local economies. Clearly, not all innovations are equal. Innovations which radically change existing technologies or form the basis of entirely new industries likely have a more profound impact on local economies than those making small improvements in minor products. For these reasons, I seek to test theories of local knowledge spillovers and examine the community contexts from which novelty and generality emerge.

The dissertation proceeds as follows. Chapter two describes technical communities - groups of co-located inventors actively developing a particular technology. I propose why we might expect the technical community's local structure, particularly its size and surrounding diversity, will shape the novelty and generality of emergent innovations. Chapter three takes a similar approach for local industries, measured by their employment. This refocuses a current debate in economic geography on innovation novelty and generality, rather than local innovation counts. Chapter four explores both technical community and local industry structures simultaneously, testing for their unique and joint effects on the novelty and generality of their innovations.

2 TECHNICAL COMMUNITIES

2.1 Introduction

In 1983, Victor Althouse in Los Altos, CA invented a semiconductor wafer and handling method, an important innovation and an interesting example of a key way in which innovations differ from one another. Althouse moved outside of the single field of semi-conductors, and drew from what was currently known in the field of adhesives and packing to invent a method for safely moving semiconductor chips without the adhesive residue left by previous methods (Althouse, 1983). Furthermore, intended or not, Althouse's innovation has contributed to subsequent innovation in many different technological fields. Not only has it been useful to subsequent innovations in semiconductors and adhesives, it has also been developed further by inventors in packaging, optical systems and elements, and other technologies. The scope of the innovation's impact surprised Althouse, and gave rise to new organizations and new lines of work.

In trying to understand social progress, scholars across disciplines seek to understand why and how some technological innovations represent radical ideas that fundamentally alter the landscape, while other innovations are incremental steps improving technologies already in use (Gilfillan, 1935; Mokyr, 1990; Schumpeter, 1934; Tushman & Anderson, 1986). In the realm of regions and civilizations, radical innovations represent great leaps forward in human development (Mokyr, 1990). In the realm of firms and industries, Tushman and Anderson (Anderson & Tushman, 1990; Tushman & Anderson, 1986) and others showed that radical innovations shift the competitive environment, destroying the value of certain advantages and giving rise to new industry leaders. No matter the label ascribed to inventions - radical or incremental, competence destroying or competence enhancing - they have important impacts on technological development, industry evolution and economic growth. Yet, for all of their consequences, the origins of these differences are not well understood.

The challenge to understanding when and where more novel innovations emerge, as the economic historian Joel Mokyr pointed out, requires researchers to move beyond cumulative innovation models to pursue the "macrofoundations of technological creativity (Mokyr, 1990: 8)." In this view, differences in innovations are not simply the unpredictable product of genius and serendipity, but rather emerge from the social and economic conditions that provide different opportunities for their development. While many scholars have explored the terrain of innovations, none have offered a clear answer to the question: where do novel or general innovations come from?

Innovations do not come from nothing, as Schumpeter (1934) noted, but are the "carrying out of New Combinations (88)" of existing knowledge and technologies. Schumpeter outlines a portrait of an entrepreneur drawing from a pool of available technologies to generate innovations. Yet inventors do not draw ideas at random from the universal pool of all that is known. Schumpeter observed that advances made by industry incumbents will likely be incremental in nature, drawing from the technologies and knowledge already common in the industry. Jaffe (1986) and Podolny and Stuart

(1995) showed that technological development tends to occur in crowded spaces, with firms building on established technological bases (Stuart & Podolny, 1996).

Innovations are cumulative and evolutionary by nature (Dosi, 1988; Gilfillan, 1935). Given the inherent uncertainty of generating something new (Dosi, 1988; Kline & Rosenberg, 1986) building on established knowledge for established goals helps reduce uncertainty and increase the likelihood of success (March, 1991). Innovators typically search for solutions to defined problems in technologies that are well understood (Fleming, 2001), and thus we should expect that inventors will draw from what society knows in systematically biased ways.

In the course of technological development, individuals developing particular products or technologies often begin to interact and support activities that support their ability to innovate. Communities form around technologies to improve information exchanges, mutually beneficial decision-making, and standards setting for all involved. Individuals within a technical community can come from different organizations in different industries, as well as from government and academia, but they share a common interest in the focal technology (Rosenkopf & Tushman, 1998). In this way they not only coalesce around a given technological opportunity, but they also influence the rate and direction which the opportunity will subsequently take (Dosi, 1982; Jaffe, 1986; Levin et al., 1987; Scherer, 1965).

In part, opportunities to innovate reflect the institutional dynamics surrounding scientific and technological development. Communities of individuals working with a technology can develop their own language, procedures, conventions and understandings of appropriate problems and solutions (Dosi, 1982; Wenger, 1998), leading them to different uses or ideas than they may come upon on their own. In part, opportunities to innovate reflect the increasing returns to knowledge resulting from the research efforts of others. Economic studies of knowledge spillovers capture the common benefits generated between research teams "working on similar things and hence benefiting much from each other's research (Griliches, 1992: S36-S37)" – even when they occur between firms and between industries. Clearly, the size and social dynamics of technical communities influence the opportunities inventors have to innovate.

Still, as Althouse and the semiconductor handling method shows, not all innovations draw from a pre-defined set of technologies. History provides another example. Koestler (1964) tells of Gutenberg's challenge to clearly put ink onto paper. Past inventions were not satisfactory for printing clear, whole pages. One day Gutenberg was watching a local wine harvest festival when: "I studied the power of this [wine] press which nothing can resist…" The solution to the problem became clear. Drawing from the printing domain's knowledge of ink, paper, scripts, wood-cutting, etc., and drawing from his own past experience with metalworking, Gutenberg combined knowledge from many technical fields with wine production to invent the printing press.

The story of Gutenberg illustrates an inventor's technological experience may tell only part of the story of novelty. Innovators are situated actors who, like other social actors, can engage in creative agency only to the extent that they are embedded in communities that provide them opportunities to observe disparate artifacts, understand disparate ideas, and interact with disparate others (Hargadon & Sutton, 1997). Thus innovations are situated in, as Mokyr (1990) suggested, macro-foundations that shape an inventor's technological opportunities. To the extent macro-foundations differ by place, *geographic location* matters too.

Past approaches to understand the relationship between geography and innovation counts characterize locations by their knowledge sources (e.g., Jaffe, 1986) and their infrastructures and institutions (e.g., Almeida & Kogut, 1999; Cooke, Gomez Uranga, & Etxebarria, 1997). Variations in the knowledge locally available, and the institutions that guide the flow of knowledge, provide local inventors with varying opportunities to innovate. These approaches paint an innovation landscape of regions with unique knowledge and local rules, cultures and networks for spreading that knowledge, all of which help determine how many innovations a group of inventors create.

My approach to regional innovation remains consistent with this view. Some critical knowledge is local and difficult to transfer across distance. Interactions between inventors allow critical knowledge to transfer, and those social and economic structures which shape inventor interactions also shape innovation. However, my approach differs in two distinct and important ways. First, I suggest looking at the demography of local inventor communities may shed light on the dynamics of local innovation. Large communities generate opportunities through common objectives and familiar technologies. The diversity surrounding a community facilitates innovation through variation and opportunities to bridge domains. This paper focuses on how these different dimensions of local community's factor into innovation. Second, I suggest we study variations in the novelty of innovations as consequents of local technical community structures. For instance, large and small communities may both generate opportunities to innovate, yet these opportunities differ in ways which are hidden when we focus solely on regional innovation counts. In this paper I argue that the size of a local technical community, and the diversity of surrounding communities, shape the type of innovations we see emerge.

2.2 Technological Opportunities and Knowledge Spillovers

While demand and the "uncharted seas" induce some innovations (Levin et al., 1987), inventors draw from available knowledge and technologies in order to innovate. There is a lot an inventor *might* do, yet what the inventor *does* is much more limited. The supply of available knowledge plays a large part in defining the technological opportunities available to the inventor. For example, in medicine the demand and need for improvement existed throughout the history of mankind. Still, it was not until the development of bacteriology in the second half of the nineteenth century that scientists actually advanced medicine (Rosenberg, 1974: 97). In their survey of managers from various industries, Levin et al. (1987) concluded that scientific development and research in public laboratories spurred research investments and innovations by increasing the knowledge available to researchers in those industries. Thus, the technological opportunity to innovate surrounding a technology results largely from the knowledge available to support it.

While unexplored territories allow inventors to do something not yet done before, inventors use available knowledge to guide them across the territory, building something a little less expensive or risky than would blind experimentation. Kline and Rosenberg (1986: 275) began their influential chapter by discussing the uncertainty inherent to innovation: "Successful outcomes thus require the running of two gauntlets: the commercial and the technological." Why are successful outcomes so difficult to predict?

Knowledge that a problem exists is usually incomplete, how to build a solution may be unknown, and precise links between consequences and actions are impossible to know (Dosi, 1988). Kline and Rosenberg (1986: 275-276) suggested "an important and useful way to consider the process of innovation is as an exercise in the management and reduction of uncertainty."

Inventors reduce uncertainty by building on familiar technologies (Fleming, 2001), their own work and the work of others. In his study of technological opportunities, Jaffe (1986) found that firms researching technologies where many other firms were also researching had, on average, higher returns to R&D expenditures in terms of both patents and profits. Similarly, Podolny and Stuart (1995) concluded that the number of actors and patents contributing to or drawing on a particular patent increases the rate at which other patents will cite the patent. Fleming (2001), also looking at the impact of individual patents, found patents using more familiar combinations of technology classes were on average more useful for subsequent technological development. These studies suggest that the number of researchers working to advance a given technology increases the chances any one of them has to innovate.

Why do technological opportunities become more favorable as the number of other researchers increases, even in the face of crowding and competition? Innovation and research are – at their core – the production of information. Arrow (1962b) explored the characteristics of information and observed the relative ease with which information can be replicated and transmitted. Arrow suggested research results spread between firms as the inventor tries to appropriate benefits; whether marketing the information on its own, or using the information in the firm's own products and processes, others gain access to the information a firm's R&D produced. Considering its fluidity, employee mobility between firms, and ability of others to design around legal-protection, knowledge - unlike other strategic assets and resources - is to a significant degree a public commodity (Arrow, 1962b).

Congruent with Arrow's observations, empirical evidence builds a strong case for the public benefits of private research, and the transfer of knowledge across researchers. Not only does knowledge transfer from scientists and public research laboratories – with their public mandates – but knowledge also "spills over" between researchers conducting private R&D as well (see Griliches, 1992 for a comprehensive review of this evidence). These spillovers benefit others because accessing and adopting the knowledge of others is cheaper that generating that knowledge oneself (Mansfield, 1977). Thus, when knowledge spills over, it generates benefits for research and development - lowering the cost and risks of working with that technology - for which the recipient did not pay. Indeed, private research may have social benefits that far exceed the inventor's private returns (Griliches, 1992). As Jaffe (1986) suggested, the size of the community available to inventors increases innovation by reducing the costs the inventor faces to make progress, and by decreasing the risk the inventor faces by offering guidance across the open terrain.

Thus, the concepts of technological opportunities and knowledge spillovers are close cousins. Knowledge spillovers are the foundation of technological opportunities. Knowledge spillovers not only expand the technology and knowledge base available for recombinations, they also define the space in which the costs and risks of technological development are decreasing, and thus the space where technological opportunities are increasing. As Griliches suggests, and Jaffe (1986) and Podolny and Stuart (1995) find, as the number of inventors and the amount of research they do increases in given technological space, the more productive inventors in that space will be. As communities increase spillovers, they create favorable opportunities for innovation.

2.3 Local Technical Communities

Recent models of regional economic growth differences propose a geographic dimension to technical communities and spillovers. Regions accumulate knowledge and technologies at different rates over time through the transfer of knowledge and technologies between local actors (Lucas, 1988; Romer, 1986). These models make technological progress a process endogenous to the region, as researchers search for new ideas to create profitable inventions. Local levels of R&D, and the spillovers that occur between local researchers, create the opportunity to innovate – i.e., technological opportunities - which differ from place to place.

Localized technological opportunities may exist even within the same technical field. This logic lies at the heart of public policy efforts to become the next Silicon Valley or biotech center. Saxenian's now famous comparative study of Silicon Valley and Route 128 showed that, in the 1980s computer industry, Silicon Valley presented inventors considerable opportunities unavailable in Route 128 (Saxenian, 1996). While she focused on local culture and institutions, I suggest studying the demography of *local* technical communities shaping technological spillovers might reveal a great deal about why innovation opportunities differ across time and space. Empirical evidence supports the importance of location and proximity to knowledge sources. In an initial test of localized knowledge spillovers, Jaffe (1989) found that university research had a positive correlation with the research productivity of private firms in the state, both directly and through the inducement of private R&D spending. A number of follow-up studies support Jaffe's findings using different techniques and at different levels of analysis (e.g., Acs et al., 1992; Anselin et al., 1997). In a more direct test of knowledge spillovers, Jaffe et al. (1993) show that an innovation has a greater impact, as captured in patent citation patterns, on others located in the same geographic area.

To understand why local matters we must first reassess our understanding of the nature of information and knowledge. New economic growth models challenge our prior notion of knowledge and where researchers search for profitable innovations. If knowledge is a public commodity, knowledge should spillover across organizations, industries *and* regions; technological opportunities should be widely available regardless of geography. Spurred by this theoretical inconsistency with new growth models, knowledge spillover studies begin to unravel the geographic constraints and influence of distance on knowledge flows. At the heart of these studies is the realization that Arrow (1962a) was only partially right because uncodifiable knowledge limits the public and non-rivalrous nature of information.

There are many reasons some knowledge may go uncodified. First, the technical community may not yet have codified new knowledge (e.g., recent scientific findings or technological advances). Jaffe (1989) found that the effect of co-location on patent citations tended to be stronger earlier in the life of the innovation, suggesting locals have a head start in noticing and understanding an innovation. Second, inventors may never fully codify and disseminate knowledge because of a lack of incentives (e.g., failed tests) or high costs (Cowan, David, & Foray, 2000). Third, some knowledge cannot be codified because it is contextual, or is incomprehensible without using the knowledge or seeing others using the technology (von Hippel, 1994). Finally, some knowledge is best transferred through informal conversation.

Inventors may not codify some knowledge, but that knowledge (e.g., early results, failed results, research processes) still lies at the heart of technological opportunities and knowledge spillovers. In their study of the geographic concentration of innovative activity, Audretsch and Feldman (1996) found that technology industries – industries who are most likely to require uncodified and semi-private knowledge - are also the industries which concentrate geographically.

While public information transfers relatively easily, particularly as communication technologies improve our ability to search for and access information, semi-private information transfers and diffuses through other mechanisms. Some knowledge transfers through informal inventor networks. Saxenian illustrated this in Silicon Valley, quoting Tom Wolfe (1983):

> Every year there was some place, the Wagon Wheel, Chez Yvonne, Rickey's, the Roundhouse, where members of this esoteric fraternity, the young men and women of the semiconductor industry, would head after work to have a drink and gossip and brag and trade war stories about contacts, burst modes, bubble memories, pulse trains, bounceless modes, slow-death episodes, RAMs, NAKs, MOSes, PCMs, PROMs, PROM blowers, PROM blasters, and teramagnitudes, meaning multiples of a million millions.

These informal conversations provided up-to-date information and gossip unavailable through journals and trade magazines (Saxenian, 1996). Furthermore, Arrow (1962b) observed that “mobility of personnel among firms provides a way of spreading information (615).” This may be particularly true for uncodified knowledge, as inventors carry with them important knowledge (Cowan et al., 2000). Almeida and Kogut (1999) demonstrated through an analysis of patent data that knowledge in the semiconductor industry spread through the mobility of key engineers, and that differences in local employee mobility may explain regional differences in innovation. Saxenian (1996) also suggested as much, noting the high degree of mobility in Silicon Valley where "people change jobs without changing carpools (35)."

The local spillover literature not only shows regional differences in innovativeness, but it also suggests that those structures which enable and guide knowledge spillovers also enable and guide local technological opportunities. The current evidence suggest that the greater the local spillovers, the greater the technological opportunities for inventors. This line of reasoning can be developed further. Technological opportunities not only define how many innovations are likely to emerge, but different opportunities will lead to different kinds of innovations. As Mokyr (1990) suggested, there are macro-foundations – conditions existing at a higher level than the inventor or firm – that spur an inventor to generate something novel. In addition to regional institutions and resources, the structure of the local knowledge base, and the size and diversity of spillovers coming from that knowledge base, is likely to play a role in an inventor's opportunity to create inventions of a more radical nature.

2.4 From Innovation Counts to Innovation Novelty and Generality

Technological opportunity has two different supply-side logics: familiar knowledge and knowledge spillovers make innovation cheaper and less risky, while diverse knowledge supports creativity. A number of theoretical debates illustrate these two dimensions. The networks literature, studying the structure of actors in a network of knowledge flows, examines the relative benefits of brokering (reaching across groups in order to access new knowledge) and closure (tight-knit groups with greater trust and reinforcing knowledge flows) (Burt, 2005). The innovation literature examines the relative benefits and dynamics of combining previously uncombined components (radical innovation) and combining already combined components in new ways (architectural innovations) (Henderson & Clark, 1990). Economic geography also studies these two supply-side logics, examining the influence of local industrial agglomerations and local industrial diversity on local innovativeness and growth (Duranton & Puga, 2001).

While more of either similar knowledge or diverse knowledge may increase opportunities to invent, the opportunities may be very different with different outcomes. A larger pool of similar knowledge lowers the cost and risk of innovating within that domain, leading to innovations which contribute back to that domain. These innovations exploit established technologies and offer relatively minor changes to existing innovations and products (Henderson & Clark, 1990). These innovations may be, in fact, the most common innovations and have – cumulatively – the largest consequences over time (Hollander, 1965).

Pools of diverse knowledge provide access to a variety of ideas. Bringing together knowledge from seemingly disparate domains is at the very heart of creativity (Amabile, 1996). Sitting at the intersection of domains allows inventors to draw from multiple domains. Hargadon and Sutton (1997) illustrated the impact of technological brokering. Industries and technical communities act as subgroups of larger social structures: they share common artifacts and concepts, they “know one another, are aware of the same kinds of opportunity, have the same access to resources, and share the same kinds of perception (Burt, 1983: 180)". Technological brokers with access to multiple communities are aware of multiple opportunities, access multiple resources, and share multiple perceptions. Accessing diverse communities leads to innovations combining technologies from multiple domains, which may unite a technical solution from one domain with a technical problem in another (Hargadon & Sutton, 1997), or which may generate solutions to more general problems (Bresnahan & Trajtenberg, 1995). When inventors successfully reach across domains, they create innovations noticeably different from innovations residing strictly within a technological domain. Given the importance of location for accessing critical information, various local technical community structures may lead to innovations of various types.

2.5 Local Technical Community Structure and the Characteristics of Innovations

2.5.1 Community Size, Novelty and Generality

At least since Marshall (1936), we have understood that the size of a local community creates benefits for innovation. Marshall (1936: 271) famously observed that agglomerations are prime location for knowledge diffusion:

> The mysteries of the trade become no mysteries… Good work is rightly appreciated, inventions and improvements in machinery, in processes, and the general organization of the business have their merits promptly discussed: if one man starts a new idea, it is taken up by others and combined with suggestions of their own; and thus it becomes the source of further new ideas.

For local technical communities, then, we should expect the benefits of being there to increase as the community adds new inventors. More inventors means more knowledge is transferred, revised, and transferred again. As localized knowledge transfers grow, local innovation in the technological field becomes cheaper and less risky, increasing technological opportunities for generating more innovation. Commonly recognized opportunities, shared resources and shared perceptions lower the cost of sharing knowledge and make one innovator's discoveries relevant to another. Thus, the knowledge cycling through large local communities increase innovation because of their relevance and familiarity: other local inventors can adopt and develop it relatively easily.

This familiarity, while spurring innovation, will most likely spur incremental advances (Fleming, 2001). As Fleming suggests, when faced with a problem innovators generally prefer familiar solutions. Boundedly rational individuals do not randomly seek solutions in the "uncharted seas", they focus on areas familiar to their expertise, and lying within the domains of the problem and current alternative solutions (Simon, 1997). The search for solutions continues until the inventor finds a satisfactory solution (Cyert & March, 1963). Given the local nature of interactions and mobility, in larger local communities an inventor's search may be satisfied within the community. Thus, large communities decrease the cost of searching the domain, and increase the likelihood of finding a solution within that domain.

Cyert and March (1963) model an incremental process of search, whereby the search for a solution expands to other domains when the more familiar domain fails to yield a satisfactory solution. Smaller communities offer a smaller within-domain network and fewer domain specific spillovers, increasing the cost of searching the domain and increasing the likelihood of exhausting search within that domain. Thus, inventors in smaller local communities are more likely to reach outside the domain for knowledge critical for innovation.

H1a: A local technical community's size is negatively associated with innovation novelty.

Both the supply of available knowledge and the nature of market demand shape innovation (Mowery & Rosenberg, 1979). While studies of localized knowledge spillovers tend to focus on the knowledge supply, the direction innovation takes likely depends on local information about what problems exist and would be fruitful to address. To conclude their examination of demand-pull studies, Mowery and Rosenberg (1979) noted the importance of "the frequency and the intimacy of interactions" among knowledge producers and users for encouraging innovation.

Co-location increases both the frequency and intimacy of interactions among inventors, part of what transfers is knowledge about what problems are valuable to address and possible to solve. Interactions in larger local technical communities likely revolve around problems particular to that community. Dosi (1982) noted that intra-community interactions generate paradigms about what problems are appropriate. With a greater intensity of intra-community interactions in larger local communities, we should expect that larger local technological communities encourage addressing problems which are more specialized and particular to that technical community. Inventor interactions in smaller local communities may include interactions outside a particular paradigm, encouraging innovations addressing more fundamental or broadly applicable problems. As a result, I expect innovations from larger local technical communities will result in innovations with a more narrow scope of subsequent impact.

H1b: A local technological community's size is negatively associated with the innovation generality.

2.5.2 Local Diversity and Novelty

Community size influences innovation largely because the number of local individuals working on a particular technology generates norms and externalities: interactions among inventors establish paradigms which focus inventors on particular solutions and increase the probability of success within those domain-solutions. Yet regions also surround inventors with other communities that may also contribute to the innovation. Because of the unique opportunities generated by local knowledge, regions with diverse local spillovers are particularly useful for pulling ideas and technologies from multiple fields and successfully combining them in an innovation.

Much of the evidence linking local diversity and innovation comes indirectly from new growth models. Jane Jacobs (1968) provided one model of local economic growth where knowledge spreading across industries benefits growth more than knowledge spreading within an industry. Growth requires innovation in the Schumpeterian sense of combining existing materials and knowledge in new ways (Schumpeter, 1934); the additive and recombinative capacity of the local economy accelerates economic development (Jacobs, 1968; Schumpeter, 1934). Underlying growth then, is the capacity of a region to innovate; this capacity increases with the variety of communities already in a region.

The number of local technical communities surrounding an inventor may not tell the whole story. The degree to which surrounding inventive activity is concentrated in a single community or is spread more evenly across many communities matters. Activity focused on few communities may not be as fecund for novel combinations as might otherwise be suggested by community counts. Thus, studies focus on the role of diversity in generating local innovation. Empirical findings suggest that local diversity does generate growth (Glaeser et al., 1992), particularly for new and innovative sectors (Henderson et al., 1995) and firms (Duranton & Puga, 2001). Furthermore, innovative activity tends to occur in diverse cities (for a review, Duranton & Puga, 2000).

As local inventors search for solutions, local technical communities provide technical options that are salient, cheaper to access and more likely to be successful (Wenger, 1998) than those less proximate. As the inventor expands her search for solutions, she likely expands that search not only to what is technologically related (March, 1991) but also to what is geographically local. Inventors surrounded by a diversity of local technical communities will thus be more likely to draw from a diversity of technical fields, leading to less familiar, more novel innovations in their field. On the other hand, focused regions limit the number of technologies an inventor can access locally. Thus, I expect that local diversity increases the novelty of innovations, while local focus decreases it.

H2a. The diversity of technical communities surrounding a local technical community is positively associated with innovation novelty

Inventor assessments of what solutions are valuable and viable are also likely shaped by local access to other communities. The ability to reach across technical communities not only provides access to knowledge leading to ‘bridging solutions’, but also to knowledge about fundamental problems whose utility lies in multiple domains. Nelson (1959) suggests that inventors focused on a narrow domain may not realize the full value of solving fundamental problems. Co-location among a diversity of technical communities may facilitate frequent and intimate interactions that cross technical boundaries and encourage innovations addressing problems with broader impact. As a result, I expect innovations from technical communities surrounded by a diversity of other technical communities will result in innovations with a broader scope of subsequent impact.

> *H2b. The diversity of technical communities surrounding a local technical community is positively associated with innovation novelty*

2.5.3 Size and Diversity as Moderators

Recent examinations of local innovation assume local size and local diversity coexist as important innovation factors independent of each other. Each is a source of technological opportunities based on a different logic of innovation. Community size generates benefits by multiplying the number of people working with a similar technology, and thus reducing the cost and risk of innovations along these lines. Local diversity generates benefits by multiplying the variety of ideas available. What is less clear is how the benefits of community size interact with the benefits of local diversity: does local diversity condition the influence of local community size?

As noted earlier, Cyert and March proposed a model of search rules and processes that relaxes the need for inventors to fully understand the costs and benefits of particular technologies. Instead, they suggest that search follows a sequential pattern, ordered by the conspicuousness of the technologies (Cyert & March, 1963). One implication of this model, I suggested earlier, is that inventors in larger communities will look for technological solutions within that community longer, and are more likely to find a satisfactory solution within the community. This focuses inventors and generates more incremental innovations.

Thus, we should consider the effects that a simple, sequential search model would have on the novelty of innovations. The first stage of innovation search for a technological solution occurs around the core technology itself. Innovators first cover familiar terrain. Both local community paradigms and the probability of finding a satisfactory technical solution reinforce the exploitation of familiar combinations for innovation (Cyert & March, 1963; Dosi, 1982).

At some point, however, inventors move away from exploiting familiar knowledge and begin exploring more broadly (Cyert & March, 1963; Dosi, 1982). When this shift occurs depends on the strength of community norms and paradigms, and the relative probability of success through broader exploration. Larger local communities with deeper pools of familiar knowledge and stronger community norms likely delay the move to broader exploration. A greater degree of surrounding diversity, however, encourages earlier shifts to exploration by providing inventors with alternative paradigms and a wider selection of technological choices. Thus, search for a technological solution shifts from exploitation to exploration depending on the size of the local community relative to the diversity of communities surrounding it. As surrounding community diversity increases, the shift from exploitation to exploration occurs earlier, decreasing the effect of community size on the novelty of innovation.

H3a. The interaction between a local technical community's size and the local diversity of innovation activity is positively associated with innovation novelty.

Until now, this paper treats an inventor's selection of a technical problem to address as a function of the degree of inter- and intra-community interactions locally available to her. However, the problem selection process may also be one of sequential search as inventors look for potentially useful innovations to work toward. In this case, we would expect the local community structure to encourage some innovations over others depending on when an inventor's problem search shifted from exploiting community paradigms to exploring other potentially useful challenges. A search for a technological problem shifts depending on the size of the local community relative to the diversity of communities surrounding it. As surrounding community diversity increases, the shift from exploitation to exploration occurs earlier, decreasing the effect of community size on the breadth of innovation an innovation's impact.

> *H3b. The interaction between a local technical community's size and the local diversity of innovation activity is positively associated with innovation generality.*

2.6 Data and Variables

2.6.1 Data Sources

For the analysis, I draw from patents registered at the United States Patent and Trademark Office (Hall, Jaffe, & Trajtenberg, 2001). Patents are public documents disclosing details of inventions and offering a large sample of innovations covering a wide range of technologies, inventors and locations. Each patent divulges details categorized in ways that enable relatively smooth comparisons between innovations. I use patent data from the National Bureau of Economic Research (NBER) dataset compiled by Hall, Jaffe, and Trajtenberg and colleagues. They include information for over 3 million patents granted between 1963 and 2002 (Hall et al., 2001). These data include:

1. the names and postal addresses of the inventor(s),
2. the organization, if any, to which the patent property right was assigned when the patent was issued,
3. a detailed technological classification of the innovation, and
4. a list of patent which subsequently cite the focal patent.

The NBER datasets contain complete data for all patents since 1977, and identifies inventors through 1999. For my purposes, patents offer three key benefits over other potential innovation data. First, using the names and addresses of inventors, and the patent's primary technology class, I am able to locate patents to the local technological communities from which they likely emerged. Second, the patent generation process creates a record of each specific innovation's ancestors and offspring. Innovation scholars gain considerable insight into technological evolution by leveraging the forward and backward citations of the patent (Powell & Snellman, 2004).

Third, examiners in the patent office act as a third-party reviewer, assigning patents to technology classes and increasing the reliability of citations by checking and adding citations when appropriate. The USPTO groups of patents by similarities in technology, to create an administrative tool for patent examiners searching existing patents determine the originality of a patent application's claims. Examiners assign each patent to one original classification and additional cross-reference classifications as needed (Rotkin & Dood, 1999). Empirically, I use patent classes to indicate the technological stream in which the patent is situated. To a degree, examiners in the patent office act as a third-party reviewer, increasing the reliability of classifications by adding and revising patent classifications when appropriate.

2.6.2 Geographic Units

Since this examination is built on the principle that local communities of inventors shape innovation through their interactions and opportunities, I must approximate what constitutes 'local' to establish community boundaries. Following Jaffe et al. (1993) - who similarly used patents to study localized spillovers - I assign patents to the metropolitan area using the inventors' city and state information. The United States Office of Management and Budget (OMB) identifies metropolitan areas in their 2000 standards (Spotila, 2000) and revisions. The OMB seeks to provide a single set of geographic definitions for the largest centers of population and economic activity, and the 2000 standards extend past standards by identifying Micropolitan Statistical Areas, covering more territory. Metropolitan Statistical Areas and Micropolitan Statistical Areas are collectively called Core Based Statistical Areas (CBSAs). Per the OMB's 2000 definitions, CBSAs range in size from the micropolitan - with at least one core, urban area of 10,000 or more inhabitants - to the metropolitan - with at least one core, urban area of 50,000 or more inhabitants. The logic underlying this definition is that "the range of services and functions provided within an area largely derive from the size of the core… [and single cores] provide a wider variety of functions and services that does a group of smaller cores, even when such a group may have a [greater] collective population... (Spotila, 2000: 82232)"

The OMB's goal is to establish geographic areas defined by the complex social and economic interactions that occur within the area. To this end, as of 2000 they identified all areas through the commuting patterns of residents between counties. Counties as building blocks offer stable, familiar boundaries and are the level of more Federal statistical programs than sub-county levels. An employment interchange measure is calculated as the sum of the percentage of region's residents who commute to some larger community, and the percentage of employment is by residents of the larger community. Scores of 25 or higher are automatically grouped in a CBSA. CBSAs with employment interchange measures between 15 and 25 may be combined based on local opinion, or may compose an additional category, the Combined Statistical Area (CSA) (Spotila, 2000). In 2006, there were 1088 CBSAs and 61 CSAs. This study uses the 2006 metropolitan area (MA) definitions to retroactively construct MAs for all areas of the country. Reclassifications and recompositions of MAs are relatively minor, and preliminary empirical tests using a different year of MA definitions show no significant effect.

Because the OMB builds metropolitan areas based on the commuting patterns of its residents, it is an ideal geographic area to study. Rather than being a political jurisdiction, these areas represent geographic communities with a high degree of social and economic integration (Spotila, 2000). Duranton and Puga (2000) observed the importance of MAs for innovation, noting most innovative activity occurs in occur in cities and thus they capture most patents. Given that CBSAs may be nested within CSAs, the analysis which follows embeds a patent in the highest MA available. Thus, some patents will be considered embedded in CSAs, a more moderately integrated region but that still captures significant commuting ties.

Assigning inventors to MAs. Each MA not only may include multiple counties, but they may also include multiple towns and cities. While city names repeat across states, almost all city-state combinations are unique, and can be placed within or outside of MAs with a great deal of accuracy. As previously mentioned, each patent includes the city-state information for each inventor, and therefore we can place innovations in an MA, extending the advantages of patent data for making comparisons across innovations, to those interested in comparing innovations across regions. Previous studies have done this with success (see Carlino, Chatterjee, & Hunt, 2005; Jaffe et al., 1993). Using a commercially available dataset, I place inventor city/states into MAs[1], an approach that past studies have used to capture the within-MA localization of citation patterns between patents (Almeida & Kogut, 1999; Jaffe et al., 1993).

The main challenge to assigning patents to MAs is when there are multiple inventors residing in different locales. Researchers have used different approaches in the past – for example, assigning patents to the MA of their primary inventor or majority of inventors. When studies have compared different methods, they do not indicate that different methods generate different outcomes[2]. Still, there may be confounding influences by inventor teams from multiple MAs – either because they draw from different experiences and networks, or because of coordinating and organizing dynamics that must occur across multiple MAs. Because I theorize about the influence of a location on the problems and solutions inventors' select, I eliminate these confounding influences by limiting my sample to those patents whose inventors come from a single MA.

Matching patents to MAs. Matching patents to metropolitan areas begins with the inventors database available from the NBER. The Inventor file includes the patent number, inventor name, city, state, zip code (where available), and inventor sequence number of inventors listed on patents generally issued from January 1, 1975 to December 31, 1999. I focus on only those inventors with addressed in the United States, particularly the 50 US states and Washington DC (thus, I dropped foreign inventors,

[1] It may be that inventors list the city/state of their employment rather than their residence. Given that MAs are constructed using local commuting patterns, I suggest that this will not add bias since any differences between residence and employment are likely lost in the MA aggregation.
[2] Carlino, Chatterjee and Hunt (2004) compared using first or second authors, and found only 15% of patents would change. Jaffe et al. (1993) used majority as the criterion for assignment, and found that only 14% of their patents could not be assigned unanimously.

inventors from US territories/commonwealths, and inventors with military post office addresses). I researched, through the USPTO website, those inventors with no country or state code, dropping twenty or so inventors where the state or country was indeterminable. Many city names appeared to be addresses or partial city names. When available, I used the inventor zip codes to confirm the appropriate city name. Repeat inventors, aligned by name and state, also helped to identify missing cities. Others, I identified by researching the actual patent. I confirmed other city names which appeared incomplete. Finally, deceased inventors (i.e., “late of”) were coded according to their city address prior to death. The resulting database contains 2,147,310 inventors on 1,209,987 patents from 1975-1999.

2.6.3 Data Sample: Single MA patents.

This paper focuses the sample of patents to a particular set which allows for more focused analysis and controls for potential confounds. As mentioned above, to avoid the noise which may arise from patents with inventors from multiple regions, I focus on patents from a single MA. This required identifying single MA patents from the population of patents and inventors above. After identifying all patents with single CBSAs and CSAs, I rank-order locations assigning patents to CSAs first, and CBSAs second. This narrows the population to 880,882 patents (with 79% assigned to CSAs and the remainder to CBSAs[3]) for the years 1977 through 1997.

The sample represents about 45% of the population of patents captured in the NBER data. Note that the percentage of patents which are from a single MA is declining

[3] 654,629 patents might have been allocated to either a single CSA or a single CBSA. 42,787 could only be allocated to a single CSA (i.e., the patents were from multiple CBSAs within the single CSA). 183,466 could only be allocated to a single CBSA (i.e., the patents were from a CBSA which was not also incorporated in a CSA.

over time. In 1977, over 55% of patents are from a single-MA. This declines to only 41% by 1996. In part, this might be due to an increase in multi-inventor patents. For US inventors, the average number of inventors has risen over time from about 1.5 to about 2.1 US inventors per patent. Over this time, single U.S. inventor patents have declined from close to 64% of patents to about 44% of patents.

Comparing the distribution of the sample across technology classes, with the distribution of the NBER population across technology classes suggests that some classes may be overrepresented and others underrepresented by the sample. While the sample's top five technology classes are the same as the NBER's top five for the years 1977-1997, the sample contains relatively more patents from some classes (e.g., Surgical Equipment: Classes 600, 604, 606) – and relatively less patents from other classes (e.g., Radiation Imagery Chemistry and Internal-Combustion Engines: Classes 430 and 123 respectively). Conceivably, the Single-MA sample may be overrepresented by innovations created outside a larger organization's R&D efforts.

To understand sample differences across assignee types, I compare the distribution of the NBER patent population (1977-1997) with the Single-MA sample. As suggested above, the percentage of unassigned and individual patents rises from 17.16% of the NBER population to 24.97% of the sample population. Also of note, the percentage of Non-U.S. assignees falls from 38.13% of the NBER patent population to 1.59% of the sample patents. Among U.S. assigned patents only, there is little difference in the distributions of patents between government and non-government (mostly corporations) assignees.

2.6.4 Innovation Measures

Testing the above hypotheses requires a measure or set of measures capturing the recombinant nature of innovations, and which are comparable across technology areas over time. Following the logic of Fleming and colleagues (Fleming, 2001), I consider the technology classes identified by the patent's examiners as a proxy for the pre-existing technologies that are the building blocks of the invention[4]. An innovation is more novel if it combines technical building block into less common combinations. In summary, the novelty of an innovation is captured by the rarity of each pairing of technical building blocks; the generality of an innovation is captured by the diversity of innovations that subsequently build on it.

To capture subclass combinations, I augment the NBER patent data with annual data from MicroPatent for the years 1977-1997. *Pair-wise novelty* focuses on pairs of subclasses appearing in the focal patent and how often each pair appeared in patents for the five years preceding the focal patent's application[5]. The application year captures the year in which the inventor filed for the patent, and is therefore closer (than the patent's subsequent grant year) to the actual timing of the invention's creation (Hall et al., 2001). I choose the five year period in general accordance with Fleming (2001), who used five years as the time constant of knowledge loss implying that a patent's influence dissipates over time as "it is more likely that an inventor will have learned from previous use of a sub-class, if that sub-class was used three years prior, instead of thirty (p. 123)." For

[4] As discussed in Fleming (2001), inventors need not be specifically aware of the USPTO's subclass definitions.

[5] For patients with an original class and no cross-classes, novelty is calculated from the count of other patents which have the same original class and no cross-classes. 90 single-metropolitan area patents were not included in the MicroPatent database; 84 patents had the same technology class listed as its original class and its cross class; these 174 patents are dropped from the analysis.

Fleming's (2001) analysis, the influence of a patent's knowledge is reduced by two-thirds over the first five-year period[6]. *Average pair-wise class frequencies* counts how often a focal patent's subclass pairs appeared during the preceding five-year period, and averages that count across all subclass pairs embodied in the patent. This measure captures the patent inventors' central tendency to make more familiar links between technological streams. To convert this to a measure of the inventions tendency to make less familiar, more novel technical links, I measure patent *novelty* as the negative of the logged *average pair-wise class frequencies.*

To capture the breadth of an innovation's impact, I measure how widely cited is the patent across USPTO patent classes by subsequent users. Following Trajtenberg et al. (1997) and others, I use the *generality* measure available in the NBER database and described in Hall et al. (2001):

$$Generality_p = (N_p/(N_p\text{-}1))\ (1\text{-}\sum s_{pq}^{\ 2})$$

Here, s_{pq} denotes the percentage of citations made *to* patent p from patent class q, out of n_p patent classes. The more widely cited a patent is across technological fields, the higher the *generality* measure will be. The Herfindahl index tends to be correlated with the number of citations made to the patent. This confounds the distribution of patent citations with the number citations received, introducing systematic bias into the measure – particularly for patents with fewer forward citations. To correct for this bias, I include the $(N_p/(N_p\text{-}1))$ adjustment to create the above bias-adjusted measure (Hall, Jaffe, & Trajtenberg, 2005). Note that patents with no or a single forward citation will have an

---

[6] Note that this time period may capture a small window from which inventor's draw knowledge. On average, only about one-third of backward citations are from the five-years preceding the patents grant data.

undefined generality measure. Since forward citations continue to accrue over time, I code those patents as censored data, suspecting that generality may still be revealed in the future. Again, the measure is confined to measures between and including 0 and 1.

Patent level controls. Given the theoretical interest in knowledge spillovers, the models should ideally control for other differences among innovations. Technological areas may differ in the intrinsic characteristics of the underlying technical knowledge, innovation demands (Jaffe, 1986) or norms for determining appropriate problems and solutions (Dosi, 1982). Following the literature, I capture differences in recombinant novelty across technological areas by including patent technology class dummy variables (Hall et al., 2001).

Furthermore, Mowery and Ziedonis (2002) show how institutional changes can influence the number and nature of patents entering the system over time. Changes in patent office routines over time also cause some variation among patents. To account for these changes, I use application year dummy variables as appropriate controls for innovation cohort effects (Hall et al., 2001).

Given the theoretical interest on local community structure, the models also control for other local influences. Universities and other local amenities are important sources of local knowledge (Jaffe, 1989), particularly knowledge which is more original and more closely tied to basic science, and may also influence the novelty of local innovations independently of community demography. I control for the potential influence of time-invariant local effects through a series of metropolitan area dummy variables.

Finally, while I am focused on the effects of local technical communities on recombinant novelty, other aspects of the innovation itself may shape its novelty. First, consider an innovation's use of science. Sorenson and Fleming (2004) created a measure of science-based novelty by noting if patents reference published materials. They find that these patents are generally more highly cited, and are cited faster. Because science-based novelty may influence the patent's impact, without being influenced by the local industrial composition, I will control for this using the number of non-patent citations for all patents through at least 1999. Furthermore, the number of the invention's components may have a strong effect. Thus, I also control for the number of sub-classes recognized by the patent examiners. Because some subclasses may be too coarse to identify the recombinant nature of its patents, I also include a dummy variable for single subclass patents (which comprise 8% of the patents.)

2.6.5 Local Community Measures

Technical community size. To measure the size of a local technical community, I focus on the number of active inventors in the technological field in a given year. Inventors come from a variety of organizations and firms in a variety of industries. However, this theory focuses on researchers "working on similar things" and "benefiting much from each other's research (Griliches, 1992)", obscuring organizational and industrial boundaries. Spillovers and the transfer of knowledge occur between individuals, and thus I focus on the number of inventors in the region actively innovating in a particular field. Following a number of recent studies, I use the USPTO classification system to define technological fields, and I count an inventor as a member of a technological field when she invents a patented innovation whose original classification is in that technological field. Note, the patent data does not provide unique identifiers for unique inventors. To determine when two different patent records refer to the same person, I adopt Singh's (2005) algorithm. Two inventor records are counted as a single inventor if the following conditions hold:

1. First and last names match exactly,
2. middle initials, if available, are the same, and
3. when the middle initial field was left blank in at least one to the two records, the records also overlapped on at least one of their technology subcategories.

With unique inventors thus identified, the local community size is calculated as:

$$Size\_Community_{kl} = \sum inventors_{kl} \qquad (3)$$

where the size of community *k* in region *j* is the sum of all inventors patenting in original class and listing a city in region *l* as their residence. I assign each inventor in a team of inventors to the technical community of their invention, and each inventor may be assigned to multiple technical communities when they patent in multiple original classifications in that year[7]. I calculate communities by metropolitan areas, generating a population of 615 MAs and 22,647 MA-technological field communities.

Surrounding community diversity. For each local technical community, I calculate the inverse of a Herfindahl concentration index of all *other* local communities to capture

[7] Trajtenberg et al offer a similar algorithm that uses more of the data and identifies unique inventors probabilistically. This algorithm warrants further exploration, although the outcome of this analysis is not likely to change.

whether the focal community is surrounded by a wide range of technical communities, or by a specialized set of communities:

$$Diversity\_Community_{kl} = 1/\sum^{n-1} Community\ Share_{nl}^{2} \qquad (5)$$

where the diversity surrounding community *k* in region *j* is a function of the squared share of all *n-1* industries in region *l*, with *n-1* denoting all local industries except industry *kj*. I use the inverse of the Herfindahl index - or “Herfindahl numbers equivalent” – which may be interpreted as the number of equal-sized communities which would have the same Herfindahl index as the actual size distribution of communities (Nelson & Winter, 1978). It gives a value of 1 when there is just one other community in the locale. For the 1494 patents whose inventors are surrounded by no other inventor communities, I code their *Diversity_Community* as zero.

Table 2-1: Description of Technical Community Variables summarizes the variables employed in the following analysis. All variables come from patent data provided by the NBER or MicroPatent except Employment and Science-base. Employment data comes from the County Business Patern data collected by the U.S. Census Bureau. Science-base data calculates the number of non-patent citiations listed by the patent: this data was collected by Bhaven N. Sampat.

Table 2-1: Description of Technical Community Variables

Construct	Variable name	Description
Recombinant Novelty	$Novelty_p$	-1*Natural log of the average # times each patent class pair in a patent occurred in the prior 5 years
Generality	$Generality_p$	1-Herfindahl of patent forward citation distribution across technology classes (bias corrected)
Local Community Size	$Size\_Community_{k,l,t}$	Natural log of the # unique inventors in each class-year-metropolitan area
Surrounding Community Diversity	$Div\_Community_{k,l,t}$	Inverse of Herfindahl of Local Community Sizes (other than the focal community)
Patent Class Size	$\#Patents_{k,t}$	Natural log of # Patents in technology class-year
Metropolitan area size	$\#Employment_{l,t}$	Natural log of # of employees in the year-metropolitan area
Science-base	$\#ScienceCites_p$	# Non-patent citiations listed in the patent
Subclass count	$\#Subclasses_p$	# subclasses identified by examiners to which patent, p, is assigned
Single subclass indicator	$SingleID_p$	Equal to 1 for patents assigned to a single subclass , 0 for more than one subclass

Subscripts *t* (time), *k* (patent class), *l* (metropolitan area), *p* (patent)

2.7 Models and Results

2.7.1 Summary Statistics

Table 2-2 provides selected summary statistics for the sample. Note, there are about 325,000 patents, from 22,451 local technological communities from 1977-1997 (101,064 specific year-MA-technology combinations). Because of the large number of patents, subsequent estimates should be quite precise. By including a large number of industry and technology fixed effects, I hope to control for most general attributes that affect innovation novelty and generality.

Table 2-2 Summary: Uncentered Technical Community Variables, Single-MA patents 77-97

Variable	Mean	St. Dev.	Min	Max
Patent-level observations				
$Novelty_p$	-0.88	1.03	-7.00	0
$Generality_p$	0.42	0.37	0	1
$\#Subclasses_p$	4.27	3.46	1	190
$\#ScienceCites_p$	5.69	14.25	0	885
$SingleID_p$	0.08	0.27	0	1
$IndividualID_p$	0.25	0.43	0	1
$GovernmentID_p$	0.02	0.14	0	1
MA-class-year observations				
$Size\_Community_{k,l,t}$	0.94	1.02	0	6.73
$Div\_Community_{k,l,t}$	53.16	37.22	1	170.74
MA-year observations				
$\#Employment_{l,t}$	10.44	1.37	7.29	15.88
Class-year observations				
$\#Patents_{k,t}$	4.74	1.31	0	8.53

Subscripts *t* (time), *k* (patent class), *l* (metropolitan area), *p* (patent)
N = 877,237 at the patent level; *N* = 269,840 at the MA-class-year level; N = 12,687 at the MA-year level; N = 8,453 at the class-year level

To better interpret the interaction terms included in the estimation models, I center key variables at their sample means. Summary statistics for the centered variables are included in Table 2-3:

Table 2-3 Summary: Centered Technical Community Variables, Single-MA patents 77-97

Variable	Mean	St. Dev.	Min	Max
MA-class-year observations				
$Size\_Community_{k,l,t}$	0.00	1.02	-0.94	5.79
$Div\_Community_{k,l,t}$	0.00	37.22	-52.16	117.58
MA-year observations				
$\#Employment_{l,t}$	0.00	1.37	-3.15	5.45
Class-year observations				
$\#Patents_{k,t}$	0.00	1.31	-4.74	3.79

Subscripts *t* (time), *k* (patent class), *l* (metropolitan area), *p* (patent)
N = XXX at the patent level; *N* = 272,234 at the MA-class-year level; *N* = 8,453 at the class-year level; N = 12,688 at the MA-year level

Table 2-4 provides correlations for the variables, including the centered variables:

Table 2-4 Technical Community Correlation Coefficients

		1	2	3	4	5	6	7	8	9	10	11	12
1	$Novelty_p$	1											
2	$Generality_p$	0.05	1										
3	$Size\_Community_{k,l,t}$	-0.22	-0.02	1									
4	$Div\_Community_{k,l,t}$	0.03	0.06	0.40	1								
5	$\#Patents_{k,t}$	-0.19	-0.05	0.53	-0.06	1							
6	$\#Employment_{l,t}$	-0.06	0.02	0.60	0.81	0.08	1						
7	$\#ScienceCites_p$	-0.14	-0.01	0.15	-0.02	0.18	0.04	1					
8	$\#Subclasses_p$	0.01	0.15	0.07	0.02	0.06	0.02	0.08	1				
9	$SingleID_p$	-0.14	-0.10	-0.01	0.01	-0.04	0.00	-0.01	-0.28	1			
10	$CoTownID_l$	-0.02	0.00	0.01	-0.24	0.04	-0.20	-0.02	0.00	-0.01	1		
11	$IndividualID_p$	0.12	-0.06	-0.26	-0.01	-0.15	-0.05	-0.08	-0.09	0.03	-0.08	1	
12	GovernmentIDp	0.02	0.00	-0.02	0.00	-0.01	-0.02	0.01	-0.01	0.00	-0.02	-0.08	1

Subscripts *t* (time), *k* (patent class), *l* (metropolitan area), *p* (patent)
Note : Correlations are at the patent level of observation, *N* = 877,237.

As shown in Table 6-1, the count of individuals working on the same technology in a given region-year ranges from one individual inventor to local communities as large as 1839. The largest technical community was San Jose's Molecular Biology and Microbiology (patent class 435) in 1995. Note that average community size has increased with the number of patents over the years. However, this increase outpaces patent counts possibly reflecting the trend toward more multi-inventor patents.

Table 6-2 shows the annual trend for the diversity of communities surrounding each focal community. *Diversity_community* ranges from 1 to a community equivalent score if 170 surrounding Los Angeles' Measuring and Testing community in 1977. Note that *Diversity_community* has generally declined over time. The decline in diversity may reflect the disproportionate growth of patenting in particular technologies or a trend toward geographic consolidation. Future studies may examine the churn of inventos within and across regions to better understand these dynamics.

Annual trends of the dependent variables reveal other dynamics of patenting. Table 6-3 and Table 6-4 show the changes in mean novelty and generality since 1977. *Patent class pair frequencies* have generally increased since 1977, likely with the increase in overall patenting. *Generality* decreases, although this is mostly likely the result of time-lags in the accumulation of forward citations rather than differences in patenting dynamics.

2.7.2 Novelty Estimation and Results

Theories of local search and knowledge spillovers suggest that inventors in larger local communities will rely on more familiar technological combinations rather than exploring more broadly, and thus create less novel innovations. Model 1 in Table 2-5 tests this hypothesis by estimating a baseline model with *size_community*, key control variables, and fixed effects for patents application year, metropolitan area, and technology class; all subsequent models include these variables and fixed effects as well. *Size_community* is centered in log natural form. In support of Hypothesis 1a, Model 1 estimates that - at the average - a 1% increase in *size_community* leads to a .074% decrease in patent *novelty*. For a community with a size similar to Boston's electric heating technical community in 1990, adding an additional unique inventor would lower expected novelty by almost .2%, all else equal.

Table 2-5 OLS Estimation: Novelty as a function of Technical Community Structure

	1		2		3	
Size_Community	-0.0739	***	-0.0737	***	-0.0771	***
	0.0053		0.0054		0.0059	
Diversity_Community			0.0007	*	0.0004	
			0.0003		0.0003	
Size*Diversity					0.0002	
					0.0001	
Patents	-0.1119	***	-0.1084	***	-0.1067	***
	0.0327		0.0330		0.0332	
Employment	0.0440		0.0296		0.0296	
	0.7542		0.0754		0.0765	
CoTownID	-0.1025	***	-0.0998	***	-0.1032	***
	0.0306		0.0307		0.0301	
IndividualID	0.1284	***	0.1284	***	0.1281	***
	0.0077		0.0078		0.0078	
GovernmentID	0.1487	***	0.1480	***	0.1485	***
	0.0198		0.0195		0.0196	
SingleID	-0.5629	***	-0.5626	***	-0.5625	***
	0.0160		0.0160		0.0160	
Subclass Count	0.0056	*	0.0056	*	0.0056	*
	0.0024		0.0024		0.0024	
Science Citations	-0.0001		-0.0001		-0.0001	
	0.0001		0.0001		0.0001	
Constant	-1.3970	***	-1.3640	***	-1.3687	***
	0.2630		0.2650		0.2643	
R-squared	0.2204		0.2203		0.2204	
Observations	875883		874496		874496	

DV: logged 5-year average frequency that a patent's technology class pairs occurred.
Robust standard errors (clulstered by metorpolitan area) in parentheses.
+ significant at 10%; * significant at 5%; ** significant at 1%.
All equations include year, metropolitan area and technology class dummy variables.

Hypothesis 2a predicts that inventors, in local communities surrounded by a diversity of other communities, will be more likely to bridge other communities to try less familiar technological combinations, and thus create more novel innovations. To test this hypothesis, Model 2 in Table 2-5 introduces *diversity_community,* and estimates a positive relationship with *novelty*. On average adding one equivalent community to the surrounding region increases the expected *novelty* of a focal community's patents by .1%. For a community like Atlanta's Electric Heating technical community, with a surrounding community equivalence score of almost 75 in 1995, the surrounding region would need to add an additional community of about 22 inventors to increase expected novelty by .1%, all else equal.

If inventor search occurs sequentially, searching outside their community occurs only once it appears a more likely place to generate a satisfactory solution, then we would expect that the diversity surrounding the local community will influence the impact local community size has on innovation novelty. Hypothesis 3a predicts that the degree to which *diversity_community* influences novelty is contingent on the size of the inventor's community. To test this hypothesis, model 3 includes an interaction term of *size_community* and *diversity_community*. Model 3 in Table 2-5 fails to estimate a significant interaction term, suggesting that across all communities, there is not a contingent relationship between *community size* and *diversity_community*. Thus, Model 3 does not support Hypothesis 3. Interestingly, once I include the interaction term, the direct and independent effect of *diversity_community* disappears. At least at average *size_community*, the impact of *diversity_community* isn't evident.

2.7.3 Post Hoc Analysis

As discussed earlier, the number of patents granted in a particular technology class provides one measure of the extent of technical opportunities in that domain; the higher the degree of patenting, the more "high-tech" the domain. Using *#Patents* as a control variable, Models 1-3 estimate that the more patenting occurring in a domain, the more likely inventors will find satisfactory solutions among familiar combinations, thus lowering the expected *novelty* of patents. This variable controls for not only the availability of patents in that domain, but also reflects the size of the technological opportunity and the importance of patenting and intellectual property. Audretsch and Feldman (1996) find that industries where research and skilled labor are most important tend to be the industries with more clustered innovative activity. Clustering, they explain, occurs because of the critical importance of local knowledge spillovers for high-tech industries.

To better understand the boundary conditions of Hypotheses 1-3, I look at the strength of the *size_community* and *diversity_community* influence on innovation *novelty* in "high-tech" domains reflected by *#Patents*. If local knowledge spillovers are more important in high-tech domains, then the greater the degree of patenting in a domain, the greater the effect that *size_community* and *diversity_community* should have on *novelty*. Models 4-5 in Table 6-5 OLS Estimation: Novelty and Community Structure interactions interact *#Patents* with *size_community* and *diversity_community*. Model 5, which includes both product-terms, estimates that the relationships are indeed amplified in high-tech domains.

Using a different approach, Models 9-12 in Table 6-6 split the data at the overall mean of 369 patents per patent technology class. As expected, in Table 6-6 the *size_community* coefficient for High-Patenting classes is greater than those for Low-Patenting classes. The negative relationship between *novelty* and *diversity_community* is also larger (significantly different from zero) for High-Patenting class patents.

Individual inventors (compared to corporate inventors) may also be more or less influenced by *size_community* and *diversity_community*. The control dummy variable, *IndividualID*, estimates that patents from individual inventors are almost 13% more novel than patents for corporate inventors[8]. For commercialization, corporations tend to focus on incremental innovations. Thus, as Kline and Rosenberg (1986) detail, many corporate activities set the stage for innovation, linking research, manufacturing, and the market through systematic trial-and-error. For individuals outside formal organizations, however, the process may be different. Without the systemization and empiricism that guides corporate innovation, chance may play a larger role in setting the stage for innovative insights (Usher, 1982: 65). To better understand inventor type as a boundary condition of Hypotheses 1-3, I compare the strength of the *size_community* and *diversity_community* influence on innovations from individuals to innovations from corporations. If individuals are less focused on systematic trial-and-error and more open to chance, then local community conventions may have less of an influence on these inventors. I expect *size_community* will have a more moderate effect on individual inventors than it has on corporate inventors. Furthermore, as individuals are open to

[8] The USPTO classifies patents according assignee type. I code IndividualID as 1 if the USPTO assignee type is U.S. individual, Non-U.S. individual or if the patent is unassigned. GovernmentID equals 1 if the assignee code is the U.S. Federal Government or Non-U.S. Governments. The USPTO codes all other patents as non-government organizations, and most of these are corporations (Hall et. al 2001).

chance, Gutenberg-like observations of the activites around them may have greater impact. I expect *community size* will have a greater effect on individuals.

Models 6 and 7 interact *IndividualID* with *size_community* and *diversity_community*. These models find support that individuals are less influenced by *size_community* than corporate inventors. They find only limited support that individuals are more influenced by *diversity_community* than corporate inventors. Using the second approach, Table 6-7 splits the data between individual inventors and corporate inventors. Comparing the models, the coefficient for *size_community* in the corporate inventor data is almost twice the size of the coefficients in the individual inventor data. Unexpectedly, the effect of *diversity_community* in the split-data models is only evident for corporations.

2.7.4 Generality Estimation and Results

As previously discussed, *generality* is measured by a Herfindahl index corrected for bias. The Herfindahl index along with the correction leads to a non-trivial number of zeros and ones in the dependent variables. While *generality* in this sample is essentially continuous between 0 and 1, 36% and 6% of the patents have generality measures of 0 and 1 respectively. Assuming there is an underlying and latent degree of generality which differentiates these corner solutions but which the corrected Herfindahl is unable to measure, I must be cautious estimating the parameters using a linear model (Wooldridge, 2002). Observations censored at 0 and 1 may shift the regression line resulting in inconsistent estimates with only asymptotic justification (Masssard & Riou, 2002). Given the larger number of zeros than ones, we might expect a linear model to underestimate the intercept and overestimate the slopes. Thus, like Mowery and Ziedonis (2002), I consider estimates of *generality* produced by tobit models.

Beyond the common concerns of heteroskedasticity and non-normal errors, estimating *generality* with Tobit models, however, presents two particular challenges. First, imprecise estimations of the fixed effects in nonlinear models may lead to inconsistent estimates of the slope coefficients (Chamberlain, 1984; Hsiao, 1986). Still, this might not be consequential for this data sample. Rosenthal and Strange (2003) note the bias resulting from noisy estimates of fixed effects in nonlinear models goes to zero as the number of observations per fixed effect increases. Since my sample has at least (depending on the model) 600 patents per fixed effect, inconsistency arising from noisy estimates of the fixed effect is likely to be small. Examining the tobit model in particular, Greene (2004) finds little bias with larger groups. Furthermore, Greene notes that estimators appear essentially unbiased as the degree of censoring approaches 50%. Thus, employing fixed effects for these tobit model is likely unproblematic.

The second challenge is likely more problematic. Ai and Norton (2003) note that interaction effects in non-linear models like the tobit model include not only the marginal effects of a change in the interacted variable, but also the cross-partial derivative of the expected value of outcome variable. Thus, the estimated coefficient of the interacted variables may not reflect the true impact in either size or direction, and cannot be tested with a simple t-test. To test the boundary conditions of *generality*, I employ both tobit and OLS estimation models. In a sense, in the OLS models I trade potential inconsistencies for the interpretability of linear interaction terms. I compare both tobit and OLS estimates to understand just how much bias may be included in the OLS models. As the following discussion illuminates, the results are compatible, providing some comfort using the OLS interaction terms for inference.

To start, Table 2-6 displays the tobit models for the above hypotheses and changes in the expected values of the latent *generality* variable.

Table 2-6 Tobit Estimation: Generality as a function of Technical Community structure

	1		2		3	
Size_Community	-0.015	***	-0.015	***	-0.016	***
	0.005		0.004		0.005	
Diversity_Community			-0.001	***	-0.001	***
			0.000		0.000	
Size*Diversity					0.000	
					0.000	
Patents	0.013	***	0.013	***	0.013	***
	0.003		0.002		0.002	
Employment	0.067	**	0.084	***	0.084	***
	0.025		0.027		0.027	
CoTownID	-0.024		-0.028	+	-0.028	+
	0.016		0.016		0.015	
IndividualID	-0.065	***	-0.065	***	-0.065	***
	0.004		0.004		0.005	
GovernmentID	-0.078	***	-0.077	***	-0.077	***
	0.010		0.010		0.010	
SingleID	-0.149	***	-0.149	***	-0.149	***
	0.005		0.005		0.005	
Subclass Count	0.019	***	0.019	***	0.019	***
	0.001		0.001		0.001	
Science Citations	0.000	**	0.000	***	0.000	***
	0.000		0.000		0.000	
Constant	0.212	***	0.199	***	0.198	***
	0.043		0.044		0.044	
Pseudo R-squared	0.053		0.053		0.053	
Observations	875965		874578		874578	

Robust standard errors (clulstered by metorpolitan area) in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%; *** significant at .5%.
All equations include year, metropolitan area and technology class dummy variables.

If local communities focus inventors on problems particular to that community, I expect inventors from large local communities to be more likely to choose problems with narrow utility leading to less general patents. In support of hypothesis 1b, Model 1 finds that for a 1% increase in community size, there is a change in a patent's expected generality of .015%, holding all other variables constant.

Hypothesis 2 proposes that the diversity of local communities provides inventors insights into the full utility of fundamental inventions, increasing the expected *generality* of those innovations. However, model two estimates the opposite: for a 1% increase in the *diversity_community*, there is a .001% decline in a patent's expected *generality*. Hypothesis 3b proposes that inventors search for problems in sequential steps, exploiting familiar and particular problems before exploring more broadly. Thus, I would expect that the size of an inventor's local community affects the impact of *diversity_community* on *generality*. Model 3 in Table 2-6 tests this hypothesis, but finds no support for it.

Paralleling the examination of *novelty*, subsequent tables explore the boundary conditions of the impact of inter- and intra-community knowledge spillovers on patent *generality*. Again, the variable *#Patents* captures the size of the technological opportunity and/ or the importance of patenting in a given technological class. Models 4 and 5 in Table 6-8 find that not only does *#Patents* increase the expected *generality* of a given patent, but it moderates the focusing effect of local *size_community*.

Table 6-9 splits the patent data between patents from technology classes with above and below the annual mean *#Patents* for all patent classes in the original NBER database. The different effect of *size_community* and *diversity_community* on patent *generality* when conditioned in this way is not obvious in the split-data models. Interestingly, the direction of the *#Patents* effect on generality changes, suggesting a non-linear, U-Shaped relationship between *generality* and levels of patenting. In an unreported test, I include a squared term for *#Patents* and estimate a positive coefficient. This suggests expected *generality* is greatest at low and high levels of technology class patenting, all else equal.

Models 6 and 7 in Table 6-8 Tobit Estimation: Generality and Community Structure interactions examine the influence of being an individual inventor. The negative examine the influence of being an individual inventor. The negative coefficient in *IndividualID* suggests these inventors create patents with less generality than corporate inventors. Furthermore, the generality of individuals' patents are also less affected by the composition of local communities: both *size_community* and *diversity_community* are moderated by the *IndividualID* variable.

Table 6-10 splits the patent data between individual inventors and corporate inventors. It reveals the relationship between community size and surrounding diversity is driven by corporate patents; the models find no evidence that the composition of local communities influences the *generality* of individual-inventor patents. Furthermore, the direction of the *#Patents* parameter changes: greater degrees of technology-class patenting reduce the expected *generality* of patents from individual inventors, while increasing the expected *generality* of patents from corporate inventors.

Note that, although the individuals and high-technology class models are slightly higher than their counterparts, goodness-of-fit does not change much across models. The McFadden pseudo R-squared value of our models remain between .053 and .056, confirming intuition that there are many factors affecting the *novelty* and *generality* of patents that cannot be accounted for by these models.

2.7.5 Interpretation

Built on theories of localized technological paradigms and closed community networks, I posited that larger local technical communities would generate innovations that were less novel and less general. The effect of community size on innovation is relatively clear. The estimates across models support these hypotheses, generating evidence from patent data of the focusing effect that local larger local communities have on innovation. Community size has a strong, negative effect on innovation novelty, robust to various specifications of the model. Community size also has a negative effect on innovation generality. Thus, larger local technical communities do seem to focus inventors on a more narrow set of technologies and problems, suggesting that these communities narrow opportunities and may develop paradigms that differ to some degree from the same technical community in other locations. While effect appears across communities, being an individual inventor seems to mute the focusing affect of community size more than with corporate inventors engaged in more systematic innovation. Still, there are some differences in when community size has the most impact on *novelty* and *generality*: for innovation *novelty* the focusing effect of community size is strongest in high-tech communities where local knowledge spillovers are particularly important, while communities with lower levels of patenting are more subject to the focusing effect of size on *generality*.

In this paper I also investigate the diversity of communities surrounding the inventor's own community, and the moderating effect that surrounding diversity might have on community size. These findings are not as clear. Across the range of community sizes, surrounding diversity has a positive influence on innovation novelty as predicted. Still, this influence is relatively small. Adding one more community of equivalent size to a locale increases innovation novelty by .1%. Furthermore, the influence of surrounding diversity may be more complicated than previously thought. While for high-tech communities, diversity facilitates novelty directly, in low-tech communities the influence of diversity appears only as a moderator of the limiting effect of community size on innovation novelty. Future work should consider the role of local diversity on innovation through two different mechanisms: where local knowledge spillovers are critical, we should expect a direct impact. Where local knowledge spillovers are less critical, diversity may have an indirect impact, relaxing the technical paradigms that tend to form over time.

Surprisingly, surrounding diversity has a negative effect on generality. I build the above hypothesis on a model of inventors choosing which problems to address – some problems might be particular to a technical community, some problems more fundamental across communities. I expected community diversity to lead inventors to address fundamental problems resulting in general innovations. However, these model estimates suggest another dynamic may drive generality.

Inventors find predicting an innovation's impact very difficult (Kline & Rosenberg, 1986). Generality may result from the aggregated choices of subsequent adopters (Bresnahan & Trajtenberg, 1995) rather than the foresight of inventors. Before a subsequent adopter builds on a focal innovation, she must be aware that the knowledge exists and how it might be useful (Rogers, 2003). Jaffe et al. (1993) found that innovations were built-on first by co-located inventors, before spreading to other locales. If we think of diffusion occurring in stages, then the second stage of adoption likely occurs with non-local inventors with collegial ties to inventors in the focal location. Thus, an innovations generality emerges from the diffusion networks originating in local community structures.

Modeling generality as the result of diffusion rather than pre-meditated choice helps explain the above findings. First, a large local community may lead to a more focused adoption as it spreads locally within the technical community, and then spreads through inventor networks to others working on the same technology elsewhere. Furthermore, Romanelli and Khessina (2005) suggested that some locales build identities around certain communities that become the focus of attention for others working in that industry or on that technology. Thus, inventors working on similar things may attend to the innovations coming from larger local communities.

Second, while we might expect local diversity to provide local touch points leading to geographic diffusion along many paths, these results suggests diversity fragments inventor attention focusing them further on their own technical community. The more diverse the composition of local communities the more likely potential adopters will overlook the innovation limiting its generality.

Third, the above models estimate that corporate patents tend to be more general than individual-inventor patents. Because of economic competition, because of quality signals, or simple because they are easier to find, corporate patent may capture the attention of a broader audience. Thus, monitoring and awareness by potential adopters, rather than inventor foresight, may explain why corporate patents tend to be more general and why the generality of corporate patents seems more affected by local community structures.

2.8 Discussion and Conclusion

The geography of innovation literature incorporates a prominent set of themes and findings relating local inventor communities to technological opportunities. These perspectives commonly hold that the availability of local interactions partially determines the opportunities an inventor has to innovate (Almeida & Kogut, 1999; Asheim, 2005; Jaffe et al., 1993). In their findings, Feldman and Audtresch (1999) lend support to the importance of technical communities sharing knowledge of a technology across industry boundaries. Yet studies of local technological opportunities have not given much attention to how opportunities to create *more* innovations might differ from opportunities to create *novel* and *general* innovations. In this paper, I argue and demonstrate that local opportunities for novelty and generality vary across the geographic landscape according to the demography of local technical communities.

In particular, the paper looks at the role of inventor community size and surrounding community diversity in the familiarity of the technical combinations patentees use in their innovations and who develops the innovation further. The results suggest that, all things equal, inventors in large local technical communities rely on more familiar combinations than inventors from smaller technical communities. These inventions further imact a focused group of inventors. Furthermore, the diversity of communities surrounding the focal community has the expected, positive effect on novelty, but through different mechanisms depending on the importance of local spillovers. Surprisingly, diversity seems to fragment subsequent development leading to less general innovations.

While this paper offers a nuanced view linking community structures and innovation, a more complete understanding of the innovation process and the role of geography requires additional research. These estimates account for only a small portion of the factors leading to innovation novelty. For example, inventor characteristics likely shape the characteristics of the innovation. This paper assumes that inventors of particular characteristics are randomly distributed across geography. However, this may not be the case. Florida (2002) suggests certain types of inventors may be attracted to certain types of regions. Large technological communities may offer employment opportunities that attract the more productive inventors; diverse regions may offer intellectual freedom attracting creative inventors. In such cases, the influence of community structure might be mediated by inventor characteristics. Moreover, if productive or creative inventors are attracted to productive or creative regions, the above estimates may suffer from endogeneity.

To overcome these limitations, future research should identify the individual characteristics responsible for differences in innovation novelty. Such research may be linked to recent studies following the geographic mobility of patentees (e.g., Marx, Strumsky, & Fleming, 2009) to better understand the geographic dynamics underlying community differences in innovations. Are inventors shaped by their communities - as is the common and necessary assumption in the current local knowledge spillover literature - or are inventors of different types attracted to communities of different types? If the later, then we might investigate the role of inventor mobility and labor market dynamics on the results reported here.

These findings have implications for regional growth models and public policy. Current regional growth models create a central place for innovation, but remain ambiguous on the role of innovation heterogeneity and the mechanisms generating growth. This paper suggests that, while innovation generates growth, the mechanisms for growth differ. In some regions, innovation and growth comes from incremental improvements of existing technologies. As Tushman and Anderson (1986) suggest, these innovations reinforce current industries and create the growth-generating externalities at the heart of the M-A-R model (Glaeser et al., 1992). In these regional-communities, we should see employment growth through doing more-of-the-same-but-better. In other regions, innovation and growth may come from recombinant improvements and Schumpeterian innovation. These innovations destabilize current industries and lead to the rise of new industries and industry players (Tushman & Anderson, 1986). Here, the Jacobian model may reign, and we should see employment growth through the emergence of entrepreneurs, new firms and new industries (Jacobs, 1968). The question for growth scholars is not which model is the right one, but where is each which model more prominent.

For policy makers and community participants alike, the co-existence of M-A-R and Jacobian innovation and growth models is not merely academic. While this paper focuses on static models of community innovation, technological obsolescence may be more problematic in one model than in another. March and colleagues (e.g., Levinthal & March, 1993; Levitt & March, 1988) coined the phrase “competency traps” to describe the threat inventors face of becoming too focused on one opportunity, and innovating themselves into obsolescence. Dosi (1982) suggested that technical communities can become myopic until swept away by something new. Locales built around large technical communities may generate a stable stream of innovations, but with increasing obsolescence (Sull, 2001). The warning provided to managers about the threat of the competence traps may be equally valid for policy makers too. Moreover, given the focus economic geography on the agglomeration benefits for innovation, we might also study the role of large local communities as incubators of technological obsolescence.

Despite results suggesting the influence of local community structures on innovation novelty and generality, clearly additional research would enhance our knowledge of localized technological opportunities. While this paper focuses on the structure of technical communities, industrial communities also provide opportunities to learn about technologies (Arrow, 1962a; Rosenberg, 1982) and to choose problems with commercial value (Mansfield, 1977; Nelson, 1959). Given the importance of industries for learning and evoking innovation, the next chapter examines the role of industrial agglomerations and local industrial diversity on novelty and generality. Additionally, Feldman and Audretsch (1999) suggest that industrial diversity within technical communities matters for innovation counts. Building on this, the final chapter considers how local industrial structures interact with local technical communities to generate innovation, and how they impact the novelty and generality of those innovations. Finally, by focusing on the role of technical communities, this study ignores the important role of organizations in innovating (e.g., Schumpeter, 1942). In this respect, future research should consider organizations, and their role in facilitating or insulating inventors from local effects, and in bridging locales and local communities.

3 LOCAL INDUSTRY STRUCTURES

3.1 Introduction

Understanding economic growth requires understanding the local knowledge flows that facilitate innovation. A current debate in economic geography centers the influence of knowledge flowing within a local industry and knowledge flowing across local industries. Glaeser et al. (1992) found that the diversity of local industries, but not local specialization, led to subsequent growth. They concluded that intra-industry knowledge and local competition for spurs industry innovations that lead to growth, although the influence of industrial structure may depend on the industries life-stage (Henderson et al., 1995).

Following Glaeser et al., a handful of studies investigated the direct impact of industrial organization on innovation. Similar to Glaeser et al. (1992), Feldman & Audretsch (1999) find no evidence for inter-industry knowledge flows, but positive effects for diversity within a given science base. Yet the jury is still out. Subsequent studies found evidence of both specialization and diversity (Greunz, 2004; Paci & Usai, 1999), and – in the case of French R&D investments - a negative effect of specialization (Masssard & Riou, 2002). There is still much to learn about the geography of innovation.

While further establishing the study of local industrial structure to reveal local knowledge flows, these studies assume that the number of innovations is the critical growth driver. Innovations differ in important ways, and innovation counts may not fully reflect local knowledge spillovers. Innovations differ in their novelty and their generality. Inventors combining existing knowledge in less familiar ways are more likely to create breakthrough innovations (Fleming, 2001) which fashion new industries and drive subsequent economic growth (Schumpeter, 1934). Inventors focused on more general technical problems create innovations with broad impact, useful to the subsequent development of many technologies and industries (Bresnahan & Trajtenberg, 1995). These differences suggest that some innovations are more likely than others to drive local economic growth and technical development. Furthermore, if these differences result from the information inventors have at hand, they may provide a more nuanced approach to revealing local knowledge flows. By examining whether local context shapes innovation characteristics, we might further understand the role local knowledge spillovers play in innovation and economic growth.

This paper examines the influence of local industrial organization on innovation novelty and generality. I employ a pooled cross-section of patents and local industry employment to investigate changes within cities over time. Section One introduces the innovation and economic geography literatures to develop specific hypotheses. Section Two describes the patent and employment data and the specific measures I use to test my hypotheses. Section Three presents the estimation models and their results. Section Four concludes with a discussion of the results and their implications.

3.2 Local Industry Structure and the Characteristics of Innovations

Industrial activity generates new knowledge important for innovation. According to Arrow (1962a): "technical change in general can be ascribed to experiences (156)": specifically, production experiences raise problems to be tackled and solutions to be tried. Outside of the research lab, industrial activity shapes the direction of technological change by promoting several forms of learning that link back to research. As Rosenberg (1982) stated: "productive activities always involve specialized kinds of knowledge which may be unique to a specific industrial process (122)." Development searches out and discovers optimal designs of a product, and benefits from close ties to manufacturing and marketing (Kline & Rosenberg, 1986). Manufacturing and marketing themselves generate new knowledge as workers identify new opportunities for improvement (Arrow, 1962a). Learning also occurs through the use of products and tools themselves (Rosenberg, 1982; von Hippel, 1986). Thus, we should expect that industrial activity is a source of knowledge feeding the innovation process.

Local industrial activity may be particularly influential for inventors. The knowledge generated from manufacturing and other activities tends to be location specific. Experiential learning is often difficult to explain to others, and shaped by the people and conditions under which the technology or knowledge is put to use (von Hippel, 1994). Inventors themselves learn about and use geographically local technologies more readily than distant technologies (Jaffe et al., 1993). Between local knowledge and distant knowledge, we expect knowledge flowing locally from industrial activity to inventors may be particularly influential. "After all," Glaeser et al. (1992) noted, "intellectual breakthroughs must cross hallways and streets more easily than oceans and continents (1127)."

New economic growth theories rely on local knowledge flows to link the present industrial activity and innovation with future development (Romer, 1986). Glaeser et al. (1992) introduce three mechanisms: intra-industry knowledge flows, inter-industry knowledge flows, and local competition.

Intra-industry knowledge flows recognize the importance of knowledge spilling over between actors within the same industry. Marshall (1936) explained the agglomeration of industries in the same locale as partly the results of these knowledge flows. Larger local industries create a place where “Good work is rightly appreciated, inventions…have their merits promptly discussed: if one man starts a new idea, it is taken up by others and combined with suggestions of their own; and thus it becomes the source of further new ideas (Marshall, 1936: 271).” Industrial actors co-locate in part because technical knowledge more readily spreads and develops among proximate actors than distant actors (Lucas, 1993). Given this benefit of co-location, we might expect that large local industries steep local inventors in familiar technical knowledge. Further, local industry knowledge flows lower the cost of acquiring and using technologies familiar to the industry, freeing resources for further experimentation and "further new ideas". This logic predicts that larger local industries generate disproportionately more innovations. Recent empirical studies provide increasing evidence for the positive relationship between local industry size and the innovation counts from local firms (e.g., Audretsch & Feldman, 1996; Baptista & Swann, 1998).

Local knowledge flows may also shape the types of innovations emerging from local firms. Inventors tend to draw from familiar knowledge for solutions to technical problems (Cyert & March, 1963), partly because familiar knowledge reduces the uncertainty surrounding innovation (Fleming, 2001). Large local industries provide deep pools of familiar technical knowledge for inventors to exploit, keeping them from having to explore for solutions more broadly. Innovations combine existing knowledge in new ways (Schumpeter, 1934). Yet some combinations are more familiar to the scientific community than others (Fleming, 2001). As the local availability of industry knowledge increases, inventors will create inventions which build on familiar combinations of technologies. Thus:

H1a: The larger the size of the local industry, the less novel the innovations emerging from that local industry.

Innovations also differ in their scope of impact. Some innovations contribute to development of many different products and technologies – the laser (Rosenberg, 1982) and electricity (David, 1990) being two common examples. Subsequent inventor adopt these general technologies to a range of further development and uses (Bresnahan & Trajtenberg, 1995). While the current literature focuses on the important consequences of generality, little attention has been paid to its antecedents and contexts (Mokyr, 1990).

In part, generality grows from an inventor's choice to focus on a fundamental technical problem or a basic solution. In addition to technical uncertainty ("Will the invention work?"), inventors face market uncertain ("Will anyone find it valuable?") To assess an invention's value, inventors often look to the expectations of potential users or others engaged in the technical community. Customer feedback guides the investment decisions of inventors (Clayton, 1993). Further, built on collective experience, the technical community converges to define interesting and 'appropriate' problems worth solving (Dosi, 1982).

With ties to manufacturing and marketing, local industrial activity not only provides knowledge about which technical solutions will likely work, but also information about which technical problems are worth solving. For inventors, deeper pools of industry activity immerse inventors in community and customer expectations focusing inventors on problems particular to the industry. Interactions with others in these pools of activity likely focus inventors on problems particularly valuable to the industry, even while ignoring problems with more general utility. Thus:

> *H1b: The larger the size of the local industry, the less general the innovations emerging from that local industry.*

While knowledge flowing within an industry may reduce the cost and uncertainty of innovation, knowledge flowing across industries may provide inventors with the spark for creative combinations. Urban scholar Jane Jacobs considered the relative impact inter-industry knowledge flows in 19th century Manchester. For Jacobs (1968), the size of the local textile industry made Manchester a city of “stunning efficiency (86).” Yet efficiency also led to Manchester's ultimate demise as a “profoundly obsolescent city (88).” Manchester’s specialization fostered little in the way of the innovations which spur new work and new industries. Comparatively, “the economy of Birmingham did not become obsolete… It’s fragmented and inefficient little industries kept adding new work, and splitting off new organizations... (89).” Rather than local industry size, local industry diversity may be more important for innovation.

A diversity of experience at the individual level, and access to diversity of knowledge at the social level, facilitates creativity (Amabile, 1996). One outstanding question is whether regional diversity provides a social context for innovation. Recent studies expand our attention from single industry agglomerations, to the diversity of industries that surround them (e.g., Feldman & Audretsch, 1999; Glaeser et al., 1992). Building from the observations of Jane Jacobs (1968), Glaeser et. al. (1992) found that industries in more diverse regions realized greater growth between 1956 and 1987, suggesting that critical knowledge spills across rather than within industries. Duranton and Puga (2001) characterized diverse cities as "nurseries" for new firms, "churning new ideas and new products (which requires a diversified base), whereas other cities specialize in more standard production (which in turn, is better carried out in a more specialized environment.) (1471)." Diverse cities and agglomerated industries offer advantages, but – like Birmingham and Manchester – the former suited for novelty and the latter suited for efficiency.

In perhaps the most direct test of industrial composition and innovation, Feldman and Audretsch (1999) tested the relationship between industrial diversity and the generation of new products by small businesses. In cities specialized in a particular industry, the local industry produced fewer new products. However cities with many others sharing a science base spurred more new products. With these studies in mind, the diversity of industrial activity provides a social context for combining ideas in new ways. As the availability of diverse industry knowledge increases, inventors should find greater opportunities to, or less uncertainty in, drawing from a variety of technical streams. In time, this leads to inventors creating less familiar, more novel combinations. Formally, I expect:

> *H2a: The more diverse the local industries surrounding an inventor, the more novel the innovations emerging from that local industry.*

Surrounding industrial diversity not only provides information about a variety of technologies, it also provides access to a variety of technical communities and customers. Nelson, explaining why private firms tend not to engage in basic research, argued that most inventors consider the value of the innovation for a limited set of current markets.

Only inventors who may realize the value of a general invention in many markets will bother with the uncertainty and expense solving general problems entails.

With a greater ability to consider the value of a solution across many industries (Nelson, 1959), inventors surrounded by a diversity of industrial activity can better assess the broad value of solving fundamental problems. This increases the incentives and reduces the uncertainty of generating something fundamental. Thus, diversity should not only correlate with novelty, but by revealing fundamental technical problems and enabling broad development, the diversity of activity surrounding a local industry should lead to innovations contributing to a wider scope of technologies. Formally, I expect:

H2b: The more diverse the local industries surrounding an inventor, the more general the innovations emerging from that local industry.

Theoretically, explanations of local knowledge spillovers focus on the size of local industries. Yet operationally, Glaeser et al. (1992) and subsequent empirical examinations consider the size of the local industry relative to what we might expect given a random distribution of industrial activity across locales. Arthur (1990) noted how the early presence of an industry in a location – even if it occurs through happenstance – can signal advantages that attracts resources and entrepreneurs. Specialization suggests that local industrial activity has not only scale advantages for innovation, but that some locales are more fertile for the industry than other locales.

Local industries exist in a wider network of local industries. They vie with others for resources and opportunities, and whether that industry dominates the local industrial activity or stands on the periphery shapes its ability to attract resources (Romanelli & Khessina, 2005). Under uncertainty, share can serve as a quality signal generated from the aggregated decisions of individuals (Caminal & Vives, 1996). A local industry commanding a larger share of regional activity than we would otherwise expect signals the quality of that industry in that location. This signal guides investments and attracts human and financial resources to that local industry (Romanelli & Khessina, 2005).

Specialization effects suggest a local gravity exists, pulling resources to some communities at the expense of others. In part, the local opportunity may be a story about local policy: politics, university initiatives, and local firm and investor decisions support industries with a large local presence. This lowers the cost of operating and innovating in that local industry, and frees the resources for further innovation. Still, empirical findings provide mixed support for the benefits of specialization on local innovation: Feldman and Audretsch (1999) found no evidence of an effect of specialization on new product introductions in the United States. Greunz (2004) and Paci and Usai (1999) find that industrial specialization had a positive effect on innovation in Europe.

Romanelli and Khessina (2005) propose that these industry clusters generate a shared understanding about the suitability of the locale for the industry's activities, which then shape local and industry investments. As an example, they note Pittsburgh's specialization in steel, and suggest that investments continued to focus on familiar technologies and financial expertise rather than broader knowledge. Thus, resources attracted to the local industry support innovation around the core technology. In his study of the tire industry, Sull (2001) suggested that such investments and local interactions in the specialized Akron tire-industry lead to myopic innovations, with a critical breakthrough innovation, the radial tire, ultimately coming from a tire-maker outside the specialized local industry. In focusing knowledge about familiar technologies and the value of solving given problems, we may expect:

H3a: The larger the degree of specialization of the local industry, the less novel the innovations emerging from that local industry.

H3b: The larger the degree of specialization of the local industry, the less general the innovations emerging from that local industry.

No discussion of local industrial structure is complete without considering the link between local competition and innovation. For Schumpeter (1942), market power drives innovation. Monopolistic firms innovate more because they have deeper pockets and because they are better positioned to capture the benefits of their efforts. On the other hand, Porter (1990) suggested competition drives local innovation and growth. Product rivalries spur firms to innovate to survive and stay ahead of other firms who also innovate (Aghion & Howitt, 1998). Given that firms tend to focus on local competitors more than distant ones (Baum & Mezias, 1992), competitive local markets likely encourage innovation. Pouder and St. John (1996) suggested a dynamic dimension, early competitive locales drive innovation, but as the local industry evolves and the number of firms decline, firms become myopic and innovation declines.

Empirical studies of both economic growth (see Combes, 2000; Glaeser et al., 1992) and innovation (Feldman & Audretsch, 1999) do not resolve this theoretical horserace. Glaeser et al. (1992) found local competition associated positively with local employment growth but negatively with local wage growth. Combes (2000) found competition in France had a negative relationship with growth in all industries and most services. For innovation, Feldman and Audretsch (1999) also get mixed results, but conclude that within cities of a given size, more competitive local industries link to more product innovations.

Investigating heterogeneity among innovations themselves may better identify the effect of local competition. Innovation counts may hide the true originality and impact of local innovations. Following prior studies (Feldman & Audretsch, 1999; Porter, 1990; Pouder & St. John, 1996), we might expect competitive local industries lead to more innovation, but these innovations may be more incremental. As local firms monitor each other, competition provides continual feedback as to the performance of the firm leading to myopic learning (Barnett & Hansen, 1996). Combining the pressures to stay neck-in-neck with local competitors (Aghion & Howitt, 1998) along with pressures to survive and appropriate returns to innovation, I expect local inventors in competitive locales will focus on less risky, more incremental and marketable innovations. Thus:

H4a: The higher the degree of competition of the local industry, the less novel the innovations emerging from that local industry.

H4b: The higher the degree of competition of the local industry, the less general the innovations emerging from that local industry.

3.3 Data and Variables

3.3.1 Data Sources

Data for the analysis come from two sources: patents registered at the United States Patent and Trademark Office (Hall et al., 2001), and employment data collected by the United States Census Bureau into the County Business Patterns (CBP) data. Patents offer a large sample of innovations covering a wide range of technologies, inventors and locations. Each patent divulges details categorized in ways that enable relatively smooth comparisons between innovations. I use patent data from the National Bureau of

Economic Research (NBER) dataset compiled by Hall, Jaffe, and Trajtenberg and colleagues. The NBER datasets contain complete data for all patents since 1977, and identifies inventors through 1999. Datasets from the NBER also link corporate assignees of over 500,000 patents to publicly traded manufacturing firms listed in Compustat[9] (Hall et al., 2005).

County Business Patterns data offer annual insights into most of the economic activity and industrial composition occurring at the local level throughout the United States. My sample includes the total employment and number of establishments in each county for the years 1977 through 1997. For some years, this information is only readily available at the 2 digit SIC code level, but even in years where 4 digit SIC code information is available, the 2 digit SIC remains appropriate for two reasons. First, not all industries are segmented to the 4 digit level. Thus, using more detailed data loses much of the local economic activity or makes industries incomparable. Second, the skills and expertise required across four digit SIC code industries may not be differentiated enough to warrant this level of detail to draw inferences on the relationship between industrial activity and innovations.

Since this examination is built on the principle that local spillovers and competition shape innovation, the county level may be too small a region of analysis. As in the previous chapter, I assign patents and aggregate the CBP data to the metropolitan area identified by the United States Office of Management and Budget (OMB) in their 2000 standards (Spotila, 2000) and revisions.

---

[9] About 50-65% of all patents of granted to U.S. corporations. Note that about ¼ of patents do not have an assignee, indicating the property rights were originally granted to an individual Hall, B. H., Jaffe, A., & Trajtenberg, M. 2005. Market Value and Patent Citations. ***The RAND Journal of Economics***, 36(1): 16-38..

Assigning inventors to MAs. Each MA may not only include multiple counties, but they may also include multiple towns and cities. While city names repeat across states, almost all city-state combinations are unique, and can be placed within or outside of MAs with a great deal of accuracy. As previously mentioned, each patent includes the city-state information for each inventor, and therefore we can place innovations in one (or many) MAs, opening the advantages of patent data for making comparisons across innovations, to data comparing regions. Previous studies have done this with success (e.g., Carlino et al., 2005; Jaffe et al., 1993). Using a commercially available dataset, I place inventor city/states into MAs[10], an approach that past studies have used to capture the within-MA localization of citation patterns between patents (Almeida & Kogut, 1999; Jaffe et al., 1993).

3.3.2 Data Sample: Single MA and Identifiable Industry Codes.

This paper focuses the sample of patents to a particular set which allows for more focused analysis and controls for potential confounds. The main challenge with assigning patents to MAs is when there are multiple inventors residing in different locales. Researchers have used different approaches in the past – for example, assigning patents to the MA of their primary inventor or majority of inventors. When studies have compared different methods, they do not indicate that different methods generate different outcomes[11]. Still, there may be confounding influences by inventor teams

[10] It may be that inventors list the city/state of their employment rather than their residence. Given that MAs are constructed using local commuting patterns, I suggest that this will not add bias since any differences between residence and employment are likely lost in the MA aggregation.
[11] Carlino, Chatterjee and Hunt Carlino, G., Chatterjee, S., & Hunt, R. 2005. Matching and learning in cities: urban density and the rate of invention. ***Federal Reserve Bank of Philadelphia Working Papers***, No. 04-16/R. compared using first or second authors, and found only 15% of patents would change. Jaffe et al. (1993) used majority as the criterion for assignment, and found that only 14% of their patents could not be assigned unanimously.

from multiple MAs – either because they draw from different experiences and networks, or because of coordinating and organizing dynamics that must occur across multiple MAs. Because I theorize about the influence of a location on the problems and solutions inventors' select, I eliminate these confounding influences by limiting my sample to patents whose inventors come from a single MA. After identifying all patents with single CBSAs and CSAs, I rank-order locations assigning patents to CSAs first and CBSAs second. Additionally, to place patents in local industries, I further reduced my sample to patents with assignees which have been linked to Compustat by Hall et al. (2001), and with application years between 1977 and 1997.

Focusing on patents from a single U.S. metropolitan area reduces the sample to 880,882 patents[12]. Further focusing on patents with an identified CUSIP number further reduces the sample size to 401,336 patents. Note that the Single-MA sample contains a higher percentage of Compustat-linked patents (45.56%) than the NBER population (28.75%).

The sample of Single MA patents with identified Compustat assignees represents about 20.88% of the population of patents captured in the NBER data for application years 1977-1997. Note that the percentage of the NBER patents captured by this sample declines over time: from almost 29% in 1977 to 15.6% in 1996. This decline is largely a result of the overall decline in NBER patents with identifiable Compustat assignees (from over 36% in 1977 to about 22% in 1996)[13].

[12] See chapter one for a comparison of Single U.S. MA patents to the NBER population of patents for years 1997-1997.

[13] Hall et al. (2001) note that, while they were able to match almost 70% of U.S. patents through the early 1980s, they percentage of patent-Compustat matches declined thereafter – a likely result of using the 1989

The Single-MA, Compustat-assignee sample's distribution across technology classes may differ from the NBER population to a degree. As with the NBER population, the two most common groups of patents are drugs and semiconductors. The sample captures almost 22% of all drug patents (Classes 424 and 514) and 27.5% of semiconductors patents (Classes 428, 438 and 439). Still, Synthetic resins/Natural rubbers (Classes 524 and 525) may be overrepresented (the sample captures over 35% of those patents) while underrepresented in Static Structures (Class 52), Land Vehicles (Class 280) and some Surgical Equipment (Classes 600 and 606) (the sample captures 11% of those patents combined). Overrepresented patents may come from established industries with large, stable firms; for example, synthetic resins patents tend to come from large chemical or petroleum companies (e.g., Dow Chemical). Underrepresented patents may come from a high-proportion of non-U.S. firms or private, supplier firms (e.g., Land Vehicles), or from a technology class with a high proportion of individual inventors or more recent growth (e.g., Surgical equipment). Thus, inference for this analysis may the bounded to innovation within large firms in more mature industries[14].

Thus, by combining patent data with County Business Patterns data, we can locate a pooled cross-section of patents in the local industrial structures of their birth. With this data set I can test for the influence of local industrial composition on the novelty and generality of innovations, and gain much insight into the role of geography on technological development and industry evolution.

Compustat file and the rapidly changing composition of patents, with many of the new entrants not yet traded by 1989 (p. 24).

[14] Differences in the distributions of patents across technology classes are more driven by the criteria limiting the sample to patents with Compustat assignees, rather than the Single-MA patents criteria. In some cases, like Class 52:Static Structures, classes overrepresented in the Single-MA sample are underrepresented in the Single-MA, Compustat-assignee sample.

3.3.3 Innovation Measures

By definition, all patented innovations are novel and useful, but defining and measuring the degrees of these two characteristics is difficult (Fleming, 2001). I use two current measures to capture the novelty and generality of a patent:

Novelty. To quantify *novelty*, I follow Fleming's (2001) study of innovation *familiarity*, examining the extent to which an innovation makes unusual combinations of technological streams, captured by patent examiner assigned technology classes. Familiarity is the average count of the number of times technology class pairs were combined in the current and preceding four years in patent *p* in industry *i* from metropolitan area*l*. Thus, if a patent is assigned to technology classes that have not been combined in the past, the $novelty_{pil}$ measure will be high; if the patent makes familiar technology class combinations, the measure will be low.

Generality. I measure the breadth of an innovation's impact by examining the extent to which an innovation contributes to subsequent innovation in a broad array of technology fields, rather to a more focused impact on one or few technological fields:

$$Generality_{pil} = (N_p/(N_p\text{-}1))\ (1\text{-}\sum s_{pq}^{2}) \qquad (1)$$

Here, s_{pq} denotes the percentage of citations made *to* patent *p* from patent class *q*, out of n_p patent classes. The more widely cited a patent is across technological fields, the higher the *generality* measure will be. The Herfindahl index tends to be correlated with the number of citations made to the patent. This confounds the distribution of patent citations with the number citations received, introducing systematic bias into the measure – particularly for patents with fewer forward citations. To correct for this bias, I include the ($N_p/(N_p$-1)) adjustment to create the above bias-adjusted measure (Hall, 2000). Note that patents with no or a single forward citation will have an undefined generality measure. Since forward citations continue to accrue over time, I code those patents as censored data, suspecting that generality may still be revealed in the future. Again, the measure is confined to measures between and including 0 and 1.

3.3.4 Local Industry Measures

Local Industry Size. To measure the size of a local industry, I aggregate the county employment data in the 2 digit SIC to the metropolitan area:

$$Size\_Industry_{il} = \sum employment_{ic} \qquad (2)$$

where the size of industry i in region l is the sum of all county employment in industry i and in count c for all counties in the region. To account for outliers and to aid with model interpretations, I log the variable.

Local Industry Specialization. I capture the degree to which a city is specialized in a particular industry by calculating a location quotient (Glaeser et al., 1992). A given community's local employment share is standardized by its share of all U.S. employment, capturing the difference in local industry activity compared to what we would expect based on a random distribution of activity across the United States:

$$Spec\_Industry_{il} = Industry\ Share_{il} \ / \ (\sum^{U.S.} Industry\ Size_l \ / \sum^{U.S.} Industry\ Size) \qquad (3)$$

where the specialization of industry i in region l is divided by the share of industry i across the United States.

Local Industry Diversity. For each local industry, I calculate a Herfindahl concentration index of all *other* local industries to capture whether the focal industry is surrounded by a wide range of industrial activity, or by a specialized set of industries:

$$Diveristy\_Industry_{il} = 1/\sum^{n\text{-}1} Industry\ Share_{nl}^{2} \qquad (4)$$

where the diversity surrounding industry *i* in region *l* is a function of the squared share of all *n-1* industries in region *l*, with *n-1* denoting all local industries except industry *il*.

Local Industry Competition. Following Glaeser et al. (1992), I measure local competition as the number of firms in the local industry, common-sized for the number of employees in the local industry.

Table 3-1 summarizes the variables employed in subsequent analysis.

Table 3-1 Description of Local Industry Variables

Construct	Variable name	Description
Recombinant Novelty	$Novelty_p$	-1*Natural log of the average # times each patent class pair in a patent occurred in the prior 5 years.
Generality	$Generality_p$	1-Herfindahl of patent forward citation distribution across technology classes (bias corrected).
Local Industry Size	$Size\_Industry_{i,l,t}$	Natural log of the employment in each 2-digit sic-year-metropolitan area.
Surrounding Industry Diversity	$Div\_Industry_{i,l,t}$	Inverse of Herfindahl of Local Industry Sizes (other than the focal community).
Local Industry Specialization	$Spec\_Industry_{i,l,t}$	Location quotient of 2-digit sic-year-metropolitan area.
Local Industry Competition	$Comp\_Industry_{i,l,t}$	# firms per employee in 2-digit sic-year-metropolitan area.
Patent Class Size	$\#Patents_{k,t}$	Natural log of # Patents in technology class-year.
Metropolitan area size	$\#Employment_{i,t}$	Natural log of # of employees in the year-metropolitan area.
Science-base	$\#ScienceCites_p$	# Non-patent citiations listed in the patent.
Subclass count	$\#Subclasses_p$	# subclasses identified by examiners to which patent, p, is assigned.
Single subclass indicator	$SingleID_p$	Equal to 1 for patents assigned to a single subclass , 0 for more than one subclass.

Subscripts *i* (industry), *k* (patent class), *l* (metropolitan area), *p* (patent), *t* (time)

3.4 Models and Results

3.4.1 Summary Statistics

Table 6-11 through Table 6-14 in the Appendix illustrate the persistent nature of local economic organization from 1977-1997 for the local industries engaged in corporate patenting and used in this analysis. The table includes all local industries captured by the County Business Patters data. Note that the number of local industries increases slightly over the years, while the average size of local industries grows steadily. Even so, the specialization of local industries and the diversity surrounding these industries, on average, remains relatively steady - peaking in the 1980s.

Table 6-15 and Table 6-16 in the Appendix show annual trends in patent *novelty* and *generality*. *Novelty* and *generality* decrease. Decreases in *novelty* may reflect overall increases in patenting. Given the time required for patents to acquire forward citations, we should also expect year to year differences in generality, particularly for more recent years, which result from the inherent process of accumulating citations rather than from a fundamental difference in the patents' generality. The more recent the patent, the fewer the citations and the more likely the patent is to have censored data. Indeed, if we focus on truncated generality (unreported here), they reveal a similar pattern, but to a much weaker degree.

Given these trends in patent characteristics, any analysis of patent characteristics likely requires time dummy variables to hold constant variance due to unobserved variables which would otherwise be spuriously captured in the models.

Summary statistics for the centered variables are included in Table 3-2.

Table 3-2 Summary: Centered Explanatory Variables, Single-MA patents 77-97

Variable	Mean	St. Dev.	Min	Max
Patent-level observations				
$Novelty_p$	-1.02	1.10	-7.00	0.00
$Generality_p$	0.45	0.36	0	1.00
$\#Subclasses_p$	0.08	0.27	1	190
$SingleID_p$	4.52	3.97	0	1
MA-sic-year observations				
$Size\_Industry_{k,i,t}$	0.00	2.02	-7.30	5.62
$Div\_Industry_{k,i,t}$	0.00	5.06	-21.77	11.76
$Spec\_Industry_{k,i,t}$	0.00	10.30	-2.16	648.14
$Comp\_Industry_{k,i,t}$	0.03	0.05	0.00	0.75
MA-year observations				
$\#Employment_{i,t}$	2.11	1.62	-2.30	5.45
Class-year observations				
$\#Patents_{k,t}$	0.18	1.14	-4.7412	3.79

Subscripts *i* (industry), *k* (patent class), *l* (metropolitan area), *p* (patent), *t* (time)
N = 326,798 at the patent level; N = 21,671 at the MA-sic-year level;
N = 21,671 at the sic-year level; N = 7,849 at the class-year level

Table 3-3 shows the correlations among these variables. Of note, *#Employment* is correlated with *size_industry* and *diversity_industry* at 74% and 50% respectively.

Table 3-3 Local Industry Correlation Coefficients

	1	2	3	4	5	6	7	8	9	10	11
Novelty$_{n}$	1										
Generality$_{n}$	0.05	1									
Size_Industry$_{k\ i\ t}$	-0.05	0.03	1								
Div_Industry$_{k\ i\ t}$	0.08	0.05	0.31	1							
Spec_Industry$_{k.i.t}$	0.01	-0.02	0.01	-0.16	1						
Comp_Industry$_{k.i.t}$	-0.02	0.01	-0.26	-0.09	-0.17	1					
CoTown$_{i.t}$	-0.02	-0.01	-0.15	-0.24	0.14	-0.08	1				
#Employment$_{i\ t}$	-0.06	0.01	0.73	0.49	-0.27	-0.02	-0.30	1			
#Patents$_{k\ t}$	-0.15	-0.05	0.06	-0.19	-0.01	0.00	0.05	0.08	1		
#Subclasses$_{n}$	0.00	0.13	0.00	0.03	0.00	0.01	-0.01	0.02	0.01	1	
SingleID$_{n}$	-0.12	-0.09	0.01	0.02	0.00	0.00	-0.01	0.01	-0.03	-0.25	1

Subscripts *i* (industry), *k* (patent class), *l* (metropolitan area), *p* (patent), *t* (time)

Note : Correlations are at the patent level of observation, *N* = 326,832.

3.4.2 Novelty Estimation

The data is a pooled cross-section of all corporate patents, allowing me to control for unobserved technology-class factors which might confound the estimates. Additionally, the patents are not identically distributed over time. Time dummy variables account for potential changes in the models' intercepts. While unreported here, the coefficients on the year dummy variables declines, suggesting that even after controlling for local economic organization and other factors, the patterns of decreasing *novelty* and *generality* remain. In additional unreported analysis, I interact these time dummy variables with the key local economic organization variables to explore potential changes in the slopes over time. Wald tests of the variables indicate they are jointly significant, but individual T-tests of the interactions are generally not significant and illuminate no discernable pattern. Including these interactions has no effect on the key results, except for the *diversity_industry* coefficient. Thus, while I do not include year-interaction variables in the final estimates, it is possible that the effect of *diversity diversity_industry* had a stronger impact in some years (particularly 1978-80, and 1981) than others. Why these years differ from other years is open for speculation.

I expect the observations are correlated among industries within MAs. To account for unobserved differences across cities, I include dummy variables for each metropolitan area focusing the analysis on variation within each city. Further, a Breusch-Pagan / Cook-Weisberg test for heteroskedasticity shows usual standard errors are likely unreliable. To adjust for potential correlation among error terms within cities, I use robust standard errors calculated with cluster-level scores (Wooldridge, 2002).

By pooling the patent data, I increase the sample size for more precise estimates of fixed effects and interactions in both the OLS estimations (for dependent variable *novelty*) and Tobit estimations (for dependent variable *generality*). Given the relationship between the patent characteristics and economic organization seems consistent over time, pooling will be helpful as the estimate models become more complex.

3.4.3 Novelty Results

Table 3-4 estimates the relationship between novelty and local industry structure with OLS and including controls for the total metropolitan area employment and metropolitan area fixed effects Model 1 is a baseline including local industry size and control variables. Note that local industries organized around particular firms - "*company towns*" - generate less novel patents through all models. Further, patents assigned by examiners to single subclasses have less novelty. Wald tests of subcategory- and sic-dummy variables support their inclusion in the models.

Table 3-4 OLS Estimation: Novelty as a function of Local Industry structure

	1	2	3	4
$Size\_Industry_{i,l,t}$	0.000	-0.001	-0.002	0.002
	0.010	0.010	0.015	0.016
$Div\_Industry_{i,l,t}$		0.002	0.002	0.002
		0.003	0.004	0.004
$Spec\_Industry_{i,l,t}$			0.001	0.001
			0.004	0.004
$Comp\_Industry_{i,l,t}$				0.240
				0.223
$\#Patents_{k,t}$	-0.014	-0.014	-0.014	-0.014
	0.012	0.012	0.012	0.012
$SingleID_p$	-0.560 ***	-0.560 ***	-0.560 ***	-0.560 ***
	0.036	0.036	0.036	0.036
$CoTownID_l$	-0.106 **	-0.105 *	-0.104 *	-0.105 **
	0.040	0.041	0.041	0.041
$\#Subclasses_p$	-0.005	-0.005	-0.005	-0.005
	0.003	0.003	0.003	0.003
$\#Employment_{l,t}$	-0.110	-0.109	-0.108	-0.111
	0.142	0.142	0.142	0.142
Constant	-0.830	-0.765	-0.768	-0.804
	0.516	0.502	0.500	0.492
Observations	322744	322744	322744	322744
Adj *R*-squared	0.136	0.136	0.136	0.136

Subscripts *t* (time), *i* (2 digit sic), *l* (metropolitan area), *p* (patent).
DV: logged 5-yr average frequency that a patent's technology class pairs occurred.
Robust standard errors (clustered by metropolitan area) in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%, *** significant at .5%.
All equations include year, technology subclass, 2-digit industry code and metropolitan area dummy variables.

The models in Table 3-4 are surprising in that they offer no evidence linking local industry structure and patent novelty. Although the large number of observations in the dataset mitigates multi-collinearity concerns somewhat, after partialing out the effects of total city employment and accounting for unobserved metropolitan area factors, the model 1-4 find no evidence of a relationship between patent *novelty* and local industry structure variables.

In Table 3-4 I assume that unobserved factors at the city-level may confound the estimates. Cities differ in ways that might share local industry size, specialization, diversity and/or competition and the creativity of its inventors. In the now classic examination of Boston and Silicon Valley, Saxenian (1996) notes persistent differences in their firms and labor markets, ascribing the differences to the subsequent divergence in innovation and growth of these two city-industries. More recently, Richard Florida (2002) argues differences in local cultures and amenities attract more or less creative workers. Over the long-run, these differences may vary; during the two decade period in this paper, we might expect these differences between cities to remain steady. Thus, to isolate the effect of economic organization from other city-level factors, I tested the results using city-level fixed effects.

Focusing on variance both within industries and within locales is an important choice. By regressing the individual economic variables on the MA dummy variables, I find that between 27.7% (for *competition_industry*) and 74.6% (for *specialization_industry*) of the variation is between-city variation; but for the *novelty* and *generality* variables, 3.7% and 1.4% of their respective variation exists between cities. While some variation remains within cities, much of the critical variation in the explanatory variables exists in the cross-section comparisons.

However, this study builds on previous estimates of local economic organization offered by Feldman and Audretsch (1999) and Greuz (2004) at the city/region level, and by Baptista and Swan (1998) at the firm level. Data limitations may have forced these papers to use variation across locations to estimate the effects of local economic structure. To capture variation across locales, in Table 6-17 I re-estimate the models without the *#Employment* control and without metropolitan area dummy variables. This allows for a test including between-city variation that doesn't net out city employment variation, but does account for the size of the local industry. Of course, this raises concerns about the model's specification that will be discussed later.

Hypothesis 1a suggests that if inventors in larger local industries draw more heavily in redundant knowledge spillovers, we should expect a decrease in novelty from these locales. Even controlling for technology and industry differences, Model 1 estimates that a 1% increase in local industry size correlates with a .02% decrease in local patent novelty. In subsequent models, controlling for other aspects of economic organization, this estimate increases to around .025% decreases with a 1% increase in size. These models support hypothesis 1a.

Hypothesis 2a suggests that inventors from local industries surrounded by a diversity of industries will draw from a diversity of knowledge spillovers, leading to more novel innovations. Model 2 introduces *diversity_industry* and finds a positive relationship with patent *novelty*. Note that this coefficient is statistically significant at .10, but the coefficient increases in subsequent models controlling for other dimensions of local economic organization. Still, the impact of local diversity seems limited. Per Model 2, a 1% increase in *diversity_industry* relates to a .0033% increase in patent novelty.

Hypothesis 3a suggests that local specialization in an industry encourages the use of intra-industry spillovers, leading to less novel innovations. Model 3 introduces *specialization_industry*. Instead of a negative relationship, the model instead estimates a positive relationship although this estimate is generally not significantly different from zero. Thus, I find no support for the specialization hypothesis.

Hypothesis 4a predicts a negative relationship between *competition_industry* and innovation *novelty*, as inventors reduce technical uncertainty. As predicted, Model 4 estimates a negative relationship between *competition_industry* and patent *novelty*. As Glaeser et al. (1992) note, the competition measure is the inverse of average establishment size. If smaller firms lack the resources necessary for exploration, we might find similar results.

Note the fixed estimates in Table 3-4 vary markedly from the estimates in Table 6-17. Allison (2009) suggested the lack of significance for the fixed estimates results from either: 1) the fixed effect coefficient is substantially closer to zero, an/or 2) the fixed effect standard error is substantially larger. Comparing the estimates shows the fixed effect models are generally less efficient with standard errors roughly twice previous estimates for the variables (other than competition.) Still, there seems to be a real and substantial change in the magnitudes of the effects when city-level effects are controlled. The inflation of standard errors in the fixed effects model suggest that they have limited utility for understanding the impact of local industrial organization. Even across two decades the variation with cities may be insufficient for estimation, despite the large number of observations included in the pooled dataset.

However, the shift in coefficients suggests that there are unobserved variables that "explain away" the observed associations between local industrial organization and innovation. Models estimated from cross-sectional data may more accurately suggest "cities supporting local industries" with certain characteristics have certain innovation outcomes, rather than the characteristics themselves directly reflecting local knowledge spillovers.

3.4.4 Novelty Post-Hoc Analysis

Technological communities may differ according to opportunities available for innovation. Table 6-18 separates patents according to the degree to which they engage in innovation and patenting. Again, *size* continues to have a negative relationship with patent *novelty*. The positive relationship with *diversity_industry*, however, occurs primarily with low-patenting technology classes; the negative influence of *competition_industry* seems driven by its effect in high-patenting technology classes.

While the split novelty models are mirror images of each other, the MA-employment and technology class patenting are uncorrelated. Further, out of the 100,000 unique year-MA-technology class combinations, 67% of local communities are low-patenting technology classes. Of those almost 67,000 communities, 56% are in areas with above average employment.

Locations differ by size. Table 6-19 estimates separate models for patents from Consolidated Statistical Areas (CSAs) and Core-Based Statistical Areas (CBSAs). Across these models, *size* continues to have a negative relationship with patent *novelty*. For *diversity_industry*, however, the collective models seem confounded by differences between CSAs and CBSAs. While *diversity_industry* in CBSAs is not significantly different from zero, *diversity_industry* has a stronger, positive effect on patent *novelty* in

CSAs. Conversely, the influence of *competition_industry* seems driven by its effect in CBSAs.

3.4.5 Generality Estimation and Results

As previously discussed, *generality* is measured by a Herfindahl index corrected for bias. The Herfindahl index along with the correction leads to a non-trivial number of zeros and ones in the dependent variables. Observations censored at 0 and 1 may shift the regression line resulting in inconsistent estimates with only asymptotic justification (Long, 1997). Given the larger number of zeros than ones, we might expect a linear model to underestimate the intercept and overestimate the slopes. Thus, like Mowery and Ziedonis (2002), I consider estimates of *generality* produced by tobit models.

To start, Table 3-5 displays the tobit models for the above hypotheses and changes in the expected values of the latent *generality* variable. Note, these models reintroduce *#Employment* and MA fixed effects[15].

[15] Table 6-23 in the Appendix reveals the generality estimates without these controls.

Table 3-5 Tobit Estimation: Generality as a function of Local Industry structure

	1	2	3	4
$Size\_Industry_{i,l,t}$	-0.005	-0.003	0.003	0.009 +
	0.006	0.005	0.005	0.005
$Div\_Industry_{i,l,t}$		-0.004 *	-0.004 *	-0.003 *
		0.002	0.002	0.002
$Spec\_Industry_{i,l,t}$			-0.004 ***	-0.004 ***
			0.001	0.001
$Comp\_Industry_{i,l,t}$				0.334 *
				0.140
$\#Patents_{k,t}$	-0.033 +	-0.035 *	-0.036 *	-0.037 *
	0.019	0.018	0.017	0.017
$SingleID_p$	-0.132 ***	-0.132 ***	-0.132 ***	-0.132 ***
	0.007	0.007	0.007	0.007
$CoTownID_l$	0.008 +	0.008 +	0.008	0.008
	0.005	0.005	0.005	0.005
$\#Subclasses_p$	0.014 ***	0.014 ***	0.014 ***	0.014 ***
	0.001	0.001	0.001	0.001
$\#Employment_{l,t}$	0.125 ***	0.122 ***	0.117 ***	0.113 ***
	0.038	0.037	0.037	0.037
Constant	-0.458 +	-0.468 +	-0.446 +	-0.493 *
	0.238	0.240	0.237	0.241
Observations	326819	326819	326819	326819
Psuedo R-squared	0.053	0.053	0.054	0.054

Subscripts *t* (time), *i* (industry), *l* (metropolitan area), *p* (patent).

Robust standard errors (clustered by metropolitan area) in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%, *** significant at .5%.

All equations include year, technology subclass, 2-digit industry code and MA dummy variables.

Model one is the baseline with s*ize_industry* and the control variables. As expected, patents assigned to a single subclass tend to be less general. However, controlling for single subclass patents, fewer subclasses are associated with greater levels of generality. Furthermore, larger cities are associated with more general patents. Given the focusing effect that inter-community knowledge flows likely have on the problems inventors choose to address, I expected larger local industries to lead to less general patents. However, Model 1 finds no evidence of this effect.

Hypothesis 2 proposes that the diversity of local industries would positively relate with patent generality. However, model two estimates the opposite: for a 1% increase in the *diversity_industry*, there is a .004% decline in a patent's expected *generality*. Hypothesis 3b proposes that, beyond *size_industry*, the degree to which the local specializes in the industry will also focus inventor problem selection. In support of this hypothesis, model 3finds a negative relationship between *specialization_industry* and patent *novelty*. Hypothesis 4b suggests that competition leads to a degree of myopic learning which focuses inventors. However, Model 4 estimates the opposite: a positive relation between *competition_industry* and patent *generality*[16].

Following the examination of *novelty*, Table 6-20 explores the boundary condition of the impact of inter- and intra-industry knowledge spillovers on patent *generality*. Again, the variable *#Patents* captures the size of the technological opportunity and/ or the importance of patenting in a given technological class. Table 6-20 splits the patent data between patents from technology classes with above and below the median *#Patents*. Note for this analysis, the subsample suffered from sparse indicator variables. To generate interpretable standard errors, I excluded all metropolitan areas and industries with fewer than 10 patents in the dataset.

Comparing the subsamples raises two points. First, *competition_industry* matters for both technologies with more patenting activity and with less patenting activity,

[16] Table 6-23 in the Appendix confirms these findings employing OLS models.

although the relationship is stronger for high-patenting technologies. Second, the negative relationship between *diversity_industry* and patent *novelty* is only evident in high-patenting technologies.

Table 6-21 splits the patent data between patents in Core-based statistical areas (CBSA) and patents from consolidated statistical areas (CSA). CSAs tend to be larger than CBSAs; in this dataset, CSAs average employment of 2,402,844 with a range of 19,769 to 7,905,173 while CBSAs average 344,063 with a range of 3,408 to 1,742,807. Comparing these tables suggests that the effects of both *diversity_industry* and *competition_industry* are driven by the larger CSAs. While *specialization_industry* limits patent *generality* in both sets of locales, this factor is also stronger in CSAs. Note that, although the CBSA models are slightly higher than their counterparts, goodness-of-fit does not change much across models. The McFadden pseudo R-squared value of our models remain between .051 and .068.

3.5 Discussion and Conclusion

3.5.1 Interpretation and Reconsideration

The above hypotheses propose that industrial structure reflects the knowledge about technical solutions and technical problems flowing within a region. These flows then shape the expected novelty and generality of local inventions. While the expected novelty of local innovations supports this view, the expected generality results suggest other processes are at work. The benefit of considering these two outcomes together is it forces us to think about the processes underlying local knowledge flows. Thus, I begin this discussion considering other localized mechanisms which may link local industrial structure with the degree of novelty and generality we may expect in focal innovations.

First, labor markets tend to be more localized than the market for information and technology (Martin, 2000) and draw our attention to what technical knowledge local inventors likely have. Second, Singh (2005) and Breschi and Lissoni (Breschi & Lissoni, 2003, 2006) found that collaboration ties explain most local knowledge spillovers and may explain the diffusion of an innovation among inventors. The following discussion addresses each – labor market dynamics and collaboration networks – in turn.

Labor market pooling may be critical for explaining industrial agglomeration. Labor markets intrinsically operate at the local level: employers hire through local advertisements and word of mouth; employees favor shorter commutes, find jobs through social networks, and generally avoid the costs of relocating (Hanson & Pratt, 1992). While Dumais et al. (Dumais, Ellison, & Glaeser, 1997) found evidence of spillovers, they concluded that the dominant force was that new plants located near other industries sharing a similar labor pool. They argue that workers in agglomerations are protected from firm-specific shocks as other firms in the locale are ready to hire them. In turn this encourages workers to invest in acquiring industry specific-knowledge (Rosenthal & Strange, 2004). In this manner we might expect workers in larger, more competitive locales to specialize in industry knowledge (Rotemberg & Saloner, 2000).

Saxenian’s (1996) comparative case of Silicon Valley and Route-128 supports this theory. She paints a picture of Silicon Valley as a "regional network" composed of larger numbers of smaller firms, while Route-128 was composed of fewer, independent firms. In Silicon Valley, firm-specific risk was reduced to the extreme through, as one observed noted, the "huge supply of contract labor (xi)." In Silicon Valley inventors with specific knowledge moved from firm-to-firm quite easily, and their investments in learning chip design, for example, paid off. Thus, we should expect individuals in larger local industries and industries with more local firms will specialize their knowledge. Linking this theory to the results of this paper, it is unsurprising that patents from large and competitive local industries have lower expected novelty.

Agglomerations reduce firm-specific risk, yet they do not limit the worker's exposure to downturns in the industry overall (Rosenthal & Strange, 2003). In diverse locations, employees may have incentives to gain broad skills and reduce their risk of an particular industry downturn. Again, as the current analysis finds, local industrial diversity will be linked to inventions with higher expected novelty.

A theory of local labor market specialization fits with both Dumais et al.'s (2002) findings and the innovation novelty findings here. Yet innovation generality seems to come through a different process. While this paper proposes that generality is a matter of inventor's selecting basic problems, inventors may have far less control over generality than that. Rosenberg (1990) noted: "If Pasteur had been asked what he thought he was doing back around 1870, he would have replied that he was trying to solve some very practical problems connected with fermentation and putrefaction in the French wine industry. He solved those practical problems – but along the way he invented the modern science of bacteriology (169)." Instead of choosing general problems, inventors may carry out basic research unintentionally. Rather than search for patent generality in the selection of basic problems by inventors, we should consider what local factors may lead to an invention's diffusion and development by subsequent inventors (Bresnahan & Trajtenberg, 1995).

While industry knowledge may exist locally “as if in the air” (Marshall, 1936), the knowledge diffuses through more tangible channels of communication (Rogers, 2003) like inventor collaboration networks. Fleming, King and Juda (2007) argued that these connections between local inventors drove knowledge flows leading to greater inventive productivity. Singh (2005) found that inventor collaboration networks explain much of the local diffusion of knowledge: inventors in connected - rather than isolated - networks are subsequently used in more future inventions. With inventor collaboration networks in mind, we might expect that specialized locations - where a locale is particularly suited for or focused on a particular industry - collaborations likely center on the local industry. Not unsurprisingly, the above analysis finds that local specialization limits the generality of innovations.

More curious, the generality estimates diverge from novelty in the effects of surrounding diversity and local competition. If we consider geographic distance as the key predictor of diffusion, the diversity effects are puzzling: more local industries should lead to collaborations across industries or have no impact at all. Yet local industrial diversity leads to less general innovations suggesting that local collaboration ties do not transcend industry boundaries. This fits with the findings of Fleming et al. (2007) who expected that regional “small worlds” - cohesive groups of inventors with occasional ties - would enhance creative knowledge flows; yet they found no effect. Local ties may not be as useful as originally thought. Wellman (1996) found that co-location increased contacts but did not translate into close personal ties. The local fragmentation of collaboration ties suggests that location alone does not overcome other boundaries. Among scientists, Blau (1974) found that they exchanged information about their research most frequently with others in their field of specialization: the intellectual division of labor has a segregating effect on specialists, creating problems for integrating ideas. Integration requires scientists who are familiar with each other along other social dimensions or through other social institutions.

What likely separates diverse locales are the number of local links that appear between two groups of specialists. As the results of Fleming et al. suggest, local integration likely depends on more than occasional gatekeepers linking two groups of specialists. Cross field ties may be less persistent (Burt, 2000) requiring multiple bridges between groups of inventors. In diverse locales, cross-group ties are thin, fragmented, and do not generate the degree of information exchanges required to build critical collaborations. Without this integration, inventions from diverse locales may spread rapidly within the local community but have a difficult time spreading more broadly. Thus, we would expect innovation from diverse regions to have limited generality.

While the fragmentation of local inventor networks increases with the number of industry boundaries, organizational boundaries within the industry do not fragment inventors. Comparisons between Silicon Valley and Boston provide some insights into the role of competition and the number of local firms on innovation. Fleming and Frenken (Fleming & Frenken, 2007) noted that engineers in both regions supported technical cooperation. As one interviewee put it: “At Digital… management thought we had all these great secrets to conceal: the engineers knew that the value was in collaboration.” All things else equal, management in regions with fewer firms may enforce distinct organizational boundaries. For Saxeninan (1996), the real benefit of Silicon Valley’s regional network was the blurring of organizational boundaries.

Blurring of organizational boundaries increase collaborations and knowledge about an inventor's research. This results in a dynamic local network. Furthermore, the blurring of organizational boundaries attracted others from outside the locale to try to tap into these dynamic local networks (Saxenian, 1996). If Silicon Valley and Boston provide two ends of a spectrum of local competition, then we might conclude that increases in local competition blurs organizational boundaries and leads to expansive collaboration networks. Thus, we might expect inventions from regions with more local competition.

Thus far the discussion focuses on a more nuanced theory of local innovation built on specialization in local labor markets and the breadth of collaboration networks to explain differences in the expected novelty and generality of innovations. The following section discusses some of the empirical limitations for interpreting the above estimates.

3.5.2 Limitations

The previous chapter, which focused on local inventor communities, suggested that the novelty of innovations and the generality of innovations result from different local process. The above results echo the previous chapter's findings. For novelty, I examined two different models. The model which accounted for variation across metropolitan areas (the MA-fixed effect model) found no evidence of a relationship between local industry structure and invention novelty, while the models without these effects (cross-sectional models) did. The cross-sectional models follow prior work, and find evidence linking local knowledge spillovers from both inter- and intra-industry sources to novelty. Across cities, a deeper pool of intra-industry spillovers is linked to innovations of limited novelty; while a diversity of inter-industry spillovers facilitates greater novelty.

However, controlling for time-invariant and unobserved differences across cities, within-city estimates provide no evidence of an effect. Empirically, distinguishing the effects of local industry structure from unobserved, site-specific factors has challenged urban. Few studies control for local characteristics sufficiently (Hanson, 2000). Still, the literature provides a couple alternatives to fixed effects models. Glaeser et al. (1992) employ a growth model to test for industrial structure effects. They use a much broader time frame (industrial structure in 1956 and growth by 1987) and focus on variation at the city-industry level. Subsequent analysis might average novelty to the city-industry level and focus on changes over a broader time frame. Head et al. (1995) took a different approach, studying the 1980 decisions of Japanese firms to locate near other Japanese firms, controlling for the number of local U.S. firms in the same industry. In a sense, the subsample of U.S. firms captures the exogenous factors, and the discussion to locate near other Japanese firms captures spillovers. To understand innovation, I might select a control industry – computer hardware for example – to study the relationship between local industry structure and innovation in semiconductors. These models may offer other means to account for local conditions that influence industrial structure and innovation novelty while using a cross-section of patents or city-industries.

Of course, even within-city studies may prove inconclusive until they address potential endogeneity biases: local economic organization and local innovation may be jointly determined. For example, firm and inventor mobility may drive results, as firms of particular type (Shaver & Flyer, 2000) and inventors of particular character (Florida, 2002) select themselves into cities with certain cultures and institutions. Until we study an exogenous "shock" (perhaps Hurricane Katrina in New Orleans), studies of local economic organization and innovation will be a challenge.

Still, geographic locations continue to "provide a platform upon which knowledge may be effectively organized" (Feldman & Audretsch, 1999: 427). However unclear the underlying sources and mechanisms, it would be wrong to conclude from this analysis that local knowledge spillovers have no influence on innovation. Innovations from similar technologies and/or in the same industry do differ according to where they were invented. The main message here is that the use of aggregate data does not reveal sufficient linkages between industrial specialization, diversity and innovation characteristics to contend that these reflect the direct drivers of innovation. Future research in this area should further study the micro linkages between city- and regional-structures and the nature of the innovation process. Through such research, it will be possible to identify when and where productive spillovers occur, and to improve our recommendations to policy makers on how to support industry evolution and economic growth.

4 THE JOINT EFFECTS OF LOCAL INDUSTRY AND TECHNICAL COMMUNITY STRUCTURES

4.1 Introduction

Inventors, like all social actors, are embedded in communities of individuals sharing knowledge and shaping what gets done by whom. Ideas and opportunities, as Almeida and Kogut (1999) noted, "because they have no material content, should be the least spatially-bounded of all economic activity (905)." Yet an ever growing body of literature describes how the spread of knowledge is, to an important degree, localized. What knowledge an inventor accesses, and what opportunities an inventor attends to, depends on her local context (Jaffe, 1986; Saxenian, 1996). In particular, the structure of local communities guides the spread of ideas and opportunities.

Chapters Two and Three examined the structure of two types of local communities: technical communities and local industries. Smaller technical communities focus inventors on novel innovations but launches innovations with a general impact. A decrease in the diversity of technical communities surrounding an inventor mitigates the focusing effect of community size but further generalizes the innovation's impact. Local industry structure had little effect within cities on the innovation's novelty, but was clearly associated with the innovation's generality. Seemingly, an innovation's characteristics reflect both the local industrial structure and technical community structure from which it emerges.

While each dimension of local structure matters when modeled in isolation from each other, in reality inventors do not work in either industries or technical communities but are members of both simultaneously. Local industries share science-bases (Feldman & Audretsch, 1999) and thus the boundaries of any given technical community very likely overlap industry boundaries. Likewise, local industries may incorporate a variety of local technical communities. Examining the coexistent influences of local industry and technical community structures gives us a full picture of the local structures we as a field should explore. By discovering confounds, we can make our models of local innovation more parsimonious and efficient. By discovering interactions we can find the boundary conditions under which each structure matters. This full picture may allow us to articulate ideal types that support theory development and public policy.

As we examine the local structural context of innovation, our understanding of innovation creation and diffusion improves, allowing us to understand better how locale shapes technical development and industry evolution. But studying technical communities and local industries in isolation ignores the reality of joint community membership. In this chapter, I combine the models in Chapters One and Two to test these structures together and propose two ideal locale types which seem to facilitate the create of novel innovations which break from the past, and general innovations which help develop a variety of technical streams.

While this chapter is exploratory, the next section offers theoretical motive and potential explanations for the empirical analysis. Then Section 3 articulates the models, first testing the coexistent but unique effects of each set of community characteristics, then by testing the joint effects through their interactions

These models reinforce and, in the case of technical community size, update the previous chapters' findings. They find support for the unique effects of the technical community structures, even when accounting for industry structures. Furthermore, they estimate joint effects between local industry and technical community structures, suggesting the local antecedents of innovation are more complex than previously studied.

4.2 Crosscutting Local Industries and Technical Communities

Given the similarities of the variables, it is tempting to think technical community structures and industrial structures are mirror images: larger industries will likely support more inventors; surrounding industrial diversity likely accompanies surrounding technical diversity. If the two communities closely resemble each other, then studying the communities jointly may only muddle our understanding of community structures and innovation novelty and generality, as we risk throwing away, through regression estimates, all but the most marginal effects.

However, previous observations suggest that the differences between technical communities and local industries are more than marginal. For situated inventors, technical communities differ from local industries in the knowledge they make available, and in the activities and goals they draw attention to. Local industries provide knowledge of particular processes applying a scientific principle toward some function or product (Arthur, 2007). Technical communities revolve around innovation: identifying new market opportunities, developing new technologies, or designing new products (McKendrick, Doner, & Haggard, 2000). The boundaries between industries and technical community cross, each generating its own norms and ways of going about its business (Dosi, 1982; Van Maanen & Barley, 1984; Wenger, 1998).

St. John and Pouder (2006) highlighted many differences between local industries and technical communities. Technical communities may grow around universities and research labs with the specific goal of generating new knowledge (Zucker, Darby, & Brewer, 1998) based on informed decisions and trial-and-error testing. What they learn and how they learn it may differ across locales even within the same technical field (St. John & Pouder, 2006). Furthermore, each technical community may support a diversity of industries (Feldman & Audretsch, 1999). Relative to local industries, local technical communities support inventors with idiosyncratic technical knowledge leading to more novel innovations than what we would expect from the local industry alone (St. John & Pouder, 2006).

In contrast, local industries comprise a multitude of occupations and activities united to support in a common process or product. While local industries include R&D and innovation, the bulk of local industry employment likely centers on manufacturing. For example, a recent report on the high-tech orthopedic devices industry in the small community of Warsaw, Indiana notes that of the 20,000 jobs attributed to the industry, about 12,000 are directly in manufacturing (Marsh, 2007). Local industries generate knowledge outside R&D, and this knowledge focuses on manufacturing, assembly and logistics (Arrow, 1962b; McKendrick et al., 2000). Product and technical innovations may occur, but the principle goal of the industry community is "to achieve operational efficiency; any new technologies they create are meant to improve production processes or supply chain management (McKendrick et al., 2000: 45)." For an inventor, the interaction with other industry activities, such as manufacturing and marketing, can direct attention to particular problems and products which the industry can effectively produce, and which the industry and its customers will value (Kline & Rosenberg, 1986).

Further, while technical communities emerge around local universities and research centers, local industries may form around suppliers and customers (Audia, Freeman, & Reynolds, 2006; St. John & Pouder, 2006). With a focus on production, and key ties to suppliers and customers, knowledge developed in local industries tracks the industry life-cycle. Compared to technical communities, we would expect local industries to focus inventors on incremental innovations with evident applications.

Local industries and technical communities differ in purpose, ties and activities. Given these differences, industrial activity and research activity need not be tied together so tightly as to make their specific structures mirror images. In semiconductors, we have long seen firms relocate manufacturing to low labor cost locations while research and development remains in the technical communities of Silicon Valley (Audretsch & Feldman, 1996; McKendrick et al., 2000) found considerable differences between the propensity of an industry's productive activity and its inventive activity to cluster geographically. Thus, we might expect the relationship between innovation characteristics and technical community structures to remain even when accounting for her industry's structure. Still, Audretsch and Feldman found that the geographic structure of production and inventive activity associate based on the importance for new knowledge in the industry. They suggested researchers need to control for production before explaining the geography of an industry's inventive activity, making concurrent tests a worthwhile enterprise.

Few studies have heeded Audretsch and Feldman's recommendation to test local industry structures and local technical community structures simultaneously. Those that did focused on the diversity and specialization of patents to understand which structures support subsequent increases in patenting or new product counts. They generally found that local industries and local science-bases have unique effects, even as they disagree as to what those effects are (Greunz, 2004; Paci & Usai, 1999; van der Panne & van Beers, 2006).

Furthermore, despite their differences, the technical community and local industry may not guide the inventor independently of each other. Instead, one may enable or curb the other. For example, the technical community's influence on the inventor may depend on the resources the industry provides her. Larger industries may provide an inventor with the resources necessary to generate broader searches (Cyert & March, 1963), mitigating the dependence of the inventor on the technical community. Conversely, large industries may provide inventors with a sizeable market for specialized innovations (Marshall, 1936), enhancing the influence of the technical community. Thus, this analysis goes a step further to study how one community's structure may affect the other's influence on innovation novelty and generality. This analysis is based on the potential that the dynamics occurring within a technical community – that is, how its structure shapes what knowledge an inventor can access or attends to – may be influenced by the industrial structure housing the inventor.

The following section extends the prior chapters' findings. For both innovation novelty and generality, I model technical community structures and local industry structures simultaneously, comparing the results to those of the previous chapters to test for unique effects. Then I estimate interactions. While local industries and technical communities differ in their networks and activities, they may amplify or moderate each other in ways that shed light on the efficacy of collocating production and research for innovation.

4.3 Data and Variables

I draw the data and variables used in this analysis from the prior two chapters. The outcomes of interest are patent *novelty* and *generality*. *Novelty* remains the average frequency with which each of a patent's pairs of subclasses appeared in other patents in the application year and in the prior five years. *Generality* remains 1 minus a Herfindahl index of the patent's subsequent citations across technology classes, adjusted for the bias that comes from the number of subsequent citations. Table 4-1provides the descriptive statistics of these variables, before the log transformation used in subsequent analysis.

Table 4-1 Summary: Untransformed Variables (with Average Pair-wise Frequency)

	Obs.	Mean	Std. Dev.	Min	Max
Average Pair Frequency	322755	7.30	24.01	1.00	1094
Generality (censored)	322789	0.45	0.36	0.00	1
Tech. Comm. Size	322541	46.71	80.96	1.00	848
Tech. Comm. Specialization	322541	7.56	52.48	0.03	17201
Surr. Tech. Diversity	322429	72.90	37.84	1.00	171
Industry Size	322789	55806	91863	0.00	1018774
Industry Specialization	322789	2.47	5.62	0.00	650
Surr. Ind. Diversity	322789	26.26	4.25	3.13	37
Avg. Establishment Size	322778	143.74	214.04	1.33	4379.13

Explanatory variables are divided into technical community characteristics and industrial community characteristics. *Technical community size* is the number of inventors patenting in that technology class and in that year who identify that metropolitan area as their location. *Surrounding technical community diversity* is the inverse of the local concentration of inventors patenting in other technology classes in the metropolitan area during the year. *Technical community specialization* is the ratio of the technology classes' local share of inventors to the technology classes' share of all U.S. inventors during that year. Local industry structure variables are calculated in similar ways using employment data rather than inventor counts. Finally, *local-industry average establishment size* is the local industry employment divided by the number of local industry establishments. Each of these variables is also included in Table 4-1, prior to being centered and log-transformations. Note *local-industry average establishment size* is the inverse of the *local competition* measure from Chapter Three. I make this substitution in light of the findings and discussion from Chapter Three. Further, in light of Chapter Three I added the *technical community specialization* variable.

The variables have noteworthy distributions that invite transformation. All variables except *generality* are positive with long right tails. Four variables (including *novelty*) are counts or average counts. The specialization variables are ratios. Subsequent analysis will use log-linear transformations of these variables[17].

Bivariate analysis helps to describe the patterns of associations among the different dimensions of local industry structure. Table 4-2 presents the correlation coefficients of the community structure variables and the characteristics of local innovations. In pair-wise correlations, all were significant ($p < .001$) except for the correlation between (logged) *novelty* and (logged) *local industry specialization*. Among

[17] Eleven local industries have employment of zero, meaning that although the local inventors were working for firms housed in a particular two-digit industry, at the location identified by the inventors there were no employees working in the industry per the Census Bureau. For these eleven observations, their employment and specialization measures were input as .01 before the log transformation.

variables capturing dimensions of the same community type, most variables are only moderately correlated. *Average local-industry establishment size* is one exception with a strong correlation with *local industry specialization* (r = .69). Within the same dimension across community type, *surrounding diversity* indicates the strongest correlation (r = .62). The various measures of community structure appear to capture distinct dimensions, with some potential for collinearity issues among inventor community structure and *local industry size*.

Table 4-2 Technical Community and Local Industry Correlation Coefficients - Logged Transformations

	Novelty	Gen.	Size Inv.	Spec. Inv	Div. Inv.	Size Ind.	Spec. Ind.	Div. Ind.	Est. Size
Novelty (ln)	1								
Generality	0.05	1							
Tech. Comm. Size (ln)	-0.21	-0.07	1						
Tech. Comm. Specialization (ln)	-0.02	-0.09	0.04	1					
Surr. Tech. Diversity	0.03	0.04	0.27	-0.51	1				
Industry Size (ln)	-0.05	0.03	0.46	-0.39	0.55	1.00			
Industry Specialization (ln)	0.00	-0.01	0.06	0.20	-0.22	0.35	1.00		
Surr. Ind. Diversity	0.08	0.05	0.05	-0.31	0.62	0.31	-0.14	1.00	
Avg. Establishment Size (ln)	0.06	-0.01	-0.09	0.19	-0.19	0.11	0.69	-0.09	1.00

4.4 Models and Results

While the bivariate relationships shed light on the relationships among the independent variables, I can draw few conclusions about their relationships with *novelty* and *generality* without employing multivariate models. To estimate the effect of community structure on innovation characteristics, I must account for how the technology and the industry itself (among other controls) confound the community structure or innovation characteristic relationships. Further, the multivariate model allows me to estimate the net effects of each community- and industry-structure variable that measure different aspects of the local context, and hence are (in some cases) correlated. Thus, to understand if technical communities and local industries exert simultaneous influence on innovations, I build on the multivariate OLS and tobit models presented in the previous chapters.

The prior chapter results parallel each other in key ways: *size_community* and *size_industry* (across cities) both had negative relationships with innovation *novelty*; *diversity_industry* (across cities) and *diversity_community* both limited innovation *generality*. One may ask if these measures capture the same or different dimensions of local context. Also, the two sets of analysis differ in interesting ways. *Novelty*, they find, has a positive relationship with *diversity_industry* but a negative relationship with *diversity_community*; *generality* has a negative relationship with *size_community* but no statistically significant relationship with *size_industry*. These differences may result from the addition of *specialization_industry* and *average establishment size* in Chapter Three. This chapter explores the technical community findings in the presence of local industry characteristics, including *specialization_industry* and *average establishment size*.

Conjecture suggests the technical community structure may interact with local industry structures, but no particular theory offers a clear advantage for hypothesizing the effect this interaction would have on *novelty* and *generality*. Chapter Two's findings offer an initial insight into the role of the technical community, and an exploration of its interactions with local industry structure sheds additional light on the potential boundaries of a community structure approach to understanding *novelty* and *generality*. Furthermore, linking technical community structure with local industry employment fits it into prior work in economic geography. To gain insight, following exploratory models include second-order interaction variables, capturing the joint influence of dimensions of technical community structure and their local industry structure counterparts.

4.4.1 Novelty

The following models build on the OLS models of *Novelty* in the prior chapters. Note, they include only the corporate patent samples from Chapter Three, rather than Chapter Two's complete sample of single-MA patents. Again, to account for key categorical differences I include fixed effects for the year of the patent's application, 2-digit industry SIC code, metropolitan area, and patent technology subcategories. Computational limitations require that I use the 36-technology subclass categories identified by the USPTO, rather than the more specific technology classes. Subclass categories have been used in prior work noted to be an acceptable alternative (Hall et al., 2001). Finally, I include *specialization_commuity* as an additional dimension of community-structure. Including this variable makes the technical community analysis more parallel with local industry analysis. Below, I discuss where these model differences change the results.

Table 4-3 OLS Estimation: Novelty, Techincal Community and Local Industry structures

	1	2	3	4	5	6	7
Size_Community	-0.115 ***	-0.115 ***	-0.146 ***	-0.147 ***	-0.147 ***	-0.144 ***	-0.145 ***
	0.014	0.014	0.044	0.043	0.043	0.043	0.044
Diversity_Community		0.002 ***	0.002 ***	0.001 ***	0.001 ***	0.002 ***	0.002 ***
		0.001	0.000	0.000	0.000	0.001	0.001
Spec_Community			0.033	0.033	0.032	0.029	0.029
			0.048	0.048	0.048	0.048	0.049
Size_Industry				0.008	-0.006 +	-0.007	-0.005
				0.010	0.016	0.016	0.016
Spec_Industry					0.025	0.027 +	0.021
					0.016	0.016	0.018
Diversity_Industry						-0.005	-0.005
						0.003	0.004
Avg. Establishment Size							0.007
							0.013
Patents	0.060 ***	0.060 ***	0.091 +	0.091 +	0.092 +	0.089 +	0.089 +
	0.020	0.020	0.051	0.050	0.051	0.051	0.051
CoTownID	-0.111 ***	-0.104 ***	-0.105 **	-0.104 **	-0.100 **	-0.103 ***	-0.102 ***
	0.034	0.035	0.035	0.036	0.036	0.035	0.036
SingleID	-0.556 ***	-0.557 ***	-0.556 ***	-0.556 ***	-0.556 ***	-0.556 ***	-0.556 ***
	0.036	0.036	0.036	0.036	0.035	0.035	0.035
SubclassCnt	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005
	0.003	0.003	0.003	0.003	0.003	0.003	0.003
Constant	-1.872 ***	-1.839 ***	-2.125 ***	-2.106 ***	-2.160 ***	-2.130 ***	-2.126 ***
	0.159	0.157	0.449	0.457	0.484	0.479	0.477
N	322507	322507	322395	322395	322395	322395	322385
Adj R-sq	0.14	0.1402	0.1403	0.1403	0.1404	0.1405	0.1405

Year, Subcategory, Sic and MA fixed effects
+ signicant at .10, * significant at .05, ** significant at .01, *** significant at .005

Ordinary least squares regression in Table 4-3 shows that even when local industry structure variables were taken into account, technical community size and surrounding diversity continue to have a significant relationship with patent *novelty*[18]. Chapter Two found a negative relationship with between *size_community* and patent *novelty*. Controlling for local industry structure, *size_community* continues to have a negative relation in these corporate patents. Accounting for local industry structure, a one percent increase in *size_community* is associated with a .14 percent increase in patent *novelty*.

[18] Wald test of the industrial variable coefficients indicates that jointly they differ from zero (P = .0692). Variance inflation factors for the local industry structure and technical community structure variables were all equal to or less than three (mean VIF=2.23).

Different from Chapter Two, holding *specialization_community* constant changes the technical community *size-generality* estimates (suggesting a refinement is needed to the Chapter Two model.) Additionally, the models in Table 4-3 estimate a positive relationship between surrounding technical diversity and patent *novelty* (which was statistically except for corporate patents in Chapter Two). Controlling for local industry structure, a one percent increase in the number of equal-sized communities leads to a .0018 increase in patent *novelty*. The model does not estimate a significant direct relationship between *specialization_community* and patent *novelty*.

While technical community structure appears impact *novelty* independent of local industry structure, industry structure might still condition the magnitude of that effect. Table 6-24 examines potential interactions between the technical community and local industry variables. Models one through three interact each dimension with its counterpart, with limited significance. Models four through six investigate how the average size of local industry establishments interacts with technical community variables. Wald test of the interaction variable coefficients indicates they are jointly different than zero (P = .0000); the relationship between local structures and innovation characteristics may not be purely linear[19].

The estimates suggest that *size_community* has a negative relationship with patent *novelty* across the range of *size_industry*, but as industries become larger the influence of *size_community* dissipates. The models find that the positive relationship between *diversity_community* and patent *novelty* is conditioned by *diversity_industry*. At average

---

[19] Variance inflation factors of the interaction variables with the local industry- and technical community-structure variables are all less than 4 (mean VIF = 2.27).

levels of *diversity_industry*, the effect of *diversity_community* is a third less than it is across all levels of *diversity_industry*. Finally, while neither structural dimension is significant on its own, the interaction between *average establishment size* and *specialization_community* is negative and significant. Seemingly, the focusing effect of *specialization_community* matters when local industrial activity occurs in larger firms.

For a clearer picture of the impact of local structures, I explore a more parsimonious model by simplifying the regression equations with the complete set of variables and interactions. Lower order estimates and interactions are not usually independent, raising questions about reducing the models. Yet in this case, strong theory predicts the main effects while the interaction terms are more exploratory. Given this motivation, I determine the parsimonious model using a step-down procedure based on the significance of the interaction terms (Aiken & West, 1991). Of course, interpreting the results of all exploratory models requires some caution given we would expect some significant terms based solely on the test.

Given the predictive improvement of the interaction-terms model, test individual terms to further characterize the nature of community structure and innovation characteristics. Beginning with the full model, I employ a step-down hierarchical examination, omitting non-significant terms sequentially beginning with the interaction terms. The resulting model of innovation *novelty* is Model 8 in Table 6-24. The source of deviation from linearity found in the prior Wald test results from three interactions: community size interactions, community diversity interactions, and the interaction between *average establishment size* and *diversity_community*.

4.4.2 Generality

The Tobit estimates in Table 4-4 show that technical community structure has a significant relationship with patent *generality* even holding local industry structure variables constant[20]. In a change from Chapter Two, the Tobit models estimate a significant relationship between *size_community* and patent *generality*; but this change is due to the inclusion of *specialization_community* and not due to the inclusion of local industry structure. Note that accounting for *specialization_community* also changes the sign and magnitude of the Patents estimate. As with the larger patent sample in Chapter Two, technical community diversity continues to have a negative relationship with patent *generality*. The final model including local industry structure also estimates that patent *generality* decreases with the added variable, *specialization_community*.

[20] Wald test of the industrial variable coefficients added to the OLS model indicates that jointly they differ from zero (P = .0000). Variance inflation factors for the local industry structure and technical community structure variables were all equal to or less than three (mean VIF =2.23)

Table 4-4 Tobit Estimation: Generality, Technical Community and Local Industry structures

	1	2	3	4	5	6	7
Size_Community	-0.030 ***	-0.030 ***	0.055 ***	0.054 ***	0.055 ***	0.056 ***	0.056 ***
	0.006	0.005	0.007	0.007	0.007	0.007	0.007
Diversity_Community		-0.001 ***	-0.001 ***	-0.001 ***	-0.001 ***	-0.001 ***	-0.001 ***
		0.000	0.000	0.000	0.000	0.000	0.000
Spec_Community			-0.092 ***	-0.092 ***	-0.091 ***	-0.092 ***	-0.093 ***
			0.008	0.008	0.008	0.008	0.008
Size_Industry				0.009 +	0.022 ***	0.022 ***	0.021 ***
				0.005	0.005	0.005	0.005
Spec_Industry					-0.023 **	-0.022 **	-0.015 *
					0.008	0.007	0.007
Diversity_Industry						-0.002	-0.002
						0.002	0.002
Avg. Establishment Size							-0.007
							0.007
Patents	0.029 ***	0.029 ***	-0.057 ***	-0.056 ***	-0.057 ***	-0.058 ***	-0.058 ***
	0.004	0.004	0.008	0.008	0.008	0.008	0.008
CoTownID	-0.033	-0.038	-0.035	-0.034	-0.037	-0.038	-0.039 +
	0.024	0.024	0.026	0.027	0.025	0.024	0.023
SingleID	-0.128 ***	-0.128 ***	-0.128 ***	-0.128 ***	-0.128 ***	-0.128 ***	-0.128 ***
	0.007	0.007	0.007	0.007	0.007	0.007	0.007
SubclassCnt	0.014 ***	0.014 ***	0.014 ***	0.014 ***	0.014 ***	0.014 ***	0.014 ***
	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Constant	0.014	-0.013	0.786 ***	0.807 ***	0.856 ***	0.870 ***	0.866 ***
	0.064	0.064	0.067	0.063	0.062	0.064	0.064
N	322541	322429	322429	322429	322429	322429	322419
Pseudo R-sq	0.0519	0.0522	0.0535	0.0536	0.0538	0.0539	0.0539

Year, Subcategory, and SIC fixed effects

+ signicant at .10, * significant at .05, ** significant at .01, *** significant at .005

Focusing on the local industry structure estimates, once I account for technical community structure, Tobit estimates of the relationship between patent *generality* and local industry structure change somewhat. Relative to the results in Chapter Three, *size_industry* has a larger expected impact on patent *generality*. Including technical community variables also mediates *specialization_industry's* and *diversity_industry's* relationship with patent *generality*. Thus, accounting for technical community structure isolates the impact of *size_industry* while capturing some of the variation previously attributed to *specialization_industry* and *diversity_industry*.

While Table 4-4 employs Tobit models to account for potential bias given the nature of the patent generality variable, interpreting interaction variables with Tobit is exceedingly difficult. Ai and Norton (1991) note that interaction effects in non-linear models like the tobit model include not only the marginal effects of a change in the interacted variable, but also the cross-partial derivative of the expected value of outcome variable. Thus, the estimated coefficient of the interacted variables may not reflect the true impact in either size or direction, and cannot be tested with a simple t-test. To examine the joint effects of technical community structure and local industry structure, I use OLS models of patent generality.

Table 6-25 in the Appendix supports the Tobit estimates with OLS estimates, although the OLS estimates tend to be both weaker relationships and lower standard errors (resulting in models with similar significance test results.)

Table 6-26 extends the OLS *generality* models by including interaction terms. A Wald test indicates the interaction term coefficients are all significantly different from zero. Models one through three interact each dimension with its counterpart, with limited significance. Models four through six investigate how the average size of local industry establishments interacts with technical community variables. Table 6-26 models suggest that the interaction variables have a strong effect over each other[21]. Model 8 simplifies the full model and adds to its efficiency by dropping the insignificant interactions and terms (Aiken & West, 1991) to generate a preferred equation. The model suggests that *size_industry* amplifies the effect *size_community*. Furthermore, the local industry's *average establishment size* strengthens the impact of *size_community* and

[21] Again, variance inflation factors all measure less than four (mean VIF = 2.27).

specialization_community to a small degree by. On the other hand, *average establishment size* moderates the focusing effect that *diversity_community* has on patent *generality*.

The resulting model of innovation *generality* is Model 8 in Table 6-26. The source of deviation from linearity found in the prior f-test results from the size interactions and the interactions of *average establishment size* and technical community structure variables.

4.5 Discussion and Conclusion

Inventor membership in both local industries and technical communities potentially confounds prior research on locale and innovation. We might expect that these two types of communities mirror each other; that larger, more diverse local industries go hand-in-hand with larger, more diverse technical communities. This is true to some degree. This chapter finds a correlation between the structural characteristics of an inventor's local industry and her local technical community.

Yet while the two co-exist, they differ in the activities and networks they support. I argue that local industries focus on manufacturing and marketing, linking inventors with suppliers, buyers and production. In contrast, local technical communities focus on technological development, and may link inventors across universities, research labs, firms and industries which share an interest in a given technology. Echoing Audretsch and Feldman (1996), geographic industry structures and inventive activities differ enough that they should be accounted for as unique attributes, but they are related enough that studying one should not preclude accounting for the other.

This chapter tested the unique and joint effects of local industry and technical community structures on the degree of novelty and generality we might expect in a local innovation. With patent data and employment data, it assigns corporate patents to both local industries and technical communities and analyzes the effects of their local size, specialization, and the diversity surrounding them. The evidence concurs with Audretsch and Feldman's recommendation: industries and technical communities have unique effects, and are spate but related communities. Yet failure to include both in past studies does not invalidate past results; while improving the models, accounting for each community does not significantly change the estimated effect of the other.

For novelty, technical community size continues to focus inventors on more familiar innovations, while surrounding technical diversity shapes broader searches and more novel innovations. Accounting for local industry structure does not change those results[22]. For generality, estimates remain steady in size and significance even holding local industry structure constant. Local industries and technical communities parallel each other: size increase expected generality, specialization limits it. Thus, we should search further for the fundamental mechanisms through which community structures influence innovation, even as communities differ in their substance.

Identifying community co-membership also provided an opportunity to explore the joint effects local industries and technical communities have on innovation type. The size of an inventor's local industry employment mitigated the focusing effect of technical community size on innovation novelty, but amplified technical community size's support

[22] Furthermore, the effect of local industry structure continues to matter for variation across cities rather than within cities.

for innovation generality. This fits with prior conclusions, that novelty is a product on an inventor's search for solutions, focused by localized technological paradigms and closed community networks. Generality requires diffusion, and all else equal large communities compliment large local industries in disseminating innovations more broadly.

Interestingly, diversity and specialization had no evident joint effects. If the structure of local industry and technical communities focus and fragment inventor searches and diffusion networks, we might expect technical communities to compliment local industries; the focusing effect of locally specialized technical community is stronger in locally specialized industries, for example. Future research may explore how community structures shape search and diffusion, as size may capture a different mechanism that those underlying specialization and surrounding diversity.

Finally, I note the joint effect that the size of local industry firms has with technical community structure. As inventor's search isn't constrained by community specialization nor by the average size of local firms. Yet they are constrained by both working in unison. For generality, local industries with larger local establishments complement the broad diffusion effect of technical community size and the focusing effect of technical community specialization. Establishment size moderated the fragmenting effect of diversity. Just how organizational demographics interact with and co-determine community structure remains an open pasture for future exploration.

This dissertation seeks to define the locales from which novel and general innovations emerge. For individual innovations, I find a small but significant effect of local industry and technical community structures. We should expect innovations from smaller technical communities and this surrounded by a diversity of technical communities to be more novel, all else considered. For generality, size matters. Large technical communities in large local industries with large establishments increase the expected generality of an innovation. Further, given the community specialization and diversity results, large surrounding technical communities may help too. These findings suggest that, while the expected effect of community structures on individual innovations is small, in aggregate it may add up, shaping regional growth and technological trajectories.

5 REFERENCES

Acs, Z. J., Audretsch, D. B., & Feldman, M. P. 1992. Real Effects of Academic Research: Comment. ***The American Economic Review***, 82(1): 363-367.

Aghion, P., & Howitt, P. 1998. ***Endogenous Growth Theory***. Cambridge, MA: MIT Press.

Ai, C., & Norton, E. C. 2003. Interaction terms in logit and probit models. ***Economics Letters***, 80(1): 123-129.

Aiken, L. S., & West, S. G. 1991. ***Multiple Regression: Testing and Interpreting Interactions***. Thousand Oaks, CA: SAGE Publications, Inc.

Alcácer, J., & Gittelman, M. 2006. Patent Citations as a Measure of Knowledge Flows: The Influence of Examiner Citations. ***The Review of Economics and Statistics***, 88(4): 774-779.

Allison, P. D. 2009. ***Fixed Effects Regression Models***. Thousand Oaks, CA: Sage Publications.

Almeida, P., & Kogut, B. 1999. Localization of Knowledge and the Mobility of Engineers in Regional Networks. ***Management Science***, 45(7): 905-917.

Althouse. 1983. Semiconductor Wafer and Die Handling Method and Means. In USPTO (Ed.). United States.

Amabile, T. 1996. ***Creativity in Context***. Boulder, Co.: Westview Press.

Anderson, P., & Tushman, M. L. 1990. Technological Discontinuities and Dominant Designs: A Cyclical Model of Technological Change. ***Administrative Science Quarterly***, 35(4): 604-633.

Anselin, L., Varga, A., & Acs, Z. 1997. Local Geographic Spillovers between University Research and High Technology Innovations. ***Journal of Urban Economics***, 42(3): 422-448.

Arrow, K. J. 1962a. The Economic Implications of Learning by Doing. ***The Review of Economic Studies***, 29(3): 155-173.

Arrow, K. J. 1962b. Economic Welfare and the Allocation of Resources for Innovation. In R. R. Nelson (Ed.), ***The Rate and Direction of Inventive Activity***. Princeton Princeton University Press.

Arthur, W. B. 1990. Positive Feedbacks in the Economy. ***Scientific American***, 262(2).

Arthur, W. B. 2007. The structure of invention. ***Research Policy***, 36(2): 274-287.

Asheim, B. T. 2005. The Geography of Innovation: Regional Innovation Systems. In J. Fagerberg, D. C. Mowery, & R. R. Nelson (Eds.), ***The Oxford Handbook of Innovation,***. Oxford: Oxford University Press.

Audia, P. G., Freeman, J. H., & Reynolds, P. D. 2006. Organizational Foundings in Community Context: Instruments Manufacturers and Their Interrelationship with Other Organizations. ***Administrative Science Quarterly***, 51(3): 381-419.

Audretsch, D. B., & Feldman, M. P. 1996. R&D Spillovers and the Geography of Innovation and Production. ***The American Economic Review***, 86(3): 630-640.

Bacon, F. 1974. New Atlantis. In A. Johnston (Ed.), ***Bacon: The Advancement of Learning and New Atlantis***. Oxford: Claredon Press.

Baptista, R., & Swann, P. 1998. Do firms in clusters innovate more? ***Research Policy***, 27(5): 525-540.

Barnett, W. P., & Hansen, M. T. 1996. The red queen in organizational evolution. ***Strategic Management Journal***, 17(S1): 139-157.

Baum, J. A. C., & Mezias, S. J. 1992. Localized Competition and Organizational Failure in the Manhattan Hotel Industry, 1898-1990. ***Administrative Science Quarterly***, 37(4): 580-604.

Blau, J. R. 1974. Patterns of Communication Among Theoretical High Energy Physicists. ***Sociometry***, 37(3): 391-406.

Breschi, S., & Lissoni, F. 2003. Mobility and social networks: localised knowledge spillovers revisited: CESPRI Working Paper No. 142.

Breschi, S., & Lissoni, F. 2006. Mobility of inventors and the geography of knowledge spillovers: New evidence on US data. Milan: CESPRI working paper no. 184.

Bresnahan, T. F., & Trajtenberg, M. 1995. General purpose technologies: engines of growth? ***Journal of Econometrics***, 65: 83-108.

Burt, R. S. 1983. ***Corporate profits and co-optation: Networks of market constraints and direc- torate ties in the American economy***. New York: Academic Press.

Burt, R. S. 2000. The Network Structure of Social Capital. In B. M. Staw, & R. I. Sutton (Eds.), ***Research in Organizational Behavior***, Vol. 22: 345. New York: Elsevier Science, Inc.

Burt, R. S. 2005. ***Brokerage and Closure: An Introduction to Social Capital***. New York: Oxford University Press.

Caminal, R., & Vives, X. 1996. Why Market Shares Matter: An Information-Based Theory. ***The RAND Journal of Economics***, 27(2): 221-239.

Carlino, G., Chatterjee, S., & Hunt, R. 2005. Matching and learning in cities: urban density and the rate of invention. ***Federal Reserve Bank of Philadelphia Working Papers***, No. 04-16/R.

Chamberlain, G. 1984. Panel Data. In Z. Griliches, & M. Intriligator (Eds.), ***Handbook of Econometrics***. New York: Elsevier Science Publishing Co.

Clayton, M. C. 1993. The Rigid Disk Drive Industry: A History of Commercial and Technological Turbulence. ***The Business History Review***, 67(4): 531-588.

Combes, P.-P. 2000. Economic Structure and Local Growth: France, 1984-1993. ***Journal of Urban Economics***, 47(3): 329-355.

Cooke, P., Gomez Uranga, M., & Etxebarria, G. 1997. Regional innovation systems: Institutional and organisational dimensions. ***Research Policy***, 26(4-5): 475-491.

Cowan, R., David, P. A., & Foray, D. 2000. The explicit economics of knowledge codification and tacitness. ***Industrial and Corporate Change***, 9(2): 211.

Cyert, R. M., & March, J. G. 1963. ***A Behavioral Theory of the Firm***. Englewood Cliffs, N.J.: Prentice-Hall.

David, P. A. 1990. The Dynamo and the Computer: An Historical Perspective on the Modern Productivity Paradox. ***The American Economic Review***, 80(2): 355-361.

Dewar, R. D., & Dutton, J. E. 1986. The Adoption of Radical and Incremental Innovations: An Empirical Analysis. ***Management Science***, 32(11): 1422-1433.

Dosi, G. 1982. Technological paradigms and technological trajectories : A suggested interpretation of the determinants and directions of technical change. ***Research Policy***, 11(3): 147-162.

Dosi, G. 1988. The nature of the innovative process. In G. Dosi, C. Freeman, R. R. Nelson, G. Silverberg, & L. Soete (Eds.), ***Technical Change and Economic Theory***. New York: Pinter Publishers.

Dumais, G., Ellison, G., & Glaeser, E. L. 1997. Geographic Concentration as Dynamic Process, ***NBER Working Papers***, Vol. 6270. Cambridge, MA: National Bureau of Economic Research, Inc.

Dumais, G., Ellison, G., & Glaeser, E. L. 2002. Geographic Concentration as a Dynamic Process. ***Review of Economics and Statistics***, 84(2): 193-204.

Duranton, G. 2007. Urban Evolutions: The Fast, the Slow, and the Still ***American Economic Review***, 97(1): 197–221.

Duranton, G., & Puga, D. 2000. Diversity and Specialisation in Cities: Why, Where and When Does it Matter? ***Urban Studies***, 37: 533 - 555.

Duranton, G., & Puga, D. 2001. Nursery Cities: Urban Diversity, Process Innovation, and the Life Cycle of Products. ***The American Economic Review***, 91(5): 1454-1477.

Feldman, M. P., & Audretsch, D. B. 1999. Innovation in cities: Science-based diversity, specialization and localized competition. ***European Economic Review***, 43(2): 409-429.

Findeisen, S., & Südekum, J. 2008. Industry churning and the evolution of cities: Evidence for Germany. ***Journal of Urban Economics***, 64(2): 326-339.

Fleming, L. 2001. Recombinant Uncertainty in Technological Search. ***Management Science***, 47(1): 117-132.

Fleming, L., & Frenken, K. 2007. The Evolution of Inventor Networks in the Silicon Valley and Boston Regions. ***Advances in Complex Systems***, 10(1): 53-71.

Fleming, L., King, C., III, & Juda, A. 2007. Small Worlds and Regional Innovation. ***Organization Science***, 18(6): 938.

Florida, R. 2002. ***The Rise of the Creative Class***. New York: Basic Books.

Gilfillan, S. C. 1935. ***Inventing the Ship***. Chicago: Follett

Glaeser, E. L. 2000. The new economics of urban and regional growth. In G. L. Clark, M. P. Feldman, & M. S. Gertler (Eds.), ***The Oxford Handbook of Economic Geography***. New York: Oxford University Press.

Glaeser, E. L., Kallal, H. D., Scheinkman, J. A., & Shleifer, A. 1992. Growth in Cities. ***The Journal of Political Economy***, 100(6): 1126-1152.

Granovetter, M. 1985. ***Getting a Job***. Chicago: University of Chicago Press.

Greene, W. 2004. Fixed effects and bias due to the incidental parameters problem in the Tobit model. ***Econometric Reviews***, 23(2): 125-147.

Greunz, L. 2004. Industrial structure and innovation - evidence from European regions. ***Journal of Evolutionary Economics***, 14(5): 1432-1386.

Griliches, Z. 1992. The Search for R&D Spillovers. ***The Scandinavian Journal of Economics***, 94: S29-S47.

Hall, B. H. 2000. A Note on the Bias in the Herfindahl Based on Count Data: UC Berkeley and Nuffeld College, Oxford.

Hall, B. H., Jaffe, A., & Trajtenberg, M. 2001. The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools ***National Bureau of Economic Research Working Paper Series***, No. 8498.

Hall, B. H., Jaffe, A., & Trajtenberg, M. 2005. Market Value and Patent Citations. ***The RAND Journal of Economics***, 36(1): 16-38.

Hanson, G. H. 2000. Firms, Workers, and the Geographic Concentration of Economic Activity. In G. L. Clark, M. P. Feldman, & M. S. Gertler (Eds.), ***The Oxford Handbook of Economic Geography***: 477-494. New York: Oxford University Press.

Hanson, S., & Pratt, G. 1992. Dynamic Dependencies: A Geographic Investigation of Local Labor Markets. ***Economic Geography***, 68(4): 373-405.

Hargadon, A., & Sutton, R. I. 1997. Technology Brokering and Innovation in a Product Development Firm. ***Administrative Science Quarterly***, 42(4): 716-749.

Head, K., Ries, J., & Swenson, D. 1995. Agglomeration benefits and location choice: Evidence from Japanese manufacturing investments in the United States. ***Journal of International Economics***, 38(3-4): 223-247.

Henderson, R. M., & Clark, K. B. 1990. Architectural Innovation: The Reconfiguration of Existing Product Technologies and the Failure of Established Firms. ***Administrative Science Quarterly***, 35(1): 9-30.

Henderson, V., Kuncoro, A., & Turner, M. 1995. Industrial Development in Cities. ***The Journal of Political Economy***, 103(5): 1067-1090.

Hollander, S. 1965. ***The Sources of Increased Efficiency: A Study of Du Pont Rayon Plants***. Cambridge, MA.: MIT Press.

Hsiao, C. 1986. ***Analysis of Panel Data***. New York: Cambridge University Press.

Jacobs, J. 1968. ***The Economy of Cities***. New York: Random House.

Jaffe, A. B. 1986. Technological Opportunity and Spillovers of R & D: Evidence from Firms' Patents, Profits, and Market Value. ***The American Economic Review***, 76(5): 984-1001.

Jaffe, A. B. 1989. Real Effects of Academic Research. ***The American Economic Review***, 79(5): 957-970.

Jaffe, A. B., Trajtenberg, M., & Henderson, R. 1993. Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. ***The Quarterly Journal of Economics***, 108(3): 577-598.

Kerr, W. R. 2010. Breakthrough inventions and migrating clusters of innovation. ***Journal of Urban Economics***, 67(1): 46-60.

Kline, S. J., & Rosenberg, N. 1986. An Overview of Innovation. In R. Landau, & N. Rosenberg (Eds.), ***The Positive Sum Strategy***. Washington, DC: National Academy Press.

Koestler, A. 1964. ***The Act of Creation***. London: Hutchinson.

Levin, R. C., Klevorick, A. K., Nelson, R. R., Winter, S. G., Gilbert, R., & Griliches, Z. 1987. Appropriating the Returns from Industrial Research and Development. ***Brookings Papers on Economic Activity***: 783-831.

Levinthal, D. A., & March, J. G. 1993. The Myopia of Learning. ***Strategic Management Journal***, 14: 95-112.

Levitt, B., & March, J. G. 1988. Organizational Learning. ***Annual Review of Sociology***, 14: 319-340.

Long, J. S. 1997. ***Regression Models for Categorical and Limited Dependent Variables***. Thousand Oaks, CA: Sage Publications.

Lucas, R. E. 1988. On the mechanics of economic development. ***Journal of Monetary Economics***, 22(1): 3-42.

Lucas, R. E., Jr. 1993. Making a Miracle. ***Econometrica***, 61(2): 251-272.

Mansfield, E. 1977. ***The Production and Application of New Industrial Technology***. New York: Norton.

March, J. G. 1991. Exploration and Exploitation in Organizational Learning. ***Organization Science***, 2(1): 71-87.

Marsh, P. 2007. Hipsville, USA, ***Financial Times***, Weekend ed.: 1-2. New york.

Marshall, A. 1936. ***Principles of Economics***. London: Macmillan and Co.

Martin, R. L. 2000. Local Laour Markets. In G. L. Clark, M. P. Feldman, & M. S. Gertler (Eds.), ***The Oxford Handbook of economic Geography***: 455-476. New York: Oxford university Press.

Marx, M., Strumsky, D., & Fleming, L. 2009. Mobility, Skills, and the Michigan Non-Compete Experiment, Vol. 55: 875.

Masssard, N., & Riou, S. 2002. L'impact des structures locales sur l'innovation en France: Spécialisation ou diversité? ***Revue Régions et Développement***, 16.

McKendrick, D., Doner, R., & Haggard, S. 2000. ***From Silicon Valley to Singapore: Location and Competitive Advantage in the Hard Disk Drive Industry***. Stanford, CA: Stanford Business Books.

Mokyr, J. 1990. ***The Lever of Riches: Technological Creativity and Economic Progress***. New York: Oxford University Press.

Mowery, D., & Rosenberg, N. 1979. The influence of market demand upon innovation: a critical review of some recent empirical studies. ***Research Policy***, 8(2): 102-153.

Mowery, D. C., & Ziedonis, A. A. 2002. Academic patent quality and quantity before and after the Bayh-Dole act in the United States. ***Research Policy***, 31(3): 399-418.

Nelson, R. R. 1959. The Simple Economics of Basic Scientific Research. ***The Journal of Political Economy***, 67(3): 297-306.

Nelson, R. R., & Winter, S. G. 1978. Forces Generating and Limiting Concentration under Schumpeterian Competition. ***The Bell Journal of Economics***, 9(2): 524-548.

Nelson, R. R., & Winter, S. G. 1982. ***An Evolutionary Theory of Economic Change***. Cambridge, MA: Harvard University Press.

Paci, R., & Usai, S. 1999. Externalities, knowledge spillovers and the spatial distribution of innovation. ***GeoJournal***, 49(4): 381-390.

Podolny, J. M., & Toby, E. S. 1995. A Role-Based Ecology of Technological Change. ***The American Journal of Sociology***, 100(5): 1224-1260.

Porter, M. E. 1990. ***Competitive Advantage of Nations*** New York: The Free Press.

Pouder, R., & St. John, C. H. 1996. Hot Spots and Blind Spots: Geographical Clusters of Firms and Innovation. ***The Academy of Management Review***, 21(4): 1192-1225.

Powell, W. W., & Snellman, K. 2004. The Knowledge Economy. ***Annual Review of Sociology***, 30(1): 199-220.

Rogers, E. M. 2003. ***Diffusion of Innovation***. Ney York: Free Press.

Romanelli, E., & Khessina, O. M. 2005. Regional Industrial Identity: Cluster Configurations and Economic Development. ***Organization Science***, 16(4): 344.

Romer, P. M. 1986. Increasing Returns and Long-Run Growth. ***The Journal of Political Economy***, 94(5): 1002-1037.

Rosenberg, N. 1974. Science, Invention and Economic Growth. ***The Economic Journal***, 84(333): 90-108.

Rosenberg, N. 1982. ***Inside the Black Box: Technology and Economics***. New York: Cambridge University Press.

Rosenberg, N. 1990. Why do firms do basic research (with their own money)? ***Research Policy***, 19(2): 165-174.

Rosenkopf, L., & Tushman, M. L. 1998. The Coevolution of Community Networks and Technology: Lessons from the Flight Simulation Industry. ***Ind Corp Change***, 7(2): 311-346.

Rosenthal, S. S., & Strange, W. C. 2003. Geography, Industrial Organization, and Agglomeration. ***The Review of Economics and Statistics***, 85(2): 377-393.

Rosenthal, S. S., & Strange, W. C. 2004. Evidence on the nature and sources of agglomeration economies. In J. V. Henderson, & T. Jacques-François (Eds.), ***Handbook of Regional and Urban Economics***, Vol. Volume 4: 2119-2171: Elsevier.

Rotemberg, J. J., & Saloner, G. 2000. Competition and human capital accumulation: a theory of interregional specialization and trade. ***Regional Science and Urban Economics***, 30(4): 373-404.

Rotkin, I. J., & Dood, K. J. 1999. A History of Patent Classification in the United States Patent and Trademark Office. ***The Patent Documentation Society***.

Saxenian, A. 1996. ***Regional Advantage: Culture and Competition in Silicon Valley and Route 128***. Cambridge, MA: Harvard University Press.

Scherer, F. M. 1965. Firm Size, Market Structure, Opportunity, and the Output of Patented Inventions. ***The American Economic Review***, 55(5): 1097-1125.

Schmookler, J. 1966. ***Invention and Economic Growth***. Cambridge, MA: Harvard University Press.

Schumpeter, J. A. 1934. ***The Theory of Economic Development***. Cambridge, MA: Harvard University Press.

Schumpeter, J. A. 1942. ***Capitalism, Socialism, and Democracy***. New York: Harper and Row Publishers.

Shaver, J. M., & Flyer, F. 2000. Agglomeration economies, firm heterogeneity, and foreign direct investment in the United States. ***Strategic Management Journal***, 21(12): 1175-1193.

Simon, H. A. 1997. ***Administrative Behavior***. New York: Free Press.

Singh, J. 2005. Collaborative Networks as Determinants of Knowledge Diffusion Patterns. ***Management Science***, 51(5): 756-770.

Smith, A. 1981. ***An Inquiry into the Nature and Causes of the Wealth of Nations*** Indianapolis: Liberty Classics.

Sorenson, O., & Fleming, L. 2004. Science and the diffusion of knowledge. ***Research Policy***, 33(10): 1615-1634.

Spotila, J. 2000. Standards for defining metropolitan and micropolitan statistical areas. ***Federal Register***, 65(249).

St. John, C. H., & Pouder, R. W. 2006. Technology Clusters versus Industry Clusters: Resources, Networks, and Regional Advantages. ***Growth and Change***, 37(2): 141-171.

Stuart, T. E., & Podolny, J. M. 1996. Local search and the evolution of technological capabilities. ***Strategic Management Journal***, 17(S1): 21-38.

Sull, D. N. 2001. From community of innovation to community of inertia: the rise and fall of the Akron tire cluster, ***Working Paper 01-025***: Harvard Business School.

Thompson , P. 2006. Patent citations and the geography of knowledge spillovers: Evidence from inventor-and examiner-added citations. ***The Review of Economics and Statistics***, 88(2): 383-388.

Trajtenberg, M., & Henderson, R. 1997. University Versus Corporate Patents: A Window On The Basicness Of Invention. ***Economics of Innovation and New Technology***, 5(1): 19-50.

Tushman, M. L., & Anderson, P. 1986. Technological Discontinuities and Organizational Environments. ***Administrative Science Quarterly***, 31(3): 439-465.

Usher, A. P. 1982. ***A History of Mechanical Inventions***. New york: Dover Publications, Inc.

van der Panne, G., & van Beers, C. 2006. On the Marshall-Jacobs controversy: it takes two to tango. ***Ind Corp Change***, 15(5): 877-890.

Van Maanen, J., & Barley, S. R. 1984. Occupational communities: Culture and control in organizations. In B. Staw, & L. L. Cummings (Eds.), ***Research in Organizational Behavior***: 287-365. Greenwich, CT: JAI Press.

von Hippel, E. 1986. Lead Users: A Source of Novel Product Concepts. ***Management Science***, 32(7): 791-805.

von Hippel, E. 1994. "Sticky Information" and the Locus of Problem Solving: Implications for Innovation. ***Management Science***, 40(4): 429-439.

Wellman, B. 1996. Are personal communities local? A Dumptarian reconsideration. ***Social Networks***, 18(4): 347-354.

Wenger, E. 1998. ***Communities of practice : learning, meaning, and identity***. Cambridge: Cambridge University Press.

Wolfe, T. 1983. The Tinkerings of Robert Noyce: How the Sun Rose on the Silicon Valley, ***Esquire Magazine***: 346-374.

Wooldridge, J. M. 2002. ***Econometric Analysis of Cross Section and Panel Data***. Cambridge, MA: The MIT Press.

Zucker, L. G., Darby, M. R., & Brewer, M. B. 1998. Intellectual Human Capital and the Birth of U.S. Biotechnology Enterprises. ***The American Economic Review***, 88(1): 290-306.

6 APPENDICES

Table 6-1 Change in Local Technical Community Size, 77-97

Application Year	Obs	Mean	Std. Dev.	Min	Max	Mean Change
1977	12058	16.83	25.77	1	216	
1978	12004	16.25	25.33	1	214	-3.44%
1979	11933	15.95	25.46	1	223	-1.86%
1980	11949	15.87	25.32	1	243	-0.48%
1981	11229	16.02	26.09	1	252	0.96%
1982	11152	17.19	27.99	1	238	7.29%
1983	10825	17.06	29.80	1	269	-0.79%
1984	11090	18.33	33.00	1	300	7.46%
1985	11395	20.61	39.89	1	357	12.45%
1986	11736	21.17	40.99	1	377	2.69%
1987	12351	22.92	45.66	1	426	8.31%
1988	13289	23.90	43.69	1	394	4.24%
1989	13805	26.67	49.92	1	460	11.62%
1990	14252	28.18	48.93	1	441	5.63%
1991	14030	30.86	52.81	1	452	9.51%
1992	14179	36.58	62.68	1	494	18.55%
1993	14482	40.71	71.45	1	566	11.29%
1994	15209	51.37	89.90	1	599	26.20%
1995	15424	74.36	130.20	1	839	44.74%
1996	14812	61.98	99.12	1	539	-16.66%
1997	13942	55.63	93.58	1	562	-10.24%

Note: For all years, the New York CSA drug, bio-affecting and body treating compositions (patent class 514) is the largest community.

Table 6-2 Change in Surrounding Community Diversity, 77-97

Application Year	Obs	Mean	Std. Dev.	Min	Max	Mean Change	Community with most surrounding diversity
1977	11987	63.4	48.3	1	170.7		Los Angeles CSA; Measuring and Testing (Class 73)
1978	11922	62.2	45.8	1	164.1	-3.87%	New York CSA; Drug, Bio-affecting compositions (Class 514)
1979	11852	61.9	46.2	1	168.9	2.93%	Los Angeles CSA; Measuring and Testing (Class 73)
1980	11871	60.4	44.3	1	160.8	-4.82%	Los Angeles CSA; Radiant Energy (Class 250)
1981	11150	58.6	43.0	1	159.9	-0.57%	Los Angeles CSA; Measuring and Testing (Class 73)
1982	11077	57.1	41.5	1	159.2	-0.39%	Los Angeles CSA; Measuring and Testing (Class 73)
1983	10753	55.9	41.4	1	155.0	-2.69%	Los Angeles CSA; Measuring and Testing (Class 73)
1984	11016	55.3	40.4	1	155.6	0.42%	Los Angeles CSA; Measuring and Testing (Class 73)
1985	11315	52.9	37.5	1	150.9	-3.05%	Los Angeles CSA; Measuring and Testing (Class 73)
1986	11681	52.9	36.9	1	148.3	-1.73%	Los Angeles CSA; Radiant Energy (Class 250)
1987	12284	53.2	36.3	1	146.8	-0.97%	Los Angeles CSA; Optical: Systems and Elements (Class 359)
1988	13226	54.2	35.6	1	146.9	0.06%	Los Angeles CSA; Surgery (Class 604)
1989	13754	52.0	34.0	1	141.5	-3.67%	Los Angeles CSA; Optical: Systems and Elements (Class 359)
1990	14203	53.3	34.0	1	144.6	2.21%	Los Angeles CSA; Surgery (Class 604)
1991	13976	51.5	32.8	1	139.3	-3.73%	Los Angeles CSA; Surgery (Class 604)
1992	14121	50.3	31.5	1	142.0	1.96%	Los Angeles CSA; Surgery (Class 604)
1993	14448	48.1	30.4	1	141.4	-0.39%	Los Angeles CSA; Surgery (Class 604)
1994	15162	45.9	28.7	1	129.8	-8.21%	Los Angeles CSA; Surgery (Class 604)
1995	15384	43.7	26.8	1	126.1	-2.88%	Los Angeles CSA; Chemistry: Molecular Biology (Class 435)
1996	14764	46.6	29.0	1	134.9	6.98%	Los Angeles CSA; Comm.: Directive Radio Wave (Class 342)
1997	13894	47.2	30.4	1	134.1	-0.60%	Los Angeles CSA; Surgery (Class 604)

Table 6-3 Change in the 5-year average of patent class pair frequencies, 77-97

Application Year	Obs	Mean	Std. Dev.	Min	Max	Mean Change
1977	35879	2.73	5.91	1	167	
1978	34677	2.93	5.97	1	176	7.19%
1979	33937	3.23	7.19	1	176	10.25%
1980	33765	3.49	8.66	1	171	7.87%
1981	31851	3.41	7.80	1	200	-2.29%
1982	31687	3.61	8.92	1	330	6.07%
1983	29827	3.61	8.58	1	225	-0.11%
1984	31278	3.75	9.69	1	352	3.86%
1985	32241	4.04	11.22	1	369	7.89%
1986	33213	4.22	12.80	1	368	4.46%
1987	36015	4.43	12.22	1	378	4.74%
1988	39602	4.71	11.66	1	394	6.44%
1989	42344	5.41	13.69	1	428	14.77%
1990	44512	5.92	15.08	1	411	9.50%
1991	44634	6.59	18.16	1	410	11.38%
1992	47060	6.87	19.27	1	514	4.25%
1993	48784	7.02	19.69	1	569	2.15%
1994	54202	7.97	23.91	1	586	13.54%
1995	62510	10.02	36.05	1	749	25.67%
1996	57477	9.50	36.65	1	870	-5.22%
1997	49968	11.71	48.99	1	1094	23.33%

Table 6-4 Change in patent generality, 77-97

Application Year	Obs	Mean	Std. Dev.	Min	Max	Mean Change
1977	36670	0.45	0.36	0	1	
1978	35142	0.45	0.36	0	1	-0.65%
1979	34412	0.46	0.36	0	1	0.91%
1980	34257	0.46	0.36	0	1	-0.09%
1981	32328	0.46	0.36	0	1	1.00%
1982	32194	0.46	0.36	0	1	-0.34%
1983	30400	0.46	0.35	0	1	1.17%
1984	31801	0.47	0.35	0	1	0.61%
1985	32866	0.47	0.35	0	1	0.08%
1986	33870	0.47	0.35	0	1	-0.36%
1987	36737	0.47	0.35	0	1	0.34%
1988	40552	0.46	0.36	0	1	-1.71%
1989	43766	0.46	0.36	0	1	0.65%
1990	45632	0.45	0.36	0	1	-2.05%
1991	46019	0.44	0.36	0	1	-2.11%
1992	48553	0.44	0.37	0	1	-1.45%
1993	50195	0.42	0.37	0	1	-3.29%
1994	55796	0.40	0.38	0	1	-5.63%
1995	64935	0.36	0.38	0	1	-9.52%
1996	59368	0.32	0.38	0	1	-11.13%
1997	51744	0.26	0.37	0	1	-18.67%

Table 6-5 OLS Estimation: Novelty and Community Structure interactions

	4	5	6	7	8
Size_Community	-0.0564 ***	-0.0461 ***	-0.0832 ***	-0.0833 ***	-0.0539 ***
	0.0060	0.0065	0.0064	0.0064	0.0072
Diversity_Community	0.0002	0.0001	0.0004	0.0005 +	0.0002
	0.0003	0.0003	0.0003	0.0003	0.0003
Size*Diversity	0.0002 +	-0.0002	0.0002	0.0002	-0.0002
	0.0001		0.0001	0.0001	0.0001
Size*Patents	-0.0134 ***	-0.0199 ***			-0.0181 ***
	0.0029	0.0032			0.0032
Div*Patents		0.0008 ***			0.0007 ***
		0.0002			0.0002
Size*Individuals			0.0283 ***	0.0316 ***	0.0248 ***
			0.0044	0.0047	0.0050
Div*Individuals				-0.0002 *	-0.0001
				0.0001	0.0001
Patents	-0.0840 **	-0.0809 **	-0.1045 **	-0.1043 **	-0.0817 **
	0.0355	0.0351	0.0334	0.0334	0.0352
Employment	0.0108	0.0276	0.0254	0.0251	0.0254
	0.0795	0.0801	0.0774	0.0775	0.0807
CoTownID	-0.1002 ***	-0.0979 ***	-0.1027 ***	-0.1029 ***	-0.0981 ***
	0.0301	0.0300	0.0301	0.0301	0.0300
IndividualID	0.1301 ***	0.1297 ***	0.1019 ***	0.1034 ***	0.1093 ***
	0.0077	0.0076	0.0072	0.0071	0.0071
GovernmentID	0.1480 ***	0.1470 ***	0.1458 ***	0.1457 ***	0.1449 ***
	0.0197	0.0193	0.0190	0.0190	0.0188
SingleID	-0.5624 ***	-0.5616 ***	-0.5623 ***	-0.5622 ***	-0.5615 ***
	0.0159	0.0159	0.0160	0.0160	0.0159
Subclass Count	0.0057 *	0.0059 *	0.0056 *	0.0055 *	0.0058 *
	0.0024	0.0024	0.0024	0.0024	0.0024
Science Citations	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	0.0001	0.0001	0.0001	0.0001	0.0001
Constant	-1.3121 ***	-1.2296 ***	-1.3517 ***	-1.3489 ***	-1.2246 ***
	0.2684	0.2717	0.2646	0.2642	0.2716
R-squared	0.2206	0.2210	0.2206	0.2206	0.2212
Observations	874496	874496	874496	874496	874496

DV is the log of the 5-year average frequency that a patent's technology class pairs occurred.
Robust standard errors (clulstered by metorpolitan area) in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%; *** significant at .5%.
All equations include year, metropolitan area and technology class dummy variables.

Table 6-6 OLS Estimation: Novelty and patenting class subsamples

OLS Estimation: Novelty and Community Structure patenting subsamples

	High Patenting Classes (>369)				Low Patenting Classes (<369)			
	9		10		11		12	
Size_Community	-0.0810	***	-0.0813	***	-0.0677	***	-0.0727	***
	0.0051		0.0052		0.0043		0.0047	
Diversity_Community	0.0011	*	0.0010	**	0.0001		-0.0001	
	0.0004				0.0002		0.0002	
Size*Diversity			0.0000				0.0002	**
			0.0002				0.0001	
Patents	-0.2660	***	-0.2657	***	-0.2343	***	-0.2355	***
	0.0322		0.0324		0.0140		0.0142	
Employment	0.0166		0.0157		-0.0328		-0.0357	
	0.0697		0.0708		0.0266		0.0270	
CoTownID	-0.0742	**	-0.0746	**	-0.1625	***	-0.1661	***
	0.0253		0.0254		0.0479		0.0470	
IndividualID	0.1481	***	0.1482	***	0.1028	***	0.1023	***
	0.0105		0.0106		0.0059		0.0060	
GovernmentID	0.1549	***	0.1550	***	0.1300	***	0.1306	***
	0.0312		0.0312		0.0130		0.0130	
SingleID	-0.5327	***	-0.5327	***	-0.5560	***	-0.5560	***
	0.0265		0.0265		0.0122		0.0122	
Subclass Count	0.0213	***	0.0213	***	0.0116	***	0.0116	***
	0.0012		0.0012		0.0017		0.0017	
Science Citations	-0.0002	*	-0.0002	*	0.0001		0.0001	
	0.0001		0.0001		0.0001		0.0001	
Constant	-0.7333		-0.7383		-1.6725	***	-1.6851	***
					0.2244		0.2246	
R-squared	0.2139		0.2139		0.2791		0.2791	
Observations	436887		436887		436004		436004	

DV is the log of the 5-year average frequency that a patent's technology class pairs occurred.
Robust standard errors (clulstered by metorpolitan area) in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%; *** significant at .5%.
All equations include year, metropolitan area and technology class dummy variables.

Table 6-7 OLS Estimation: Novelty and inventor type subsamples

	Individuals				Corporations			
	13		14		15		16	
Size_Community	-0.0376	***	-0.0435	***	-0.0807	***	-0.0839	***
	0.0041		0.0042		0.0065		0.0071	
Diversity_Community	0.0002		0.0000		0.0009	*	0.0006	+
	0.0002		0.0002		0.0004		0.0004	
Size*Diversity			0.0002	+			0.0002	
			0.0001				0.0001	
Patents	-0.2425	***	-0.2407	***	-0.0750	+	-0.0737	+
	0.0119		0.0118		0.0384		0.0386	
Employment	-0.0149		-0.0156		0.0439		0.0437	
	0.0260		0.0263		0.1073		0.1088	
CoTownID	-0.2344		-0.2465		-0.0913	***	-0.0938	***
	0.2202		0.2170		0.0257		0.0252	
SingleID	-0.5854	***	-0.5851	***	-0.5429	***	-0.5428	***
	0.0125		0.0124		0.0226		0.0225	
Subclass Count	0.0215	***	0.0215	***	0.0039		0.0039	
	0.0013		0.0013		0.0026		0.0026	
Science Citations	0.0000		0.0000		-0.0002	+	-0.0002	+
	0.0001		0.0001		0.0001		0.0001	
Constant	-1.6407	***	-1.6484	***	-1.2763	***	-1.2827	***
	0.4858		0.4824		0.3036		0.3030	
R-squared	0.204		0.204		0.215		0.215	
Observations	219936		219936		636870		636870	

DV is the log of the 5-year average frequency that a patent's technology class pairs occurred.
Robust standard errors (clulstered by metorpolitan area) in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%; *** significant at .5%.
All equations include year, metropolitan area and technology class dummy variables.

Table 6-8 Tobit Estimation: Generality and Community Structure interactions

	4		5		6		7	
Size_Community	-0.025	***	-0.027	***	-0.015	***	-0.016	***
	0.004		0.005		0.005		0.005	
Diversity_Community	-0.001	***	-0.001	***	-0.001	***	-0.001	***
	0.000		0.000		0.000		0.000	
Size*Diversity	0.000		0.000		0.000		0.000	
	0.000		0.000		0.000		0.000	
Size*Patents	0.006	***	0.006	***				
	0.002		0.001					
Size*Individuals			0.008	***				
			0.003					
Div*Patents					0.0001		0.000	
					0.0001		0.000	
Div*Individuals							0.0003	***
							0.0001	
Patents	0.009	***	0.008	***	0.012	***	0.012	***
	0.003		0.003		0.002		0.002	
Employment	0.091	***	0.091	***	0.088	***	0.087	***
	0.027		0.027		0.027		0.027	
CoTownID	-0.029	+	-0.029	+	-0.028	+	-0.027	+
	0.015		0.015		0.015		0.015	
IndividualID	-0.066	***	-0.074	***	-0.066	***	-0.072	***
	0.005		0.004		0.005		0.004	
GovernmentID	-0.077	***	-0.077	***	-0.077	***	-0.077	***
	0.010		0.010		0.010		0.010	
SingleID	-0.149	***	-0.149	***	-0.149	***	-0.149	***
	0.005		0.005		0.005		0.005	
Subclass Count	0.019	***	0.019	***	0.019	***	0.019	***
	0.001		0.001		0.001		0.001	
Science Citations	0.000	***	0.000	***	0.000	***	0.000	***
	0.000		0.000		0.000		0.000	
Constant	0.207	***	0.210	***	0.204	***	0.203	***
	0.044		0.044		0.044		0.044	
Pseudo R-squared	0.0531		0.0531		0.053		0.0531	
Observations	874578		874578		874578		874578	

Robust standard errors (clulstered by metorpolitan area) in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%; *** significant at .5%.
All equations include year, metropolitan area and technology class dummy variables.

Table 6-9 Tobit Estimation: Generality and patenting class subsamples

	High Patenting				Low Patenting			
	8		9		10		11	
Size_Community	-0.015	*	-0.016	*	-0.020	***	-0.017	***
	0.006		0.007		0.003		0.004	
Diversity_Community	-0.001	***	-0.0011	***	-0.001	***	-0.0005	*
	0.000		0.0004		0.000		0.0002	
Size*Diversity			0.000				-0.0001	*
			0.000				0.0000	
Patents	0.027	***	0.026	***	-0.007	*	-0.006	*
	0.006		0.006		0.003		0.003	
Employment	0.107	***	0.105	***	0.041	+	0.043	+
	0.034		0.035		0.023		0.024	
CoTownID	-0.029	*	-0.030	*	-0.019		-0.017	
	0.014		0.013		0.024		0.024	
IndividualID	-0.072	***	-0.072	***	-0.058	***	-0.057	***
	0.005		0.005		0.004		0.004	
GovernmentID	-0.078	***	-0.078	***	-0.069	***	-0.070	***
	0.011		0.011		0.011		0.011	
SingleID	-0.110	***	-0.110	***	-0.178	***	-0.178	***
	0.008		0.008		0.004		0.004	
Subclass Count	0.021	***	0.021	***	0.018	***	0.018	***
	0.001		0.001		0.001		0.001	
Science Citations	0.000	**	0.000	**	0.000	+	0.000	+
	0.000		0.000		0.000		0.000	
Constant	0.316	***	0.310	***	0.202	***	0.209	***
	0.016		0.018		0.043		0.042	
Pseudo R-squared	0.0585		0.0551		0.0550		0.0551	
Observations	436947		436947		436026		436026	

Robust standard errors (clulstered by metorpolitan area) in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%; *** significant at .5%.
All equations include year, metropolitan area and technology class dummy variables.

Table 6-10 Tobit Estimation: Generality and inventor type subsamples

	Individuals				Corporate			
	12		13		14		15	
Size_Community	0.007	+	0.008	+	-0.022	***	-0.023	***
	0.004		0.004		0.005		0.005	
Diversity_Community	0.000		-0.0002		-0.001	***	-0.0012	***
	0.000		0.0002		0.000		0.0003	
Size*Diversity			0.000				0.0000	
			0.000				0.0001	
Patents	-0.019	***	-0.018	***	0.021	***	0.021	***
	0.003		0.003		0.003		0.003	
Employment	-0.003		-0.003		0.129	***	0.129	***
	0.022		0.022		0.029		0.029	
SingleID	-0.159	***	-0.159	***	-0.134	***	-0.134	***
	0.007		0.007		0.006		0.006	
Subclass Count	0.039	***	0.039	***	0.017	***	0.017	***
	0.001		0.001		0.001		0.001	
Science Citations	0.000	*	0.000	*	0.000	*	0.000	*
	0.000		0.000		0.000		0.000	
Constant	0.064		0.067		0.236	***	0.235	***
	0.046		0.047		0.047		0.047	
Pseudo R-squared	0.057		0.057		0.0534		0.0534	
Observations	219958		219958		636929		636929	

Robust standard errors (clulstered by metorpolitan area) in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%; *** significant at .5%
All equations include year, metropolitan area and technology class dummy variables.

Table 6-11 Change in Local Industry Size

Application Year	Obs	Mean	Std. Dev.	Min	Max	Mean Change	Largest Local Industry
1977	14635	49187	64710	3	426792		New York Health Services
1978	13795	52240	69106	0	390867	6.21%	New York Business Services
1979	13580	55147	75002	3	437709	5.57%	New York Business Services
1980	13516	53465	71117	0	444269	-3.05%	New York Business Services
1981	13035	51493	71323	3	512881	-3.69%	New York Business Services
1982	13309	51179	72647	3	485174	-0.61%	New York Business Services
1983	11952	50828	77216	3	505007	-0.69%	New York Business Services
1984	12307	49738	76789	3	591278	-2.14%	New York Health Services
1985	12479	51853	82059	3	618358	4.25%	New York Health Services
1986	12273	52217	84498	3	637675	0.70%	New York Health Services
1987	12805	52249	88955	3	670302	0.06%	New York Health Services
1988	14132	47336	72320	3	712581	-9.40%	New York Health Services
1989	15135	48598	73719	3	857673	2.67%	New York Health Services
1990	16079	48097	75472	3	881124	-1.03%	New York Health Services
1991	16439	51347	85730	3	910236	6.76%	New York Health Services
1992	17464	52639	87055	3	936861	2.52%	New York Health Services
1993	17659	50137	79961	3	968166	-4.75%	New York Health Services
1994	19886	57242	102787	3	1002545	14.17%	New York Health Services
1995	24649	65127	120119	3	1004357	13.77%	New York Health Services
1996	22613	70616	126276	3	1013335	8.43%	New York Health Services
1997	19077	74381	135407	3	1018774	5.33%	New York Health Services

Table 6-12 Change in Surrounding Industry Diversity

Application Year	Obs	Mean	Std. Dev.	Min	Max	Mean Change	Most surrounding industry diversity
1977	14635	29.22	5.70	3.13	36.66		New York Health Services
1978	13804	29.22	5.10	3.58	35.55	-0.01%	York-Gettysburg, PA Industrial machinery and equipment
1979	13580	29.02	5.23	3.70	35.22	-0.70%	Los Angelas Health Services
1980	13520	28.78	4.98	3.78	34.84	-0.81%	New York Business Services
1981	13035	28.36	4.96	3.39	35.01	-1.47%	New York Business Services
1982	13309	27.93	4.70	5.94	34.75	-1.51%	Charlotte, NC Textile mill products
1983	11952	27.40	4.43	3.31	34.40	-1.92%	Charlotte, NC Textile mill products
1984	12307	27.47	4.26	4.24	34.96	0.28%	Charlotte, NC Textile mill products
1985	12479	27.40	3.94	4.29	35.62	-0.25%	Charlotte, NC Textile mill products
1986	12273	27.13	3.96	4.03	35.71	-1.00%	Charlotte, NC Textile mill products
1987	12805	26.88	3.59	4.45	35.48	-0.92%	Charlotte, NC Textile mill products
1988	14132	27.40	3.63	5.98	35.25	1.93%	Charlotte, NC Textile mill products
1989	15135	26.25	3.25	6.31	34.29	-4.20%	Charlotte, NC Textile mill products
1990	16079	26.00	3.05	5.09	34.32	-0.93%	Charlotte, NC Textile mill products
1991	16439	25.28	3.14	4.12	33.13	-2.77%	New York Health Services
1992	17464	24.67	3.08	6.68	32.87	-2.42%	New York Health Services
1993	17659	24.28	2.73	7.81	31.98	-1.56%	New York Health Services
1994	19886	23.93	2.63	5.25	31.26	-1.46%	New York Health Services
1995	24649	23.97	2.60	5.48	30.85	0.15%	Charlotte, NC Textile mill products
1996	22613	23.74	2.60	5.43	31.37	-0.95%	Charlotte, NC Business Services
1997	19077	23.24	2.57	5.45	30.91	-2.08%	Charlotte, NC Business Services

Table 6-13 Change in Local Industry Specialization

Application Year	Obs	Mean	Std. Dev.	Min	Max	Mean Change	Most specialized local industry
1977	14635	2.57	4.88	0.00	66.51		Borger, TX Petroleum and coal products
1978	13804	2.72	5.66	0.00	75.08	5.99%	Richmond,VA Tobacco products
1979	13580	2.53	5.14	0.00	80.43	-7.08%	Borger, TX Petroleum and coal products
1980	13520	2.53	5.33	0.00	69.36	0.10%	Richmond,VA Tobacco products
1981	13035	2.46	5.19	0.00	72.16	-2.71%	Richmond,VA Tobacco products
1982	13309	2.46	5.02	0.00	73.55	-0.29%	Richmond,VA Tobacco products
1983	11952	2.43	4.66	0.00	76.62	-1.08%	Borger, TX Petroleum and coal products
1984	12307	2.34	4.51	0.00	86.06	-3.91%	Borger, TX Petroleum and coal products
1985	12479	2.51	5.06	0.00	97.00	7.63%	Borger, TX Petroleum and coal products
1986	12273	2.65	5.17	0.00	79.10	5.39%	Borger, TX Petroleum and coal products
1987	12805	2.67	5.72	0.00	93.93	0.87%	Borger, TX Petroleum and coal products
1988	14132	2.71	10.31	0.00	616.58	1.27%	Richmond,VA Tobacco products
1989	15135	2.58	4.92	0.01	89.63	-4.67%	Borger, TX Petroleum and coal products
1990	16079	2.65	7.38	0.00	623.73	2.66%	Borger, TX Petroleum and coal products
1991	16439	2.77	8.55	0.01	637.63	4.75%	Elko, NV Metal mining
1992	17464	2.61	5.61	0.00	85.73	-6.05%	Richmond,VA Tobacco products
1993	17659	2.30	3.67	0.00	124.65	-11.93%	Borger, TX Petroleum and coal products
1994	19886	2.28	7.48	0.00	650.29	-0.46%	Elko, NV Metal mining
1995	24649	2.20	3.64	0.00	89.89	-3.63%	Borger, TX Petroleum and coal products
1996	22613	2.24	3.05	0.00	144.78	1.66%	Borger, TX Petroleum and coal products
1997	19077	2.31	3.03	0.00	78.09	3.15%	Dalton, GA Textile mill products

Table 6-14 Change in Local Industry Competition

Application Year	Obs	Mean	Std. Dev.	Min	Max	Mean Change
1977	14635	0.02	0.03	0.0003	0.73	
1978	13795	0.02	0.03	0.0003	0.40	-11.95%
1979	13580	0.02	0.03	0.0003	0.40	-2.02%
1980	13516	0.02	0.03	0.0003	0.50	2.11%
1981	13035	0.02	0.03	0.0003	0.40	1.25%
1982	13309	0.02	0.03	0.0004	0.73	8.52%
1983	11952	0.02	0.03	0.0004	0.42	10.41%
1984	12307	0.02	0.03	0.0005	0.67	-1.16%
1985	12479	0.02	0.03	0.0004	0.40	-3.41%
1986	12273	0.02	0.03	0.0004	0.40	0.59%
1987	12805	0.02	0.03	0.0004	0.40	4.03%
1988	14132	0.02	0.02	0.0004	0.75	-9.08%
1989	15135	0.02	0.02	0.0003	0.40	-3.47%
1990	16079	0.02	0.02	0.0004	0.40	5.41%
1991	16439	0.02	0.02	0.0004	0.40	3.18%
1992	17464	0.02	0.02	0.0004	0.60	7.75%
1993	17659	0.02	0.02	0.0003	0.40	1.90%
1994	19886	0.02	0.02	0.0003	0.40	6.19%
1995	24649	0.02	0.02	0.0003	0.50	0.10%
1996	22613	0.02	0.02	0.0002	0.40	-0.62%
1997	19077	0.02	0.02	0.0005	0.40	-4.27%

Note: Mulitple local industries have max competition measure

Table 6-15 Change in Corporate Patent Novelty (natural log)

Application Year	Obs	Mean	Std. Dev.	Min	Max	Mean Change
1977	14635	-0.62	0.77	-5.1	0	
1978	13804	-0.67	0.82	-5.2	0	8.92%
1979	13580	-0.74	0.87	-5.2	0	9.35%
1980	13520	-0.74	0.88	-5.1	0	1.25%
1981	13035	-0.79	0.91	-5.3	0	5.78%
1982	13309	-0.81	0.92	-5.8	0	2.46%
1983	11952	-0.82	0.92	-5.4	0	1.85%
1984	12307	-0.84	0.94	-5.9	0	1.66%
1985	12479	-0.87	0.99	-5.9	0	4.46%
1986	12273	-0.89	0.99	-5.9	0	2.49%
1987	12805	-0.94	1.00	-5.9	0	4.57%
1988	14132	-1.00	1.06	-6	0	7.10%
1989	15135	-1.09	1.11	-6.1	0	9.09%
1990	16077	-1.16	1.15	-6	0	6.44%
1991	16439	-1.20	1.20	-6	0	3.43%
1992	17462	-1.19	1.21	-6.2	0	-1.21%
1993	17658	-1.17	1.20	-6.3	0	-1.97%
1994	19880	-1.19	1.21	-6.4	0	1.85%
1995	24640	-1.26	1.27	-6.6	0	5.87%
1996	22604	-1.24	1.22	-6.8	0	-1.45%
1997	19072	-1.36	1.27	-7	0	9.50%

Table 6-16 Change in Corporate Patent Generality (censored and bias corrected)

Application Year	Obs	Mean	Std. Dev.	Min	Max	Mean Change
1977	14635	0.47	0.36	0	1	
1978	13804	0.47	0.36	0	1	-1.62%
1979	13580	0.47	0.35	0	1	1.88%
1980	13520	0.48	0.35	0	1	0.83%
1981	13035	0.48	0.35	0	1	0.20%
1982	13309	0.47	0.35	0	1	-1.74%
1983	11952	0.48	0.35	0	1	2.15%
1984	12307	0.48	0.35	0	1	-0.13%
1985	12479	0.48	0.35	0	1	0.70%
1986	12273	0.49	0.35	0	1	0.52%
1987	12805	0.49	0.34	0	1	0.46%
1988	14132	0.48	0.35	0	1	-2.19%
1989	15135	0.48	0.35	0	1	-0.57%
1990	16079	0.47	0.35	0	1	-0.73%
1991	16439	0.46	0.35	0	1	-2.69%
1992	17464	0.46	0.36	0	1	-0.77%
1993	17659	0.45	0.36	0	1	-0.39%
1994	19886	0.44	0.36	0	1	-3.93%
1995	24649	0.39	0.38	0	1	-9.49%
1996	22613	0.36	0.38	0	1	-7.86%
1997	19077	0.30	0.38	0	1	-16.67%

Table 6-17 OLS Estimation: Novelty as a function of local industry structure; without MA fixed effects or local employment control (cross-MA variation)

	1		2		3		4	
$Size\_Industry_{i,l,t}$	-0.017	*	-0.021	***	-0.022	***	-0.025	***
	0.007		0.007		0.007		0.008	
$Div\_Industry_{i,l,t}$			0.003	+	0.004	*	0.004	*
			0.002		0.002		0.002	
$Spec\_Industry_{i,l,t}$					0.001		0.001	
					0.001		0.001	
$Comp\_Industry_{i,l,t}$							-0.546	*
							0.222	
$\#Patents_{k,t}$	-0.021	+	-0.020	+	-0.020	+	-0.020	+
	0.012		0.012		0.012		0.012	
$SingleID_p$	-0.559	***	-0.560	***	-0.559	***	-0.559	***
	0.036		0.036		0.036		0.036	
$CoTownID_l$	-0.112	*	-0.105	*	-0.107	*	-0.110	**
	0.046		0.043		0.044		0.042	
$\#Subclasses_p$	-0.005	+	-0.005	+	-0.005	+	-0.005	+
	0.003		0.003		0.003		0.003	
$\#Employment_{l,t}$								
Constant	-1.151	***	-1.155	***	-1.154	***	-1.137	***
	0.132		0.132		0.132		0.132	
Observations	322744		322744		322744		322744	
Adj R-squared	0.127		0.127		0.127		0.127	

Subscripts *t* (time), *i* (2 digit sic), *l* (metropolitan area), *p* (patent).

The DV is the natural log of the average frequency that a patent's technology class pairs occurred over 5 years.
Robust standard errors (clustered by metropolitan area) in parentheses;+ significant at 10%; * significant at 5%; ** significant at 1%, *** significant at .5%.

All equations include year, technology subclass, and 2-digit industry code dummy variables.

Table 6-18 OLS Estimation: Novelty and patenting class subsample (cross-MA variation)

	High-patenting technology class				Low-patenting technology class			
	5	6	7	8	9	10	11	12
$Size\_Industry_{i,l,t}$	-0.016 *	-0.018 **	-0.020 **	-0.023 ***	-0.018 *	-0.024 ***	-0.024 ***	-0.027 ***
	0.008	0.007	0.007	0.008	0.008	0.008	0.007	0.008
$Div\_Industry_{i,l,t}$		0.002	0.003	0.003		0.004 *	0.005 *	0.005 *
		0.003	0.003	0.003		0.002	0.002	0.002
$Spec\_Industry_{i,l,t}$			0.002	0.002			0.000	0.000
			0.001	0.001			0.001	0.001
$Comp\_Industry_{i,l,t}$				-0.675 *				-0.455
				0.280				0.282
$\#Patents_{k,t}$	-0.088 **	-0.087 **	-0.087 **	-0.087 **	-0.030 *	-0.030 *	-0.030 *	-0.030 *
	0.032	0.032	0.032	0.031	0.015	0.015	0.015	0.015
$SingleID_p$	-0.583 ***	-0.583 ***	-0.583 ***	-0.583 ***	-0.537 ***	-0.537 ***	-0.537 ***	-0.537 ***
	0.053	0.053	0.053	0.053	0.025	0.025	0.025	0.025
$CoTownID_l$	-0.126 ***	-0.122 ***	-0.127 ***	-0.130 ***	-0.084	-0.071	-0.071	-0.074
	0.034	0.033	0.034	0.033	0.064	0.062	0.062	0.060
$\#Subclasses_p$	0.020 ***	0.020 ***	0.020 ***	0.020 ***	-0.017 ***	-0.017 ***	-0.017 ***	-0.017 ***
	0.002	0.002	0.002	0.002	0.003	0.003	0.003	0.003
$\#Employment_{l,t}$								
Constant	-0.515 ***	-0.519 ***	-0.518 ***	-0.472 ***	-1.162 ***	-1.153 ***	-1.152 ***	-1.137 ***
	0.143	0.142	0.142	0.147	0.110	0.111	0.111	0.111
Observations	179709	179709	179709	179709	143080	143080	143080	143080
Adj R-squared	0.137	0.137	0.137	0.137	0.139	0.139	0.139	0.139

Subscripts t (time), k (patent class), l (metropolitan area), p (patent).

Robust standard errors (clustered by metropolitan area) in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%, *** significant at .5%.

All equations include year, technology subclass, and 2-digit industry code.

Table 6-19 OLS Estimation: Novelty and MA subsamples (cross-MA variation)

	CSA				CBSA			
	13	14	15	16	17	18	19	20
$Size\_Industry_{i,l,t}$	-0.024 ***	-0.028 ***	-0.029 ***	-0.030 ***	-0.018 **	-0.014 +	-0.015 +	-0.028 ***
	0.008	0.008	0.010	0.010	0.007	0.008	0.008	0.009
$Div\_Industry_{i,l,t}$		0.007 *	0.007 *	0.007 *		-0.005	-0.004	-0.003
		0.003	0.003	0.003		0.003	0.003	0.003
$Spec\_Industry_{i,l,t}$			0.001	0.001			0.001	0.001
			0.004	0.004			0.001	0.001
$Comp\_Industry_{i,l,t}$				-0.236				-0.869 ***
				0.287				0.236
$\#Patents_{k,t}$	-0.024 +	-0.024 +	-0.024 +	-0.023 +	-0.006	-0.006	-0.006	-0.006
	0.014	0.014	0.014	0.014	0.020	0.020	0.020	0.020
$SingleID_p$	-0.559 ***	-0.559 ***	-0.559 ***	-0.559 ***	-0.565 ***	-0.566 ***	-0.566 ***	-0.566 ***
	0.043	0.043	0.043	0.043	0.038	0.038	0.038	0.038
$CoTownID_l$	-0.120 *	-0.101 *	-0.106 **	-0.106 *	-0.125	-0.135 +	-0.135 +	-0.148 *
	0.049	0.046	0.053	0.053	0.080	0.071	0.072	0.072
$\#Subclasses_p$	-0.003	-0.003	-0.003	-0.003	-0.014 **	-0.014 **	-0.014 **	-0.014 **
	0.003	0.003	0.003	0.003	0.005	0.005	0.005	0.005
$\#Employment_{l,t}$								
Constant	-1.109 ***	-1.126 ***	-1.124 ***	-1.118 ***	-0.910 ***	-0.912 ***	-0.912 ***	-0.890 ***
	0.134	0.134	0.133	0.133	0.134	0.136	0.136	0.135
Observations	264896	264896	264896	264896	57893	57893	57893	57893
Adj R-squared	0.128	0.128	0.128	0.128	0.133	0.134	0.134	0.134

Subscripts t (time), k (patent class), l (metropolitan area), p (patent).
Robust standard errors (clustered by metropolitan area) in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%, *** significant at .5%.
All equations include year, technology subclass, and 2-digit industry code.

Table 6-20 Tobit Estimation: Generality and patenting classes subsamples

	High Patenting Classes				Low Patenting Classes			
	6	7	8	9	10	11	12	13
$Size\_Industry_{i,l,t}$	-0.005	-0.003	0.014 +	0.014 +	-0.004	-0.003	0.001	0.006
	0.007	0.006	0.007	0.007	0.005	0.005	0.006	0.006
$Div\_Industry_{i,l,t}$		-0.005 **	-0.004 *	-0.004 *		-0.001	0.000	0.000
		0.002	0.002	0.002		0.002	0.002	0.002
$Spec\_Industry_{i,l,t}$			-0.006 ***	-0.006 ***			-0.002 *	-0.003 *
			0.001	0.001			0.001	0.001
$Comp\_Industry_{i,l,t}$				0.414 *				0.259
				0.190				0.160
$\#Patents_{k,t}$	0.005	0.004	0.004	0.004	-0.011 *	-0.011 *	-0.011 *	-0.011 *
	0.010	0.010	0.010	0.010	0.005	0.005	0.005	0.005
$SingleID_p$	-0.102 ***	-0.101 ***	-0.101 ***	-0.101 ***	-0.160 ***	-0.160 ***	-0.160 ***	-0.160 ***
	0.011	0.011	0.011	0.011	0.008	0.008	0.008	0.008
$CoTownID_l$	-0.022 ***	-0.025 ***	-0.027 ***	-0.027 ***	-0.045	-0.045	-0.046	-0.047
	0.008	0.008	0.008	0.008	0.049	0.048	0.049	0.048
$\#Subclasses_p$	0.016 ***	0.016 ***	0.016 ***	0.016 ***	0.012 ***	0.012 ***	0.012 ***	0.012 ***
	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
$\#Employment_{l,t}$	0.109 **	0.111 **	0.098 *	0.098 *	0.083 *	0.082 *	0.079 *	0.075 *
	0.042	0.042	0.042	0.042	0.036	0.036	0.037	0.036
Constant	-0.018	-0.039	-0.056	-0.056	0.120	0.117	0.124	0.104
	0.053	0.052	0.052	0.052	0.080	0.080	0.079	0.083
Observations	181358	181358	181358	181358	143961	143961	143961	143961
R-squared	0.058	0.058	0.058	0.058	0.057	0.057	0.057	0.057

Subscripts *t* (time), *i* (industry), *l* (metropolitan area), *p* (patent).

Robust standard errors (clustered by metropolitan area) in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%, *** significant at .5%.

All equations include year, technology subclass, 2-digit industry code and metropolitan area dummy variables.

Table 6-21 Tobit Estimation: Generality and MA subsamples

	CSA				CBSA			
	14	15	16	16	17	18	19	20
$Size\_Industry_{i,l,t}$	-0.008	-0.006	0.002	0.012	-0.002	-0.002	0.003	0.002
	0.007	0.006	0.007	0.007	0.005	0.005	0.006	0.008
$Div\_Industry_{i,l,t}$		-0.005 ***	-0.005 **	-0.004 **		0.000	0.000	0.000
		0.002	0.002	0.002		0.003	0.003	0.003
$Spec\_Industry_{i,l,t}$			-0.005 **	-0.006 ***			-0.002 *	-0.002 +
			0.002	0.002			0.001	0.001
$Comp\_Industry_{i,l,t}$				0.594 ***				-0.010
				0.151				0.188
$\#Patents_{k,t}$	0.006	0.006	0.006	0.005	0.020 *	0.020 ***	0.019 ***	0.019 ***
	0.006	0.006	0.006	0.006	0.007	0.007	0.007	0.007
$SingleID_p$	-0.131 ***	-0.131 ***	-0.131 ***	-0.131 ***	-0.130 ***	-0.130 ***	-0.131 ***	-0.130 ***
	0.008	0.008	0.008	0.008	0.014	0.014	0.014	0.014
$CoTownID_l$	-0.034 +	-0.037 *	-0.039 *	-0.040 *	0.133 +	0.132 +	0.128	0.128
	0.018	0.017	0.018	0.017	0.071	0.080	0.080	0.080
$\#Subclasses_p$	0.014 ***	0.014 ***	0.014 ***	0.014 ***	0.014 ***	0.014 ***	0.014 ***	0.014 ***
	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
$\#Employment_{l,t}$	0.126 **	0.130 ***	0.126 ***	0.118 ***	0.138 *	0.139 **	0.136 *	0.136 **
	0.047	0.046	0.048	0.047	0.047	0.053	0.053	0.053
Constant	-0.486 *	-0.505 *	-0.478 *	-0.563 *	0.123	0.124	0.128 +	0.129 +
	0.240	0.243	0.239	0.245	0.077	0.078	0.078	0.078
Observations	264896	264896	264896	264896	57893	57893	57893	57893
R-squared	0.051	0.051	0.051	0.051	0.068	0.068	0.068	0.068

Subscripts *t* (time), *i* (industry), *l* (metropolitan area), *p* (patent).

Robust standard errors (clustered by metropolitan area) in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%, *** significant at .5%.

All equations include year, technology subclass, 2-digit industry code and metropolitan area dummy variables.

Table 6-22 Tobit Estimation: Generality as a function of Local Industry structure (cross-MA variation)

	1		2		3		4		5	
Size_Industry$_{i,l,t}$	0.007	*	0.008	*	0.008	***	0.010	***	0.010	***
	0.003		0.003		0.003		0.003		0.003	
Div_Industry$_{i,l,t}$			-0.001		-0.002		-0.002		-0.001	
			0.001		0.001		0.001		0.001	
Spec_Industry$_{i,l,t}$					-0.002		-0.002		-0.002	
					0.001		0.001		0.001	
Comp_Industry$_{i,l,t}$							0.243	*	0.299	*
							0.126		0.130	
Size*Diversity									-0.001	*
									0.000	
#Patents$_{k,t}$	-0.015		-0.017		-0.014		-0.012		-0.013	
	0.028		0.029		0.027		0.027		0.028	
SingleID$_p$	-0.134	***	-0.134	***	-0.134	***	-0.135	***	-0.134	***
	0.007		0.007		0.007		0.007		0.007	
CoTownID$_l$	0.014	***	0.014	***	0.014	***	0.014	***	0.014	***
	0.001		0.001		0.001		0.001		0.001	
Constant	-0.164	*	-0.167	*	-0.169	*	-0.175	*	-0.178	**
	0.066		0.066		0.067		0.068		0.068	
Observations	326819		326819		326819		326819		326819	
Psuedo R-squared	0.046		0.046		0.046		0.046		0.046	

Subscripts *t* (time), *k* (patent class), *l* (metropolitan area), *p* (patent).

Robust standard errors (clustered by metropolitan area) in parentheses.

+ significant at 10%; * significant at 5%; ** significant at 1%, *** significant at .5%.

All equations include year, technology subclass, and 2-digit industry code.

Table 6-23 OLS Estimation: Generality as a function of local industry structure

	1	2	3	4
$Size\_Industry_{i,l,t}$	-0.003	-0.002	0.002	0.005
	0.003	0.003	0.003	0.003
$Div\_Industry_{i,l,t}$		-0.002 *	-0.002 *	-0.002 *
		0.001	0.001	0.001
$Spec\_Industry_{i,l,t}$			-0.002 ***	-0.002 ***
			0.001	0.001
$Comp\_Industry_{i,l,t}$				0.196 *
				0.091
$\#Patents_{k,t}$	0.003	0.003	0.003	0.003
	0.003	0.003	0.003	0.003
$SingleID_p$	-0.075 ***	-0.075 ***	-0.075 ***	-0.075 ***
	0.003	0.003	0.003	0.003
$CoTownID_l$	-0.024 +	-0.025 *	-0.026 *	-0.026 *
	0.013	0.013	0.013	0.013
$\#Subclasses_p$	0.010 ***	0.010 ***	0.010 ***	0.010 ***
	0.001	0.001	0.001	0.001
$\#Employment_{l,t}$	0.064 ***	0.062 ***	0.059 ***	0.057 ***
	0.020	0.020	0.020	0.020
Constant	0.042	0.061	0.066	0.036
	0.147	0.145	0.144	0.147
Observations	326819	326819	326819	326819
R-squared	0.088	0.088	0.088	0.088

Subscripts t (time), k (patent class), l (metropolitan area), p (patent).

Robust standard errors (clustered by metropolitan area) in parentheses.

+ significant at 10%; * significant at 5%; ** significant at 1%, *** significant at .5%.

All equations include year, technology subclass, 2-digit industry code and MA dummy variables.

Table 6-24 OLS Estimation: Novelty, Technical Community and Local Industry interactions

	1	2	3	4	5	6	7	8
Size_Community	-0.142 ***	-0.148 ***	-0.150 ***	-0.146 ***	-0.149 ***	-0.146 ***	-0.152 ***	-0.152 ***
	0.045	0.043	0.044	0.043	0.043	0.044	0.045	0.044
Diversity_Community	0.002 ***	0.002 ***	0.001 +	0.002 ***	0.002 ***	0.002 ***	0.001 +	0.001 +
	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Spec_Community	0.027	0.035	0.035	0.031	0.036	0.030	0.040	0.040
	0.049	0.046	0.049	0.048	0.046	0.049	0.046	0.047
Size_Industry	-0.005	-0.007	-0.005	-0.007	-0.006	-0.006	-0.005	0.008
	0.016	0.016	0.016	0.016	0.016	0.016	0.017	0.013
Spec_Industry	0.022	0.025	0.022	0.021	0.025	0.025	0.028	
	0.018	0.019	0.018	0.018	0.018	0.019	0.020	
Diversity_Industry	-0.005	-0.004	-0.004	-0.005	-0.005	-0.004	-0.003	-0.003
	0.004	0.003	0.003	0.003	0.003	0.003	0.003	0.003
Avg. Establishment Size	0.009	0.009	0.009	0.006	0.009	0.009	0.011	0.022
	0.014	0.013	0.013	0.014	0.012	0.013	0.013	0.012
Size Interactions	0.007 +						0.008 *	0.007 *
	0.004						0.004	0.003
Specialization Interactions		-0.014					-0.001	
		0.009					0.012	
Diversity Interactions			0.000 +				0.000 +	0.000 +
			0.000				0.000	0.000
Avg. Est. Size * Community Size				-0.004			0.000	
				0.004			0.000	
Avg. Est. Size * Community Spec					-0.018 **		-0.017 *	-0.017 *
					0.007		0.008	0.007
Avg. Est. Size * Community Div						0.000	-0.003	
						0.000	0.003	
Patents (ln)	0.085 +	0.093 +	0.095 +	0.090 +	0.094 +	0.090 +	0.096 +	0.095 +
	0.051	0.050	0.051	0.050	0.050	0.051	0.051	0.051
CoTownID	-0.104 ***	-0.102 ***	-0.103 ***	-0.103 ***	-0.105 ***	-0.104 ***	-0.108 ***	-0.109 ***
	0.034	0.034	0.035	0.035	0.034	0.036	0.032	0.033
SingleID	-0.556 ***	-0.556 ***	-0.556 ***	-0.556 ***	-0.556 ***	-0.556 ***	-0.556 ***	-0.556 ***
	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035
SubclassCnt	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005	-0.004	-0.004
	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
Constant	-2.103 ***	-2.164 ***	-2.255 ***	-2.135 ***	-2.194 ***	-2.140 ***	-2.298 ***	-2.248 ***
	0.484	0.465	0.490	0.473	0.462	0.478	0.484	0.474
N	322385	322385	322385	322385	322385	322385	322385	322385
Adj R-sq	0.1406	0.1407	0.1406	0.1405	0.1409	0.1406	0.1411	0.1411

Year, Subcategory, Sic and MA fixed effects

+ signicant at .10, * significant at .05, ** significant at .01, *** significant at .005

Table 6-25 OLS Estimation: Generality, Technical Community and Local Industry structure

	1	2	3	4	5	6	7
Size_Community	-0.022 ***	-0.022 ***	0.033 ***	0.032 ***	0.032 ***	0.033 ***	0.033 ***
	0.003	0.003	0.004	0.004	0.004	0.004	0.004
Diversity_Community		-0.001 ***	-0.001 ***	-0.001 ***	-0.001 ***	-0.001 ***	-0.001 ***
		0.000	0.000	0.000	0.000	0.000	0.000
Specialization_Community			-0.059 ***	-0.059 ***	-0.059 ***	-0.060 ***	-0.060 ***
			0.005	0.005	0.005	0.005	0.005
Size_Industry				0.006 +	0.013 ***	0.013 ***	0.012 ***
				0.003	0.003	0.004	0.004
Specialization_Industry					-0.013 ***	-0.012 ***	-0.008 *
					0.005	0.004	0.004
Diversity_Industry						-0.001	-0.001
						0.001	0.001
Avg. Establishment Size							-0.004
							0.005
Patents_ln	0.019 ***	0.018 ***	-0.037 ***	-0.037 ***	-0.037 ***	-0.038 ***	-0.038 ***
	0.002	0.002	0.005	0.005	0.005	0.005	0.005
CoTownID	-0.025	-0.028	-0.026	-0.024	-0.026	-0.027	-0.027
	0.017	0.017	0.018	0.019	0.018	0.017	0.017
SingleID	-0.073 ***	-0.072 ***	-0.072 ***	-0.072 ***	-0.072 ***	-0.072 ***	-0.073 ***
	0.003	0.003	0.003	0.003	0.003	0.003	0.003
SubclassCnt	0.010 ***	0.010 ***	0.010 ***	0.010 ***	0.010 ***	0.010 ***	0.010 ***
	0.000	0.000	0.000	0.001	0.001	0.001	0.001
Constant	0.211 ***	0.196	0.714 ***	0.727 ***	0.754 ***	0.762 ***	0.760 ***
	0.039	0.039	0.043	0.040	0.039	0.040	0.040
N	322541	322429	322429	322429	322429	322429	322419
R-sq	0.0886	0.089	0.0912	0.0914	0.0917	0.0917	0.0918

Year, Subcategory, and SIC fixed effects

+ significant at .10, * significant at .05, ** significant at .01, *** significant at .005

Table 6-26 OLS Estimation: Generality, Technical Community and Local Industry interactions

	1	2	3	4	5	6	7	8
Size_Community	0.034 ***	0.033 ***	0.032 ***	0.032 ***	0.033 ***	0.033 ***	0.031 ***	0.032 ***
	0.004	0.004	0.005	0.004	0.004	0.004	0.005	0.005
Diversity_Community	0.000 ***	0.000 ***	-0.001 ***	0.000 ***	-0.001 ***	-0.001 ***	-0.001 ***	0.000 ***
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Spec_Community	-0.060 ***	-0.060 ***	-0.059 ***	-0.058 ***	-0.059 ***	-0.060 ***	-0.058 ***	-0.058 ***
	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.004
Size_Industry	0.012 ***	0.012 ***	0.012 ***	0.011 **	0.012 ***	0.012 ***	0.010 ***	0.008 ***
	0.003	0.004	0.004	0.004	0.004	0.004	0.004	0.002
Spec_Industry	-0.008 +	-0.008 +	-0.008 +	-0.007	-0.008 +	-0.006 +	-0.004	
	0.004	0.005	0.004	0.005	0.004	0.005	0.005	
Diversity_Industry	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	
	0.001	0.001	0.001	0.001	0.001	0.001	0.001	
Avg. Establishment Size	-0.004	-0.004	-0.004	-0.006	-0.004	-0.004	-0.005	0.007 +
	0.005	0.005	0.005	0.005	0.005	0.004	0.004	0.003
Size Interactions	0.001						0.002 *	0.002 *
	0.001						0.001	0.001
Specialization Interactions		0.000					0.001	
		0.002					0.002	
Diversity Interactions			0.000				0.000	
			0.000				0.000	
Avg. Est. Size * Community Size				-0.005			0.000 **	0.000 ***
				0.002			0.000	0.000
Avg. Est. Size * Community Spec					-0.001		-0.007 **	-0.007 ***
					0.002		0.002	0.002
Avg. Est. Size * Community Div						0.000 *	0.002	0.003 *
						0.000	0.002	0.001
Patents (ln)	-0.039 ***	-0.038 ***	-0.037 ***	-0.037 ***	-0.038 ***	-0.038 ***	-0.037 ***	-0.037 ***
	0.005	0.005	0.005	0.004	0.005	0.005	0.004	0.004
CoTownID	-0.028	-0.027	-0.027	-0.028 +	-0.027	-0.028 +	-0.031 +	-0.030 +
	0.017	0.017	0.017	0.017	0.017	0.016	0.016	0.016
SingleID	-0.072 ***	-0.072 ***	-0.073 ***	-0.072 ***	-0.073 ***	-0.072 ***	-0.072 ***	-0.072 ***
	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
SubclassCnt	0.010 ***	0.010 ***	0.010 ***	0.010 ***	0.010 ***	0.010 ***	0.010 ***	0.010 ***
	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Constant	0.764 ***	0.759 ***	0.738 ***	0.749 ***	0.755 ***	0.753 ***	0.725 ***	0.737 ***
	0.040	0.040	0.046	0.040	0.040	0.040	0.049	0.040
N	322419	322419	322419	322419	322419	322385	322385	322385
Adj R-sq	0.0918	0.0918	0.0918	0.0921	0.0918	0.0919	0.0925	0.0924

Year, Subcategory, Sic and MA fixed effects

+ significant at .10, * significant at .05, ** significant at .01, *** significant at .005