ABSTRACT

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An understanding of how the built urban environment affects innovation will contribute significantly to the current high tech economic development policies across the country. With the employment competition in the globalized economy, city and county governments have identify knowledge based economic activities, including innovation, as a new source to create high pay jobs. They pursue high-tech economic development policies by creating special high tech centers and parks, providing tax breaks to high tech companies, and increasing funding to research activities. If urban environment can be shown to have impacts on innovative activities, city planners could devise land use policies to improve innovation and thus create new jobs. Urban sprawl, characterized with leap frog development and low population density, is a common phenomenon in American urban landscape and has attracted a fair amount of attention from planning scholars. Urban sprawl leads to longer commute distances and automobile dependence, which likely creates impediment to face-to-face interaction important to the innovation process.

To answer that question, the current paper examines the mechanism of urban environment that may influence innovative activities, based on what has been discussed in the literature regarding urban sprawl, social cohesion, and knowledge localization. The empirical analysis uses the US patent data by application years from 1990 through 2002 (Hall, Jaffe, and Trajtenberg 2001, Hall 2003), the county compactness data (Ewing et al. 2003), and the Social Capital Benchmark Survey data (Roper Center 2005).

Among important findings, urban form has some impacts on innovation activities. However, more compact counties are associated with lower innovation after controlling for other factors. Social trust is positively associated with innovation meanwhile faith ties are negatively associated with innovation. The results regarding urban form and innovation may not be conclusive because of certain limitations in the way urban form has been captured. The study sets up a solid framework for future studies before we advocate using the land use planning tool as part of innovation policies.

THE SPATIAL AND SOCIAL DIMENSIONS OF INNOVATION

By

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Dedication

To my parents, Pat, Greg, and Linh.

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Chapter I: Introduction and Statement of the Problem

1. Introduction

Job loss due to the outsourcing trend of parts of or entire production in different industries has created challenges to state and city planners across the United States. With the advantage of cheap labor, developing countries in Latin America and Asia are able to attract manufacturing jobs that used to be located in the United States (Friedman 2005). In a report to the US-China Economic and Security Review Commission in 2004, Bronfenbrenner and Luce predicted that as many as 406,000 jobs would be shifted from the US to other countries in 2004, an increase of nearly 100% compared to 2001. The authors found that manufacturing industries that experienced outsourcing to China in 2004 were composed of apparel and footware, household goods, industrial equipment and machinery, electronics and electrical equipment, metal fabrication and production, chemicals and petroleum, textiles and plastics, glass and rubber. Among the important findings, it is noticeable that job outsourcing heavily affected the Midwest, which served as the major center for many of those manufacturing industries during its prime time. Job loss in those traditional industries or in some production phases of those industries has made it more difficult for state and local economic development agencies to increase tax base, reduce unemployment, and combat poverty in their economic development strategies.

Meanwhile, knowledge has increasingly become an important component of competitive advantage to the United States. So is technological innovation. New high-tech industries including nanotechnology, biotechnology, and computer hardware keep most or all of their important production phases inside the US.

According to a report by the National Science Foundation, the number of scientists and engineering grew from 200,000 in 1950 to more than 4 million in year 2000. Also in the same report, the National Science Foundation shows that the development of new and improved goods, services, and processes is “dominated by industry” in 2004. Those factors indicate the necessity to maintain high innovation, especially technological innovation in the US and an ability to use brainpower as a source of competitive advantage. Recognizing that, nationwide state governments have shifted their focus to attracting high-tech industries by giving certain tax credits including R&D incentives. For example, the state of Maryland revised its tax law to include R&D tax credit; the state also gives tax credits to specific high tech industries such as biotechnology. In 2007, the Maryland legislature considered a proposal to offer tax credits to firms located in designated high tech research parks such as the University of Maryland and the Science & Technology Park at Johns Hopkins. Most local governments often offer tax abatement and other financial form of assistance to businesses regardless of industry and nature of jobs created. But when it comes to high tech, local governments often rely more upon their zoning power. For example, Montgomery County in Maryland has formed a Business Innovation Network to support advanced and high technology companies. This network comprises several business centers strategically located along regional arteries and Metro stations and within close proximity to federal research-involving agencies such as FDA, NIH and NIST. Those centers are equipped with broadband internet capabilities and lab amenities. Similarly, the city of Boston has the Life Tech initiative to support the growth of life sciences companies. This initiative includes zoning opportunities, workforce training, transportation, and financing. Its financing tools do not only allow qualified firms to borrow loans at low interest rates but also give small high tech start-ups a boost.

As nationwide city and county governments try to be more creative in designing policies targeting innovation and high tech industries, it is important for planners to improve their understanding of knowledge intensive activities including the process of innovation at the regional level. A number of scholars (Florida 2001, Acs 2002) emphasize the role of cities as a milieus of innovation which tap into advanced education and research infrastructure that the US has already had. US metropolitan areas nowadays house the majority of population and most patenting activities across the country. It is estimated that US metropolitan areas account for 81% of high technology employment and 91% of total patents. However, there is evidence of uneven distribution of innovation across those metropolitan areas. Places such as New York- Northern New Jersey-Long Island and San Francisco-Oakland-San Jose are top innovative metropolitan areas with over 70,000 patents per area from 1990 through 2002. Meanwhile, Both Victoria and Abilene of Texas are struggling with fewer than 10 patents during the same period. The huge gap between the regional innovation leaders and laggards indicates existing issues in creating and sustaining innovation and innovative work force that planners need to understand and address.

Space has emerged as another key tool that planners should include in their toolbox when innovation oriented policies are concerned. The variation in innovative capability among different metropolitan areas is attributable to a range of possible factors including the concentration of scientists and engineers, the concentration of supporting industries, and the amount of R&D investment from the government and within firms. In addition, this variation is possible due to specific living conditions within each metropolitan area and how the area is spatially configured. In the last 20 years, regional scientists have talked about how clustered firms can benefit from easy knowledge transfer and how knowledge spills over close proximity. Sociologists have talked about how urban sprawl can affect social face to face interaction, a crucial factor in the exchange of knowledge leading to innovation. Those discussions in different disciplines imply the intervening role of place in the process of innovation. More specifically, they suggest a possibility of more compact places to generate more innovation. Planners can affect land use patterns in metropolitan areas to change human behaviors if such behaviors result in negative or positive externalities to society. In this case, planners can create more innovative places which will provide new jobs, products, and services to the regional and local economies.

2. Research Questions

Economic studies on knowledge spillovers and regional innovation suggest that the accumulation of information and knowledge and the flow of ideas depends on the concentration of firms and of research and development activities (Malecki 1985, 2000; Jaffe 1989; Feldman 1994; Feldman and Florida 1994; Audrestch and Feldman 1996; Anselin, Varga, and Acs 1997, 2000; Allen 1997; Almeida and Kogut 1997, 1999; Saxenian 1998, Ohuallanchain 1999, Acs 2002, Nunn and Worgan 2002; Acs, Anselin, and Varga 2002, Black 2004). Those studies provide supports for further efforts to examine how the urban form affects knowledge accumulation at a larger geographical scale. Compact urban form, with some concentration of employment and housing and high street accessibility, can reduce the costs of interaction, thus increase knowledge workers' opportunities to engage in face-to-face interactions. As a result, the metropolitan area which is more compact can improve the innovative productivity of existing knowledge workers and/or attract them from less compact areas to more compact urban areas.

Social capital can be defined as one's ability to connect with other individuals and to use those connections as resource to achieve certain ends. Social capital under the perspective of a region portrays the level of connectedness among the region's residents. The larger the network and the higher number of networks, the more opportunities for face-to-face interactions among knowledge workers; and the more opportunities they have, the faster information flows and knowledge is acquired. Trust, social connection, and faith ties are three important social capital factors that have been correlated with innovation (Fukuyama 1996, Knack and Keefer 1997, Tsai and Ghoshal 1998, Putnam 2000, Florida 2002, Johnson, Lorenz and Lundvall 2002; Dakhli and De Clercq 2004).

The existing bodies of literature concerning innovation, knowledge spillovers, social capital, and sprawl have led to three original questions as follows:

1. Is there a relationship between compact urban form and innovation?

2. Is there a relationship between innovation and three factors of social capital (trust, social connectivity, and faith ties)?

3. And is there a relationship between urban form and the level of trust, and between urban form and the level of social connectivity?

The contribution of this dissertation to planners' understanding of regional innovation is extending an existing framework to explain regional innovation to include spatial and social factors. Besides providing original results, this dissertation set the first steps to enable planners in the future to continue dwelling into the relationships between urban form and innovation, between urban form and certain factors of social capital including trust, connectivity, and faith ties, and between those social capital factors and innovation.

3. Organization of the Dissertation

In the next Chapter, the underlying quantitative and qualitative literature is presented. There are three different bodies of literature contributing to the construction of the study's conceptual framework. They include the literature on the economic impacts of social capital, the planning literature on the impacts of sprawl, and the economics literature on knowledge spillovers. Chapter Three presents the theoretical framework for a model explaining regional variations in innovation. The model combines the complex network of relationships among social and spatial factors and their interactions that are hypothesized to influence innovation. These relationships are drawn from the rich quantitative and qualitative literatures that have occurred over the past twenty years and my own original hypotheses. Details of the datasets used in the analysis are in Chapter Four. In order to test the hypotheses, three main datasets are to be used. Innovation data come from the study by Hall, Jaffe, and Trajtenberg (2001) for the years 1963 to 1999 and for the years 1999 to

2002 data updated by Hall (2003). Measures for different social capital factors are from the Roper Center (2005)'s Social Capital Community Benchmark Survey Restricted Use Data in 2000. The urban form dataset is based on the sprawl index obtained from the work by Ewing et al. (2003). In Chapter Five, the spatial patterns across the country of major variables for innovation, urban form, and social capital are illustrated using GIS maps. Chapter Six consists of two analyses. The first analysis addresses the primary research questions related to the possible impacts of urban form and social capital on innovation. Because of the hierarchically structure dataset, multilevel modeling is applied. The second analysis addresses the question of whether or not urban form affects different social capital factors. Again, due to the hierarchical nature of the data, multilevel modeling is utilized to tease out the effects of urban form at the county level and the effects of other factors at census tract and person levels. Finally, Chapter Seven discusses the findings, linking them to the research questions. The Chapter also discusses limitations of the study and provides the conclusion of the study.

Chapter II: Literature Review

The planning and urban design literature does not address directly the question of how to build innovative cities. However, there exist quantitative and qualitative studies in different fields that reveal important information essential to answer that question. Despite the fact that some findings of those studies could be debatable and need further testing, they all contribute significantly to the construction of the conceptual framework of the current dissertation study and therefore need to be reviewed.

This chapter is divided into three sections. The first section explores the literature body highlighting the role of social capital in innovative activity. This body of literature is largely composed of works which have had large impacts on the academia and invoked continuous debates. Among those works are Richard Florida's (2002) The Rise of the Creative Class and Robert Putnam's (2000) Bowling Alone: The Collapse and Revival of American Community. In the second section, the discussion is focused on the literature consisting of studies which aim at identifying urban form's possible impacts on social capital and innovation. The last section reviews the related quantitative literature on the evidence of spatially bound knowledge spillovers.

1. The Link between Social Capital and Innovation: From the Rise of the Creative Class to Bowling Alone

In The Rise of the Creative Class, Richard Florida (2002) has attempted to address the issue of how to build a city that attracts creative workers. Unlike other economic growth models which are based on human capital such as the one suggested by Glaeser (1999), Florida is interested in the "creative capital" associated with the

Creative Class. This group includes scientists, engineers, university professors, poets, novelists, artists, entertainers, actors, designers, architects, think tank researchers, analysts and opinion makers. This group of Super Creative Core, as Florida labels them, engage in the creative process in their professional tasks, i.e. the process which results in “new forms or designs”, “new theorems or strategies”, or music. The Creative Class extends beyond the Super Creative Core and includes lawyers, technicians, managers, and many others who are involved in problem solving, problem finding and in a variety of knowledge intensive activities. People who are not likely to belong to the Creative Class are low skilled workers who do not exercise creativity in their routinized tasks. Florida also notes that people can move from outside the Creative Class into its core such as full time students who work part time in manual jobs before becoming a scientist or engineer. Thus, there exists a high fluidity between the Creative Class and other possible classes. Drawn from his observation, Florida contends that unlike other groups of people, creative people are more entrepreneurial and they are attracted to stimulating living places with a high level of social and cultural diversity. Working with a flexible schedule and high mobility, creative people are not tied only to spectator sports or fancy opera theaters. Instead, creative people also opt for active individual sports and outdoor recreation such as biking, hiking, or street activities to compensate for their sedentary working hours. Florida concludes that any environments tolerant to bohemian values and have more diversity and population density to generate lively street activities will attract creative people.

When reaching the above conclusion, Florida also recognizes the role of social capital among factors that help communities attract the Creative Class. In communities appealing to creative people, weak ties exist among the old and new members allow for "entry of new people" and "rapid absorption of new ideas" (Florida 2002). Strong or dense ties are marked by high levels of trust, a tightly knit community, and a smaller group of people that one can share a network with; meanwhile, a larger network built upon weak ties is favorable to the gathering of ideas and information (Florida 2002) from different resources. He writes: "Places with dense ties and high levels of traditional social capital provide advantage to insiders and thus promote stability, whereas places with looser networks and weaker ties are more open to new comers and thus promote novel combinations of resources and ideas." Florida believes that communities should embrace weak ties, marked with diversity and openness, while de-emphasizing the role of trust among other aspects of the so-called "traditional social capital", which consequently makes the reader take one step backward and wonder how weak ties, strong ties, and social capital are related to innovation.

In order to understand the relationship between social capital and innovation as well as to answer some issues that Richard Florida may have failed to adequately address, one has to turn to the social capital literature. Even though Coleman (1988) was the first to use the term "social capital" as a resource to achieve certain ends and to link it with economic performance, the leading scholarship of the topic should be attributed to Putnam's (1993, 200) empirical works in Italy and in the US. He suggests that social networks or connections among individuals are one type of resource which provides members in the network with actual and potential benefits (Putnam 1993). In his seminal book Bowling Alone: The collapse and Revival of American Community, Putnam's premise of social capital is that social networks have value. In general, social capital functions through enabling people to work with each other in the same network more effectively and efficiently. The concept of social capital underscores the importance of who we know, not what we know. Within a specific network, this know-who knowledge involves information about who has what information; thus being able to tap into this network resources allows individuals to have useful information or to have other kinds of support and cooperation. However, Putnam warns about the counterproductive economic results that social capital may create such that even though individuals' gain from the network is positive, the aggregate outcome is not always positive. He provides an example of strong ethnic ties in which less economically successful members excessively demand for assistance from more successful ones to an extent that "drags down" them economically (Putnam 2000). Other scholars also share the same view of social capital. Knack and Keefer (1997) contend that when economic objectives of one group are in conflict with other groups' or unorganized interests, the aggregate effects of associational activity could be negative to the whole economy.

Putnam introduces two types of social capital: bonding and bridging social capital. Bonding social capital is "exclusive" and good for "mobilizing solidarity" and is provided within dense ethnic enclaves, bridging social capital is inclusive and is good for linkage to "external assets" enabling "information spillovers" (Putnam 2000). The distinction of two types of social capital has important implication in how we approach the issue of innovation and the concern about possible impacts of social capital on innovation.   As its name suggests, bonding social capital provides the "social glue" that stick people in the group together, it creates in-group loyalty and creates animosity toward alien values and cultures (Putnam 2000). People in such groups interact less with other groups which do not share similar sets of values or culture. On the contrary, a community or organization which allows for "weak ties" to prosper would enable its member to have both out-group and in-group interactions. Bridging social capital in this case increases the number of linkages in society by exposing members of the community to a pool of opportunities to interact with individuals from other communities. The increased level of social interaction results in knowledge spillovers leading to more innovation and improved creativity.

Putnam (2000) also warns that both types of social capital may coexist in a community and it is not easy to distinguish them neatly. In an example, an Internet chat group brings people together from different places and from different economic backgrounds while being homogeneous in aspects such as education or ideology. I would also add that depending on the nature of the association or social connection, either bridging or bonding type of social capital can dominate the culture of specific communities. The associations of knowledge workers and the Creative Class as Florida (2001) describes would resemble the type of organization dominated by bridging social capital. As already discussed elsewhere, places with high level of social and cultural diversity or heterogeneity appear to be ideal for creativity. From the social capital perspective, this could be explained that such places have high bridging social capital that promotes social interactions between different groups of creative people, thus make them more creative. Putnam (2000) suggests that residents of ethnically diverse communities have "weak ties". This is because in-migrants and immigrants threaten local community integrity and they are not able to create ties with the existing residents in a short period of time. The above examples indicate that there are several ways to dissect social capital into different components to investigate their effects.

Obviously, it is not convenient to examine the bridging-bonding dichotomy of social capital although bridging social capital has been shown to be favorable to innovation. In Bowling Alone, Putnam considers and discusses in detail a set of factors of social capital. Those factors include political participation, civic participation, religious participation, social connection (including informal and workplace interaction), philanthropy, and trust (Putnam 2000). Those factors characterize both bridging and bonding social capital; and compared with bridging and bonding social capital, those factors refer to more concrete activities and behavior commonly discussed and operationalized in various studies. Therefore, this study analyzes those social capital factors and is especially focused on trust, connectivity, and religious participation or faith ties.

1.1. Trust

Among factors of social capital that may have impact on innovation, trust receives significant attention because most scholars consent that it is the building block for most types of connection and interaction (Putnam 2000, Patton and Kenney 2004). It is also the norm of reciprocity: economic actors support one another because they believe they form a community based on mutual trust (Fukuyama 1996, Putnam 2000). In general, trustworthiness can reduce high legal fees and thus significantly reduces transaction costs (Knack and Keefer 1997, Putnam 2000, Johnson, Lorenz, Lundvall 2002). Within an organization, high trust and group cohesion increase team effectiveness and knowledge advantage (Karlson, Flensburg and Horte 2004). Low trust increases costs for economic and social transactions, prohibiting people from making long term investment and from cooperating effectively (Knack and Keefer 1997). In the innovation process, the trusting relationship among inventors guarantees that they can cooperate with each other and can mutually from this cooperation. Low trust discourages innovation since the entrepreneur has to devote his or her time and money to monitoring his or her partners and employees (Knack and Keefer 1997). Trust is important not only in the intra-organizational environment but also at inter-organizational and societal levels. Cooperation among different organizations or among different inventors from various places and agencies facilitates the knowledge spillover, leading to innovation (Dakhli and De Clercq 2004). Without trusting relationships, such cooperation among innovators is doomed to failure or, at least, becomes excessively costly.

A few empirical studies focus on the impacts of trust on economic activities at the societal or country level; their findings are consistent with the theory of social capital and provide statistical evidence of positive relationship between trust and economic performance. In a comparative international study, Knack and Keefer (1997) use indicators of trust and civic cooperation from the World Values Surveys to measure their causal effects on average annual growth in per capita income during1980-1992. The survey data are pooled from 29 market economies in two survey waves in 1981 and 1990-1991. After controlling for the proportion of students in secondary and primary education in 1960, per capita income at the beginning of the examined period, and the price level of investments goods relative to the US, the authors detect statistically significant and positive relationship of the social capital variables and growth. Similarly, Dakhli and De Clercq (2004) examine the effect of human capital and social capital on innovation by using the World Value Survey data from 59 different countries from a survey in 1995. However, the set of survey questions used in 1995 and in the earlier years remained the same. Dakhli and De Clercq (2004) assess the level of trust, associational activity, and civic norms by using the same method of Knack and Keefer (1997). They also obtain country level innovation based on the World Bank database of innovation. However, unlike Knack and Keefer (1997), they look into the relationship of social capital and three measures of innovative activity including national patent counts, R&D expenditures (% of GNI), and high technology exports. Their findings indicate that once controlled for human capital, country sizes, and national income gap, generalized trust has positive correlation with R&D expenditure and institutional trust has positive correlation with national high tech exports.

At the organization level, fewer studies have been conducted with respect to trust and innovation. In a study conducted at a multinational electronics company, Tsai and Ghoshal (1998) survey management team members from 15 business units on issues related to social interaction, trust and trustworthiness, the inter-departmental exchange and combination of company resources such as information, personnel, products and support, and product innovation in each business unit. They evaluate the overall research model's goodness of fit index using structural equation modeling and are able to show that trustworthiness is positively associated with the degree of which information, personnel, products, and support flow among different departments. Product innovation in each business unit benefits from this positive relationship. Their findings suggest that social capital creates economic values inside the firm, just as human capital and physical capital do. In particular, trusting relationships affects the knowledge production process, raising firm innovation.

At the regional level, scholars have sought to answer the analogous question of what role trust plays in economic development and innovation. However, most studies conducted at this level are not of quantitative nature. This might have been due to the lack of a social capital dataset until recently. In The Rise of the Creative Class, Florida (2002) uses Robert Cushing's correlation results that creative regions score low on most social capital factors including social trust to substantiate his argument in favor of weak-ties communities. However, throughout his book, Florida does not suggest that the lack of trust would promote innovation. In a discussion paper on innovation and social capital in Silicon Valley, Patton and Kenney (2004) concluded that trust was the "coordinating mechanism" of professional and social networks in the region. Therefore, even though Silicon Valley's talented workers appeared highly mobile and strangers to their residential neighborhoods as suggested by Saxenian (1997) and Cohen and Field (2000), the region has managed to thrive on the same ground that Northern Italy's communities did as described in Putnam's (1994) book Making Democracy Work. They also contended that due to the high level of trust among professionals, the region fostered an unparalleled level of innovation. Nevertheless, most of those studies at the regional level suffer from a lack of rigorous statistical analysis to control for the influence of other possible factors.

1.2. Connectivity

Like trust, social connection or social interaction is hypothesized to play a crucial role in the innovation process (Tsai and Ghoshal 1998, Putnam 2000, Florida 2002). Trust and connectivity are two different factors of social capital but they are strongly related. Trust could well affect the level of connectivity but the latter may or may not affect the former. Connectivity refers to the degree of connectedness among individuals as indicated by their participation in networking activities. In regards to knowledge flow and innovation, face-to-face social interaction plays a crucial role in determining the degree of information exchange. When people participate in various networking activities, the format of those activities can range from informal interactions over a picnic lunch to organized formal events. Regardless of their format, face-to-face social interaction accounts for an important share of networking activities. Via networking activities and especially face-to-face social interaction, people get employed and promoted and businesses obtain information about new products and technologies and potential employees.

A number of studies have established that face-to-face interaction is conducive to knowledge accumulation leading to innovation (Polanyi 1962, Lundvall 1992; Johnson 1992; Spender 1993; Lundvall and Johnson 1994; Nahapiet and Ghoshal 1998; Lam 1998; Bellandi 2001, Johnson, Lorenz, and Lundvall 2002; Moretti 2002, Glaeser 2002). This line of studies argues that knowledge crucial to innovation can only be transferred via face-to-face interactions despite the fact that telecommunication advances enable individuals and firms to cooperate with one another from distant places. Nevertheless, empirical evidence found across different studies does not always support the theory. In the multinational study, Knack and Keefer (1997) measure the density of associational activity from the World Values Surveys and examine its causal effects on average annual growth in per capita income in the 1980-1992 period using similar regression techniques as in their models for trust. They capture associational activity with the average number of groups cited per respondent in each country participating in the survey. That connectivity variable is not statistically significant in their models to explain economic performance 1980-1992. Dakhli and De Clercq (2004) use the updated World Values Survey data with more countries and found that the connectivity variable has positive impacts on the level of national R&D expenditures as a percentage of a country's GNP, but not on patent counts nor the percentage of high tech export. Both studies suggest that individuals' associational activity may not always create positive effects for other groups or society as a whole. Also, there is no evidence at the cross-national level that connectivity improves the aggregate rate of innovation. However, the insufficient evidence of the relationship between connectivity and innovation may be rooted in the operationalization of the connectivity variable. The method of using the number of groups that individuals participated instead of the intensity of interaction possesses two drawbacks. Firstly, group affiliation does not always make one participate in group activities and thus will not contribute to one's networking. Secondly, group affiliations may include those that are only built upon membership dues instead of member interaction. Therefore, the large number of groups one participates does not necessarily imply that she or he is actively seeking to cultivate her or his network. And at the cross-national level, the country whose citizens are members of many groups does not necessarily lead to improvement of its economic performance and innovation. A variable that captures the intensity of participation in group activities could adequately address the disadvantages of using membership counts because it certainly portrays functioning networking activities.

In empirical studies carried out at the regional level, researchers offer evidence based on their observation to support the correlation of connectivity and innovation. Most of those studies look at the economic success of Silicon Valley. In one study of the region's business environment, Saxenian (1997) discovered a web of connections that spanned beyond office cubicles, business units, and even firm boundaries. Those professional and social connections have blurred firm boundaries and workers are less loyal to particular firms. Instead, they are loyal to their groups as those networks allow them to find another company once being laid off, to have answers to daily technical questions, to get finance for entrepreneurial projects, and to innovate. Regarding informal interaction, Saxenian wrote: "By all accounts, these informal conversations were pervasive, and served as an important source of up-to-date information about competitors, customers, and changes in markets and technologies. Local entrepreneurs came to see social relationships and even gossip as a crucial aspect of their businesses. In an industry characterized by vigorous technological change and intense competition, informal communication was often of more value than formal, but less timely forums, such as industry journals." (p. 32).

The study suggests that those networks serve as an important type of capital to contribute to the success of the entire region and of individual workers. In a different study of the Silicon Valley area, Patten and Kenney (2004) found that technical workers and engineers created networks among those undertaking the same activities and between suppliers and customers. Such networks were valuable in the knowledge intensive production of the region.

1.3. Faith ties

Unlike the other two factors of social capital, the direct relationship between faith ties or religious participation and innovation is harder to establish. Religious participation is another form of social capital which, like trust and connectivity, plays some role in the resource mobilization of a network. As Putnam (2000) notes, faith communities are the "most important repository of social capital in America." He acknowledges that religious institutions support a wide range of social activities including face-to-face interaction. Devout worshipers are reported to be more likely to visit friends and to belong to sports, political, civil and professional groups (Putnam 2000). Religious ties, or faith ties, therefore can impact the level of trust and associational activities, the other two factors of social capital. The remaining question is whether strong faith ties will result in better economic performance and more innovation. People living in faith communities are bonded together by a set of beliefs and faith. However, any person in those communities can participate in religious and non-religious interactions. And because religious interaction are often geared toward building bonding social capital, the intensive participation in bonding activities may result an individual's limited number of groups that one builds network with. Putnam (2000) suggests that this lack of bridging social capital may offset any economic benefits that religious groups or communities possibly generate.

Florida (2002) looks at the impacts of faith ties from a different angle but offers a similar conclusion. He contends that faith ties could create tightly- knit communities which exhibit strong homogeneity because their resident loyalty to a certain set of social and cultural principles and identities is required. According to Florida, this homogeneity sends an unwelcoming message to the Creative Class workers in which tolerance to unconventional thinking and culture are not acceptable. Individuals living in such communities can be less tolerant to new ideas, which does not allow for cross-breeding of ideas and knowledge leading to innovation. One way or the other, communities strongly bounded by faith are not ideal residential choices for innovators and do not foster innovation.

1.4. Social capital, diversity, and innovation

There appears one dominant view of the interaction between social capital and diversity. Scholars such as Saguaro Seminar (2000), Costa and Kahn (2002) and Florida (2002) have found that increased diversity is associated with lower social capital. Costa and Kahn (2002) examine the impact across metropolitan areas' of racial makeup, income, and ethnic diversity on volunteering, non-church memberships, and trust in different databases. They suggest that volunteering, membership, and trust are lower in more diverse communities. In particular, after controlling for this diversity, the authors explain "from one-third to almost all" of the declines in volunteering, non-church memberships and trust. This is because people tend to self-segregate and they only interact with those who remind them of themselves (Costa and Kahn 2002). Their research is consistent with the findings of the Saguaro Seminar research team that interracial and social trust is lower in ethnically diverse communities and residents of more diverse communities are less likely to have connections with others, even informally (Roper Center 2005). Similarly, Florida (2002) uses the analysis results of Robert Cushing, in which 13 aspects of social capital in the Social Capital Benchmark Survey (2000) are compared against indices for innovation, diversity, and high technology concentration. He is able to show that regions scoring high on his social diversity index, high tech index, and innovation index score below average on most measures of social capital. Those social capital measures include social trust, racial trust, civic participation, number of formal group involvements, faith-based social capital, organized group interactions, informal social interactions, giving and volunteering, and electoral politics. The diverse and high tech regions only score high on protest politics and diversity of friendship. Florida, however, does not elaborate on the possible reasons why creative regions score low on some important aspects of social capital such as social trust or number of formal group involvements or organized group interactions.

With respect to the relationship between innovation and diversity, a number of researchers consent that diversity fosters innovation. As mentioned elsewhere, one form of social capital, bridging social capital, is assumed to exist and enable one to build connections with others outside his or her community (Putnam 2000). Heterogeneous communities enable individuals to reach out and tap into other communities or networks with complementing skills, information, or knowledge.

This implies that communities where individuals come from different professions that are related may form interaction such that different professional groups are better off because of the presence of the others. In his book, Florida suggests that cultural and social diversity might weaken ties among individuals but it also signals the level of tolerance of the environment to nonconformists. Cultural diversity is viewed to render incentive for innovation among the people of the Creative Class (Florida and Gates 2001, Florida 2002). Being exposed to a diverse culture, one's intellectual collection is enhanced with a multitude of different ideas, different methods of doing things, and different ways of thinking. One does not feel alienated because of his or her identity or culture in a community characterized by diversity. In addition, social and cultural diversity allows for new ideas to meet, to mix and to form, which is a part of knowledge accumulation leading to innovation. For example, in-migrants and immigrants contribute to the local knowledge stock by combining ideas that are transported with them with the ideas that already exist in the arrival community to give birth to innovative ideas (Simon 1999).

Florida (2002)'s discussion about social and cultural homogeneity should also be extended to include professional homogeneity. One may argue that the diversity among people taking different types of work could also affect the creativity rate. A place which has a homogeneous pool of a single creative professional group such as mathematicians or engineers may not better off their creative/innovative activity. The in-class diversity of workers who participate in different tasks and who have different backgrounds and expertise is necessary to the innovation process. Saxenian (1997, 1998) points out that the Silicon Valley workers perform similar tasks and those who work in different fields such as software development, hardware development, and finance are connected together via this network to support one another successfully. Silicon Valley's network of horizontal and vertical linkages, thus, best exemplifies the importance of professional diversity.

Along this line of theoretical and exploratory literature, one complicated picture of interaction has been disclosed. Some factors of social capital such as trust, social connectivity appear to decrease in communities characterized by racial, ethnic, and income diversity. Trust and connectivity have been shown to have positive association with creation/innovation. Social, cultural, and professional diversity may also have a positive association with innovation and this is because diverse communities could support cross-group learning and interaction. However, diversity may also reduce social trust which stifles innovation. The combined effects of diversity may depend on which form of social capital dominates the community.

2. Urban Form and Its Possible Impacts on Social Capital and Innovation

Urban form can be defined as the spatial pattern of land use, transport and communication infrastructure within a metropolitan area (Anderson et al 1996). Different arrangements of land use, population density, and street accessibility, i.e. urban form, will have different economic, social, and environmental implications. Empirical planning studies have started to explore urban form's impacts on human behavior including economic activities (Ewing and Cervero 2001; Cervero 2001, 2004; Cervero and Duncan 2003; Handy 2004; Bento et al. 2005). Most recent discussion along this line has been developed around the theme of sprawl versus compact urban form. Smart growth and New Urbanism advocates support a combination of neighborhood and citywide design guidelines that favor compactness and a diverse mix of activities and housing options. They claim that those features reduce car reliance and sprawl while increasing activity of and interaction among community residents (Lund 2003).

The concept of sprawl refers to low density, leapfrog development, a wasteful suburbanization, commercial strip development and discontinuity (Ewing 1997, Wetz and Moore 1998, Galster et al. 2001, Burchell et al. 2002, 1998). Meanwhile, compact urban form is characterized by some concentration of employment, some clustering of housing and some mixing of land uses, and monocentric development (Anderson et al 1996; Ewing 1997; Gordon and Richardson 1997). In a sprawled city, the distance from one developed area to another is unnecessarily lengthened, involving more driving with a lot of in-between open space which is not fully functional. It is important to notice the implication of compact development on population density. High density is not necessarily parallel to high accessibility even though as density rises, vehicle miles traveled reduce (Ewing 1997). Residents living in a high density block separated from nearby commercial land use by high speed traffic roads and cul-de-sacs do not have good accessibility. The concept of compact urban form thus includes both high density and high street accessibility. In a compact city area, people are able to go out for different purposes but using many city facilities with minimal traveling.

There are two poles of research on the consequence of sprawl. There are researchers who speak against sprawl and those who support it. Sprawl opponents believe that because sprawl implies greater travel distances, it is responsible for the reduction in quality of life due to the increased automobile dependence. They argue that sprawl leads to an increase in vehicles miles traveled and traffic congestion (Ewing 1994, Cervero and Wu 1998, Burchell et al 1998, 2002; Bento et al. 2003), increase in energy consumption (Anderson et al. 1996; Ewing 1997), social segregation (Ewing 1997, Burchell et al. 1998), physical inactivity and obesity (Cervero and Duncan 2003, Ewing et al 2003), and depletion of land and air quality (Anderson et al. 1996, Burchell et al 1998, 2002). More recently, a number of researchers contend that sprawl does not only have negative impacts on our physical resources but it also affects the formation of communities. To neighborhoods, sprawl weakens linkages with neighbors because people are living far away while the number of meeting places is reduced (Burchel et al 1998).

In his discussion about causes to the loss of social capital, Putnam (2000) lists sprawl and suburbanization among other major suspects such as time pressure, technological advances (television and the internet), and generational change. What is the proposed relationship between sprawl and community? There is agreement among researchers including those speaking against compactness that sprawl means larger spatial separation between home and workplace (Ewing 1994, Gordon and Richardson 1997, 2000; Burchell et al 1998, 2002; Kahn 2006). Putnam (2000) believes that this spatial separation poses two direct consequences in conjunction with community life. Firstly, as people are living far away from their workplaces and other amenities such as shopping centers, entertainment centers, etc., they have to invest more time on commuting. With a fixed total number of hours that they have for all activities, time spent on commuting has to be taken from other tasks including networking activities. On top of this is the use of cars for commute which, according to Putnam, puts more people into isolation status. By using the Americans' Use of Time survey archives and controlling for all demographic variables, Putnam (2000) is able to show that, in general, time spent on commuting is negatively associated with various dimensions of social capital including informal social interaction and civic participation. Secondly, he suggests that sprawl has also deprived the public of the spaces necessary for social interaction. He argues that strip malls have replaced the downtown and neighborhood shopping, which fails to support the social and spontaneous interaction in a "common social network" (Putnam 2000) that often takes place in a more compact, high density and lively city downtown. In short, Putnam believes that the "spatial fragmentation" between home and workplace and between home and shopping centers does not reinforce work-based ties and place-based ties, and even undermines some, if not all, factors of social capital.

Putnam is not the first one to link the lack of a strong city core and street accessibility, which characterize urban sprawl, to diminishing social capital. Jane Jacobs (1961) in her famous book *The Death and Life of American Great Cities* expresses similar concerns about the lack of liveliness associated with a sprawling metropolitan area. As a planner at heart, she strongly believes that a combination of mixed land use, short blocks, a variety of building types, and some concentration of people are necessary to create urban diversity (Jacobs 1961). Arguing for compactness, she recognizes the importance of compact development with respect to city liveliness, social capital and economic prosperity.   In high density and diverse urban areas, Jacobs sees more opportunities for city neighborhoods to maintain strong “neighborhood networks”, the city’s social capital: “ A good city street neighborhood achieves a marvel between its people’s determination to have essential privacy and their simultaneous wishes for differing degree of contact, enjoyment or help from the people around.” She suggests that a combination of high density, mixed land use and smaller blocks with better street accessibility bring about socially active communities where people can gather in informal meeting places such as on the street in the neighborhood and in the park. Following Jacob’s vision of urban architecture and planning, New Urbanism and Smart growth promote infill development and building guidelines that are in favor of creating walkable and compact neighborhoods with mixed land use and high diversity. New Urbanists argue that with such development as an allegedly better alternative to sprawl, we could increase the sense of community and social interaction by creating the “public realm” i.e. interesting and lively streets, parks, and squares for people of “diverse ages, races, and beliefs” to meet and to exchange ideas (Duany et al. 2000). However, the New Urbanists have not successfully proved that those developments achieve what they have been intended for.

In light of this, an inference subject to testing can be made that sprawl can affect innovation directly and indirectly via urban form's impact on social capital. With the described lack of a city center and population proximity and interaction, sprawl makes it more difficult for innovators and potential innovators to interact face to face formally and informally. Restricted mobility and accessibility associated with sprawl leads to a decline of opportunities for knowledge exchange via face-to-face social interaction. Contrary to a sprawled urban area, compact places have high level of street culture with plenty of opportunities for social interactions.

Compact places provide a lot of interaction venues such as coffee shops, bookstores, movie theaters, restaurants and multi-purpose buildings. One may argue that in this kind of context, social interaction and especially face-to-face interaction blossoms. The environment provides the innovator/creator with stimuli, feedback during the process of innovation, and learning opportunities to improve his or her knowledge inventory. As Florida (2002) and Saxenian (1997) suggest, knowledge workers and innovators need formal and informal interactions regardless of whether it is inside or outside workplace. And this means increasing the demand for travel and amenities serving interaction purposes. When citywide accessibility increases with convenient arrangements of transport patterns, generous parking space, or good public transport to meet with the demand of knowledge workers or creative people, it is highly possible that innovators choose to stay in the city and they will create more innovations.

Theoretical works by urban sociologists and planners and publications by New Urbanism advocates indicate that sprawl could adversely affect communities and neighborhood by creating a spatial separation among communities, workplaces, and homes. City citizens living in sprawled communities may have to spend more time on traveling and less on social interaction with their neighbors and colleagues. Less trust and social interaction appears to be the direct consequence of sprawl. However, empirical evidence of sprawl’s impact on social capital is scarce and inconclusive.

In one of very few empirical studies concerning sprawl and social capital, Freeman (2001) attempts to test the hypothesis that a sprawling urban form is harmful to neighborhood social ties by examining the survey data from the Multi City Survey of Urban Inequality in 1993 and 1994 focusing on Atlanta, Boston, and Los Angeles. To capture social capital, he measures neighborhood social ties by constructing two variables, one indicates whether an individual has any neighborhood ties and the other indicates the number of ties. He also controls for individual and neighborhood demographics and socio-economic characteristics in an ordinal logistic regression model. His findings reveal that while population density does not have statistically significant impact on both social capital variables, the proportion of people neighborhood who drive alone to work, a proxy for sprawl, has a negative relationship to whether or not an individual has a neighborhood social tie. The proportion of people in the neighborhood who drive to and from work also has negative relationship with the number of neighborhood social ties that one has. In particular, an increase of 1% in the proportion of those who drive alone to work is associated with a 73% and 71% decrease in the probability of a resident having a neighborhood social tie and having more neighborhood social ties, respectively. This result is, however, far from being conclusive due to the imperfect measures of social capital and sprawl, and the lack of control for self-selection. Freeman suggests that at least one characteristic of sprawl, the proportion of community residents who drive alone to and from work, could be demonstrated to have some relationship to neighborhood social ties, but more studies with better measures of sprawl and social capital are needed in the future.

Meanwhile, sprawl proponents argue that compactness does not alleviate problems caused by sprawl nor is better than sprawl in addressing issues such as improving social interaction and reducing commute time (Audirac et al 1990, Gordon and Richardson 1997, 2000; Gordon et al. 1998; Hayward 1998; Kahn 2000, 2001, 2006; Glaeser and Kahn 2003). Specifically, in his most recent article, Kahn (2006) compares sprawling and compact cities along the several dimensions of quality of life, including housing consumption, commute times, public safety, and auto emissions. He uses Ewing et al (2002)'s metropolitan sprawl index and examines the outcomes for people who live in sprawl and compact cities. By using the 2003 American Household Survey, Kahn shows that even though workers in sprawling cities commute on average 1.8 miles further each way, their commute is on average 4.3 minutes shorter compared with workers in compact cities. Using the Neighborhood Change Database report, Kahn (2006) also shows that the share of commuters with a short work commute declines from 0 to 10 miles from the Central Business District (CBD) while starting from the 11th miles from the CBD, the share of commuters with a short commute stays constant. This result implies that most workers living further from the CBD enjoy short commutes, which is made possible by the suburbanization of firms and businesses. However, Kahn does not control for transportation modes and therefore his aggregated time and distance measures do not reveal distinctive differences between driving commuters and those who ride public transports. In a reply to Ewing (1997) and many sprawl opponents who justify compact development by citing the knowledge spillover benefits of agglomeration, Gordon and Richardson (1997) argue that lower costs of communication will make face-to-face interaction no longer necessary. They suggest that as advances in telecommunication allow for a reduction in communication costs worldwide. More interaction can be done using technologies, firms and people are better off when they are located at greater spatial extent. Gordon and Richardson (1997) do not offer evidence to buttress their arguments. Some other scholars make the counter-argument that electronic communication complements, not substitutes, for face-to-face social interaction (Castells 1996; Ewing 1997; Atkinson 2001; Audirac 2002).

Economists have established that agglomeration economies of scale benefit innovation. The economic theory underlying agglomeration forces states that for most industries, firms benefit from being co-located: their average costs decrease as the total output increases, which is captured in the notion of agglomeration economies of scale (Marshall 1920; Henderson 1989; O'Sullivan 2003). Localized firms belonging to an industry gain advantages of a shared pool of specialized skills as compared to an isolated company. They also gain from reduced transportation costs as distances between firms and customers, and between suppliers and firms decrease. In addition, clustered firms benefit from knowledge spillovers: their workers interact with each other formally and informally across firm and business units to collect important information. This knowledge spillover can be increasingly important in industries where information about opponents, clients, new trends, and new technology is vital to the daily operation. It has been shown that the proximity among producers, suppliers, users, and knowledge workers facilitates communication among firms and thus has fostered the circulation of inventive ideas in the region (Angel 1994; Saxenian 1998, 1994, 1990). In his canonical book, *Principles of Economics,* Marshall (1920) indicates the important role of communication and interaction in innovation when he writes "[I]nventions 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." (p. 225-227).

3. Geographic Proximity and Innovation

Many researchers who study the innovative milieu are able to collect evidence of the localized nature of knowledge and patenting activities, indicating the impact of distance on innovative activity. An important finding of this economic literature is the evidence that innovation is not equally distributed across the landscape and is more concentrated around the source of research activities such as research universities and research labs (Malecki 1985, 2000; Jaffe 1989; Feldman 1994, 1999; Feldman and Florida 1994; Audrestch and Feldman 1996; Anselin, Varga, and Acs 1997, 2000; Allen 1997; Almeida and Kogut 1997, 1999; Saxenian 1998; Ohuallanchain 1999; Acs 2002; Nunn and Worgan 2002; Acs, Anselin, and Varga 2002; Black 2004). The theoretical backbone of this literature is built upon the knowledge production function developed by Griliches (1979). Jaffe (1986) used this model to examine the effects of R&D investment in the "spillover pool" of related firms in similar industries on one firm's output as measured by patent counts. In his later study, Jaffe (1989) examined the spillovers of knowledge from university research and found some evidence of impacts of geography on the spillovers. The

Griliches-Jaffe model (which has the spatial dimension) can be expressed in algebraic terms as follows:

K = f(I, U)

Where

K is some measure of knowledge output such as patents

I is corporate R&D

U is university research

Following the study by Jaffe (1986), a line of empirical studies begins to explore this missing puzzle of space in the innovation process using the Griliches-Jaffe's knowledge production function (Feldman 1994, 1999; Feldman and Florida 1994; Audrestch and Feldman 1996; llen 1997;Almeida and Kogut 1997, 1999; Ohuallanchain 1999; Acs 2002; Nunn and Worgan 2002; Black 2004). Those studies analyze the location of R&D facilities and high technology firms and the effect of local university research on the regional innovative capability. Especially, the role of local universities in the process of technological innovation is clarified in a series of work by Feldman (1994), Audrestch and Feldman (1996), Anselin et al. (1997, 2000), Acs 2002, Acs et al. (2002) among others. This body of literature suggests that innovation benefits from the clustering of related institutions such as research universities, private, and corporate R&D institutions. Feldman and Florida (1994) argue that an area's technological infrastructure facilitates the flow of information needed for innovation and the geographical proximity of those inputs "facilitates knowledge sharing and cross-fertilization of ideas, and promote face-to-face interactions of the sort that enhances technology transfer." As a result, geographical proximity of firms and research institutes will essentially lower the cost associated with innovation and we would observe more innovation.

Using states as a unit of analysis and controlling for population, Feldman and Florida (1994) find that industrial R&D, university R&D, the presence of related industries, and the size of business services have positive and significant effects on innovation. This result confirms Jaffe (1989)'s earlier findings of the importance of spillovers from university research on state-level corporate patenting activities. Acs (2002), Acs et al. (2002), and Anselin et al. (2000, 1997) extend the above studies by using the spatial econometric method and adopting sub-state units of analysis. Anselin et al. (2000, 1997) start to look at the spatial distribution of innovation and use a detailed data set on innovation counts and R&D employment at both state and MSA levels of geographic aggregation. In those spatial economics models, Acs and his colleagues create spatial lagged variables that capture effects of university and private R&D in counties surrounding the MSAs within a certain distance. They also compare the models using innovation counts based on the 1982 US Small Business Administration Innovation data. All regressions including OLS and spatial models with spatial lags for university and private R&D show that university and private R&D have a positive impact on innovation. Among other important results, the spatial lag indicates that university research in counties outside MSAs could affect innovation generated by firms inside MSAs (Anselin et al. 2000, Acs 2002, and Acs et al. 2002). They also find that business services are important for innovation to most industrial sectors (including Machinery, Electronics and Instruments) except for Drugs and Medicals (Anselin et al. 2000, Acs 2002).

The contribution of this line of research is that the Griliches –Jaffe knowledge production function has been extended to include knowledge spillovers in the geographic realm. Those studies are able to show that local research universities and R&D facilities are the source for generating local knowledge and innovation. Most importantly, those studies point out the localization of knowledge diffusion, which is linked to personal contacts and face-to-face social interactions. In addition, this line of studies has addressed issue of geographical scale and as a result, scholars have started to study regions and metropolitan areas.

The effects of agglomeration via concentration of economic and research activities in the geographical space have important implications for planners and urban designers. If technical knowledge resulting in innovation is spatially bounded as the economics literature suggests (Acs et al. 1998), should more compact metropolitan area affect innovation? With better street accessibility and higher population density, compactness appears to possibly increase the level of face-to-face social interaction among knowledge workers. In addition, compact urban areas potentially create better agglomeration economies because institutions and people in the metropolitan area are located within shorter distances from each other. The remaining question is whether those possible advantages of compact urban areas can actually materialize in a higher level of innovation. In the following section, I will investigate all important factors including urban form.

Chapter III: Conceptual Framework

Cities with their surrounding urbanized areas provide a supporting system of infrastructure and human capital for different industries. Throughout human history, cities have always played the central role to facilitate political and economic activities. For example, Venice and Boston became market centers as merchants were able to take advantage of the scale economies in sea transportation. Factory and industrial cities were formed by the concentration of workers and factories in an industry, or in related industries. The city of Detroit, for example, only thrived into a city when mass automobile production began in the early 20th century. With the industrial growth, Detroit experienced a significant increase in the population who came to look for employment opportunities. Pittsburgh evolved as a steel city because of its proximity to the iron ore fields and steel intensive industries located near Pittsburgh. It is more difficult to classify modern cities by function because of their complexity, but most cities in the world still are characterized by agglomeration economies within specific industries. For example, London is a center for international finance. The Washington D.C. region serves as a center for biotechnology research and innovation. Recently, scholars have started to talk about the role of cities and metropolitan areas in "generating new innovations" (Glaeser 1999; Acs 2002). There is evidence that most innovations, as indicated by patent counts and other innovation measures, occur in metropolitan areas across the country (Acs 2002, Black 2004). This fact implies that as our economy becomes more knowledge-based, the question of what makes cities more innovative and more creative is important in the design of public policies.

The literature addresses three major factors influencing innovation including corporate and university R&D, human capital, and social capital. This thesis proposes that planners and urban designers consider urban form as the fourth factor in the innovation process. The thesis also attempts to shed light into the question of what factors of social capital affect innovation and how. Chapter Three presents the theoretical framework of a model that explains regional variations in innovation. This model links a set of social and spatial factors to regional innovation. These hypothesized linkages are drawn from various studies that have been conducted over the past twenty years. My primary contribution to the literature is the compilation of those linkages and factors in a comprehensive framework to allow planners to investigate urban/metropolitan conditions that foster innovation. In addition to the proposed framework, my original contributions include testing relationships between urban form and innovation, between urban form and certain factors of social capital including trust, connectivity, and religious ties, and between those social capital factors and innovation.

The research explores three questions as follows:

1. Is there a relationship between compact urban form and innovation?
2. Is there a relationship between innovation and three factors of social capital (trust, social connection, and faith ties)
3. Is there a relationship between compact urban form and the level of trust, and between urban form and the level of social connection?

However, to measure the complex relationships and interaction among innovation, urban form and social capital factors, we must control for a range of social, economic, and institutional factors that are known to influence innovation, such as regional levels of research and development (R&D) and education. The causal paths among factors are illustrated in the following graphs using directional arrows. The boxes represent regional inputs to innovation. The relationships are combined in the final flow chart in figure 3.7. The chapter extends the discussion of the literature review and bridges the existing literature to my hypotheses.

1. Major Inputs to Innovation: R&D, Human Capital, Social Capital

1.1. Research and development (R&D)

Financial outlays in R&D play a major role in the innovation process. R&D funding invested in research activities does not necessarily result in new products. However, there is always new knowledge produced in every successful and failed experiment. This knowledge can be confirmation or invalidation of what has been known or it can be completely new. Research and development activities are present in corporate R&D laboratories as well as in research universities. Those two types of institutions benefit society by generating new and useful knowledge which result in innovation. The line of studies by Acs and Audretsch (Acs 2002, Acs and Audretsch 1988, 1990, 1991) suggests that each type of R&D works in favor of different firm sizes. While corporate R&D often exists in big companies such as Microsoft, IBM, and Eli Lilly, small firms usually can rely on universities for innovative ideas and knowledge, which is always open to commercialization. Federal agencies such as the National Institute of Health (NIH), Department of Defense (DOD), Department of Commerce (DOC), and the National Science Foundation (NSF) fuel most academic R&D at present (Jankowski 2005). Using federal funding, research universities generate innovation by collaborating with other institutions of higher education or with firms. Taken together, corporate and academic R&D funding provides necessary capital for research activities directly responsible for new products and innovation. However, the relationship between R&D expenditure and innovation is not only uni-directional – from R&D investment to innovation. The relationship can also loop back with a time lag because firms also react to its innovations. Successful innovations can encourage firms to invest more in the research and development process. Failed attempts to create new products and unsuccessful innovations that do not help firms improve their competitiveness undermine corporate funding for R&D activities. Nevertheless, the feedback process can take the opposite direction: failure in R&D activities can force firms to appropriate more resources to research. The effect of innovation on universities and federal and state agencies can be very much similar. Innovation can create incentives for more funding from government agencies but research that does not result in innovation can also trigger for more funding in the subsequent periods of time.

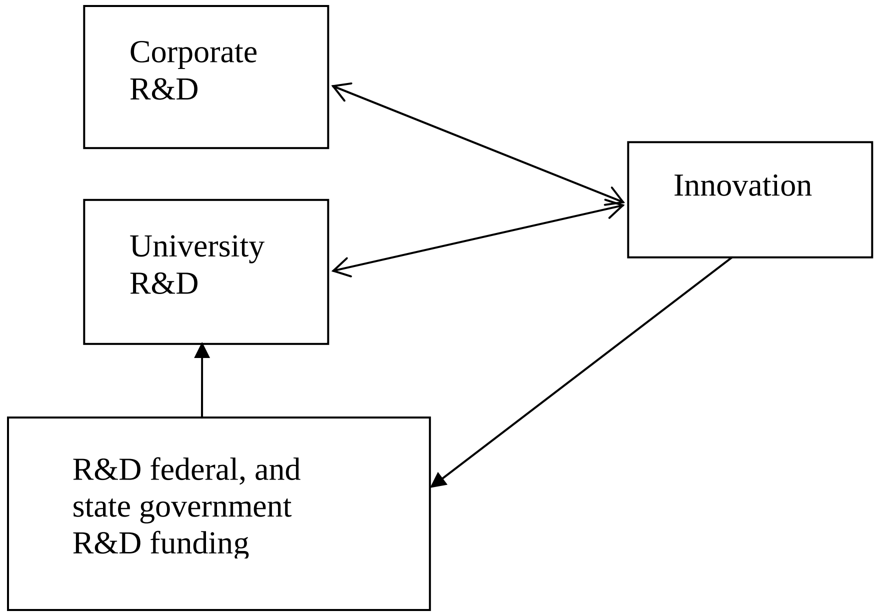

Figure 3-1 The Relationship between R&D and Regional Innovation

1.2. Human capital

Human capital is a crucial element and even a major input into the innovation process. In a usual context, human capital refers to education; but for innovation, human capital is associated with highly trained knowledge workers. Even though Peter Drucker (1969) did not invent the term "knowledge economy", he is the one who coined the term "knowledge worker" in his series of books and articles written about the global shift to the knowledge based economy. According to Drucker, a knowledge worker is the one who "applies to productive work ideas, concept, and information rather than manual skill or brawn" (p. 264); and Drucker links this group to what the Census Bureau labeled "professional, managerial, and technical people" in 1960. Unlike manual workers who do not own the "means of production", knowledge workers own knowledge and apply it to their work on daily basis to create products. They take it with them wherever they go. Like manual workers, their knowledge comes from two sources: formal education in school and from their more skilled colleagues and/or neighbors. However, the type of knowledge used in the innovation process is significantly more advanced than as required for manual work. In this process, the knowledge worker does not just create new knowledge from what he or she has obtained from school or textbooks. The knowledge worker creates new knowledge in a process that also uses the type of knowledge he or she learns from working and interacting with others. Therefore, the factor of human capital in the knowledge production process is not the same as in the context of traditional production process. A higher level of education attainment and an ability to create new knowledge through learning and interacting helps distinguish a knowledge worker from a manual worker in the age of knowledge economy.

It is also important to notice that regions that are active in innovative activity attract knowledge workers from other places outside the region. This has been pointed out by Drucker (1969, 1994) and Florida (2001) among other innovation researchers. Taking their means of production with them where they go, knowledge workers and the Creative Class vote by their feet. They choose places where they can be confident that they can learn, apply what they learn, and create. Most or all of them participate in the innovation process in their daily tasks or get involved indirectly in supporting activities inside firms or research universities. Thanks to their work, the region is able to generate innovations of which quality and quantity become important factors to help further generate more innovations. Regions with lots of high quality innovations send a positive signal of openness, promising employment opportunities, and potential industrial expertise to people outside the regions, creating motivation for everyone including knowledge workers to get inside the regions.

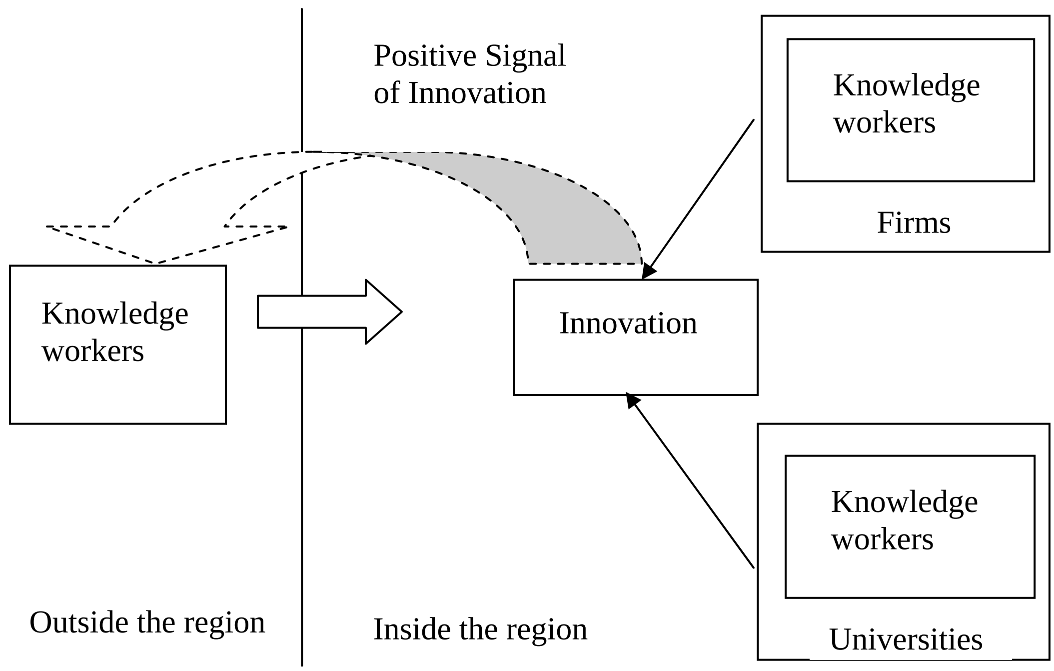

Figure 3-2 The Relationship between Human Capital and Regional Innovation

Young new professionals look for opportunities to work with talented people in innovative regions while talented people are drawn into innovative regions and industrial clusters because they believe that their talent is appreciated. Knowledge workers also extend their network of connections by moving into regions well perceived as more innovative. And because of the presence of more knowledge workers, there will be more innovations, which in turn attract more knowledge workers from beyond the region's boundary.

1.3. Social capital

A third area addressed in the literature is the role that regional variations in levels of social capital play in explaining regional variations in innovation. Having been vaguely defined as one's ability to connect with other individuals and to use those connections as resource to achieve certain ends, social capital under the perspective of a region portrays the level of connectedness among the region's residents. The larger the network and the higher number of networks, the more opportunities for face-to-face interactions among knowledge workers. And the more interactions they have, the more knowledge is acquired. As the review of both the organizational and innovation literatures indicates, innovation depends on face-to-face interaction (Lundvall and Johnson 1994; Lam 1998, Acs 2002; Johnson, Lorenz, Lundvall 2002; Patton and Kenney 2003).

To better understand knowledge spillover and the relationship between social capital factors and innovation, one should turn to theories of organizational learning and knowledge creation. Most theories suggest that knowledge has an important component that is not transferable via media such as telephone or email (Lam 1998). This component is called by different names such as tacit knowledge (Polanyi 1962) or the knowledge of know-how and know-who (Lundvall, Johnson 1994; Johnson, Lorenz, Lundvall 2002). This component of knowledge is attached to the knower's experience and has the nature of incommunicability. It is shaped by culture, practice and experience; it is subtly acquired in people's daily activities, during their upbringing, at work, and in any places where social interaction occurs (Johnson 1992; Lundvall 1992; Spender 1993). Know-how is the kind of knowledge that the apprentice learns from the master by working with him. Know-who is the knowledge of who has the information and who to learn from. Combined together, the knowledge of know-how and know-who enables the knowledge worker to tap into the resource of his or her web of connections for solutions. In any region, institutions such as firms, research universities, and libraries, and individual knowledge workers function as knowledge depositories. However, even though institutions store knowledge, only individuals carry out knowledge transfer through learning from and interacting with others. Therefore, creative and innovative ideas, as part of new knowledge, are created from the knowledge inventory of the region in a process to which face-to-face interactions are vital.

There is an association between face-to-face interaction and social capital factors including trust, connectivity, and faith ties. Face-to-face social interaction is viewed as much a cause as a sign of healthy social capital. According to Putnam (2000), face-to-face interaction is one dimension of social capital among others such as civic, religious, and work-related organization participation. He also describes a set of activities that we engage in our informal networking activities such as getting together after work for drinks, having friends or colleagues over at one’s house, and even gossiping with neighbors. Most of those networking activities involve face-to-face interaction. It appears that a higher level of social capital would result in a higher level of face-to-face social interaction. Putnam (2000) laments what he considers as a decline in American public social capital which is in part due to the increase in lonely activities that people commit to. He contends that automobiles, side by side with television and personal audio-video devices, create a private environment surrounding people. Consequently, this lack of engagement in collective activities which involve face-to-face interaction erodes social capital. To the extent of the current study, the relationship between face to face interaction and trust, connectivity, and faith ties provides a link between social capital and innovation. The following graph illustrates social capital affects innovation via the process of knowledge accumulation and knowledge creation.

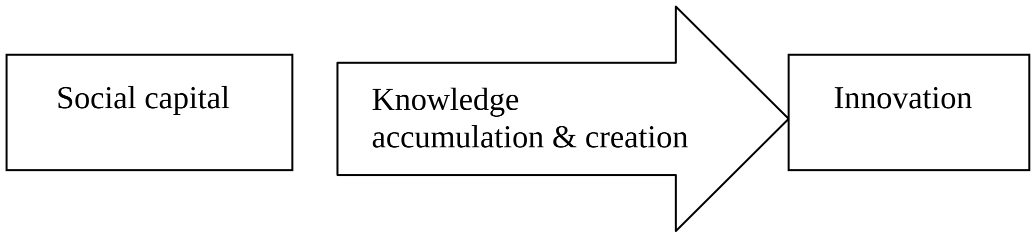

Figure 3-3 Social Capital and Its Relationship to Innovation

2. Urban Form and its Connection to Innovation

2.1. Innovation, Urban Agglomeration, and Compactness

Various empirical studies in the context of regional innovation suggest that the accumulation of information and knowledge and the flow of ideas need urban agglomeration to evolve and be sustained (Glaeser 1999; Ohuallanchain 1999; Acs 2002; Nunn and Worgan 2002; Black 2004). As mentioned in the previous chapter of this dissertation, some evidence shows that clustered firms enjoy agglomeration economy from sharing knowledge among firms in an industry besides sharing suppliers of intermediate inputs and a common labor pool. Firm clusters provide an environment conducive to innovative activity. Face-to-face interaction among researchers and engineers who work for different firms in the same industry facilitates the transmission of information and knowledge. The exchanged information can be about technical problems they have run into or solutions to problems in their daily work. The shared information is used to develop new products or to avoid potential problems. Consequently, most firms are likely to benefit from the knowledge spillovers and the innovative performance of the whole cluster and the industry is improved. The effective innovative performance of firms within the cluster renders a positive feedback to firms outside the region and thus draws new firms into the region. Similarly, more knowledge workers will be attracted to the region because they perceive the region provides valuable information and opportunities for them to thrive. As a result, there is an increase of returns to innovation activity that all firms and innovators enjoy in large metropolitan areas (Ohuallanchain 1999).

A compact metropolitan area is also able to increase the returns to innovative activity. Residents of more compact metropolitan areas commute over shorter distances to and from their workplace and other places of interest. They can invest more time in activities that enhance quality of life and in acquiring new knowledge. High level of street accessibility together with land use mix allows for improved communication in the metropolitan area. Given the profusion of suppliers, customers, business supporting organizations, and knowledge workers in a compact area, the speed at which the innovator receives feedbacks with respect to his or her particular product or invention is faster. The result is the innovator can modify his or her invention and respond to the technological demand in a timely manner. Despite the fact that not all of the innovator’s inventive ideas eventually materialize in innovations, an urban environment favorable to innovators’ efficient communication would lead to increasing returns research activities, meaning more technological innovation occur. Planners can change the configuration of urban amenities and infrastructure to create favorable settings for learning and interacting activities, and thus change the region's innovative performance accordingly. The question of how planners change the urban physical settings is central to this dissertation.

2.2. Compactness, Social Capital, and Innovation

Compact urban form increases knowledge workers' opportunities to engage in face-to-face interactions, which is critical to learning, knowledge dissemination, and innovation. As already mentioned, via face-to-face interactions, knowledge accumulation occurs in the region when knowledge workers interact with and learn from their colleagues. Embedded in the metropolitan area are firms of the same industries, firms from different industries, research universities, workplaces, homes, cafes, etc. each of which serves as a node in a network of venues, where social interaction can take place. In light of this, it is possible that urban form affects social capital, which in turn affects innovation as graphically described in Figure 3.4.

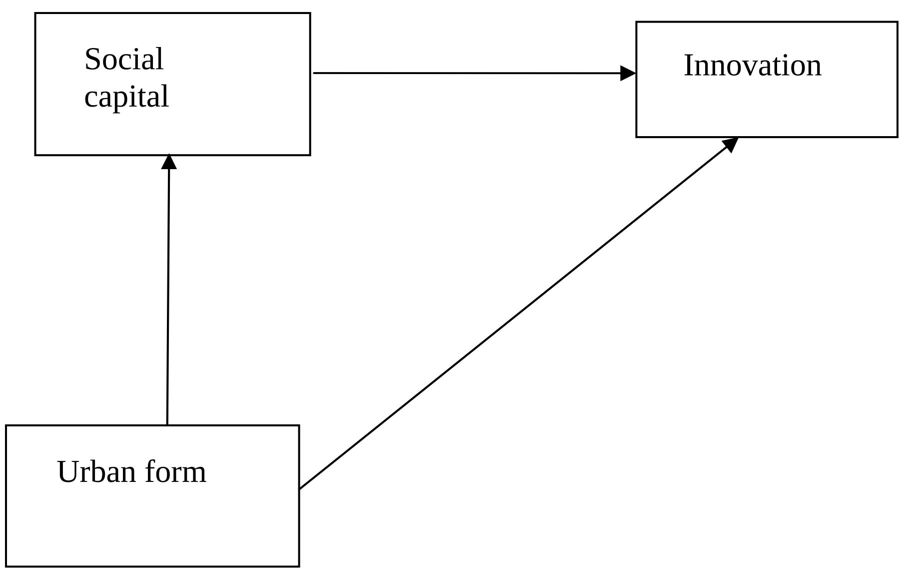

Figure 3-4 Urban Compactness, Social capital and Innovation

Among the three factors of social capital including trust, social connection, and faith ties, urban form could directly influence the first two factors, which in turn affects innovation. This is because compact urban form implies a high level of population density and high street accessibility, both of which possibly influence the level of connection and social interaction among the urban dwellers. As repetitive as it may sound, when city size and population density increase, opportunities for interaction also increases. Nevertheless, the literature on the impact of sprawling versus compact urban form on social capital is not adequate to enable researchers to have a conclusive result. According to Putnam (2000) and Florida (2001), sprawled developments scattering over the urban space fail to have the mechanism to support social capital for a number of reasons. Firstly, just pure longer distances lengthen car driving time for anybody living in the metropolitan area. And so the time invested in activities to increase one's prospective networking activities is reduced and the habit of socializing also fades away. As a result, residents living in sprawled areas would be less likely to interact with their neighbors and to develop trusting relationships. This is in addition to the other consequences such as lost time that could be spent on acquiring new knowledge and interacting. Secondly, greater distances among different communities could increase their homogeneity and separating them further from each other along lines of ethnicity, culture, and income (Putnam 2000). This homogeneity can enforce bonding social capital and weaken bridging social capital for the residents living in those communities.

Communities in compact urban areas are closer together and there are chances that people living in different communities come to mingle with others. Both Jacobs

(1961) and Florida (2002) consent that in compact city areas with high density and convenient street accessibility, communities become more socially active and people can balance their level of trust (desire to have privacy) and the degree of social connectedness. Living in compact and diverse communities, people get exposed to other people with different background and values. Consequently, contacts and interactions with people from other communities can prosper in more compact urban areas. When a metropolitan is both compact and socially and culturally diverse, it could possess an enormous potential network of connections with great tolerance to unconventional ideas. With respect to the relationship between social capital and innovation, Figure 3.5 illustrates the complex inter-relationship among the facets of social capital that are directly related to innovation and not captured in figure 3.4. Both trust and connectivity have direct relationship with innovation. Trust also determines the level of connectedness among people, including knowledge workers. It is possible that the more trust people have, the more connected they are. It is also possible that connectivity and social trust mutually reinforce each other, therefore, an increase in the level of connectivity could lead to a higher level of social trust.

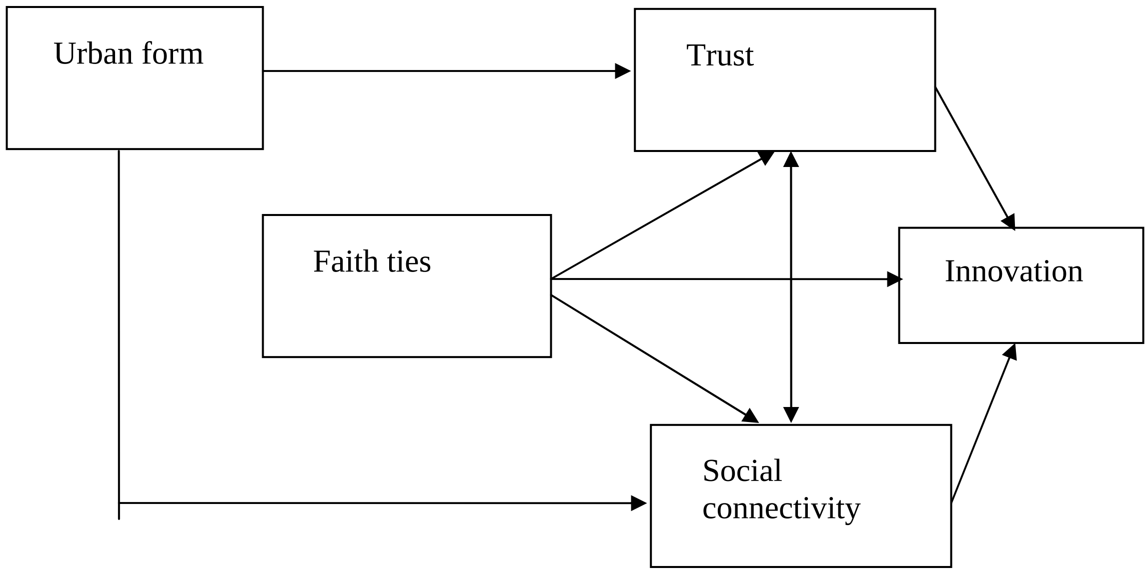

Figure 3-5 Faith ties, Trust, Social Connectivity and Innovation

2.3. Faith ties

Figure 3.5 also highlights the relationship between faith ties and innovation. As discussed elsewhere, sprawl and faith ties can create homogeneous communities that are bounded by beliefs. In such communities, there may be more chances for internal relationship and social interaction and less for the out-reaching type of connections for the purpose of knowledge exchange. If there is a geographic coincidence of those religious communities and technological and professional communities of knowledge workers, it could be that their high level of trust and strong bonding social capital work in favor of innovation. Otherwise, the innovative performance of those communities can be hampered. Florida (2002) raises the issue of signaling which may further complicate the relationship of faith tied communities and innovation. Creative and innovative people interpret strong faith ties as a sign of disapproval of new and unconventional knowledge and products. Because of the above reason, faith ties may have negative or positive impact on the innovation process. Figure 3.5 shows that faith ties affects the other two dimensions of social capital, trust and social connection, which in turn affect innovation.

3. Other Factors to Innovation

3.1. Diversity

According to Florida (2002), social and cultural diversity indicates tolerance to unconventional thinking, which is part of creativity and of innovation. Therefore, regions with high levels of social and cultural diversity are able to attract the Creative Class. In addition, social diversity may have certain impact on trust, connectivity, and faith ties because it creates opportunities for interaction among people from different backgrounds. Figure 3.6 describes both direct and indirect relationship between social and cultural diversity and innovation. The diversity among knowledge workers is also important because it allows for interaction among those who own different knowledge and information related to problem solving. Even though this diversity may not strengthen one's network and connection, it can contribute greatly to scale of one's network. By interacting and becoming involved in each other's network, the mathematician can contribute greatly to the software engineer's problem solving capability. The software engineer can improve the mathematician's knowledge by providing him with practical feedbacks. The pool of knowledge in more diverse urban areas therefore is likely to increase when there exists professional diversity among knowledge workers. Both Jacob (1969) and

Florida (2002) also share similar views toward the ability of compact cities to generate street liveliness that provides venues for social interaction and stimulation for innovation. Whereas sprawl increases distances among communities which could help create more homogeneous communities, compact urban areas could allow people from different communities to mingle and communities to blend to increase diversity. However, the extent to which compactness affects diversity could be argued and needs further empirical investigation.

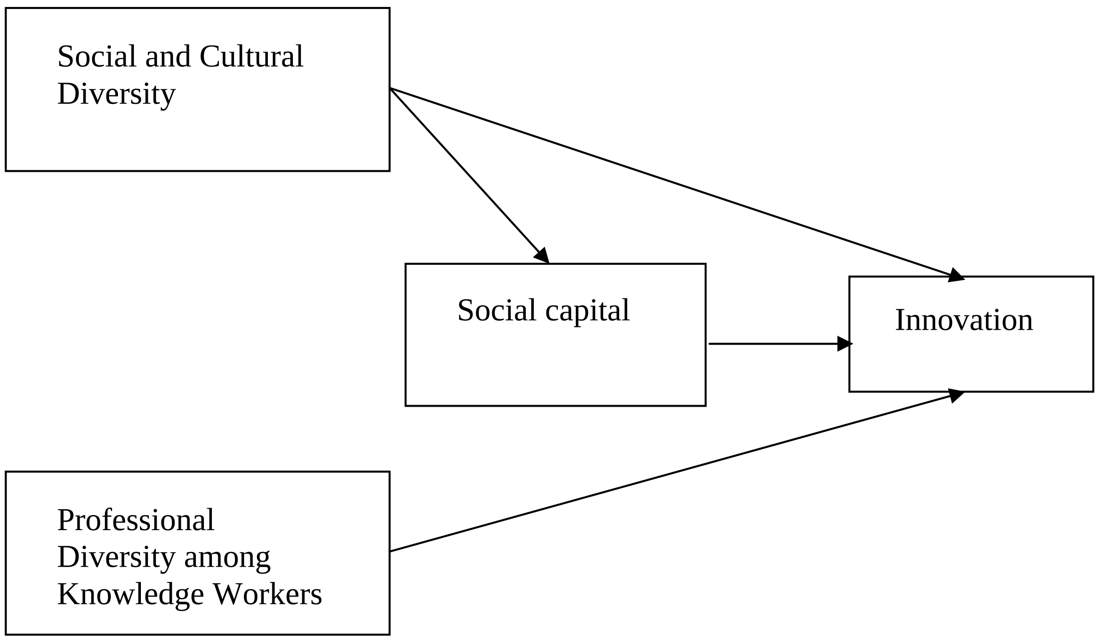

Figure 3-6 Diversity, Social capital and Innovation

3.2. Supporting Business Sector

The contemporary empirical literature on knowledge spillovers pioneered by Acs (2002) and others recognizes the role of the business sector as one of the key factors to technological innovation. In this current framework, the supporting business sector (SIC 73) is also considered to positively affect the rate of innovation.

Even though the sector's operation may not have levels of knowledge intensity as high as in innovative activity, business services are crucial to knowledge workers' performance. They deliver different services to firms such as advertisement, graphic design, data processing, and information retrieval. Since their services are needed in a variety of firm activities from employee recruitment, R&D to the main production, more suppliers in the sector reflects the increasing demand by firms in those activities. The concentration of the sector in the region can help improve firm performance. It is because trivial and uncreative work can be outsourced to the business services sector, firms can dedicate time and resources to more important activities including research. This could result in an increase in innovative activity at the regional level. As more innovations being generated, there will be more firm startups and many firms move into the region. The business sector expands in size to meet with the rise in demand. Therefore, the association between supporting businesses and innovation is to be indicated by a bi-directional arrow in Figure 3.7.

4. Consolidation of Hypotheses into the Model

This chapter presents the framework that I will model to explain regional innovation. The framework captured in Figure 3.7 suggests that in compact urban areas, geographical proximity among workplaces, research institutes, restaurants, cafes and residences is reduced, leading to increased human interaction. This increase should be associated with a rise in knowledge workers' opportunities for learning and interacting. Subsequently, the region's knowledge base expands and more innovations will be created. Compact urban form could also positively affect the level of trust and social connection among ordinary people and knowledge workers so that they could form effective professional and social networks.

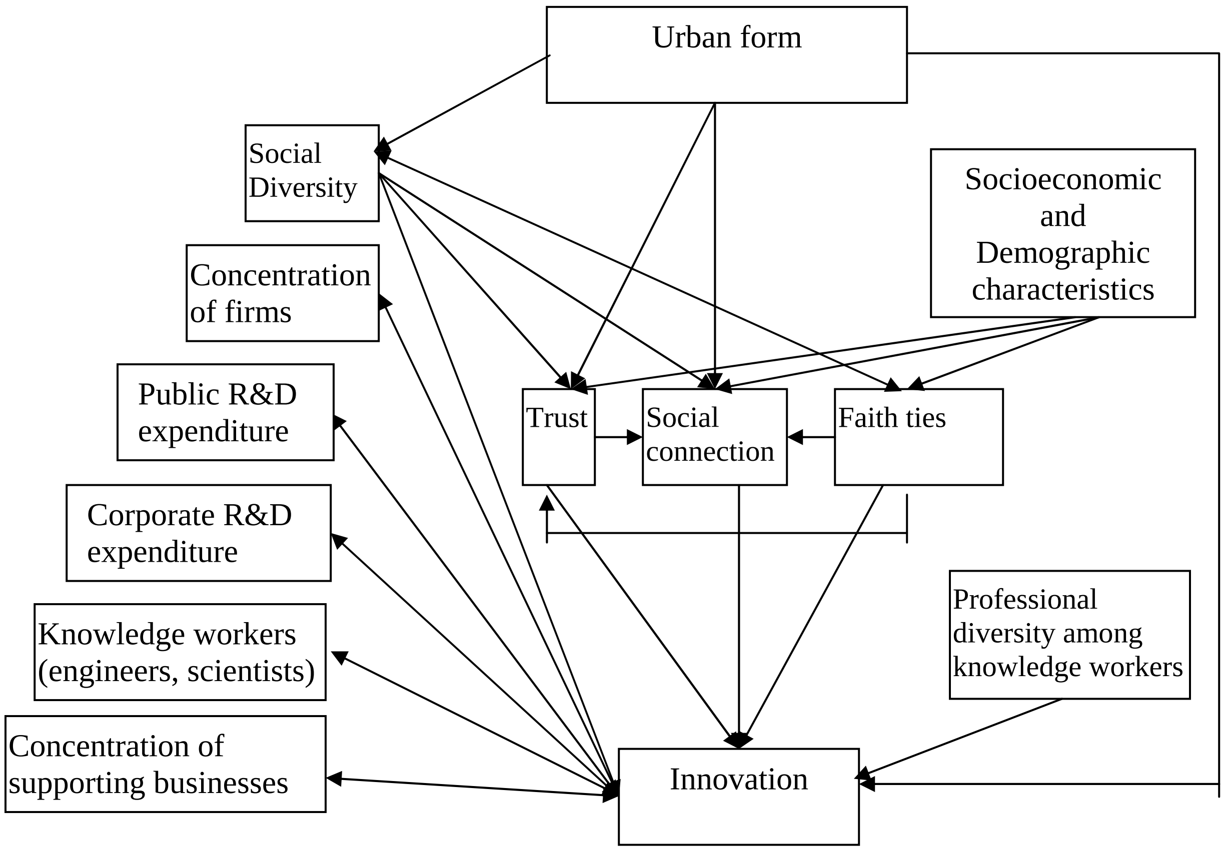

Figure 3-7 Theoretical Framework of Regional Innovation

Trust, connectivity, and faith ties are also hypothesized to be correlated with regional innovative activity. Trust and connectivity should be positively associated with innovation while the other factor could have positive or negative association with innovation. The degree of social and cultural diversity could have some association with trust, social connection, and faith ties. A high degree of social and cultural diversity could improve trust across different groups and the level of outreach connection. Social and cultural diversity may also have impact on innovation.

However, faith ties, the other dimension of social capital, could decrease social and cultural diversity, which in turn, have impact on innovation. Faith ties may constrain the exposure to invention and unfamiliar ideas and thus may affect innovation in a negative way. Finally, occupational diversity among knowledge workers could have positive impact on innovative activity in the region.

The framework illustrated in Figure 3.7 is drawn from the different bodies of literature summarized in Chapter Two. I also included original hypotheses about the association between compact urban form and innovation and the interrelationship between social trust, social connection, faith ties and compact urban form. In addition to exploring these new relationships between spatial and social factors and innovation, my contribution is to consolidate this literature and convert it into a testable empirical model. Extensive empirical research has supported the impact of R&D investment and human capital on innovation. There has been little empirical evaluation of the impact of urban form on social capital; and there has been no empirical estimation of urban form's impact on innovation and of social capital's impact on innovation at the regional level. The model in Figure 3.7 allows me to use statistical methods to test hypothesized relationships. The operationalization of constructs of social capital, urban form, and innovation and the description of datasets are presented in Chapter Four.

Chapter IV: Data

This chapter discusses the sources of the data and the operationalization of the constructs to analyze the impact of social capital and urban form on innovation. In order to test the hypotheses laid out in Chapters One through Three, I use three main datasets. The first data set measures innovation based on U.S. patent statistics assembled by Hall, Jaffe, and Trajtenberg (2001) for the years 1963 to 1999 and updated by Hall (2003)[1] for the years 1999 to 2002. The second data set is the Social Capital Community Benchmark Survey Restricted Use Data in 2000 provided by Harvard University through the Roper Center of the University of Connecticut (2005). This dataset captures a number of social capital factors and individuals' demographic and socio-economic information. The third data set measuring urban form is based on the sprawl index obtained from Ewing et al.'s (2003) work. The remaining variables are from national sources such as the 1990 Population census, the County Business Pattern data 1990, and the National Science Foundation Survey of Scientific and Engineering Expenditures at Universities and Colleges (1996).

1. Patent and Inventor Location Data

1.1. The patent file and patent statistics as a measure of innovation

A patent for an invention is the grant of a property right to the inventor (USPTO, 2005). Generally, the term of a new patent is 20 years from the date on which the application for the patent was filed in U.S. The United State Patent and Trademark Office (USPTO) classified patents into three distinct categories: design, plant, and utility. Utility patents are those indicating new and useful improvements,

[1] This dataset is available to public access on Bronwyn Hall's website at http://elsa.berkeley.edu/~bhhall/.

processes, or machines. Design patents are granted to those who invent new and original ornamental design for an article of manufacture. Plants patents are granted to anyone who invents or discovers and asexually reproduces any distinct and new variety of plant.

In order to evaluate innovative activity and capability, researchers have used different measures such as research and development expenditures, new product announcements in trade and professional journals, Small Business Innovation Research awards, and patents. The possible use of utility patent statistics as a proxy for innovative output has recently become widely recognized because of the direct relationship between technological inventing activities and the patent data. Using utility patent data, however, poses certain issues and limitations that could be subject to criticism. Some observers have contended that a number of factors can affect the patenting activities during different time periods. For example, Sokoloff (1988) and Sokoloff and Khan (1990) noticed that the relationship between the level of invention activity and the number of patents granted could be seriously affected by institutional and cultural factors such as changes in the property right enforcement.   In addition, the proportion of inventions and innovations that are patented may vary across industries, which is commonly known as "the propensity to patent" (Comanor and Scherer 1969, Sokoloff and Khan 1990; Hall and Harn, 1999). The relationship between inventive activity and the number of patents granted can also be altered by the change in the Patent Office staff's conception of what is innovative in the granting process (Griliches 1989). Therefore a rise or decline in the number of patented innovations may not be parallel with a similar trend in the actual innovative activity.

Longitudinal analyses which use patent claims and patent statistics could be hampered by the fluctuation in patenting activities (Comanor and Scherer 1969).

The challenge to using patent statistics also comes from the propensity to patent which varies by industry and by firm. There is some evidence that certain companies hide their innovation in their production and products instead of relying on intellectual property protection (Black 2004, Gascoigne 2005). In contrast, pharmaceutical and chemical companies tend to protect their intellectual property through utility patents because it is more difficult to conceal technological innovation in their products. In this case, patent statistics more accurately reflects innovation within an industry. In short, there will be innovations which never get patented and the researcher has to be cautious when interpreting the results of a cross-sectional analysis using patent statistics. Griliches (1990) suggested using industry dummies or avoiding aggregated patent counts for all industries to address this issue.

Another concern about using patent data centers on the economic value of specific innovation or in other words, innovation quality. Any patented innovation does not indicate its underlying economic significance within a short period of time after the patent being granted. To address this issue, some authors (Hall, Jaffe, and Trajtenberg 2001) recommend using the number of citations received by a patent as a way to screen for high quality patents. However, it could take many years for the value of a patent to be recognized and the popularity of a patent is correlated with its life. Likewise, few citations that a patent received within the first few years do not always mean that patent is not economically important or highly innovative; on the contrary, a high quality innovation may take years to be appreciated and widely cited.

Therefore, using citations as a measure of innovation might lead to other shortcomings.

Despite those concerns and challenges, a number of researchers were convinced that patent data could not be ignored and the use of patent as a measure of innovative/inventive activity can yield results as good as or, in some cases, better than other indicators. Hagedoorn and Cloodt (2002) compared R&D inputs, patent statistics, patent citations, and new product announcements in their study of innovative performance of an international sample of companies. The outcome of their factor analysis suggests that there was no "major systematic disparity" among those indicators in individual high tech sectors and the whole sample. In a different study, Acs et al (2002) used a spatial regression model to test whether the patent data was a reliable proxy of innovative activity at the regional level compared to the "literature-based innovation" i.e. new product announcements in trade journals. Their results support the usage of patent statistics in examining technological change and innovative activity at the metropolitan level. Following other authors (Jaffe 1989, Fieldman 1994; Audrestch and Feldman 1996, Anselin, Varga, and Acs 1997, 2000; Allen 1997, Almeida and Kogut 1997, 1999; Feldman and Florida 1999, Ohuallanchain 1999; Acs, Anselin, and Varga 2002; Nunn and Worgan 2002, Black 2004), I used the patent data combined with the inventor's residential location data to explore innovation at the sub-state level.

The utility patent data used in this current study were systematically collected and analyzed by Hall, Jaffe, and Trajtenberg (2001) in multiple research projects funded by the National Bureau of Economic Research. They compiled utility patent data from 1963 to 1999 and citation data from 1975 to 1999. There are a total of 1,784,989 patents claimed by American citizens from 1963 to 1999. In her recent work, Hall (2003) extended the patent data to include utility patent that were filed through December 2002. The researchers developed multiple layers of patent classification to aggregate 400 patent classes developed by the US Patent and Trademark Office (USPTO) into 36 2-digit technological sub-categories, and further aggregated those 2-digit subcategories into six main categories: Chemical, Computers and Communications, Drugs and Medical, Electrical and Electronics, Mechanical, and Others. In addition to the technological categories, the patent data file includes original variables developed by the USPTO staff and those developed by Hall, Jaffe, and Trajtenberg (2001). The original variables consist of grant year and date, application year, country of first inventor, state of first inventor, assignee identifiers if the patent was assigned to another party, assignee type, and number of claims. Also, the researchers computed citation-based measures and included the number of citations made and received, percentage of citations made by this patent to patents granted since 1963, measure of generality and originality, mean forward and backward citation lag, and percentage of self-citations made (for the methodology and detailed discussion, see Hall, Jaffe, and Trajtenberg 2001).

For the purpose of the current study, I selected five main utility patent categories and the application year. Because the application date should be close to the date the innovation was created, the application year was selected. The five main utility patent categories include Chemical, Computers and Communications, Drugs and Medical, Electrical and Electronics, and Mechanical patents. Even though the technological classification may not be perfect, it is ideal for the current analysis for two reasons. Firstly those broad categories provide sufficient control for technology in the current analysis. Secondly any grouping schemes of 400 original subcategories developed by the USPTO would possess similar arbitrariness.

1.2. The “Inventors” file

This patent dataset, however, does not contain geographic information; therefore the “Inventors” file is needed to link each utility patent to its inventor’s place of residence. The “inventors” file was provided by the USPTO for all patents applied and granted from 1975 to 2003. The file contains patent registration numbers, last name and first name of the inventor, street address and zip code the of inventor's residence, city and state of the inventor's residence, and the inventor sequence number of inventors listed on the patents. The street address and zip code data are blank where patent rights are assigned to an organization at the time of grant. Since the file includes inventor information for every patent record, inventors’ name and residence information can be repeated in multiple patent records when the inventor applied for more than one patent. When there are several inventors in a patent, each of them has a sequence number to indicate the order in which each inventor appears in the application form.

There exist some difficulties in matching inventors’ cities of residence and their counties. Identifying the inventor’s residential county is important because the unit of analysis for the study will be at the county level, the most detailed geographic level at which socio-demographic and employment data are available. However, the county of residence was not included in the patent file and the inventor’s street address was only available when the patent was not assigned to another party at the time of grant.   For example, patent number 4918376 was assigned to a US non-government organization and only its inventor's city, Needham Heights, and state of residence, MA, were kept on file. For the inventor's county of residence to be retrieved, the Federal Information Processing Standard (FIPS) 55-3 database had to be used to this information based on the inventor's city and the state of residence[2]. This database comprises FIPS codes and names for populated places, primary county divisions such as townships, and other location entities of the United States such as American Indian and Alaska Native areas and areas under jurisdiction of the United States.

There are five issues and assumptions accompanying the inventor file data set which may affect the findings and conclusion of the study:

1. First inventor location information was used where multiple inventors share a patent. Only first inventor's information was used under the assumption that she was the principal contributor in the innovation process.

2. In some cases, one city or town crossed into several county jurisdictions. When this was the case, the primary county as determined by US Geological Survey and the US Board on Geographic Names in the FIPS 55-3 was selected.

3. When there was the same town name in different counties in a state, only the first county by alphabetical order was selected unless there were obvious reasons not to do so. This limitation is because the Microsoft Excel algorithm was designed to do so with lookup and match functions.

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[2] The data set is disseminated by the US Geological Survey and is available to be download at http://geonames.usgs.gov/fips55.html

4. Inaccurate location information was reported in the patent application form for various reasons (Hibayashi 2005). For example, the applicant may have filed his or her immediate future residence if anticipating such a move. In another example, an applicant for personal reasons may have intentionally obscured her location information. The other source of error also came from the Patent and Trademark office. When application forms were scanned into electronic files, some handwritten characters may have been inaccurately recognized. This type of errors was more likely to occur in the earlier days of computer technology.

5. The inventor could have misspelled her state abbreviation or place name. Some common misspelling cases were found for WA and VA, CA and GA, and CA and CO. This type of error could also be due to the scanner at the US Patent and Trademark Office. There are three situations in which certain assumption were made to correct errors so that the location information was still useful.

a) When two or more states have similar town or city names, it is impossible to determine whether the inventor misspelled her town or city unless that inventor had other correct patent records in the database. If this was the case, the suspicious record was assumed to be "as reported" and no change was necessary.

b) When a town or city name had one or two letters misspelled and the correct alternative was obvious, this alternative was selected. Examples include San Francisco and SanFrancisco, and San Francisco and Sans Francisco.

c) When a town or city name was misspelled and there were several correct alternatives, the first alternative by alphabetical order was selected unless indicated otherwise. For examples, Almon appeared to be spelled for either Almond (AL) or Almont (AL) and Almond was selected as the correct town.

Those misspelling cases were identified during the matching process. The inventor file was compared with the FIPS 55-3 data base and the county names and county FIPS code were returned to the inventor file by using MS Excel formulas. The records with error were separated and rerun using a combination of Microsoft spelling check and eyeballing through the FIPS 55-3 list of place names. However, there remained cases in which it was not possible to determine correct names and thus those cases were not included in the analysis.

From 1990 through 2002, there were a total of 778,895 first inventor's residential locations associated with filed patents across the country, among which 10,778 cases had some errors that were successfully corrected (1.38%). After being screened for different misspelling possibilities, 594 inventor residential location cases were still untraceable and not counted in the study (0.08%). Among those unaccounted cases are also records that did not have location information or missed state or city.

The “inventors” file was combined with the patent file to create a new database to include location variables and technological classification. The matching process was done by using patent number as the key index to link a patent with its application year and technological type to its first inventor’s county and state of residence. Then the data were aggregated by county. The finalized innovation dataset includes utility patent counts in six technological categories for 2,932 counties nationwide.

In addition to the measure of innovation, a rough measure of innovators in any county was also created. By discounting the number of patents that a specific first inventor living in a county received, I was able to approximate the number of first inventors in any county from 1990 through 2002. This discounting step was performed using the Statistical Package for Social Sciences (SPSS) and MS Excel. During the process, duplication of the inventor's first and last names and his county of resident was counted and a frequency-based weight variable was created for each patent. For example, for ten patents which had the same first inventor from 1990 through 2002 in a specific county, each would receive a weighted value of one tenth. This approximation had certain drawbacks as it does not take into account the jointly filed patents in which some innovators were active but took the second or the third stand in their patent applications. Consequently, the approximation of innovators is likely to undercount the actual number of innovators in any county across the country. It is also reasonable to assume that the problem is more serious in counties with high numbers of patents and innovators.

1.3. Limitation of the patent data

There are several limitations to the patent dataset. The study examines the impact of urban form and social capital on innovation by using patent counts as a proxy for output of innovative activity. The drawback of using patent data is that its technological classification can be somewhat arbitrary. This arbitrariness exists during the patent application review process at the US Patent and Trademark Office and in patent aggregation into five major categories by Hall, Jaffe, and Trajtenberg (2001): Chemical, Computers &Communications, Drugs &Medical, Electrical &Electronics, and Mechanical patents. This issue is attributable partly to the patent examiner's personal judgment of the field in which an invention could be used. Patent examiners can also interfere with the total patent count in different years because of certain variance in their granting process (Griliches 1989). However, as the current study uses patent counts across several years, the effects of patent examiners do not change the result significantly. The other limitation of using patent data is the fact that firms and inventors in different industries respond differently to patenting activity. This issue has been at the center of discussion among economists since the early days of patent use (Comanor and Scherer 1969, Sokoloff and Khan 1990; Hall and Harn, 1999). Labeled as the propensity to patent, this tendency is assumed to exist in industries where it is not possible to hide inventions in new products or the production process. Since patenting may be costly to individuals and small firms, they could be more reluctant to do so. Freelance computer programmers are an example. Big corporations such as Microsoft® for the fear of intellectual property violation are more likely to patent their programmers' computer codes. As a result, individuals working for big corporations or foreseeing their inventions to be used by big corporations are more willing to apply for patent and they have resources to do so. In other words, patent data appear to favor certain industries and large firms; nevertheless, no study has successfully documented the extent of propensity to patent. Left with patent data as an imperfect proxy for innovation, I am aware of the possibility of data biasedness that may deflate the true innovative capabilities of some regions for the above reason.

It is important to point out the fact that not all patents lead to innovative products or process. Turning a patent to real innovative products and process is not an easy step. It requires investment in marketing of product among other factors. However, most of the process to realize patents into successfully commercialized products is often performed inside firms, the private sector apparently takes over the process and there is not much left for planners to affect. The role of government is, perhaps, more important during the initial phase when the innovation is conceived and developed.

Some limitations also exist in the method of extracting the innovator's residential information. They include inaccurate information and errors that primarily came from the patent applicants and from the USPTO granting process. Some errors may have found their ways into the analysis during the match of residential city and county. Even though the best identified information was used in the analysis, it should be acknowledged that a small number of systematic spelling errors and matching errors may slightly alter the final results of the analysis.

Additionally, only the residential information associated to the first inventor for each patent was used but there may be more than one inventor in each patent application. For the convenience of data analysis, one patent is only linked to the first inventor, assuming that the first inventor took major responsibilities in developing the innovation. This drawback may result in underestimation of innovative capabilities in regions where there are more patents with multiple inventors. This underestimation may also take place when a patent has several inventors from more second and third inventors will appear to be less innovative. Counties with more higher numbers of second or third inventors and less first inventors will appear to be less innovative. In general, using only first inventor information may lead to the underestimation of regional innovation.

2. Social Capital Data

In order to test the association between innovation and social capital, I used the Social Capital Community Benchmark Survey data. The 2000 Benchmark Survey was conducted by the Saguaro Seminar at the John F. Kennedy School of Government, Harvard University from July to November 2000. 26,230 people from 41 communities nationwide were interviewed over the phone (except for West Oakland, California where the survey was conducted from December 2000 to February 2001). The data also includes a national sample (N=3,003) which contains an over-sampling of black and Hispanic respondents (Roper Center 2003).

In the community survey, the researchers sampled 41 communities to measure “various manifestation” of social capital. Those sampled areas were composed of one county (Maricopa County AR, Kalamazoo County MI, and San Diego County CA), contiguous counties (Cincinnati Metro OH, Silicon Valley CA, and Kanawha Valley WV) or the entire state (Indiana, Montana, and New Hampshire). Proportionate sampling was implemented for most communities to avoid over- or under- sampling. The community sample sizes are proportionate to community sizes and vary from 500 to 1,500.

To ensure proper representation of the community population, the researchers created a weight for each interviewee. The data weighting involved the initial and balancing weight. The initial weight was proportionate to the ratio of the number of adults in the household to the number of phone lines in the same household via which an adult could be reached over the phone. The purpose of this initial weight is to control for the odd that some households could have been more likely to be selected because they had more than one phone number listed. The balancing weight accounted for the population distribution in the sample on four demographic characteristics: age, education, gender, and race/ethnicity. The univariate distributions of each of the four characteristics were entered into a program which used an iterative process to estimate weights. The purpose of this "raking" method (or also known as iterative proportional fitting) was to weigh the data simultaneously for age, education, gender, and race/ethnicity based on the population estimates (for detailed discussion about the calibration method and issues, see Brick, Montaquila, and Roth 2003). The final weight for each respondent then is equal to the product of the initial weight and the balancing weight.

2.1. The survey instrument

The survey instrument was designed to measure 11 different factors of social capital including social trust, inter-racial trust, protest politics, political engagement, giving and volunteering, faith-based engagement, informal social interaction, involvement in association, civic leadership, diversity of friendship, and equality of civic participation. The survey questionnaire has 70 multi-part questions. Some have only one item while others have several. The Benchmark survey includes mostly multiple-choice and some open-ended questions. The respondents were asked about various aspects of their life and their responses were later used to develop indices for the 11 social capital factors. Only four factors of social capital from the dataset were used in relation to innovation and urban form in the current analysis.

2.2. Operationalizing different social capital factors

I used four social capital indices from the Social Capital Benchmark Survey data as proxies for three different factors of social capital: trust, connectivity and religious participation. Social trust index is used to measure trust. Two other indices are used to measure connectivity, they include the index of organized group activities and informal social interaction. The two measures of connectivity are complementing each other in an attempt to capture the intensity of both formal and informal social interaction. The use of frequency of interaction to proxy connectivity helps avoid due-based memberships, which often contribute nothing to one's networking building and social capital. Religious participation is measured by using the faith-based social capital index. The indices were standardized using the national norms obtained national level survey conducted simultaneously. Where necessary, the polarity of the variable was reversed so that a higher score meant more instead of less of that variable.

Specifically, social trust index is based on two questions. One item asks whether in general, most people can be trusted or the respondents cannot be too careful in dealing with people. The next item further asks of levels from one to four (with one being trust a lot) at which respondents trust different groups in society (people in the neighborhood, people working with, people at church or places of worship, people working in stores, local police). The social trust index is then the mean of the standardized responses to those questions with respect to the national norms.

Faith-based social capital index is measured using a combination of questions that ask participants whether they are a member of a local church or other religious community, how often they attend religious services, whether they have taken part in any activity with other people at their church or place of worship other than attending services, and whether they have any affiliation with non-church religious organizations. In addition, their levels of contributing and volunteering were recorded to calculate the index. The index was computed as the mean of the standardized variables obtained from answers to those items.

The index of organized group interactions is calculated as the mean of the scores standardized against the national norms of a 3-item question. It asks how many times in the past 12 months the respondent has attended 1) any public meetings in which there was a discussion of town or school affairs, 2) a club meeting, and 3) a celebration, parade or an event in his or her community.

Informal social interaction index is computed as the mean of standardized responses to the question asking the respondent to supply the estimate of the number of time he or she has undertaken certain social activities in the past 12 months. Those activities include times of playing cards with others, visiting relatives or having them visit, of having friends over, socializing with co-workers outside of work, and socializing with friends in public places.

Using the same approach of deriving aggregate measures of trust and association in earlier studies by Knack and Keefer (1997) and Dakhli and De Clercq (2004), I aggregated individual respondents' scores for each index to the county level. First, individuals' scores in each of four social capital factors were weighted by applying the survey individual weight. Then the county arithmetic mean was calculated for weighted individual social capital scores of the residents across any specific county. Most counties have less than ten respondents. Those counties that have sample sizes of over 25 were selected for the regression analysis.

2.3. Limitations of the social capital data

Limited sample sizes and sampled communities, and the aggregation of data are two main drawbacks of using the Social Capital Benchmark Survey data. First, only 41 communities across the country were selected and as a result. Missing communities range from important ones such as those in the Washington D.C-Baltimore area with an increasing number of immigrants to small suburban and exclusive suburban areas. While the presence of small and rural communities in the data may not affect the quality of the analysis of innovation, the absence of such important metropolitan areas such as the Washington D.C-Baltimore metro could prevent the researcher from generalizing the results. In addition, because the definition of communities was loose and 500 respondents were sampled from each community, the number of surveyed residents by county varies from less than 5 to 500. In counties that were identified by the research team as communities, sample sizes are consistent and high. On the contrary, counties that were considered as part of larger communities such as a metropolitan area or a state have smaller sample sizes and they vary significantly across component counties. Therefore, any conclusion drawn from this analysis has to be done with caution especially in the context of policy implication.

The aggregation of social capital could be also subject to criticism. As the county social capital value equals arithmetic mean of each social capital factor for county residents, county social capital is assumed to be in linear relationship with individuals' social capital. The data aggregation is similar to the aggregation method used in prior studies (Knack and Keefer 1997, Dakhli and De Clercq 2004). The aggregation of individuals' scores of social capital to create county measure for social capital may present a complex issue (Glaeser, Laibson, and, Sacerdote 2000). The underlying assumption of data aggregation can be best described that determinants of individuals' social capital always determine the county's social capital and as individuals' social capital increases, so does social capital for the entire region or community. However, Glaeser, Laibson, and, Sacerdote (2000) suggest that this is not always true. To illustrate this complexity, they use an example of a used car salesperson that has lots of social capital and successfully sells bad cars to his customers but his seemingly negative social capital does not contribute to social capital of the society.

3. Compactness Index

In order to examine the effect of urban form on innovation, I use the compactness index developed by Ewing and his colleagues in their series of studies on urban sprawl's impacts. In the study of sprawl at the metropolitan level, Ewing, Pendall, and Chen (2002) used a combination of methods to develop the metropolitan sprawl index for 83 metropolitans in the US. In a different study of sprawl at the county level, Ewing et al (2003) studied the effect of sprawl on obesity using county sprawl index. The county sprawl index was derived using a similar method as for the metropolitan sprawl index.

Ewing et al. (2003)'s county sprawl index captures two urban form dimensions that have been observed and extensively discussed throughout the literature on land use impacts (Ewing, Pendall, and Chen 2002). They include residential density and degree of street accessibility. Residential density was defined to include gross and net population density and the percentage of population residing at different densities. More compact urban form implies higher gross and net population density and a higher percentage of people living in high densities. Street accessibility was defined in terms of the length and sizes of blocks. The length of each side of the block and its size in a more compact urban neighborhood should be smaller than those in a less compact suburban area with less connected cul-de-sacs and fewer alternative routes.

Because of the geographical difference between counties and metropolitan areas, the county sprawl index only captures two out of four urban form factors in the metropolitan sprawl index. At the metropolitan level, land use mix and degrees of centering are present. Land use mix was defined as the degree of which jobs and residents were mixed and balanced. As an urban neighborhood has a high degree of balance of employment and population, it is said to be less sprawled or more compact. The degree of centering was defined as the extent of concentration of activities around metropolitan centers. A high degree of metropolitan centeredness with respect to population or employment is the best image contrasting compact metropolitans versus sprawled ones. To derive those urban form dimensions, Ewing et al. (2003) conducted principal component analysis to reduce the number of variables from different sources measuring the same dimensions. Table 4.1 presents six variables used in the factor analysis to derive county sprawl index.

Table 4.1 Six Variables Captured by County Sprawl Index

Gross population density in persons per square mile
% of population living at densities < 1500 persons per square mile
% of population living at densities > 12,500 persons per square mile
County population divided by the amount of urban land in square miles
Average block size in square miles
% of blocks 1/100 of a square mile or less in size (about 500 feet on a side)

The analysis allowed the researchers to have one composite factor that captured the largest share of common variance among the variables measuring population density and block sizes. The component was transformed to a scale with a mean value of 100 and standard deviation of 25. (See detailed discussion on the methodology and the variables used in Ewing, Pendall, and Chen (2002) and Ewing et al (2003)).

The county sprawl index measures compactness of county urban form and is available for 951 counties, statistically equivalent entities such as independent cities, and groups of adjacent counties or cities. For the purpose of the current study, the term “sprawl” in the sprawl index was replaced by “compactness” and the higher the value, the less sprawl or more “compact” an urban area is (Ewing et al. 2003).

4. Other Data

4.1. Employment data

To control for variables that have been discussed in other scholars' studies including localization economies, corporate research and development, and business services sector, I used the 1990 County Business Pattern dataset calculate location quotient index. The County Business Patterns dataset provides employment data by industry. It covers most of the country's economic activity (except for farming and government employment) and reports establishment count, payroll, and mid-March employment count. County Business Pattern data for 1990 were based on the Standard Industrial Classification (SIC) System. In cases where the data are likely to disclose the operation of an individual business, the Census Bureau reports a range of value in place of the actual employment number. To address this issue, I selected a mid-range point. For example, if the county employment number was reported as between 0 and 19, its actual value was assumed to equal 10. Table 4.2 provides in details all used employment value ranges and their corresponding approximated values. The suppression of data could threaten the reliability of the study if the data were sought at more detailed geographical and industrial levels (3 digit SIC to 4 digit SIC categories). For this reason, I used the 2-digit SIC categories to capture more accurate county employment.

Table 4.2 County Business Pattern Data Range and Chosen Values for Undisclosed Data

Flag	Range values	Chosen values
A	0-19	10
B	20-99	60
C	100-249	175
E	250-499	375
F	500-999	750
G	1,000-2,499	1750
H	2,500-4,999	3750
I	5,000-9,999	7500
J	10,000-24,999	17500
K	25,000-49,999	37500
L	50,000-99,999	75000
M	100,000 or More	120000

There are more manufacturing industries than the number of patent categories even at the broadest industry level and one patent type can be linked to several industry sectors; therefore, it is necessary that some related industries be selected and assigned to one patent type. Those selected variables include employment combination of SIC 20 Food, SIC 28 Chemical and Allied product, SIC 33 Primary metal industries, SIC 34 Fabricated Metal, SIC 35 Industrial machinery and equipment, SIC 36 Electronic equipment, SIC 37 Transportation equipment, and SIC 38 Instrument and related products. Comparing their Standard Industry Classification descriptions with the patent categories ascertains that those industries contribute most innovation in the corresponding patent categories. As indicated by Table 4.3, in each patent category except Mechanical, one or two specific industry sectors were assigned to a patent category and their employment data were recorded. Because mechanical innovations are related to the use of machinery, mechanical equipment, and tools, it is reasonable to assume that mechanical innovations can take place extensively in many industry sectors. As a result, employment in the mechanical category consists of employment in SIC 33, SIC 34, SIC 35, and SIC 37 (Table 4.3).

Table 4.3 Industrial Sectors and Patent Categories

CHEM_EMP	Food + Chemical employment
COMP_EMP	Industrial machinery and equipment employment
DRUG_EMP	Chemical and allied product + Instrument and related product employment
ELEC_EMP	Electronic equipment employment
MECH_EMP	SIC 33 employment + SIC 34 employment + SIC 35 employment + SIC 37 employment

The county employment data were downloaded from the Census website for each industry sector, aggregated into corresponding patent types, and then summed across component counties of Metropolitan Statistical Areas (MSA) which served as labor markets for all county residents. In the final phase, the location quotient was estimated for each MSA (in 2000 boundary definition) and each patent category. This location quotient proxies the concentration of related industry and is defined as the employment concentration of a specific industry in a metropolitan in relation to its national share.

$$LQ_i = \frac{(e_i / e)}{(E_i / E)}$$

Where e_i = local employment in industry i
e = total local employment
E_i = National employment in industry i
E = Total national employment

The location quotient being equal to one indicates that the relative distribution of the industry employment at the metropolitan level is the same as the nation, meaning there is no concentration. The higher the location quotient for any specific industry, the higher employment concentration of that industry is in the metropolitan area.

The 1990 County Business Pattern employment data were also used to create proxies for corporate research and development and for the business service sector. The first proxy controls for the research and development expenditure of companies working in the metropolitan area, which also affects the innovative activity in the metro and in its component counties. Using a similar method of extracting employment in 2 digit SIC sectors, the county employment for SIC 873 Research development and testing service in 1990 was downloaded and aggregated to the MSA level. This sector includes employment in commercial physical and non-physical research, in non-commercial research organizations, and in testing laboratories. The underlying assumption to use this proxy is that the productivity of research laboratory employees would not change over time and remain stable across all studied industries. The second employment variable from the same dataset is a proxy to capture activities in supporting business services. Those services include advertisement, credit, mailing, services to building, equipment rentals and leasing, personnel supply services, computer and data processing, and other business services. Following earlier studies of innovation (Acs 2002, Black 2004), employment of SIC 73 Business services in 1990 was also used to capture the agglomeration economies of the entire metropolitan area.

4.2. Knowledge workers

In addition to the concentration of industry employment, a variable is included to control for the number of potential innovators in the county. For this purpose, the 1990 Population Census data were used to compute the number of county's mathematicians, architects, technicians, scientists, and engineers. The computation was based on the data from question P078 of the 1990 Census, which reports the number of total employed people in different occupation categories (Table 4.4). Unfortunately, those occupation categories do not reveal the needed information. In the 2000 Population Census, the Census Bureau introduced a new system of occupation classifications listing categories that can be used to derive directly a rough estimate of knowledge workers in a county. The Census Bureau also provides a template to convert the 1990 classification into 2000 classification at "any level of detail" (US Census Bureau, 2003).

Table 4.4 1990 STF-3 Data for P078. OCCUPATION - Universe: Employed Persons 16 Years and Over

Managerial and professional specialty occupations (000-202): Executive, administrative, & managerial occs (000-042) Professional specialty occupations (043-202)
Technical, sales, and administrative support occs (203-402): Technicians and related support occupations (203-242) Sales occupations (243-302) Administrative support occupations, incl. clerical (303-402)
Service occupations (403-472): Private household occupations (403-412) Protective service occupations (413-432) Service occupations, exc. protective & household (433-472) Farming, forestry, and fishing occupations (473-502) Precision production, craft, and repair occupations (503-702)
Operators, fabricators, and laborers (703-902): Machine operators, assemblers, and inspectors (703-802) Transportation and material moving occupations (803-863) Handlers, equipment cleaners, helpers, & laborers (864-902)

By using the 1990-2000 crosswalk template to convert 1990 Census STF-3 categories to 2000 Census classifications, I was able to present the knowledge labor force of 1990 under the desired classification. The uniform distribution of knowledge workers at different geographical degrees regardless of demographic characteristics was assumed. The following formulas adopted from the STF-3 Template contain adjustment factors needed for the conversion across 1990-2000 categorical gap:

- Computer & mathematical occupations = 0.01x((Executive, administrative, & managerial occupations x0.187762688438283) +(Professional specialty occupations x4.99984289494722) +(Technicians & related support occupations x15.1059349848475))
- Architects, surveyors, cartographers, & engineers=0.01x((Professional specialty occupations x10.6804268801036) + (Technicians & related support occupations x0.292671428213934))
- Drafters, engineering & mapping technicians =0.01x((Technicians & related support occupations x28.5703311050382) + (Handlers, equipment cleaners, helpers, & laborers x0.0891803874110485))
- Life, physical, & social science occupations = 0.01x((Executive, administrative, & managerial occupations x0.0154870540607262) + (Professional specialty occupations x4.56841363149125)+(Technicians & related support occupationsx10.8241781215367))
- Health technologists & technicians = 0.01x((Professional specialty occupations x0.0817536344986763)+(Technicians & related support occupations x27.833709475916) + (Administrative support occupations,

including clerical x0.0359042918852045)+(Service occupations, except protective & household x0.0863882858187157)+(Precision production, craft, & repair occupations x0.367334013538901))

The number of knowledge workers is the sum of the above four new occupational categories whose data came from 1990 classification in table 6.

4.3. Racial and professional diversity index

The diversity index was borrowed from biological diversity context and is based on the Simpson's Index of Diversity, one among a family of diversity indices (Keylock 2005). This measure is intended to capture the agglomeration economies in addition to the size of the business sector and the industry concentration. Costa and Kahn (2003) used an index similarly constructed to estimate racial and birthplace fragmentation. The index has value from 0 to one and represents the probability that two individuals randomly selected from the studied sample are from different groups. Therefore, as the value of D approaches one, diversity increases in the sample.

$D = 1 - \sum_{i=1}^{S} (\frac{n_i}{N})^2$ where n represents the number of individuals of the same group i in the sample, and N is the total sample size.

In the current study, the Simpson's Index of Diversity D measures the heterogeneity in racial composition and industrial structures in the metropolitan areas. The employment data came from the manufacturing sectors used in estimating the industry concentration. The demographic data came from the 1990 Population Census and available for four main groups of White, Black, Hispanic, and Asian. Both diversity indices were computed for the whole MSA. The shortcomings of this measure include the fact that diversity depends of the geographical scale. As the unit of analysis becomes geographically larger, the odd of two individuals belonging to two different ethnic groups or industrial sectors increases.

4.4. Academic research and development investment

Another variable was needed to proxy research and development activities in universities. We expected innovation to be greater in regions where university R&D is higher. The National Science Foundation provides estimates of academic R&D expenditures in its series of survey of scientific and engineering expenditures and does not categorize the funding by types of research. Specifically, its survey in 1996 provides the R&D expenditures at doctorate granting universities for all universities across the country. In the current study, the reported 1990 amount of academic R&D expenditures (in thousands of dollars) of each university was aggregated across all doctorate granting universities in the studied MSAs and not for individual patent types. However, using only R&D expenditure data of schools in the sampled MSAs may result in overlooking possible spillover effects of schools outside the studied MSAs. Also, because the aggregate number is used for all patent types, I can only obtain some information about the relationship between spending in research activities in universities and innovation. Thus, the dissertation does not try to answer the questions related to efficiency of academic R&D dollar amounts spent in specific type of research, or if the governments should have R&D investment in Electrical & Electronic rather than in Chemical or Drugs & Medical.

4.5. The finalized dataset

Limited county sample sizes of the Social Capital Benchmark Survey data results in the constraint on the number of counties used for the main regression analysis of social capital, urban form, and innovation. The final dataset includes 85 counties which had over 25 respondents participating in the Social Capital Benchmark survey. The socio-demographic and socio-economic data came from the 1990 Population Census. Table 4.5 and 4.6 present the constructs as identified in the conceptual framework and list their operationalizing variables and their summarized data sources. In the next chapter of the dissertation, geographical distribution of innovation, social capital, and urban form data will be presented.

Table 4.5 Constructs and Their Operationalizing Variables

Construct	Operationalizing variables
Innovation	INNOVATION
Knowledge workers (engineers, architects, scientists, etc.)	KNO_WORKER
Social connectivity	INFORMAL
Social connectivity	ORGANIZED
Trust	SOCIAL_TRUST
Faith ties	FAITH_BASED
Urban form	COMPACT
Concentration of supporting businesses	BIZ_SERVICE
Concentration of firms	LQi
Academic R&D expenditure	ACA_R&D
Corporate R&D expenditure	R&D_EMP
Professional Diversity	IND_DIVERSITY
Social Diversity	RAC_DIVERSITY

Table 4.6 Variable and Data Sources

Variable	Definition
INNOVATION	Patent (1990 through 2002)
KNO_WORKER	County number of knowledge workers (engineers, scientists, etc.) (1990 Population Census)
INFORMAL	County average informal socializing index (Social capital survey 2000)
ORGANIZED	County average formal group participation index (Social capital survey

	2000)
SOCIAL_TRUST	County average social trust index (Social capital survey 2000)
FAITH_TIES	County average faith-based social capital (based on FAITHBASE2 variable in the survey) (Social capital survey 2000)
COMPACTNESS	County compactness index (Ewing's sprawl data for 2000)
BIZ_SERVICE	MSA Business Service employment SIC 73 (CBP 1990)
LQi	MSA location quotient index for industry i (CBP for 1990)
ACA_R&D	MSA Academic R&D (NSF for 1990)
R&D_EMP	MSA R&D& testing services SIC 873 (CBP 1990)
IND_DIVERSITY	Diversity index for MSA industrial sectors in 1990
RAC_DIVERSITY	Diversity index for MSA racial composition in 1990

Chapter V: Empirical Regularities

This chapter reports the spatial patterns of innovation, social capital, and urban form. For innovation, I employ the US Patent and Trademark Office's patents from 1990 through 2002 with Hall, Jaffe, and Trajtenberg (2001)'s technological classification. I assigned those patents to counties based on the residential information of the first inventors associated with the patents. The spatial pattern of patent distribution is examined at the state, metropolitan, and county level. In the case of county, I compare both raw patent counts and the number of patents per 1,000 county population. Additionally, I include in this spatial analysis an estimate of innovators, which was derived by discounting patent counts filed by the same inventors. In the second part of the analysis, I inspect the spatial distribution for compactness index, which is from Ewing et al. (2003)'s county sprawl index. Finally, I present spatial distribution across different counties for three social capital factors: trust, connectivity, and faith ties. Those three factors are operationalized using the Roper Center (2005)'s Social Capital Benchmark Survey Data. In particular, social trust is used to measure trust, informal social interaction and organized group interaction measure the degree of connectivity, and finally faith-based social capital to measure faith ties. When analyzing urban form and social capital across different counties, I also compare and contrast innovative capabilities of some counties based on their remarkable performance on the other two variables.

1. *Innovation*

1.1. Overview of patent data

This section presents an overview of the patent data based on Hall, Jaffe, and Trajtenberg (2001)'s technological classification. They assigned patents to five major technological categories including Chemical, Computer & Communication, Drugs & Medical, Electrical & Electronic, and Mechanical. Since any patent's grant year may lag the year of application by from one to several years, I report the data by date of application in my analysis. Because the purpose of this dissertation is to explore how innovation was formed, using application years starting from 1990 enables me to correlate other factors in 1990 to the innovative activity that materialized in actual products in 1990 through 2002. The US Patent and Trademark Office (USPTO) granted approximately 778,781 patents to American inventors during the period, 1990 to 2002. Among those innovations, Computer & Communication, Electrical & Electronic, and Mechanical patents all equally accounted for approximately 17% of total granted patents. Chemical patents accounted for 15% of all patents. 13 % of total patents were granted to the Drugs & Medical category, while patents classified under Other accounted for the remaining 21%.

The absolute number of patents per patent category varied over application years and significantly dropped starting from 1998 (Figure 5.1). Because there is a time lag between application years and grant years, Figure 5.1 does not explain the drop in patent approvals in later years. Instead, it is indicative of the fact that few patent applications were approved within the first or second year. This is particularly obvious for patents applied in 2002, the number of patents applied for in 2002 and granted in following years until the year data were published is smaller than the number of patents applied in previous years. The drop-off in patents across different patent types illustrates the possible lag variation across different technological types. Hall, Jaffe, and Trajtenberg (2001)'s study suggests that the application-grant lag is on average three years; however, the lag can be seven years and even longer.

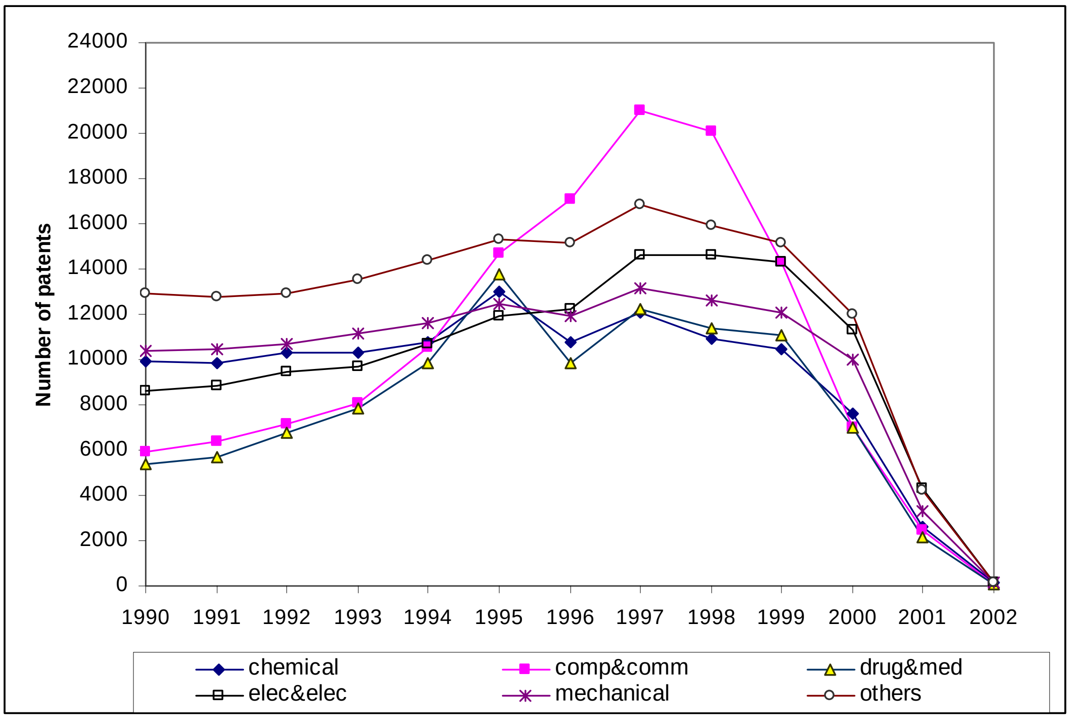

Figure 5-1 Distribution of Approved Patents 1990-2002 (in Absolute Number) by Application Year

Figure 5.1 also illustrates patenting activities in different technological categories and their propensity to patent. Innovations in Chemical and Drugs & Medical appear to experience a more dramatic decline in 1995. This decline is not necessarily related to the quantity of innovations but perhaps is entirely attributed to the time lag. The number of patents that was successfully applied for in 2002 only accounted for from 0.7% to 0.14% of total patents approved across different categories. Similarly, patents with an application year of 2001 than 2002 contributed between 1.83% to over 3.3% to overall patent counts depending on patent types. By and large, patents successfully applied for in 2001 and 2002 accounted for about 2.5% of total patents granted to US innovators till the end of 2002. As the last date in the dataset moves beyond 2002, the number of patent grants in the application years of 2000, 2001, and 2002 will rise.

Figure 5.2 reveals the each category's share of total patents by application year from 1990 through 2002. Starting from the early 1990s, patent share in traditional industries such as chemical and mechanical steadily declined while drug & medical and computer & communication grew.

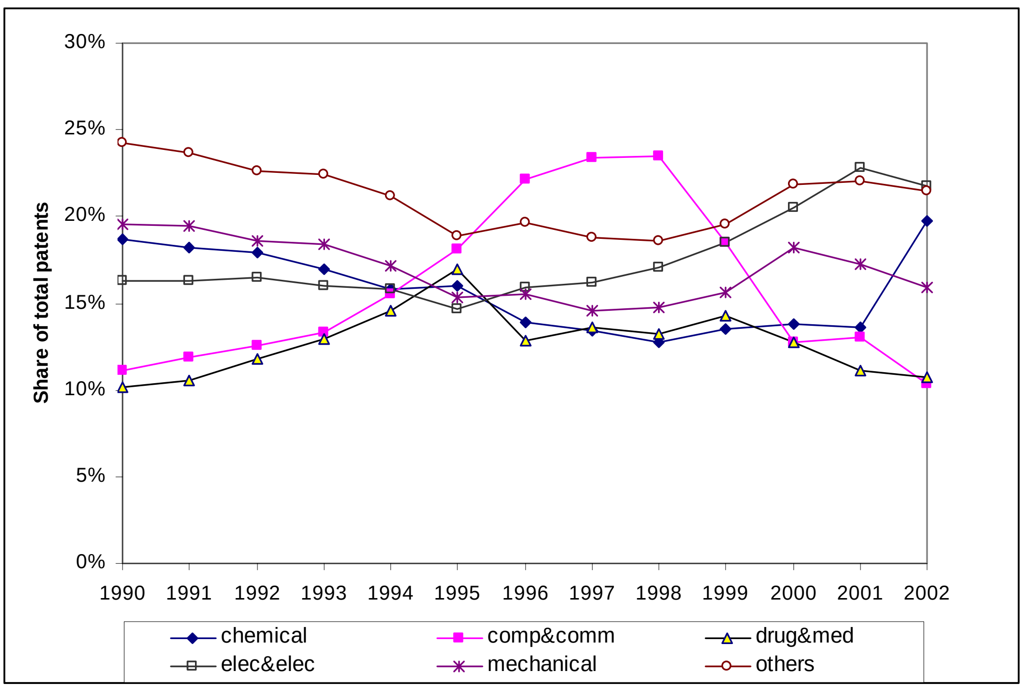

Figure 5-2 Distribution of Approved Patents 1990-2002 (in Share) by Application Year

For Electrical & Electronic, its patent share stayed fairly constant in the early 1990s (15%-17%) and started to expand from the late 1990s into 2000s (23%). The turning point for Computer & Communication was in 1997-1998, after peaking at

23% in 1997, innovation in this category decreased dramatically in relative terms and only accounted for 10% of total granted patents that were applied for in 2002 and granted by 2002. This trend may reflect the collapse of the Dot Com bubble in the late 1990s but it could also be a universal trend in research activities in Computer & Communication. In the early 2000s, most patent categories shrank except for chemical with its share soaring up from 14% in 2001 to 20% in 2002.

Figure 5.3 shows the distribution of the annual number of innovators by patent application year. By discounting the number of patents that a specific inventor was filed as the first inventor living in a county received, I was able to approximate the number of first inventors living in any county from 1990 through 2002 (See Chapter Four for detailed discussion of the method). As a result, this measure of the number of the first inventors captures the number of innovators in an industry category and the extent to which innovation occurs because of many individual inventors or a few very productive inventors. Comparing Figures 5.2 and 5.3, there are similarities between the patent distribution and inventor distribution across the five industry categories. The number of recognized innovators reported is also affected by the application-grant lag, causing the absolute numbers to decline in application years after 1998.

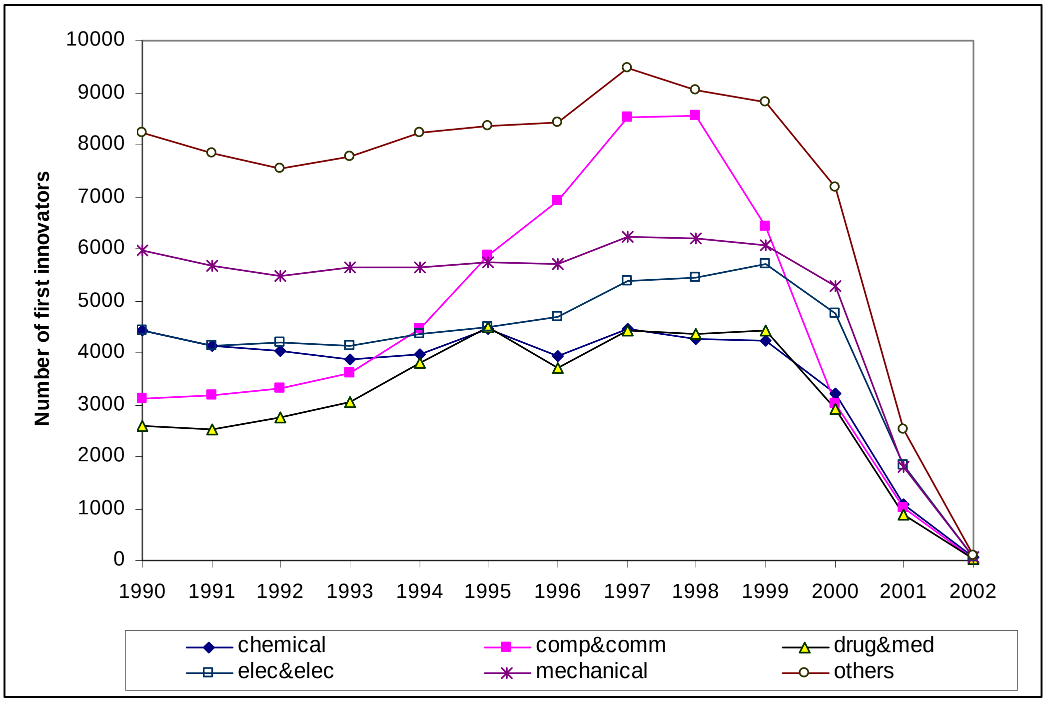

Figure 5-3 Distribution of Innovators by Patent Application Year

Computers & Communication innovators peaked before the time lag was likely to affect the patent distribution (approximately 8,000 innovators in 1998). While there were more Electrical & Electronic patents than Mechanical patent applications in the second half of the 1990's decade (Figure 5.2), Figure 5.3 shows that the annual number of innovators was higher every year for Mechanical patents than for the Electrical & Electronic category.

1.2. Spatial patterns of patent distribution

1.2.1. State level

The examination of the distribution of patents based on application years from 1990 through 2002 could shed light on the question of which place is the most innovative or the most attractive to innovators. The distribution of patents across the US landscape is displayed on GIS maps for the five main categories: Chemical, Computer & Communication, Drugs & Medical, Electrical & Electronic, and

Mechanical. The data allow me to examine geographical distribution of innovative activity via the number of innovations and via the number of innovators. However, since the approximation of innovators has certain limitation, the discussion in this part focuses on the number of innovations.

Because patent counts at the state level are largely available, scholars have investigated the patent distribution across different states to understand the geography of innovation in the US from the early days of innovation studies. The findings in this current study at the state level are consistent with the results of other studies which used patent data for different time periods and based on grant years instead of application years (Black 2004, Koo 2006). Figure 5.4 illustrates the distribution of total patents by state. California is the innovation leader of the country with 144,826 patents, followed by New York, Texas, New Jersey, Michigan, and Illinois among the top ten innovative states in the US. The gap between California and the second most innovative state, New York, is huge with 80,000 patents even though California lags far behind New York in terms of patents per 1000 persons (5 in California compared to 96 patents per 1000 persons in New York). The leading position of California in the national system of innovation is attributable to its strengths in the fields of Computer & Communication, Drugs & Medical, and Electrical & Electronic. In those fields, numbers of patents in California are triple or quadruple to those in the state of New York. The median of total patents among all states is only 6,413 patents; and the total number of patents that the bottom 25 states contribute to the nation reaches 69,000 patents, less than half of California's figure. The uneven distribution of patents at the state level suggests that some states are better in attracting innovative workers than others.

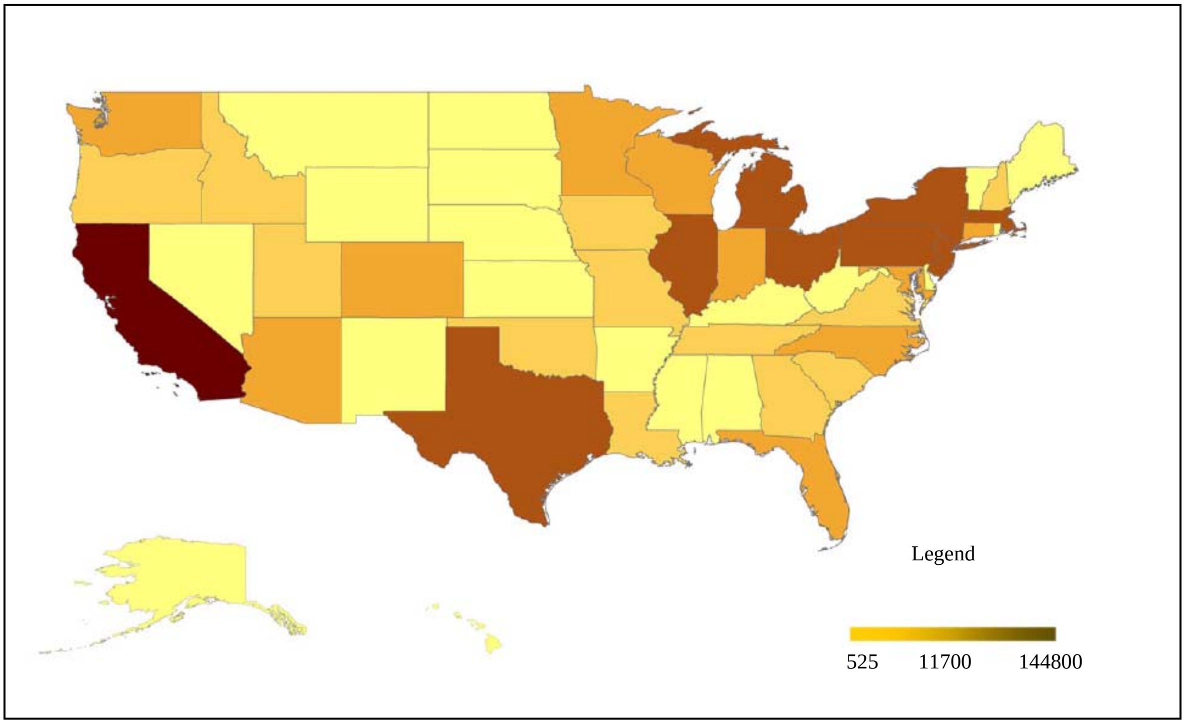

Figure 5-4 Distribution of Patents by State

1.2.2. Metropolitan and County Level

At the sub-state levels, metropolitan and county levels, the data indicate similar spatial variations across the country. In this section of the spatial analysis of patent data, I examine several potential measures of innovation. First, I show that the spatial distribution of raw patent counts across all counties favor major metropolitan areas and counties such as Silicon Valley or Boston Route 22, which is supported by other innovation studies. Secondly, by using similar map layouts for total patents and five patent types, I am able to show that using patents per 1000 county population favor small places with a few very innovative firms or individuals. Finally, I also include a brief discussion of the use of innovator counts.

Considering economic activities, US metropolitan areas have always been centers of employment and population. According to the 2000 population census, 81.4% of the US population lives in metropolitan areas. Similarly, innovative activity in US metropolitan areas has accounted for from 87% to 97% of patents nationwide depending on patent types. By and large, more than 90% of total patents of the US (applied from 1990 through 2002) came from inside the Metropolitan Statistical Areas (boundary definition based on 1999 MSA definition used for the 2000 Population Census).

Table 5.1 Top 10 Metropolitans with Highest Total Approved Patents

Metro area	Total patents
New York-Northern New Jersey-Long Island CMSA	72008
San Francisco—Oakland--San Jose CMSA	70870
Los Angeles—Riverside--Orange County CMSA	48038
Boston--Worcester--Lawrence CMSA	35493
Chicago--Gary--Kenosha CMSA	30085
Detroit--Ann Arbor--Flint CMSA	23953
Philadelphia--Wilmington--Atlantic City CMSA	22908
Minneapolis--St. Paul MSA	19980
Washington--Baltimore CMSA	18032
Houston--Galveston--Brazoria CMSA	17034

Metropolitans such as New York- Northern New Jersey-Long Island (72,008 patents) and San Francisco-Oakland-San Jose (70,870 patents) are among the top ten most innovative metropolitan areas. By contrast, Victoria, TX and Abilene, TX show less than five patents each during the same period. This huge gap between the innovative leaders and laggards indicates important issues in creating and sustaining innovation and innovative work forces. Not only population sizes of the innovative leaders and laggards are different, their economic structures also differ significantly from one another. For example, San Francisco-Oakland-San Jose houses some members of the University of California system and Stanford University, which contribute tremendously to research activities in the region. In addition, this metropolitan also has high concentration of high technology companies in Computer & Communication, Electrical & Electronic, Drugs & Medical. At the low end of innovation, Abilene's biggest employers in the service sector dominate the region's economy (BlueCross BlueShield of Texas) and the whole region is served by much less educational institutions. In 2002, the city finally got Texas Tech to open an engineering program at Abilene and the size of the program then was modest with 30 students[3].

At the county level, Table 5.2 reports the top 20 counties with highest total number of patents and their respective metropolitan area. In this list, California contributes up to seven counties in the top 20 list; San Francisco-Oakland-San Jose CMSA, Los Angeles-Riverside-Orange County CMSA, and San Diego MSA. Santa Clara County, CA, generated more patents than any other county in the U.S. in Computer & Communication (16,833 patents) and in Electrical & Electronic (12,717) which brings its total number of patents to 40,400. The county is immediately followed by another California county, Los Angeles. This county has a total of 22,918 patents. Those two counties alone accounted for over 63,000 patents, up to 40% of total innovation in California during 1990-2002. The counties in this list include those that form big metropolitan areas in California, Texas, New York, Illinois, and Massachusetts that also appear in the list of top innovative metropolitan areas in the US.

[3] According to Abilene Economic Development website: http://www.developabilene.com

Table 5.2 Top Counties with Highest Patent Counts

County	CMSA/MSA	Patents
Santa Clara	San Francisco-Oakland-San Jose	40400
Los Angeles	Los Angeles-Riverside-Orange	22918
Cook	Chicago-Gary-Kenosha	15338
Orange	Los Angeles-Riverside-Orange	15284
Middlesex	Boston-Worcester-Lawrence	14693
San Diego	San Diego	14219
Monroe	Rochester	13982
Harris	Houston-Galveston-Brazoria	11165
Travis	Austin-San Marcos	11129
Maricopa	Phoenix-Mesa	10443
Oakland	Detroit-Ann Arbor-Flint	9944
King	Seattle-Tacoma-Bremerton	9867
San Mateo	San Francisco-Oakland-San Jose	8663
Ada	Boise City	7679
Hennepin	Minneapolis-St. Paul	7664
Contra Costa	San Francisco-Oakland-San Jose	7354
Fairfield	New York--Northern New Jersey--Long Island	6608
Collin	Dallas-Fort Worth	6430
Dupage	Chicago-Gary-Kenosha	6217
Alameda	San Francisco-Oakland-San Jose	6107

The patent data suggest that innovation is unevenly distributed at the county, state, and metropolitan levels. In a metropolitan area, there is more innovative activity in some counties than in others. The following section reports this spatial variation in the dynamics of patenting and innovative activity across the country.

Tables 5.3, 5.4, 5.5, 5.6, and 5.7 show the top 20 counties with highest innovation in five major technological categories. The counties that have highly innovative environments tend to be part of big metropolitan areas with sizable population, skilled labor force, and important research universities.

However, not all counties in the same apparently innovative metropolitan areas benefit from the entire region's generous endowment. For example, Napa County, of the San Francisco-Oakland- San Jose metropolitan, had only 203 patents even though Santa Clara, another county within the same metropolitan, is ranked first among the top innovative counties. Perhaps, local factors of the county can explain high and low patent counts across different counties.

In a county, the spatial concentration of innovation is not the same for all technological categories. For example, Monroe County (NY) is ranked first among the top 20 counties in Chemical, 9^{th} in Computer & Communication, 11^{th} in Electrical & Electronic, and 3^{rd} in Mechanical. However, the county is not among 20 top counties in Drugs & Medical patents. The county's position in the map of innovation coincides with the heavy presence of the optics, imaging and photonics industry in Rochester metropolitan area. Big corporations in the industry including Eastman Kodak, Bausch & Lomb, and other global companies are all located in Rochester and the Monroe County vicinity. Similarly, Oakland County (MI), which is part of the Detroit-Ann Arbor- Flint metropolitan, is ranked top in Mechanical. The county borders Wayne County, where the city of Detroit is located, to the south and is the heart of the "Automation Alley", a name for the Interstate 75 corridor traversing the county and the program to attract high technology companies to the Oakland and its neighboring counties. The county houses national research partnerships such as United States Army National Automotive Center and automotive corporation headquarters or major subsidiaries such as DaimlerChrysler and Delphi. Oakland County is ranked 12^{th} in Electrical & Electronic but could not get into the top 20 counties in Chemical, Computer & Communication, and Drugs & Medical. On the contrary to Oakland (MI) and Monroe (NY), Santa Clara County (CA) is ranked highest in Computer & Communication, Drugs & Medical, and Electrical & Electronic. Its innovative performance in the remaining categories is impressive with the second rank after Monroe County in Chemical, and 6th in Mechanical. The county houses Silicon Valley, which has been known for being most innovative place in the country in the fields of Computer & Communication and Electrical & Electronic.

Table 5.3 Top 20 Counties with Highest Chemical Patent Counts

County	CMSA/MSA	Patents
Monroe	Rochester MSA	3864
Santa Clara	San Francisco-Oakland-San Jose CMSA	3158
New Castle	Philadelphia-Wilmington-Atlantic City CMSA	2597
Harris	Houston-Galveston-Brazoria CMSA	2460
Cook	Chicago-Gary-Kenosha CMSA	2290
Los Angeles	Boston-Worcester-Lawrence CMSA	2175
Middlesex	Los Angeles-Riverside-Orange CMSA	2175
Orange	Los Angeles-Riverside-Orange CMSA	1866
San Diego	San Diego MSA	1773
Allegheny	Pittsburgh MSA	1627
Bay	Saginaw-Bay City-Midland MSA	1428
Mercer	New York-Northern New Jersey-Long Island CMSA	1323
DuPage	Chicago-Gary-Kenosha CMSA	1287
Hamilton	Cincinnati-Hamilton CMSA	1272
Somerset	New York-Northern New Jersey-Long Island CMSA	1183
Middlesex	New York-Northern New Jersey-Long Island CMSA	1138
Montgomery	Philadelphia-Wilmington-Atlantic City CMSA	1101
Fairfield	New York-Northern New Jersey-Long Island CMSA	1088
Chester	Philadelphia-Wilmington-Atlantic City CMSA	1076
Contra Costa	San Francisco-Oakland-San Jose CMSA	1062

Table 5.4 Top 20 Counties with Highest Computer & Communication Patents

County	CMSA/MSA	Patents
Santa Clara	San Francisco-Oakland-San Jose CMSA	16833
Travis	Austin-San Marcos MSA	5859
Middlesex	Boston-Worcester-Lawrence CMSA	3809
Los Angeles	Los Angeles-Riverside-Orange CMSA	3515
King	Seattle-Tacoma-Bremerton CMSA	3340
San Diego	San Diego MSA	3259
Cook	Chicago-Gary-Kenosha CMSA	2698
San Mateo	San Francisco-Oakland-San Jose CMSA	2689
Monroe	Rochester MSA	2637
Maricopa	Phoenix-Mesa MSA	2621
Collin	Dallas-Fort Worth CMSA	2509

Orange	Los Angeles-Riverside-Orange CMSA	2468
Ada	Boise City MSA	1887
Boulder	Denver-Boulder-Greeley CMSA	1836
Contra Costa	San Francisco-Oakland-San Jose CMSA	1823
Harris	Houston-Galveston-Brazoria CMSA	1821
Wake	Raleigh-Durham-Chapel Hill MSA	1739
Monmouth	New York-Northern New Jersey-Long Island CMSA	1655
Dallas	Dallas-Fort Worth CMSA	1538
San Bernardino	Los Angeles-Riverside-Orange CMSA	1497

Table 5.5 Top 20 Counties with Highest Drugs & Medical Patents

County	CMSA/MSA	Patents
Santa Clara	San Francisco-Oakland-San Jose CMSA	3582
Middlesex	Boston-Worcester-Lawrence CMSA	3371
San Diego	San Diego MSA	3319
Orange	Los Angeles-Riverside-Orange CMSA	3166
Los Angeles	Los Angeles-Riverside-Orange CMSA	2948
San Mateo	San Francisco-Oakland-San Jose CMSA	2383
Hennepin	Minneapolis-St. Paul MSA	2071
Bronx	New York-Northern New Jersey-Long Island CMSA	1828
King	Seattle-Tacoma-Bremerton CMSA	1818
Montgomery	Washington-Baltimore CMSA	1726
Contra Costa	San Francisco-Oakland-San Jose CMSA	1725
Montgomery	Philadelphia-Wilmington-Atlantic City CMSA	1712
Cook	Chicago-Gary-Kenosha CMSA	1466
Norfolk	Boston-Worcester-Lawrence CMSA	1331
Hamilton	Cincinnati-Hamilton CMSA	1243
Bergen	New York-Northern New Jersey-Long Island, CMSA	1096
Ramsey	Minneapolis-St. Paul MSA	1094
Alameda	San Francisco-Oakland-San Jose CMSA	1085
San Francisco	San Francisco-Oakland-San Jose CMSA	1082
Lake	Chicago-Gary-Kenosha CMSA	1059

Table 5.6 Top 20 Counties with Highest Electrical & Electronic Patents

County	CMSA/MSA	Patents
Santa Clara	San Francisco-Oakland-San Jose CMSA	12717
Los Angeles	Los Angeles-Riverside-Orange CMSA	4197
Ada	Boise City MSA	4101
Maricopa	Phoenix-Mesa MSA	3309
Travis	Austin-San Marcos MSA	3018
Middlesex	Boston-Worcester-Lawrence CMSA	2618
Cook	Chicago-Gary-Kenosha CMSA	2413
Orange	Los Angeles-Riverside-Orange CMSA	2313
San Diego	San Diego MSA	2177
Collin	Dallas-Fort Worth CMSA	2175

Monroe	Rochester MSA	1672
Oakland	Detroit-Ann Arbor-Flint CMSA	1656
Dallas	Dallas-Fort Worth CMSA	1566
San Mateo	San Francisco-Oakland-San Jose CMSA	1495
Dutchess	New York-Northern New Jersey-Long Island CMSA	1457
Alameda	San Francisco-Oakland-San Jose CMSA	1356
San Bernardino	Los Angeles-Riverside-Orange CMSA	1347
Contra Costa	San Francisco-Oakland-San Jose CMSA	1342
King	Seattle-Tacoma-Bremerton CMSA	1215
Westchester	New York-Northern New Jersey-Long Island CMSA	1211

Table 5.7 Top 20 Counties with Highest Mechanical Patents

County	CMSA/MSA	Patents
Oakland	Detroit-Ann Arbor-Flint CMSA	4317
Los Angeles	Los Angeles-Riverside-Orange CMSA	4227
Monroe	Rochester MSA	4149
Cook	Chicago-Gary-Kenosha CMSA	2353
Orange	Los Angeles-Riverside-Orange CMSA	2246
Santa Clara	San Francisco-Oakland-San Jose CMSA	2222
Wayne	Detroit-Ann Arbor-Flint CMSA	2004
San Diego	San Diego MSA	1615
Maricopa	Phoenix-Mesa MSA	1606
King	Seattle-Tacoma-Bremerton CMSA	1339
Macomb	Detroit-Ann Arbor-Flint CMSA	1316
Middlesex	Boston-Worcester-Lawrence	1299
Harris	Houston-Galveston-Brazoria CMSA	1217
Fairfield	New York-Northern New Jersey-Long Island CMSA	1076
Hartford	Hartford MSA	1054
DuPage	Chicago-Gary-Kenosha CMSA	1044
Allegheny	Pittsburgh MSA	1016
Hennepin	Minneapolis-St. Paul MSA	970
Cuyahoga	Cleveland-Akron CMSA	869
Suffolk	New York-Northern New Jersey-Long Island CMSA	835

The breakdown of patents by category in above tables also reveals interesting information about Electrical & Electronic and Computer & Communication. As Santa Clara County holds most innovations in several key patent types, the number of patents in Electrical & Electronic and Computer & Communication that came from this county at least three times exceed that of the second most innovative counties.

Such a huge concentration of innovation in a county raises could be linked to a number of local characteristics of the county including high number of knowledge workers (i.e. engineers and scientists) and firm clustering. Despite the fact that Santa Clara County has more innovations in Electrical & Electronic and Computer & Communication than in other patent categories, any inference made with respect to local factors should be in a cautious manner. As discussed in the previous chapter of the dissertation, other factors not necessarily related to the characteristics of the county or of the entire metropolitan area can impact patenting rates in different industries. Comanor and Scherer (1969), Griliches (1989), Sokoloff and Khan (1990), and Hall and Harn (1999) indicate that such fluctuation in patenting activities may reflect different propensities to patent in different industries. It can also be affected by certain variation in the USPTO's patenting process in determining which is innovative in different industries.

Figure 5.5 displays the spatial distribution of total patent and Figures 5.6 – 5.10 report by industry category. Those figures provide a bird's eye view of innovative activity in the country. As a result, they reveal prevailing patterns of innovative activity at both the county level and the regional level. In general, innovative activity are strikingly exuberant along the two coastlines, the Great Lake area, and in Texas. There is not much going on in the middle of the country, between Indianapolis and Denver (Figure 5.5).

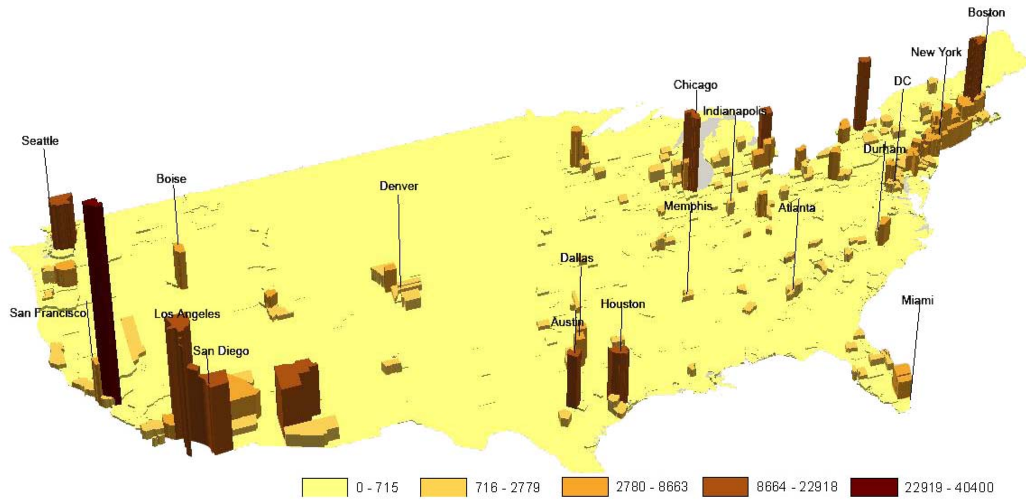

Figure 5-5 Distribution of Total Patents across Counties

The Northeast of the country marked by large metropolitan areas such as New York and Boston is where most innovative activity in Chemical takes place (Figure 5.6). Counties in this region account for 48% of total patents the top 20 counties generated in Chemical (Table 5.3). Counties in the West Region along the Pacific Coast appear to lead the whole country in terms of innovation in the other patent categories (Figure 5.7, 5.8, 5.9, and 5.10). This region includes high technology hubs in San Francisco, Los Angeles, and Seattle metropolitan areas and accounts for 67%, 64%, and 54% of total innovations in the top 20 counties in Electrical & Electronic, Computer & Communication, and Drugs & Medical, respectively (Table 5.4, 5.5, and 5.6). Counties in the South Region make up 20% total patents in the top 20 counties in the field of Computer & Communication, which is also the largest share of innovation the region has, compared to its other shares in other technological fields.

Table 5.4 reveals that Travis County, Collin County, Dallas County, and Harris County of Texas and Wake County of North Carolina are the innovation hubs of the South Region. Important cities in those hubs include Austin, Dallas, and Houston in Texas and Raleigh in North Carolina, which are also renowned for their efforts to attract high technology industries and innovative talents.

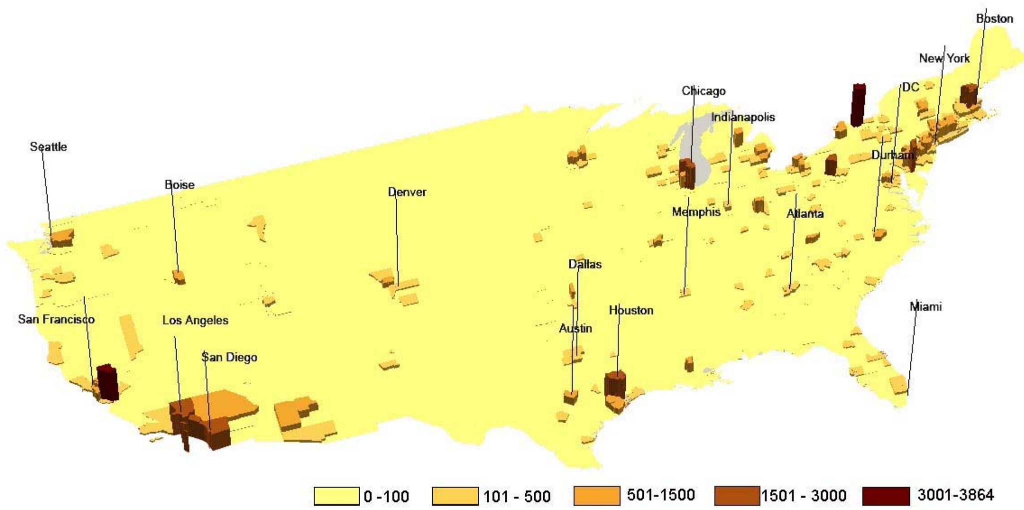

Figure 5-6 Distribution of Chemical Patents across Counties

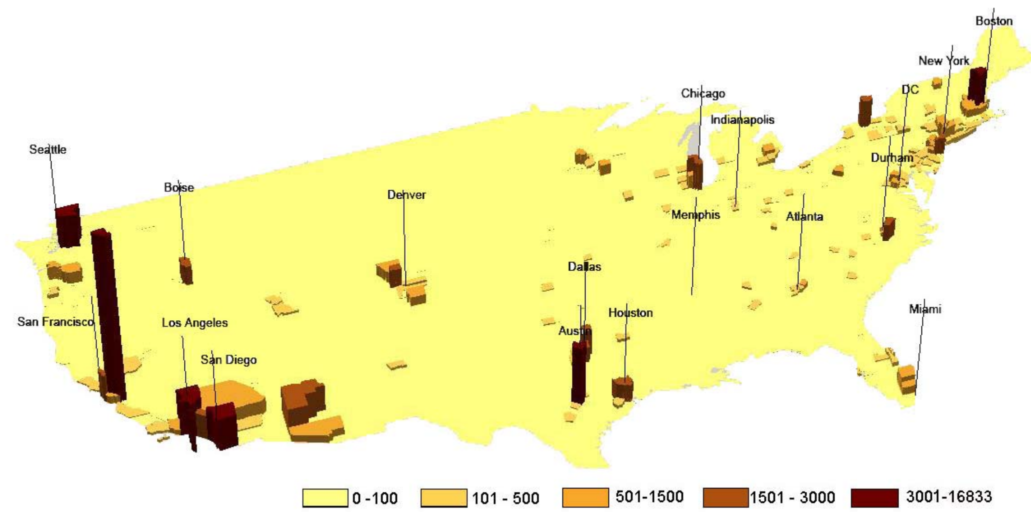

Figure 5-7 Distribution of Computer & Communication Patents across Counties

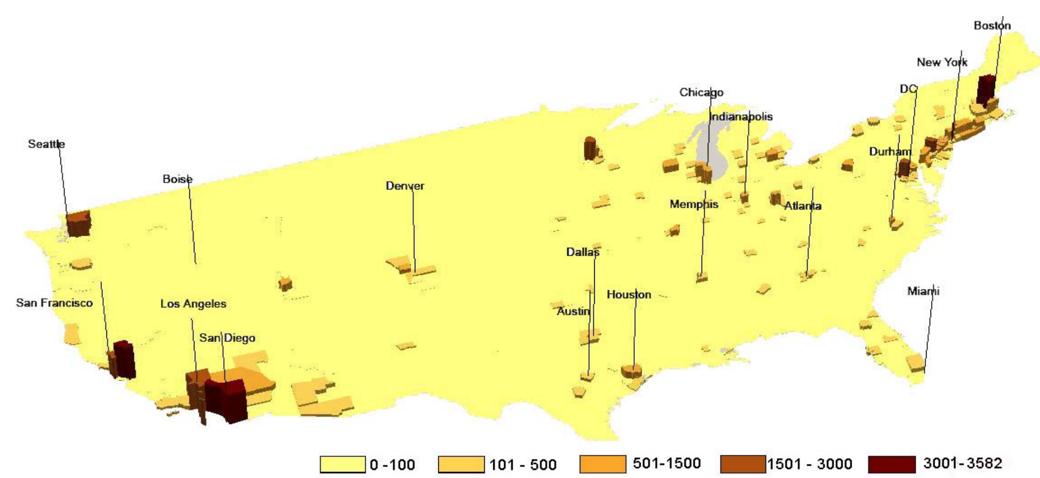

Figure 5-8 Distribution of Drugs & Chemical Patents across Counties

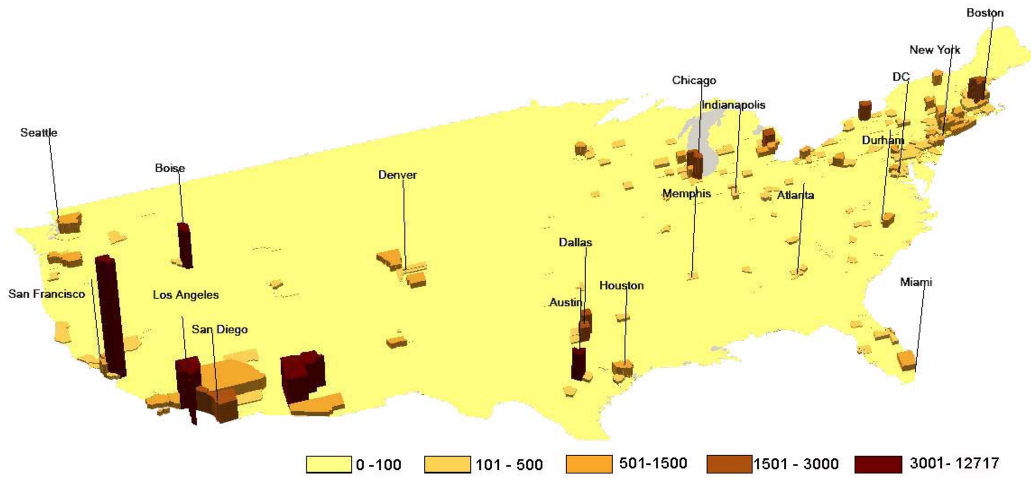

Figure 5-9 Distribution of Electrical & Electronic Patents across Counties

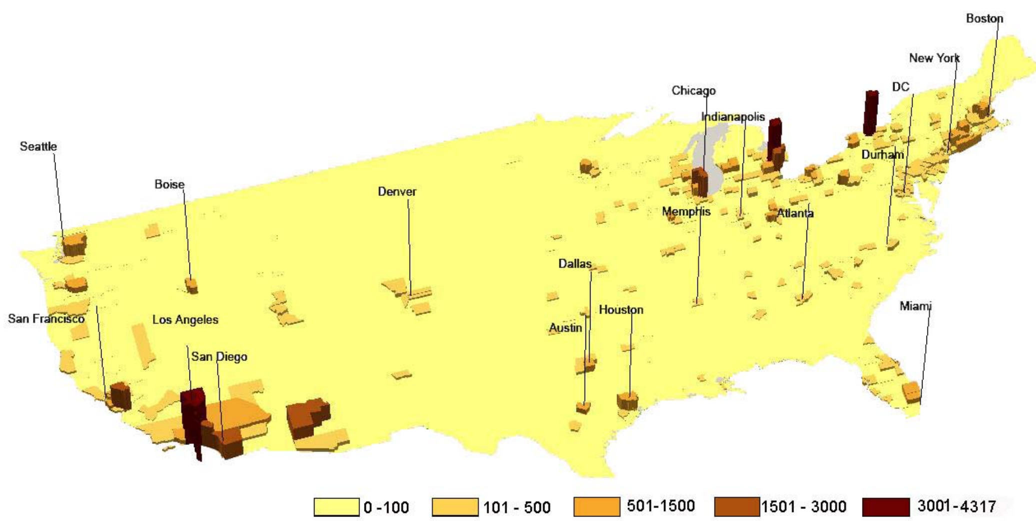

Figure 5-10 Distribution of Mechanical Patents across Counties

Innovative activity is correlated with the urbanization agglomeration economies of scale as indicated by the county population size. Some counties that have large urban centers or are part of large urban areas are also very active in innovation. The test of correlation between county population and county patent counts indicates that overall, patents have some relation with population (correlation coefficient is 0.72, $p<.01$). The correlation coefficient statistics for county population and Chemical, Computer & Communication, Drugs & Chemical, Electrical & Electronic, Mechanical, and Others are 0.63 ($p<0.0001$), 0.45 ($p<0.0001$), 0.66 ($p<0.0001$), 0.53 ($p<0.0001$), 0.76 (0.0001), and 0.90 ($p<0.0001$), respectively. In addition, places with the high number of patents in Computer & Communication also tend to have the high number of patents in Electrical & Electronic (Pearson correlation is .95, $p<0.01$). This high correlation has not been found among other patent types in the current studies. The result could be consistent with O'huallachain's (1999) conclusion about the geographic distribution of patents across the country. However, his observation that patents are closely related to population in the manufacturing belt but less in the non-manufacturing belt could have been biased because he only observed total patent distribution at the regional level. Unfortunately, different places specialize in different industries and the manufacturing belt may focus on traditional industries and thus have more innovation in Mechanical.

1.3. Distribution of patents per 1000 county population

Figures 5.11, 5.12, 5.13, 5.14, 5.15 and 5.16 present the distribution of patents per 1000 population (in 1990) across all counties. The variation in patent rates shows a different dynamics compared to that of patent counts. By using patents per 1000 county population, I am able to show that innovation does not always happen where big names such as Silicon Valley the Research Triangle are. When referenced against population size, innovation favors small places which have a few important manufacturing companies or a few very innovative and talented individuals. This is obvious in Figure 5.11 with the emergence of numerous places that are flat when raw patent counts are used (as in Figure 5.5-5.10).

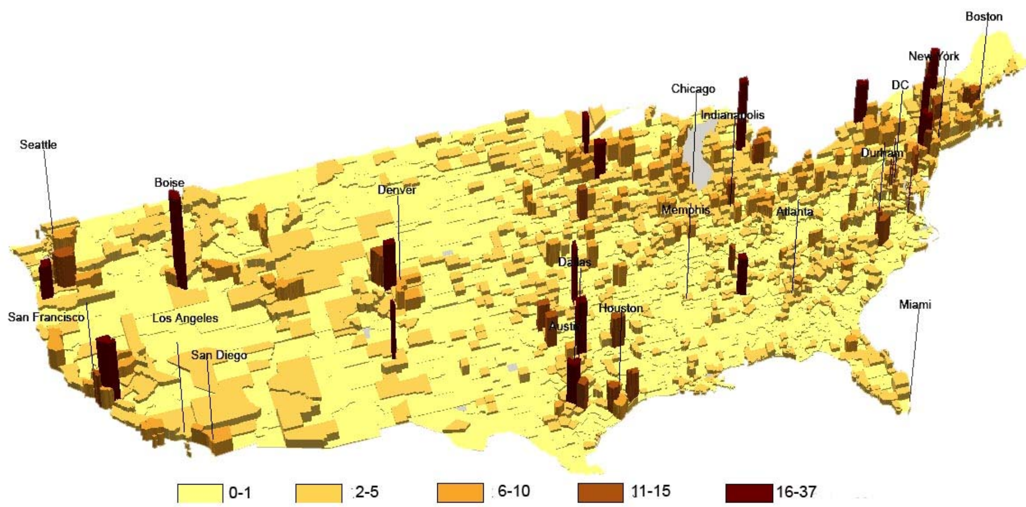

Figure 5-11 Distribution of Total Patents per 1000 County Persons

Table 5.8 shows the top 20 counties with highest patent counts per 1000 county population. In the top position is Ada County of the Boise City Metropolitan area with highest patent rate of 37 per 1000 county population. However, as indicated by Table 5.2, Ada County has a raw count of 7,679 patents, ranked 14 among the top counties. Some large corporations in major fields have their headquarters located in Boise, the county seat. Those companies include Micron

Technology, a semiconductor manufacturer, and Boise Cascade, an engineered wood and paper manufacturer. Ada County is also ranked first in Electrical & Electronic.

Midland County, which is part of the Saginaw-Bay City-Midland Metropolitan area, is ranked second with a total 28 patents per 1000 population (Table 5.8). The county, where Dow Chemical is located, is ranked first with 19 patents per 1000 population in Chemical. Also in this patent category, Nowata County (OK) is ranked 10^{th} with about 5 patents per 1000 population, as much as Somerset County (NJ) generated even though Nowata County had only 9,992 population in 1990 compared to the population of 240,279 in Somerset County. This is because one inventor in Nowata held at least 40 patents from 1990 through 2002.

Table 5.8 Top 20 Counties With Highest Total Patent Per 1000 Population

Ada County	Boise City MSA	37.32
Midland	Saginaw-Bay City-Midland MSA	28.46
Santa Clara	San Francisco-Oakland-San Jose CMSA	26.98
Collin	Dallas-Fort Worth CMSA	24.35
Los Alamos	Santa Fe MSA	24.01
Washington	OK	23.47
Falls Church city	Washington-Baltimore CMSA	21.61
Boulder	Denver-Boulder-Greeley CMSA	20.30
Washington	Minneapolis-St. Paul MSA	20.24
Monroe	Rochester MSA	19.58
Travis	Austin-San Marcos MSA	19.31
Hunterdon	New York-Northern New Jersey-Long Island CMSA	18.49
Schenectady	Albany-Schenectady-Troy MSA	18.11
Williamsburg city	Norfolk-Virginia Beach-Newport News MSA	17.95
Chittenden	Burlington MSA	16.75
Somerset	New York-Northern New Jersey-Long Island CMSA	16.57
Benton	Corvallis MSA	15.66
Limestone	Huntsville MSA	15.22
Olmsted	Rochester MSA	15.19
Dutchess	New York-Northern New Jersey-Long Island CMSA	14.06

In the remaining categories, Santa Clara is leading in Computer & Communication with 11 patents for every 1000 population in the county; Dallas

County in Des Moines MSA has highest patent rate of 7 in Drug & Medical, and the city of Williamsburg, part of Norfolk-Virginia Beach-Newport News MSA, has the highest patent rate of 7 in Mechanical. Counties such as Santa Clara (CA), Collin (TX), Monroe (NY), and Travis (TX) continue to be among the top innovative places in terms of innovation per 1000 county population. Washington County (OK) borders Tulsa County (OK) and Osage County (OK), part of the larger metropolitan area of Tulsa MSA. In 1990, Washington had a population of 48,066 while Tulsa had 503,341 and Osage had 41,645 but the number of patents originated from Washington is almost as high as that in Tulsa (1128 patents versus 1268 patents) and is apparently much more innovative than Osage with a total of 24 patents. Therefore, in terms of innovation per 1000 population, Washington is among top innovative counties overall and in Chemical.

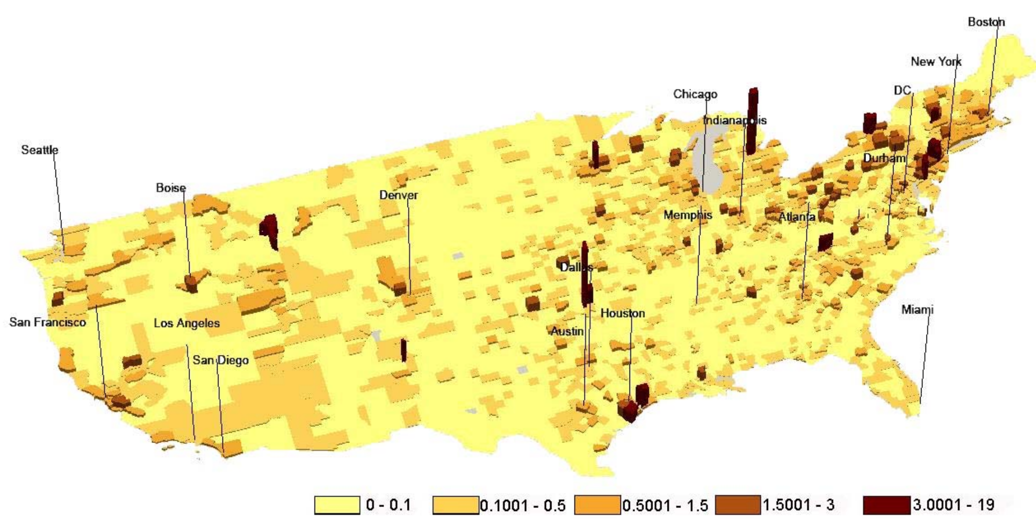

Figure 5-12 Distribution of Chemical Patent per 1000 County Persons

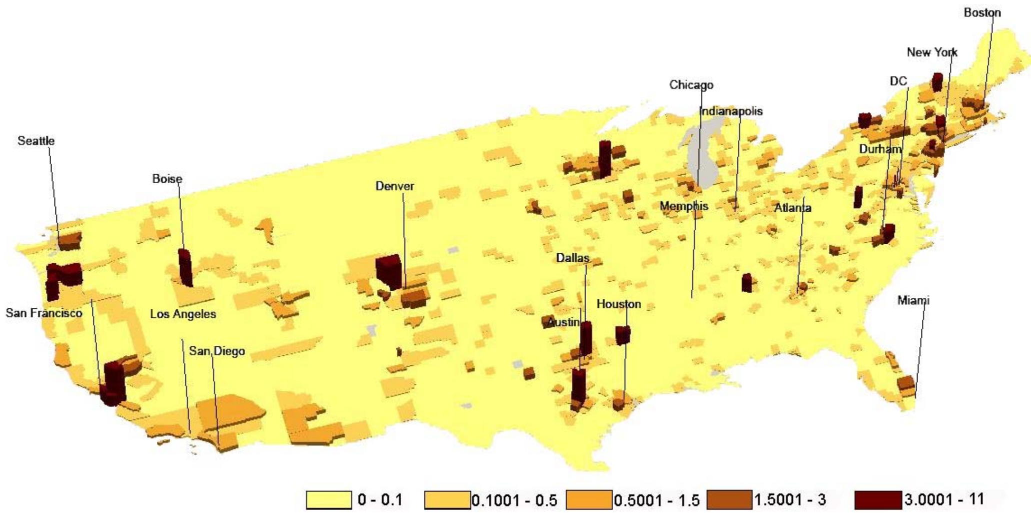

Figure 5-13 Distribution of Computer & Communication Patents per 1000 County Persons

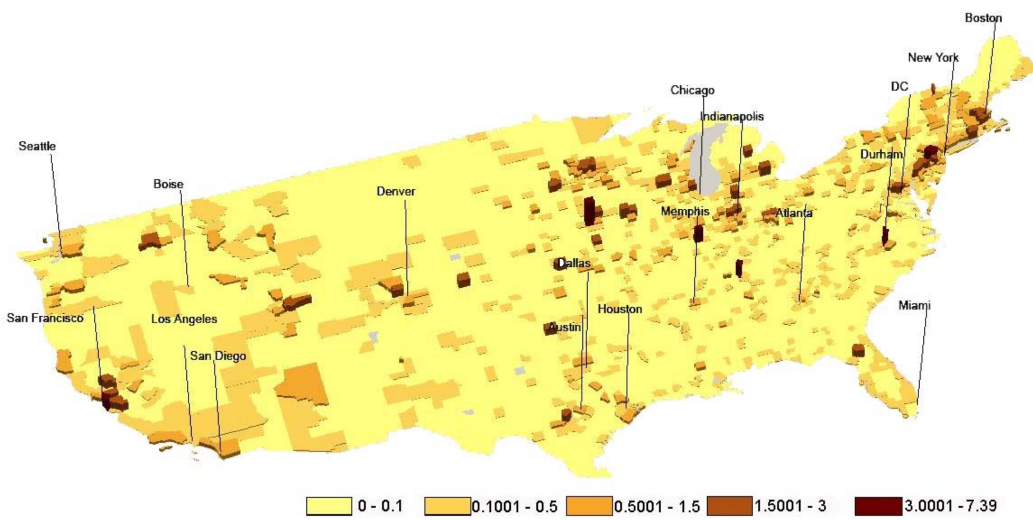

Figure 5-14 Distribution of Drug & Medical Patents per 1000 County Persons

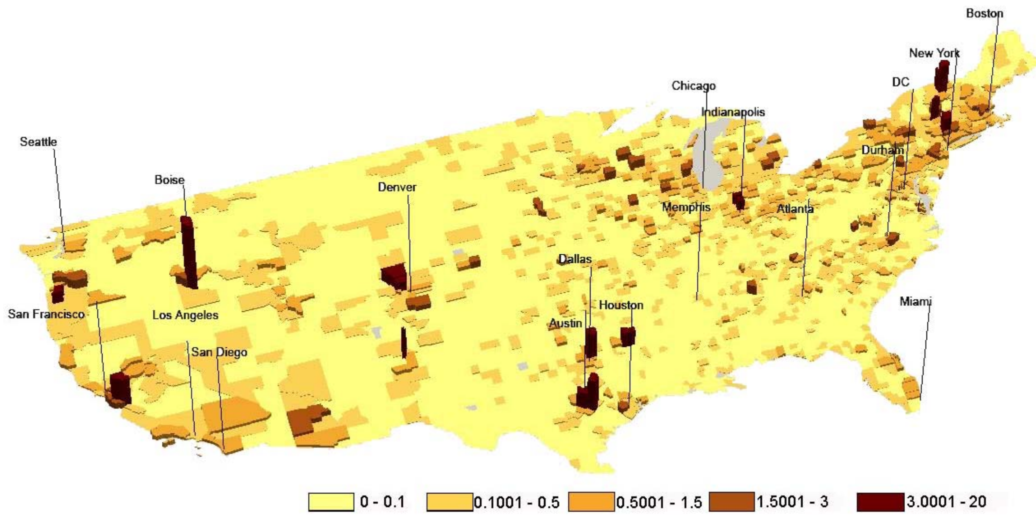

Figure 5-15 Distribution of Electrical & Electronic Patents per 1000 County Persons

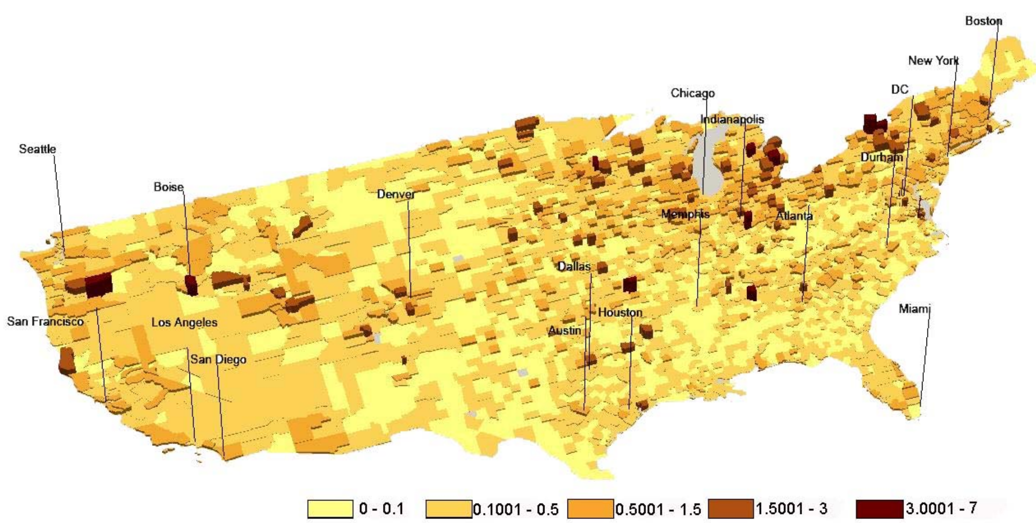

Figure 5-16 Distribution of Mechanical Patents per 1000 County Persons

1.4. Distribution of innovators

Finally, the presentation of innovator data is in Table 5.9 and Figure 5.17 and 5.18. By and large, the distribution of innovators is similar to the distribution of patents and the distribution of innovators per 1000 county population is also similar to that of patents per 1000 county population. Table 5.9 allows us to compare the top 20 counties with highest innovator counts and the similar list of 20 counties with highest patent counts in Table 5.2.

Table 5.9 Top Counties with Highest Innovator Counts

County	CMSA/MSA	Inventors
Santa Clara	San Francisco-Oakland-San Jose	13536
Los Angeles	Los Angeles-Riverside-Orange	11249
Cook	Chicago-Gary-Kenosha	7111
Orange	Los Angeles-Riverside-Orange	6749
Middlesex	Boston-Worcester-Lawrence	6342
San Diego	San Diego	6087
Harris	Houston-Galveston-Brazoria	4971
Maricopa	Phoenix-Mesa	4784
Oakland	Detroit-Ann Arbor-Flint	4565
King	Seattle-Tacoma-Bremerton	4533
Travis	Austin-San Marcos	3894
Monroe	Rochester	3854
Hennepin	Minneapolis-St. Paul	3205
San Mateo	San Francisco-Oakland-San Jose	3113
Contra Costa	San Francisco-Oakland-San Jose	3048
DuPage	Chicago-Gary-Kenosha	2859
Alameda	San Francisco-Oakland-San Jose	2785
Bronx	New York-Northern New Jersey-Long Island	2696
Allegheny	Pittsburgh	2595
Fairfield	New York-Northern New Jersey-Long Island	2549

The lists of innovations and innovators share a lot in common. Santa Clara, Los Angeles, Cook, Middlesex, and San Diego maintain the same position of being most innovative counties and having the most innovators. Specifically, Santa Clara has 13,536 inventors who successfully applied for patents from 1990 through 2002. The 20th county in this list, Fairfield County, has 2549 innovators. Many counties that appear in the top 20 counties with most innovation also appear in the other list of top 20 counties with most innovators but their ranks may not be the same. The correlation coefficient for the total number of patents and the total number of inventors across counties is highly statistically significant (.98). Not surprisingly, the high correlation shows that the more innovators a county has, the more innovation it generates. The high correlation between patent counts and innovator counts necessarily leads to similarities between Figure 5.17 and Figure 5.5 for total patents, as well as between Figure 5.18 and Figure 5.11 for total patents per 1000 county population.

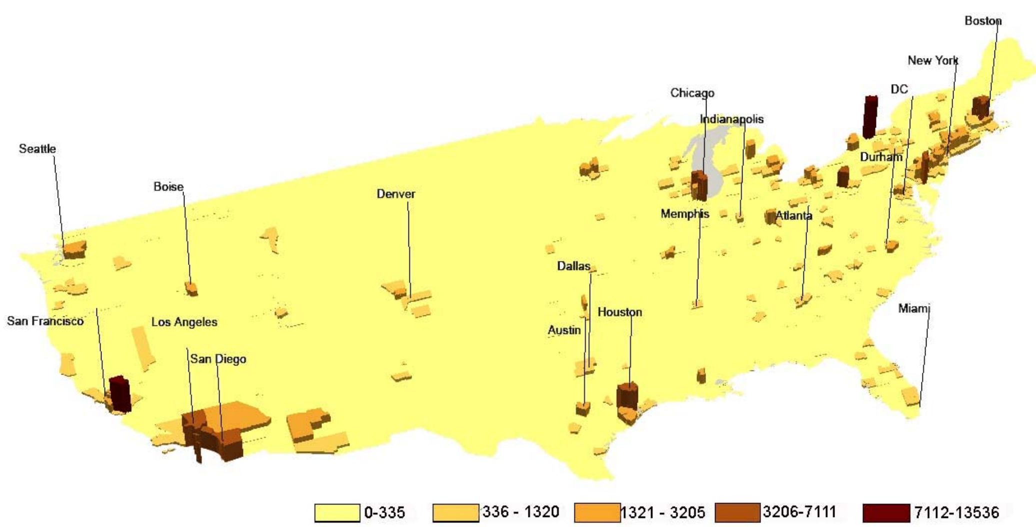

Figure 5-17 Distribution of Total Innovators across Counties

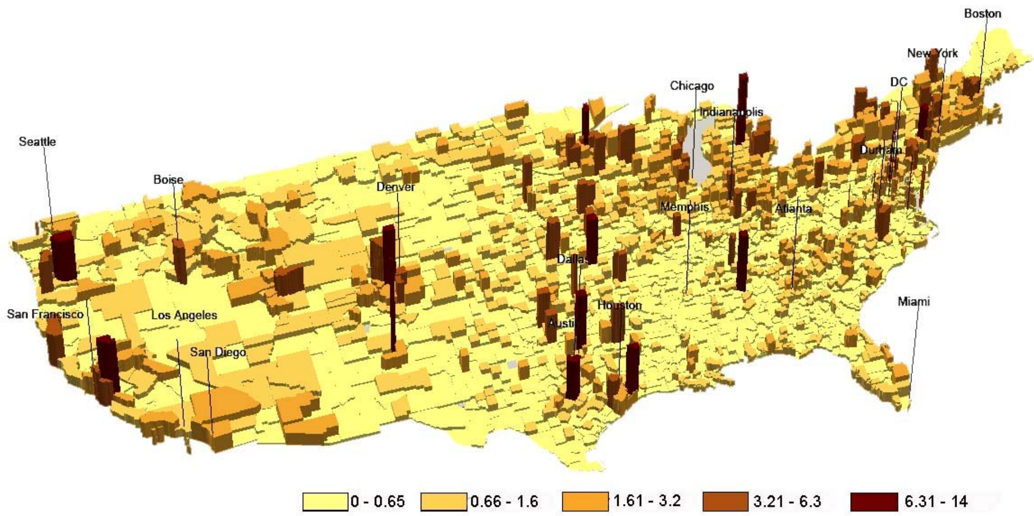

Figure 5-18 Distribution Of Total Innovators per 1000 County Persons

2. Urban Form across 951 US Counties

To operationalize urban form, I use Ewing et al.'s (2003) county sprawl index. Also, for the convenience of the study and the data construction, sprawl is call compactness. The higher the value, the more compact a county is. The index is available for 951 counties, statistically equivalent entities such as independent cities, and groups of adjacent counties or cities.

Figure 5.19 presents the compactness data for 951 counties and county-equivalent cities within metropolitan areas. It is obvious that the core counties of the metropolitan area are more compact than the counties that lie further away from the metropolitan core. The data range from 55 to 352 with the mean compactness of 94 and standard deviation of 20.

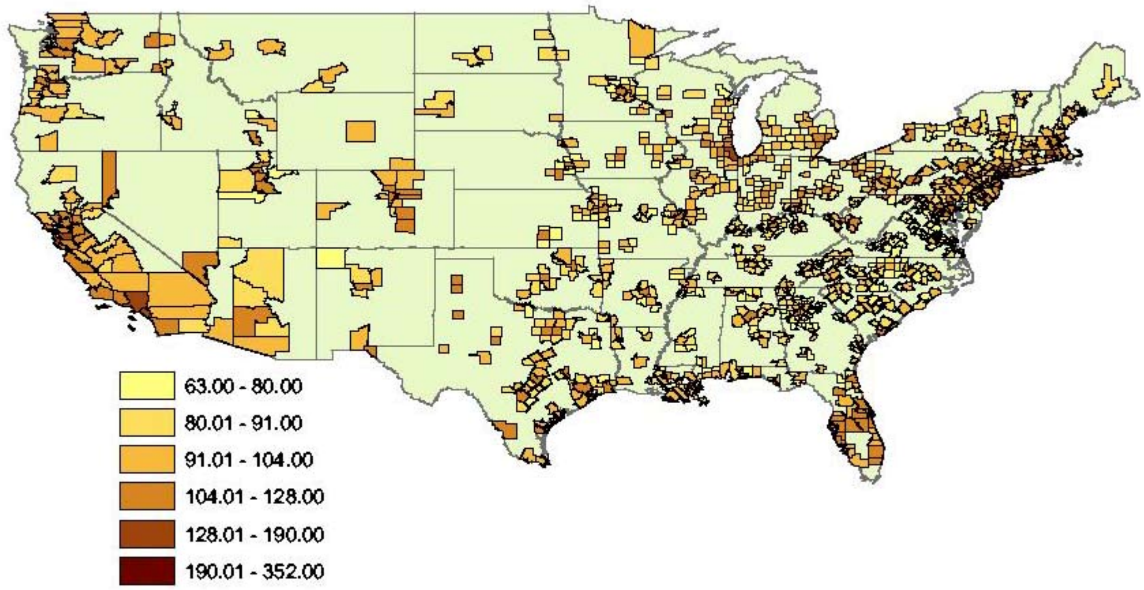

Figure 5-19 Distribution of Compactness Index across Counties with Data

Table 5.10 shows 20 most compact counties and county equivalent cities and their according metropolitan areas. Most of the counties in this list are from large metropolitan areas with high population and population density such as New York, San Francisco, Boston, Chicago, and Los Angeles. Among those 20 most compact places are Los Angeles County, Cook County, and Alameda County, which also achieve high performance in innovation as measured by patent counts. Half of counties listed belong to the New York-Northern New Jersey-Long Island CMSA. Especially, New York County, Kings County, Bronx County, and Queens County that correspond to four boroughs of New York City (Manhattan, Brooklyn, the Bronx, and Queens) are the most compact. Jackson (KS), Bedford in Lynchburg metro area (VA), Geauga in Cleveland metro area (OH), and Chester in Jackson metro area (TN) are least compact or in other words, most sprawled counties with index values of 55 for Jackson and 63 for the other counties.

When innovation is related to the degree of compactness, less compact counties do not perform well in terms of innovation. For example, Jackson (KS) does not appear to be innovative or attractive to innovators as it did not generate any patent during the period 1990 through 2002. Bedford had 218 patents while Geauga had 555 patents and appears to be the most innovative county among 20 most sprawled counties. Several counties in this group such as Chester County (TN), Green County (NC), Andrew (MO), and Lawrence (AL) had less than ten patents and most of the remaining counties had less than 100 patents. In contrast to counties with the most sprawl, the top 20 compact counties generated over 1000 patents during the same period. Specifically, Los Angeles County generated 22,918 patents and Cook County generated 15,397 patents. The total number of patents generated in the most compact counties is more than 60 times that from the 20 most sprawling counties.

Table 5.10 Top 20 Most Compact Counties

County	MSA/CMSA	Compactness
New York	New York-Northern New Jersey-Long Island CMSA	352
Kings	New York-Northern New Jersey-Long Island CMSA	263
Bronx	New York-Northern New Jersey-Long Island CMSA	250
Queens	New York-Northern New Jersey-Long Island CMSA	218
San Francisco	San Francisco-Oakland-San Jose CMSA	209
Hudson	New York-Northern New Jersey-Long Island CMSA	190
Philadelphia	Philadelphia-Wilmington-Atlantic City CMSA	187
Suffolk	Boston-Worcester-Lawrence CMSA	179
Richmond	New York-Northern New Jersey-Long Island CMSA	162
Baltimore city	Washington-Baltimore CMSA	162
Essex	New York-Northern New Jersey-Long Island CMSA	152
Cook	Chicago-Gary-Kenosha CMSA	150
Orleans Parish	New Orleans MSA	149
Los Angeles	Los Angeles-Riverside-Orange County CMSA	141
Passaic	New York-Northern New Jersey-Long Island CMSA	140
Alameda	San Francisco-Oakland-San Jose CMSA	136

Nassau	New York-Northern New Jersey-Long Island CMSA	136
Miami-Dade	Miami-Fort Lauderdale CMSA	136
Union	New York-Northern New Jersey-Long Island CMSA	136
Milwaukee	Milwaukee-Racine CMSA	132

Table 5.11 presents the correlation matrix for compactness and different patent types. By and large, county compactness is statistically significantly correlated with the innovative performance of the county as measured by the number of patents and the number of innovators. However the correlation differs across patent types and is not very high (less than 0.7). The correlation between compactness and innovation data appears to be highest in Drugs & Medical and lowest in Computer & Communication.

Table 5.11 Correlation between Compactness and Patent Data

	Compactness
Total patents	**0.45******
Chemical patents	0.42**
Computer & Communications	0.32**
Drugs & Medical patents	0.55**
Electrical & Electronic patents	0.33**
Mechanical patents	0.35**
Total innovators	**0.49******
Chemical innovators	0.49**
Computer & Communication innovators	0.36**
Drugs & Medical innovators	0.59**
Electrical & Electronic innovators	0.39**
Mechanical innovators	0.39**

** significant at level of 0.01

The weak correlation between urban form and innovation may indicate challenges to the regression analysis. In addition, this weak correlation may suggest that urban form does not play a crucial role in innovative activity.

3. Distribution of Social Capital across 87 US counties

In this section, I address the spatial distribution of three social capital factors trust, connectivity, and faith ties by using the Roper Center (2005)'s Social Capital Community Benchmark Survey data. Four measures from the survey data are used to capture the three factors. Those measures include social trust, informal social interaction, organized group interaction, and faith-based social capital. Individual data are aggregated to the county level. Using the minimum number of survey participants of 25 as a filter, I reduced the total number of 268 counties to 87 counties. As discussed in Chapter Four, the social capital data were standardized against national data (using national mean and standard deviation).

Figures 5.20, 5.21, 5.22, and 5.23 reveal spatial distribution of social capital across those 87 counties. Table 5.12 includes descriptive statistics for four measures of three social capital factors.

Table 5.12 Descriptive Statistics of Social Capital Data

Social capital variables	Min	Max	Mean	Std. Deviation
Social trust index	-0.35	0.39	0.048	0.155
Informal social interaction index	-0.27	0.45	-0.002	0.121
Organized group interaction index	-0.29	0.22	-0.018	0.0921
Faith-based social capital index	-0.75	0.40	-0.056	0.202

The social trust index ranges from -0.35 to 0.39 for 87 counties. Counties with highest social trust indices include Washington County in Minneapolis-St. Paul MSA, Burleigh County of Bismarck MSA, and Wayne County of Rochester MSA. Washington County had a total of 2953 patents in the study years, 1990 to 2002; Burleigh had a total of 15 patents; and Wayne had 855 patents during the same time. At the least trusting end lie Kane County, Los Angeles County, and Cook County.

Kane had 694 patents and is part of the Chicago-Gary-Kenosha CMSA. Los Angeles and Cook are among top 20 most innovative counties. Beside Los Angeles and Cook, two top innovative counties also are among 20 counties where people felt least trusting compared to national standard. Those counties include Harris (TX) and Hennepin (MN).

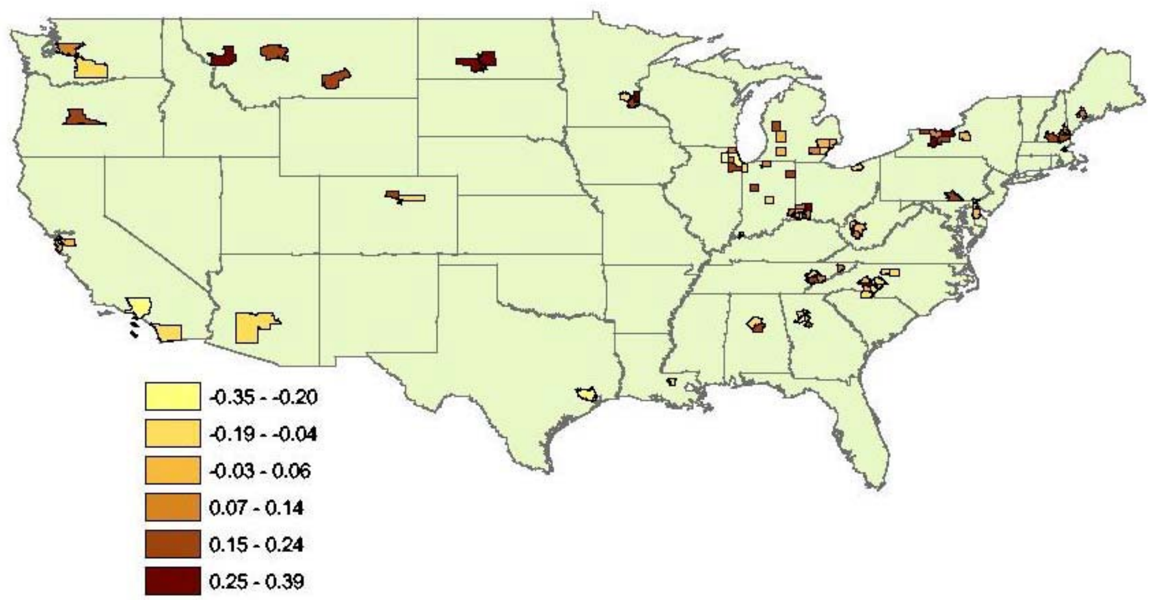

Figure 5-20 Distribution of Social Trust Index across Counties with Data

The informal social interaction index ranges from -0.29 to 0.22 for 87 counties. The index indicates the frequency of having friends' visits, interacting with co-workers outside workplaces, hanging out with friends in public places, and playing cards and board games. The distribution of the index displayed in Figure 21 does not match with that of social trust index. Some counties that scored very low on the social trust scale do score better on the informal social interaction scale. Vanderburgh County, Livingston County, and Kenton County are three top counties. Vanderburgh is part of the Evansville-Henderson IN-KY MSA and had 355 patents from 1990 through 2002. Livingston is part of the Rochester metropolitan area in the state of New York and had 285 patents during the same time. Kenton is part of Cincinnati-Hamilton OH-KY-IN CMSA and had a total of 121 patents. Burleigh County, the second highest on the scale of social trust, is ranked 7th highest in terms of informal social interaction. On the contrary, top innovative counties such as Los Angeles, DuPage, Harris, and Alameda take the 5th, 6th, 7th, and 10th position of counties with lowest average informal social interaction index. Lincoln County scores the least and it had only 61 patents during the period 1990-2002. As the list of counties with lowest average informal social interaction index extends further, highly innovative counties such as San Diego and Santa Clara are also among the bottom 20.

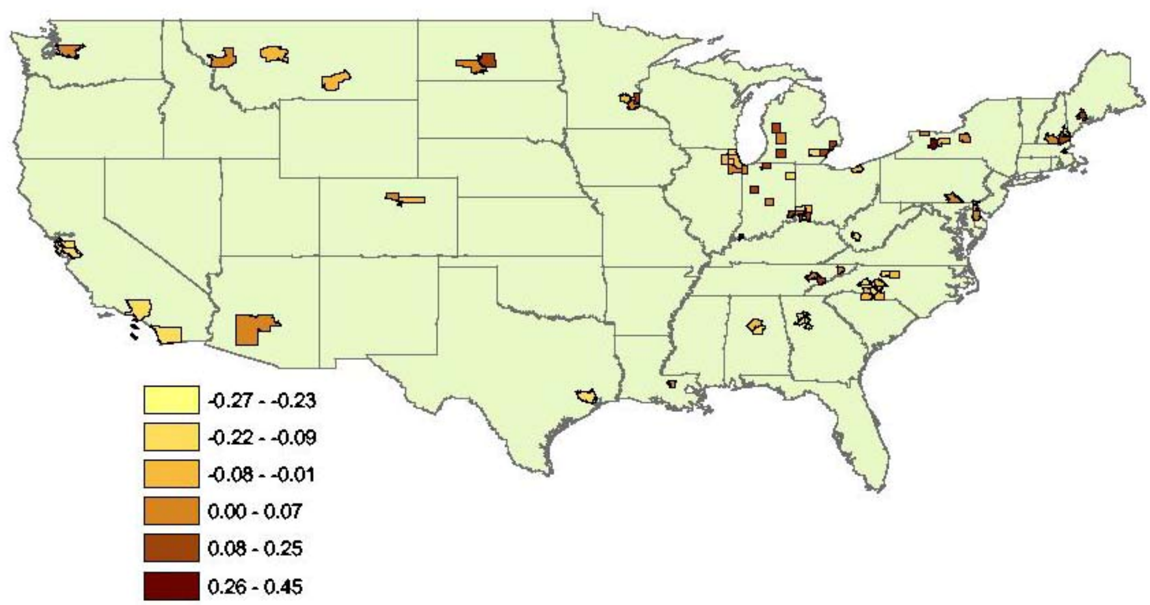

Figure 5-21 Distribution of Informal Social Interaction Index across Counties with Data

Regarding the organized group interaction, the index ranges from -0.29 to 0.22. Counties with highest scores include Dearborn, Livingston, and Blount as the 1st, 2nd, and 3rd highest. Dearborn County is part of Cincinnati-Hamilton OH-KY-IN CMSA and had only 68 patents. Livingston County also appears in the top three counties of highest informal social interaction index. Blount County is part of Knoxville MSA (TN) and had 173 patents. At the low end of the organized group interaction scale, Henry County, part of the Atlanta metropolitan, only had a total of 76 patents. It is followed by Lincoln County, which is part of Charlotte-Gastonia-Rock Hill, NC-SC MSA and had only 61 patents. Similarly, Rowan County in Charlotte-Gastonia-Rock Hill, NC-SC MSA had 34 patents and takes the 3rd position in this list.

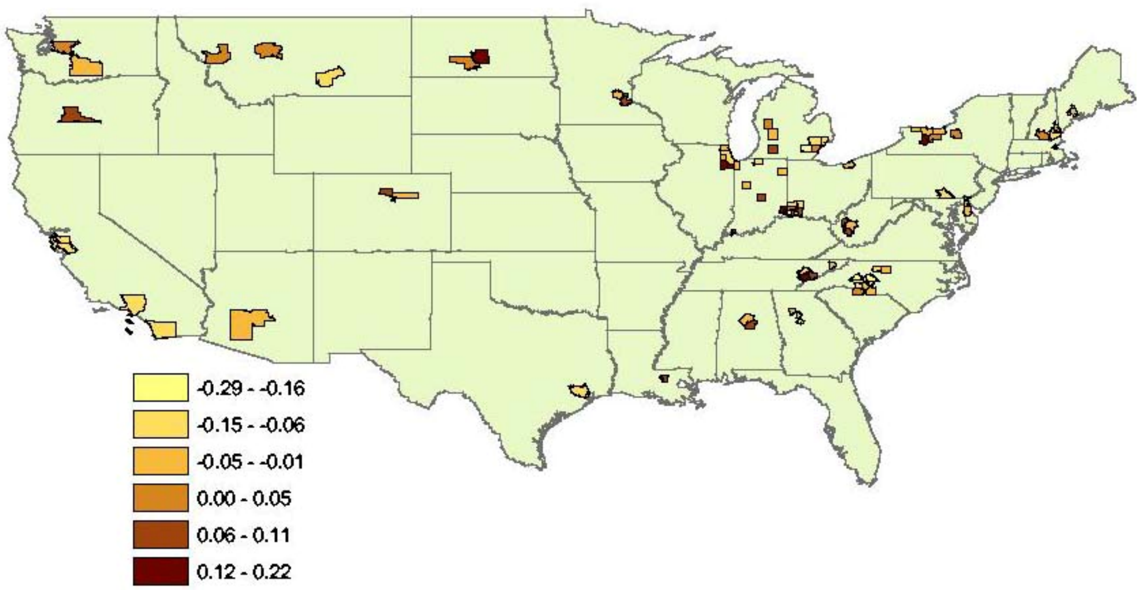

Figure 5-22 Distribution of Formal Group Interaction Index across Counties with Data

While there are only two highly innovative counties, Boulder (CO) with 4,574 patents and Ramsey (MN) with 4,270 patents, in the top 20 counties with highest organized group interaction index, many top innovative counties such as Oakland (MI), San Diego (CA), San Mateo (CA), Los Angeles (CA), Harris (TX), Santa Clara (CA), and Alameda (CA) score at the low end for organized group interaction.

Figure 5.22 shows similar patterns of distribution of the informal social interaction index and the organized group interaction index. Counties in California and the South Census region appear to score low on both scales while counties in the Northeast Census region where data area available appear to score higher.

Figure 5.23 presents the distribution of the faith-based social capital index for 87 counties across the country. Unlike the other social capital factors, it appears that most counties in the South Census region score above the national standard while counties in the North East and the West region score below the national standard. The data ranges from -0.75 to 0.40.

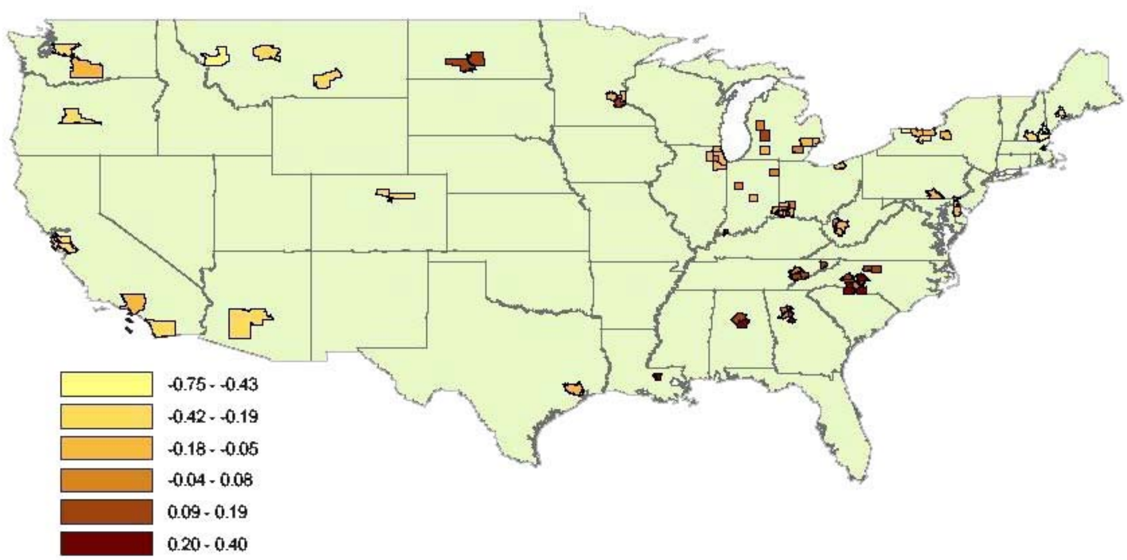

Figure 5-23 Distribution of Faith-based Social Capital Index across Counties with Data

The close examination of faith-based social capital data reveals that most counties in the top 20 counties with highest scores are located in the South Census region. Those counties include Shelby in the Birmingham MSA (AL), York in Cincinnati-Hamilton OH-KY-IN CMSA, Henry in Atlanta MSA, and other counties scattering in Louisiana, Alabama, Georgia, and Tennessee. Shelby had 44 patents, York had 181 patents, and Henry had 76 patents from 1990 through 2002. There are a few counties that are somewhat innovative in this group such as East Baton Rouge in Baton Rouge MSA with 1,555 patents and DeKalb County in Atlanta MSA with 2,571 patents. Counties that score least on the faith-based social capital scale include Strafford in the Boston-Worcester-Lawrence MA-NH-ME-CT CMSA, Missoula in Missoula MT MSA, and Rockingham in Boston-Worcester-Lawrence MA-NH-ME-CT CMSA. Compared to the other two, Rockingham is fairly innovative with 1,359 patents. Other highly innovative counties in this group include San Francisco County, Alameda County, Boulder County, San Mateo County, Satan Clara County, San Diego County, Maricopa County (AZ), and King County (WA). The group of bottom 20 counties is composed mostly of counties from the West and Northeast Census region.

The descriptive statistics of the social capital data for 87 counties, where survey sample sizes are over 25, suggest that many top innovative counties did not perform well in terms of informal social interaction, organized group interaction, and faith-based social capital. In addition, more counties in the South Census region scores higher on the faith-based social capital scale than the West and Northeast regions. It is less obvious in case of the other social capital factors that the index is higher in one region than in the others.

Table 5.13 shows the correlation matrix of social capital factors and innovation data. Most coefficients are negative and weak for all patent categories and social capital factors. Social trust appears to have more statistically significant relation with the total number of patents and innovators, as well as in the number of innovators in Computer & Communication and in Drugs & Medical, compared to the other social capital factors. However, the association of social capital factors and innovation is not certain during this preliminary examination of the data because of other covariates that have not yet been controlled for.

Table 5.13 Correlation Matrix of Social Capital Factors and Patent Data

	Informal social interaction	Organized group interaction	Social trust	Faith-based social capital
Total patents	**-0.23***	**-0.19**	**-0.28****	**-0.23***
Chemical patents	-0.22*	-0.15	-0.27*	-0.16
Computer & communications	-0.19	-0.14	-0.14	-0.22
Drugs & medical patents	-0.27*	-0.16	-0.27*	-0.28*
Electrical & Electronic patents	-0.19	-0.17	-0.19	-0.20
Mechanical patents	-0.13	-0.18	-0.27*	-0.15
Total innovators	**-0.24***	**-0.20**	**-0.33****	**-0.23***
Chemical innovators	-0.25*	-0.16	-0.33	-0.17
Computer & Communication innovators	-0.20	-0.14	-0.17**	-0.23*
Drugs & medical innovators	-0.28*	-0.17	-0.31**	-0.27*
Electrical & Electronic innovators	-0.21	-0.19	-0.25*	-0.22*
Mechanical innovators	-0.14	-0.18	-0.32	-0.15

* significant at level of 0.05
** significant at level of 0.01

4. Conclusion

The chapter provides descriptive analysis for patents, compactness, and social capital data. All three datasets show spatial variation across different counties at all examined geographical levels, especially the patent data. In the same metropolitan area such as San Francisco-Oakland-San Jose CMSA, some counties are more innovative than others. The use of raw patent counts shows us a spatial pattern of innovation that favors places with access to large metropolitan areas with high education institutions and some concentration of firms and employment. On the other hand, the use of rates of patents per 1000 county population appears to favor smaller places with a few very innovative firms or individuals. The regional distribution of patents raises questions about contributing factors available which extend beyond the existing literature on innovation. This dissertation aims at addressing some of those possible factors by simultaneously examining social capital and urban form. I found that the measure of innovators is highly correlated with patent counts. Simple tests of correlation indicate that the relationship between urban form and innovation can be significant and positive for all patent types. Meanwhile, the relationship between social capital and innovation can be significant and negative or insignificant. However, because of other uncontrolled factors, the correlation results do not reflect proper relationship between those variables. In the next chapter, the relationship between urban form, social capital and innovation will be dissected using regression techniques. The next chapter will also present descriptive statistics for other variables.

Chapter VI: Analysis

1. Introduction

The dissertation study contributes to the existing literature by conceptually suggesting that urban spatial characteristics also need to be included in studies of regional innovation. Previous studies of knowledge spillovers and spatial distribution of innovation are built upon the knowledge production function introduced by Griliches (1979). Those studies are mainly focused on the effects of R&D activities and their spillover effects on regional innovation. This body of literature indicates that innovation benefits from the concentration of research laboratories and universities, of employment, and of firms in related industries. The geographical proximity among knowledge generating entities creates scale economies and facilitates knowledge sharing and cross-fertilization of ideas (Feldman and Florida 1994). In addition, the emerging literature on social capital raises the question of whether social capital would affect innovation and if so, to what extent and how. This dissertation study also addresses the above question by including in the analysis three social capital factors – trust, connectivity, and faith ties.

This analysis chapter is going to explore three hypotheses. First, the more compact a county, the more innovative it is. Second, the more trusting its residents are, the more innovative the county. Third, the more connected its residents are, the more innovative the county. And finally, the relationship between faith ties and innovation can take a negative or positive sign. The knowledge production function developed by Griliches (1979) and the study's framework are described in detail in Chapter Two and Three. The analysis is divided into three sections. The first section presents the underlying theory of multilevel modeling and the rationale for using this method. The second section addresses the impact of urban form and social capital on innovation using the Ordinary Least Squares (OLS) model and the hierarchical linear model. I use the Hall, Jaffe, and Trajtenberg's (2001) patent statistics and the USPTO (2002)'s inventor file to create a proxy for innovative output at the county level for five different industries. The Roper Center's (2005) Social Capital Community Benchmark Survey provides measures for three social capital factors: trust, connectivity, and faith ties. The county compactness index is used to capture urban form and the variable is from Ewing et al.'s (2003) county sprawl data. The final section examines the possible impacts of urban form on the three factors of social capital using similar hierarchical techniques.

2. The Hierarchical Model

The nested or hierarchical design is a common approach in social sciences to address hierarchically structured data. It was first used in educational research to study the contextual effects on students' and teachers' performance (Snijders and Bosker 1999). The hierarchical model contains more than one level of analysis: a detailed level and its higher hierarchical level (or levels). For example, students are naturally nested within classrooms who receive similar treatment administered at the classroom level. Conceptually, the hierarchical model differs from multivariate regression models in several aspects but most importantly, the former has more than one error term in its equation to account for errors at different levels of analysis. In the earlier example, when using the Ordinary Least Square (OLS) models, the researcher is likely to ignore the fact that students in the same classroom or even in the same cohorts may be related, which violates OLS assumptions that the observations are independent, leading to mis-estimation of standard errors. Multilevel modeling properly accounts for the errors at the student level and at the classroom level in the analysis. In addition, multilevel modeling also addresses the issue of heterogeneity of regressions. The researcher can realistically assume there exists some cross level interaction between students' characteristics and classrooms' characteristics (Raudenbush and Bryk 2002). For those reasons, the multilevel modeling approach is superior to other approaches such as OLS models at the individual level or at the group level, which ignores the hierarchical structure of data, and ANCOVA models, which uses dummy variables to represent different groups or contexts (Kreft and DeLeeuw 1998, Raudenbush and Bryk 2002).

The multilevel or hierarchical modeling is an appropriate approach for the analysis of impacts of urban form and social capital on innovation because some key variables are at the county level while others at the metropolitan level. Those county variables include compactness index, social trust, informal social interaction, organized group interaction, and faith-based social capital. Meanwhile, variables that capture employment and R&D activities necessarily do so at the metropolitan level because the larger region naturally serves as the labor market for knowledge workers and innovators living in component counties. Counties in the same metropolitan area will be related because innovative activity in those counties benefits from the same labor pool, R&D activities, firm clustering, and business services sector of the entire metropolitan area. It is possible that the relationships between county characteristics and county innovation vary from metropolitan to metropolitan and as a result there is a unique regression line for counties within each metropolitan area instead for all counties. This variation at the metropolitan level can be explained by the metropolitan characteristics or it can be totally random; but in either case, the OLS model assuming one error term is no longer appropriate. As a result, to analyze the impacts of social capital and urban form on innovation, a hierarchical 2-level model will be specified. This hierarchical model will have two error terms r and u at the county level and metropolitan level respectively.

The data structure also inhibits using OLS and favors hierarchical models in the analysis of impacts of urban form on social capital. Surveyed individuals are nested in communities, which are nested in different counties. The potential model should have individuals' level of social capital as the dependent variable and compact urban form measured at the county level. More importantly, the use of hierarchical models allows for correlating neighborhood income level and racial composition residents' social capital (Putnam 2000, Freeman 2001, Leyden 2003). Using hierarchical model in this case is equivalent to assuming that there exist a set of regression lines to explain the variation in individuals' social capital. Those lines are the same for individuals in the same community and will vary across different communities in the same county and across different counties. Consequently, there are three levels of analysis: person, community, and county.

In general terms, a simple two level model could be formulated as follows (Raudenbush and Bryk 2002):

There are n_j level 1 units nested within j = 1,…,J level 2 units.

Level 1 (person's level): $Y_{ij} = \beta_{0j} + \beta_{1j} X_{ij} + r_{ij}$

Level 2 (organization's level): $\beta_{0j} = \gamma_{00} + \gamma_{01} W_j + u_{0j}$

$$\beta_{1j} = \gamma_{10} + \gamma_{11} W_j + u_{1j}$$

Where

γ_{00} is the average intercept across the level 2 units (fixed effect)

γ_{10} is the average slope across the level 2 units (fixed effect)

X_{ij} is the level 1 predictor

W_j is the level 2 predictor

r_{ij} is the level 1 random effect

u_{0j} u_{1j} are the level 2 random effects

The combined model

$$Y_{ij} = \gamma_{00} + \gamma_{10} X_{ij} + \gamma_{01} W_j + \gamma_{11} X_{ij} W_j + (u_{0j} + u_{1j} X_{ij} + r_{ij})$$

Where we assume E(r_{ij}) = 0 and Var(r_{ij}) = σ^2

E $\begin{bmatrix} u_{0j} \\ u_{1j} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$, and Var $\begin{bmatrix} u_{0j} \\ u_{1j} \end{bmatrix} = \begin{bmatrix} \tau_{00} & \tau_{01} \\ \tau_{10} & \tau_{11} \end{bmatrix}$

Cov(u_{0j} u_{1j}) = τ_{01} = covariance between the level I intercepts and slopes.

Cov (u_{0j} r_{ij}) = Cov (u_{1j} r_{ij}) = 0

The researcher can choose to specify the model as above and this model is called intercepts- and- slopes- as- outcomes. Different variations of the above model exist. The researcher can hypothesize that the model has only a fixed slope (u_{1j} = 0) or the level 1 intercepts and/or slopes varying randomly across different groups or organizations but not as a function of group characteristics (γ_{10} and/or γ_{11} equal 0).

The unbiased estimator of γ will be the generalized least squares estimator, given the normality assumptions for u and r, γ can be estimated by maximum likelihood (See details in Raudenbush and Bryk 2002).

3. Analysis of the Effects of Social Capital and Urban Form on Innovation

3.1. The models

I extend the often cited production function to include the urban form and social capital variables that have been discussed intensively in the literature. The dependent variable is the natural log of patent counts. The key variables include county compactness index, social trust, informal social interaction, organized group interaction, and faith-based social capital. I control for other factors that are also present in previous studies, capturing university and firm R&D in the metropolitan area, the number of knowledge workers in the county, the concentration of employment of the same industries in the metropolitan area, and the concentration of the business services sector in the metropolitan area. Where possible, the variable is transformed by using natural log.

Since there are metropolitans that had no research universities with R&D expenditure recorded for 1990, their aggregated R&D dollar amounts are used. Similarly, county variables of social trust, informal social interaction, organized group interaction, and faith-based social capital are not log-transformed because they have both negative and positive values. For the comparison purpose, both OLS and multilevel models are specified for the data but only multilevel results are to be discussed.

Ordinary Least Square model:

$$Y_i = \beta_0 + \beta_{1j}(LN(COMPACT)_i) + \beta_2(LN(KNO\_WORKERS)_i) + \beta_3(INFORMAL)_i +$$

$$+ \beta_4(ORGANIZED)_i + \beta_5(SOCIAL\_TRUST)_i + \beta_6(FAITH\_BASED)_i +$$

$$+ \beta_7(MSA\_ACADEM\_R\&D)_i + \beta_8(LQ(RESEARCH\_EMP)_i) +$$

$$+ \beta_9(LQ)_i + \beta_{10}(LN(BIZ\_SERVICE)_i) + u_i$$

Where:

LNCOMPACT:	natural log of county compactness
SOCIAL_TRUST:	county average social trust index
INFORMAL:	county average informal social interaction index
ORGANIZED:	county average organized group interaction index
FAITH_BASED:	county average faith-based social capital index
LN(KNO_WORKERS):	natural log of county number of knowledge workers
MSA_ACADEM_R&D:	MSA aggregated academic R&D at research universities for all patent types
LQ(RESEARCH_EMP):	MSA location quotient of research lab employment
LQi:	MSA location quotient of employment in specific industry i for each patent type
LN(BIZ_SERVICE):	natural log of MSA business services sector employment

As aforementioned, the presence of urban form and social capital at the county level and of employment and R&D variables at the metropolitan level has rendered a 2-level hierarchical model to be appropriate and necessary. Level 1 has county variables that measure urban form, social capital, and the number of knowledge worker. Level 2 has metropolitan variables including academic R&D, corporate R&D, employment concentration, and size of business services sector. The multilevel model implies that counties in the same metropolitan are spatially correlated while all adjacent counties in neighboring metropolitans are not.

In order to test the validity of the 2-level model, a fully unconditional model similar to a simple ANOVA is specified for each patent type:

Level 1: $Y_{0j} = B_{0j} + r_{ij}$

Level 2: $B_{0j} = \gamma_{00} + u_{0j}$

Where: γ_{00} is the average natural log of patent count at the county level; r_{ij} and u_{0j} are error terms at the county and metropolitan levels respectively. This model decomposes total variation in the patent data into two variance components for the county and for the metropolitan. Table 6.1 indicates that patent variation attributable to factors at the county level and at the metropolitan level account for considerable shares of total variation, which warrants the use of a 2-level model. The fully unconditional model also suggests that factors at the metropolitan level are responsible for the larger share of variance in Computer & Communication.

Table 6.1 Variance Decomposition for Fully Unconditional Model of Innovation

	Chemical	Computer & Communication	Drugs & Medical	Electrical & Electronic	Mechanical
Level 1 variance	69%	37%	63%	52%	60%
Level 2 variance	31%	63%	37%	48%	40%

To specify the appropriate 2-level hierarchical model, I examine a number of possibilities. First, the model can have the intercepts varying randomly from metropolitan to metropolitan, thus only level 1 intercept has the error term or random effect. Second, the model can be specified to have both the slopes and the intercepts to vary randomly across metropolitan areas or both the slope and the intercept at the metropolitan level have random effect components. However, because most studied MSAs have too few counties (less than 2), the addition of random effect for the slopes at this level does not allow for the metropolitan level variance components to be effectively measured (degrees of freedom reduced significantly). Consequently, a random intercept model is specified for this 2-level hierarchical analysis.

Using algebraic terms, two levels of the random intercept model can be expressed as follows:

Level 1:

$$Y_{ij} = \beta_{0j} + \beta_{1j}(LN(COMPACT)_{ij}) + \beta_{2j}(LN(KNO\_WORKERS)_{ij}) + \beta_{3j}(INFORMAL)_{ij} +$$

$$+ \beta_{4j}(ORGANIZED)_{ij} + \beta_{5j}(SOCIAL\_TRUST)_{ij} + \beta_{6j}(FAITH\_BASED)_{ij} + r_{ij}$$

Level 2:

$$\beta_{0j} =$$

$$\gamma_{00} + \gamma_{01}(MSA\_ACADEM\_R\&D)_j + \gamma_{02}(LQ(RESEARCH\_EMP)_j) +$$

$$+ \gamma_{03}(LQ)_j + \gamma_{04}(LN(BIZ\_SERVICE)_j) + u_j$$

$$\beta_{1j} = \gamma_{10}$$

…

$$\beta_{6j} = \gamma_{60}$$

The data are entered into Hierarchical Linear and Non-Linear Modeling (HLM™) 6, a software developed by Raundenbush, Bryk, and Congdon for multilevel analysis. The software allows the user to run linear models for 3 level data as in this analysis and the reported standard errors are heteroskedastic-consistent to address the prevalent problem of heteroskedasticity in cross sectional analyses. The results from the OLS model and from the hierarchical model are compared in the next part of this chapter.

3.2. Findings

This section starts with a basic linear regression model similar to those used by Black (2004), Carlino, Chatterjee, and Hunt (2007) based on the original Griliches (1979)'s knowledge production function. This model has variables for university and corporate research in the metropolitan area, the number of knowledge workers in the county, the concentration of employment of the same industries in the metropolitan area, and the concentration of the business services sector in the metropolitan area. Table 6.2 indicates that the relationship between urban form and social capital does exist, however, the magnitude of the relationship is not strong and does not threaten the OLS assumption.

Table 6.2 Correlation Matrix for Social Capital and Natural Log of Compactness Index

	1	2	3	4	5
Ln(Compact)	1.00	-0.51**	-0.14	-0.06	-0.31**
Social trust	-0.51**	1.00	0.21	0.27*	-0.08
Informal social interaction	-0.14	0.21	1.00	0.56**	-0.06
Organized social involvement	-0.06	0.27*	0.56**	1.00	-0.09
Faith-based social capital	-0.31**	-0.08	-0.06	-0.09	1.00

* Correlation is significant at the p= 0.05 level.
**Correlation is significant at the p= 0.01 level.

Comparison of the adjusted R-squares for the base model and the new models across five technological categories are indicative of improvement in my model. The addition of spatial and social capital variables has successfully increased the adjusted R-squares by at least three percentage points for Chemical. The improvement ranges from two to eight percentage points in the case of Mechanical (Table 6.3 and 6.4). R-squares are not estimated for the multilevel models.

Table 6.3 OLS Model – Dependent Variable: Natural Log of Patent Count

Variable	Chemical	Computer& Communication	Drugs & Medical	Electrical &Electronic	Mechanical
C	**-8.36**** (1.05)	**-10.67**** (1.25)	**-8.81**** (1.36)	**-9.27**** (0.88)	**-5.02**** (0.77)
LN(KNO_WORKERS)	**1.10**** (0.10)	**1.29**** (0.12)	**1.42**** (0.12)	**1.26**** (0.08)	**0.98**** (0.08)
LQ	0.26* (0.12)	0.59* (0.25)	0.13 (0.09)	**0.63**** (0.15)	**0.66**** (0.16)
MSA_ACADEM_R&D	-6E-07 (6E-07)	1E-06 (8E-07)	9E-07 (8E-07)	-4E-07 (6E-07)	3E-07 (5E-07)
LQ(RESEARCH_EMP)	-0.06 (0.08)	0.12 (0.09)	0.09 (0.09)	0.10 (0.06)	-0.02 (0.06)
LN(BIZ_SERVICE)	**0.31**** (0.10)	0.20 (0.12)	-0.02 (0.12)	0.17* (0.08)	0.06 (0.08)
R-square	0.76	0.80	0.74	0.86	0.82
Adjusted R-square	0.75	0.78	0.72	0.85	0.81

In general, the hierarchical model has improved standard errors of the coefficient estimates. The coefficients for the county number of knowledge workers and social trust appear to be most robust with statistically significant effects on innovation in different models. For knowledge workers, the elasticity of innovation in the multilevel models ranges from 1.35 for Mechanical to 1.63 for Electrical & Electronic (Table 6.5). In the OLS model, the elasticity of patent count with respect to the number of knowledge workers varies from 1.25 for Chemical to 1.65 for Computer & Communication (Table 6.4). The positive sign of the coefficient for knowledge workers is indicative of the contribution of this group in the innovation process. Counties with higher numbers of knowledge workers will also have higher patent counts.

Table 6.4 OLS Model - Dependent Variable: Natural Log of Patent Count

	Chemical	**Computer & Communication**	**Drugs &Medical**	**Electrical &Electronic**	**Mechanical**
C	**-12.445**** (4.254)	-4.007 (4.766)	**-18.525**** (5.262)	-1.157 (3.147)	3.055 (2.641)
LN(KNO_WORKERS)	**1.246**** (0.131)	**1.650**** (0.149)	**1.477**** (0.163)	**1.646**** (0.096)	**1.335**** (0.083)
LQ	**0.385**** (0.117)	0.400 (0.250)	0.078 (0.085)	**0.567**** (0.124)	**0.482**** (0.134)
MSA_ACADEM_R&D	-1.8E-06* (7.6E-07)	3.0E-07 (8.6E-07)	-8.6E-07 (9.4E-07)	-5.6E-07 (5.7E-07)	-3.5E-07 (4.8E-07)
LQ(RESEARCH_EMP)	-0.046 (0.073)	0.147 (0.083)	0.102 (0.089)	0.124* (0.054)	0.007 (0.045)
LN(BIZ_SERVICE)	**0.453**** (0.103)	0.300* (0.125)	0.175 (0.130)	**0.219**** (0.077)	0.128 (0.067)
LNCOMPACTNESS	0.238 (0.975)	-2.329* (1.098)	1.589 (1.215)	**-2.635**** (0.725)	**-2.589**** (0.606)
SOCIAL_TRUST	**2.832**** (0.845)	2.445* (0.998)	**3.744**** (1.027)	**2.047**** (0.617)	**1.802**** (0.534)
INFORMAL	0.999 (1.038)	-1.007 (1.236)	0.212 (1.297)	1.502 (0.768)	0.841 (0.713)
ORGANIZED	-1.330 (1.374)	0.002 (1.596)	0.051 (1.715)	-1.030 (1.023)	-0.642 (0.889)
FAITH_BASED	-1.109 (0.590)	**-2.126**** (0.656)	-1.029 (0.727)	*-1.009** (0.434)	**-1.580**** (0.365)
R-square	0.81	0.85	0.79	0.92	0.91
Adjusted R-square	0.78	0.83	0.76	0.90	0.89

Localization economies of scale, as measured by location quotients of industry employment, are positively and statistically significantly associated with innovation in three out of five categories, consistent with the economic literature. There is a positive association between innovation and firm localization for Chemical, Electric & Electronic, and Mechanical.

Table 6.5 Multilevel Model – Dependent Variable: Natural Log of Patent Count

	Chemical	Computer & Communication	Drugs &Medical	Electrical &Electronic	Mechanical
For Level 1 INTERCEPT					
Level 2 INTERCEPT	**-13.741**** (3.428)	-7.770 (3.919)	**-15.606**** (3.939)	-0.620 (3.367)	2.225 (2.528)
LQi	**0.768**** (0.196)	0.478* (0.218)	0.192 (0.121)	**0.605**** (0.113)	**0.505**** (0.160)
MSA_ACADEM_R&D	**-2E-06**** (1E-06)	0E+00 (1E-06)	0E+00 (1E-06)	0E+00 (1E-06)	0E+00 (1E-06)
LQ(RESEARCH_EMP)	-0.052 (0.033)	**0.175**** (0.035)	0.077* (0.034)	**0.114**** (0.040)	0.013 (0.064)
LN(BIZ_SERVICE)	**0.491**** (0.112)	**0.433**** (0.128)	0.107 (0.149)	0.181* (0.075)	0.061 (0.083)
LN(KNO_WORKERS)	**1.439**** (0.106)	**1.573**** (0.064)	**1.522**** (0.139)	**1.626**** (0.067)	**1.345**** (0.077)
LN(COMPACT)	-0.059 (0.769)	-1.662* (0.840)	0.991 (0.929)	**-2.631**** (0.795)	**-2.297**** (0.557)
SOCIAL_TRUST	**3.418**** (0.643)	**2.178**** (0.599)	**3.125**** (0.703)	**1.624**** (0.501)	**1.440**** (0.494)
INFORMAL	0.891 (0.820)	-0.739 (0.919)	-0.463 (1.027)	0.939 (0.850)	0.059 (0.631)
ORGANIZED	-1.824 (0.937)	0.110 (0.755)	0.096 (1.487)	-0.571 (0.852)	-0.264 (0.749)
FAITH_BASED	-1.147* (0.546)	**-2.119**** (0.688)	-0.585 (0.639)	-0.798 (0.503)	**-1.405**** (0.385)

Contrary to the earlier findings in the innovation literature, academic R&D from research and doctoral universities in 1990 aggregated to the MSA level is not statistically significant for most patent types in the all models. It is only significantly related to Chemical patents in both the extended OLS and multilevel models. However, the coefficient sign is negative. The other measure of R&D, the concentration of research lab employment in the metropolitan area, is statistically significant and positive for most patent types in the multilevel model (Table 6.5) and only for Electrical & Electronic patents in the OLS model (Table 6.4).

Those results imply the importance of social trust in innovation varies by industry and appears to be most important in Drugs & Medical and in Chemical and least important in Mechanical. The findings are consistent with prior studies of the importance of trust at cross-national and intra-organizational levels to national and organizational innovation (Knack and Keefer 1997, Tsai and Ghoshal 1998; Putnam 2000; Johnson, Lorenz, and Lundvall 2002; Dakhli and De Clercq 2004).

Regarding faith-based social capital, the models predict that for one unit increase in faith-based social capital, patent counts decrease by 68% in Chemical, 88% in Computer & Communication, 75% in Mechanical, holding other variables constant (Table 6.5). The negative relationship between innovation and faith ties may suggest that faith ties are representative of binding social capital (Putnam 2000), which exists in building solidarity among members in communities. According to Putnam, religiously bounded communities may lack bridging social capital needed for knowledge transfer and innovation.

The other two social capital variables, informal social interaction and organized group interaction are not statistically significant in both the OLS and multilevel models. The insignificance of both measures for connectivity suggests that not all networking activities will necessarily lead to knowledge transfer. For example in organized group activities, not only club meetings but also parent teacher association meetings and community events are included. Or in the case of informal social interaction, while activities such as socializing with co-workers outside of workplace and socializing with friends at public places may be opportunities for the exchange of innovative ideas, visiting relatives or having them visits will not directly contribute to innovation. The presence of those items in the measure for face-to-face social interaction activities might lead to insignificant results in all examined models.

Compact urban form, however, is shown in Table 6.4 and 6.5 to be statistically significant and negatively related to innovation for three out of five technological categories. Specifically, the multilevel models indicates that in response to one percent change in compactness, the percentage change in patent counts is -1.66 for Computer & Communication, -2.63 for Electrical & Electronic, and -2.3 for Mechanical (Table 6.5).

I also test different specifications for the existing models. The results for those models are presented in the Appendix. First, I replace the academic R&D expenditure aggregated for research universities I and II in 1990 with the state aggregated academic R&D expenditure in 1990. This variable captures academic R&D for universities, especially those in the same system such as the University of California system, that are more likely to benefit from the cooperation with other universities in a state. However, using this variable leads to the failure to perform multilevel modeling because state boundaries are not often aligned with metropolitan boundaries. When replaced with total state academic R&D in 1990, the coefficient signs for the input of academic R&D become positive and significant for Computer & Communication, Electrical & Electronic, and Mechanical in the basic and the extended OLS models (Appendix Table 2 and 3). The signs of other model coefficients remain the same as in the case of using MSA R&D values.

Second, I include proxies for industrial diversity and racial diversity in the extended OLS models for all patent types. The industry diversity index ranges from 0 to one with one indicating the same percentage of employment in five major industries of Chemical, Computer & Communication, Drugs & Medical, Electrical &

Electronic, and Mechanical. Similarly, the racial diversity ranges from 0 to one with one equivalent to the equal presence of major racial groups Caucasian, African American, Asian, and Hispanic in the metropolitan area. The comparison of the adjusted R-squares of this model with the OLS models without diversity variables shows that those diversity variables add almost no change to the explanatory power of the OLS models (Table 6.4 versus Appendix Table 4). Only industrial diversity is found to be positively and significantly related to Drugs & Medical patents, controlling for others.

Finally, I rerun OLS and multilevel models with natural log of the number of innovators instead of patents for all five technological categories (Appendix Table 5 and 6). As defined in Chapter Four, this variable roughly estimates the number of inventors in a county. These models for innovators show that the effects of business services sector are statistically significant for all patent types except Drugs & Medical. It also shows a negative association between faith-based social capital and the number of innovators in Computer & Communication and Mechanical. Using innovator counts instead of patent counts has slightly improved the estimates of the OLS model as well as its overall fit. The OLS R-squares increase by from one to two percentage points across different patent types. Standard errors of the coefficient estimates in the hierarchical model are smaller but the coefficient magnitudes can be either smaller or larger than those in the OLS models. In both sets of models, while the coefficient for faith-based social capital is statistically significant for Electrical & Electronic innovation, it is insignificant for innovators. The impact of urban form is also found to be statistically significant for two out of five patent types: Electrical &

Electronic and Mechanical. It is not statistically significant for Computer & Communication. The comparison of models for patents and innovators indicate the robustness of the coefficient for social trust in explaining the variation of innovation across space.

4. Analysis of Impacts of Urban Form on Social Capital

This section contributes to the literature of impacts of built environment on social capital by addressing the question of whether or not urban form affects social capital. Earlier studies suggest that a person's demographic characteristics, socio-economic status, house ownership, length of tenure in community, are likely to affect his social capital (Campbell and Lee 1992, DiPasquale and Glaeser 1999, Freeman 2001). In addition, different authors also assert that neighborhood characteristics such as income level and racial composition might affect neighborhood residents' social capital (Putnam 2000, Freeman 2001, Costa and Kahn 2003). As mentioned, because individuals are nested in communities which in turn are nested in different counties, a hierarchical model is needed to properly account for variance at each levels of analysis. The literature on urban form suggests that sprawl can negatively affect social capital (Jacobs 1961, Putnam 2000 Freeman 2001, Burchell et al. 1998). However, there has been no multilevel study of social capital to successfully test the contextual effects of urban sprawl and urban form on individual's social capital. As discussed earlier, because individuals are nested in communities which in turn are nested in counties, any researchers that aim at measuring the impacts of county urban form on social capital of county residents have use hierarchical or multilevel modeling approach.

The multilevel model allows the researcher to identify how much variation in social capital measured at the person level (level 1) is attributable to factors at the individual level (level 1), community level (level 2), and county level (level 3). The model also allows the researcher to examine possible cross level interaction between urban form and person's characteristics. For example, it is possible that urban form affects employed individuals' social capital because they have to commute to and from work on daily basis.

4.1. Unconditional models

In order to test the validity of a three level hierarchical models, I conduct a fully unconditional model which is similar to ANOVA. This fully unconditional model partitions total variance of in the dependent variables into variance among different surveyed individuals within census tracts, variance among tracts within counties, and a variance component among different counties.

For each factor of social capital, a simple 3-level hierarchical model is specified as follows:

Level 1: $Y_{ijk} = \pi_{0jk} + e_{ijk}$

Level 2: $\pi_{0jk} = B_{00k} + r_{0jk}$

Level 3: $B_{00k} = \gamma_{000} + u_{00k}$

Where: γ_{000} is the average social capital measure and e_{ijk}, r_{0jk}, and u_{00k} are random effects at level 1, 2, and 3 respectively.

Table 6.6 suggests that most of variance in social capital measures lies among individuals. The variance among different census tracts are statistically significant for all investigated social capital factors while the variance among different counties are strongly statistically significant for social trust, informal social interaction, and faith-based social capital at ($p<0.01$). The results indicate that individual characteristics are more likely to affect an individual's levels of social capital. Even though place characteristics at the census tract and county level do not strongly affect individuals' social capital, evidence of variation across those two place levels requires the inclusion of tract level and county level predictors in the analysis.

Table 6.6 Variance Decomposition for Fully Unconditional 3 Level Models

	Social trust	Faith-based social capital	Informal interaction	Organized group interaction
Level 1 Variance	91.7%	89.5%	93.3%	94.0%
Level 2 Variance	6.9%	6.0%	5.8%	5.8%
Level 3 Variance	1.4%	4.5%	0.9%	0.2%

The next question to be tested is related to the specification of the 3-level model. Similar to the multilevel analysis of impacts of urban form and social capital on innovation, the researcher has several options to specify the current model. Depending on the data structure and the hypotheses to investigate, the researcher can reduce the number of random effects either at the county level or at the tract level to increase the degrees of freedom. If all individual level variables are assumed to have error terms at the tract and the county level, the combined model will have a huge number of cross product terms and the model maximum likelihood estimation becomes cumbersome and inaccurate. Therefore, reducing the number of random effects or error terms in the model is needed. Because I am interested mainly in the urban form variable and its possible interaction with person level characteristics, I assume that the random effect components only exist for the intercept and slopes at the county level and for the intercept at the tract level. Then the next step is to proceed with an unconditional model which has only person level variables as follows:

Level 1: $Y_{ijk} = \pi_{0jk} + \pi_{1jk} a_{1ijk} + \pi_{2jk} a_{2ijk} + ... + \pi_{pjk} a_{pijk} + e_{ijk}$

Where

Y_{ijk} is the social capital factor measure of person i in census tract j in county k;

π_{0jk} is intercept for all persons in tract j in county k or the average;

a_{pijk} are p different socio-economic and demographic characteristics of person i;

π_{pjk} are p according coefficients of person level characteristics; and

e_{ijk} is the random effect at level 1

The explanatory variables at the person level include person's age and dummy variables for education attainment, race, gender, house ownership, marital status, residence length in the community, employment status, income brackets, and family structure. The dependent variables include measures for social trust, informal social interaction, organized group interaction, and faith-based social capital. Those measures and the person level explanatory variables are from the Social Capital Community Benchmark Survey data (Roper Center 2005).

Level 2: $\pi_{0jk} = \beta_{00k} + r_{0jk}$

$\pi_{1jk} = \beta_{10k}$

…

$$\pi_{pjk} = \beta_{p0k}$$

And level 3: $\beta_{00k} = \gamma_{000} + u_{00k}$

…

$$\beta_{p0k} = \gamma_{p00} + u_{p0k}$$

The purpose of performing this step is to check if it is necessary to specify random effects for all β models as in the random coefficient model or one error term u_{00k} for the intercept β_{00k} is sufficient. The variance components at level 3 being statistically significantly different from 0 and having high reliability estimates indicate the presence of random effects in the model (Snijders and Bosker 1999, Raudenbush and Bryk 2002). The examination of the model runs for all four social capital variables reveals that most variance components are not significantly different from 0 (most have p value of .40 or higher and very few have p value of less than .01 (Appendix Table 8)). Therefore, it is reasonable to assume one error term for the intercept β_{00k}. This model is called random intercept model with non-randomly varying slopes. The full model specification is presented in the next section.

4.2. Full model specification

In the person level model, dummy variables have been selected such that the intercept is indicative of the average social capital measure for a single white female renter who lived in the community for 10 years or more, had high school diploma or received less than high school education, currently not employed, did not live with any children of 17 years old or younger, and whose household income in 1999 was less than $30,000. The use of symbols here follows Raudenbush and Bryk (2002).

Level 1: $Y_{ijk} = \pi_{0jk} + \pi_{1jk} a_{1ijk} + \pi_{2jk} a_{2ijk} + ... + \pi_{pjk} a_{pijk} + e_{ijk}$

Where

Y_{ijk} is the social capital factor measure of person i in census tract j in county k;

π_{0jk} is intercept for all persons in tract j in county k or the average;

a_{pijk} are p different socio-economic and demographic characteristics of person i;

π_{pjk} are p according coefficients of person level characteristics; and

e_{ijk} is the random effect

In level 2, the slopes have been assumed to be fixed and only the intercept has the random effect component. Variables of interest at level 2 (census tract) include tract racial diversity in 1990, median household income in 1989, and percentage of college graduates in 1990. The data are from the 1990 Population Census. Census tract racial diversity has been calculated based on the calculation method of the Simpson's index of diversity (see Chapter Four). The index has a value from 0 to one and as the index approaches one, it indicates higher racial diversity in the census tract. To reduce complex computation due to the presence of cross level interaction terms, I assume that variables at the tract level only affect the intercepts of the set of regressions at the individual level. This assumption allows me to correlate urban form variable with personal level variables and still have practical interpretation of the interaction coefficients.

Level 2:

$$\pi_{0jk} = \beta_{00k} + \beta_{01k}(TRACTINCOME)_{jk} + \beta_{02k}(PERCOLGRAD)_{jk} + \beta_{03k}(RACEDIVERSITY)_{jk} + r_{0jk}$$

$$\pi_{1jk} = \beta_{10k}$$

$$\pi_{2jk} = \beta_{20k}$$

$$\ldots$$

$$\pi_{pjk} = \beta_{p0k}$$

Where

β_{00k} is the track level intercept in modeling the person level intercept π_{0jk};

β_{01k} is the effect of median household income in a census tract on the person level intercept π_{0jk} within county k;

$(TRACTINCOME)_{jk}$ is the median household income in census tract j within county k;

β_{02k} is the effect of the percentage of college graduates in a census tract on person level the intercept π_{0jk} within county k;

$(PERCOLGRAD)_{jk}$ is the percentage of college graduates in census tract j within county k;

β_{03k} is the effect of the racial diversity in a census tract on the intercept within county k;

$(RACEDIVERSITY)_{jk}$ is the value of racial diversity index measured for census tract j within county k;

$\beta_{10k} \ldots \beta_{p0k}$ are p fixed coefficients across census tracts in county k for the corresponding person level coefficients, in other words, effects of p socioeconomic and demographic characteristics in county k;

r_{0jk} is the random effect of the intercept across different census tracts in county k.

In level 3, none of the countywide population socioeconomic and demographic characteristics are assumed to affect a person's social capital. General county population size, urban form, and percentage of county population living in rural areas are assumed to affect the intercept of the model. This is equivalent to saying that models to predict social capital have intercepts varying across different counties depending on the county population size, urban form, and how rural the county is. In addition, as discussed in Chapter Two, different studies of sprawl suggest that urban sprawl affects work trip commute times and vehicle miles traveled (Burchell et al. 1988, 2002), which implies possible impacts on employed individuals, who have to commute on daily basis. Sprawl also has differential impacts on racial and income groups because of their housing preferences (Rong 2006). I also hypothesize that urban form may be related to the effect of having children in the household on social capital. Therefore, county compactness is assumed to be correlated with the slopes of individuals' income, race, employment status, and whether there was a kid of 17 or younger in the household.

$$\beta_{00k} = \gamma_{000} + \gamma_{001}(LNCOMPACT)_k + \gamma_{002}(LNPOP)_k + \gamma_{003}(PERCRURAL)_k + u_{00k}$$

$$\beta_{10k} = \gamma_{100} + \gamma_{101}(LNCOMPACT)_k$$

$$\ldots$$

$$\beta_{80k} = \gamma_{800} + \gamma_{801}(LNCOMPACT)_k$$

$$\beta_{90k} = \gamma_{900}$$

…

$$\beta_{p0k} = \gamma_{p00}$$

Where

γ_{000} is the intercept in modeling the census tract intercept;

γ_{001} is the effect of natural log of compact urban form at the county level on the tract intercept;

γ_{002} is the effect of natural log of county population on the tract intercept;

γ_{003} is the effect of percentage of county population living in rural areas on the tract intercept;

$\beta_{10k}, \ldots, \beta_{80k}$ are 8 level 2 slopes for 8 according person level predictors of income, race, having kids of 19 or younger in the household, and employment status.

$\gamma_{100}, \ldots, \gamma_{800}$ are 8 county means for 8 corresponding tract level slopes predicting individuals' social capital by individuals' income, race, having kids in the household, and employment status;

$\gamma_{101}, \ldots, \gamma_{801}$ are the effects of compact urban form at the county level on individuals' income, race, having kids in the household, and employment status;

$\gamma_{900}, \ldots, \gamma_{p00}$ are (p-8) fixed coefficients (the county means) of the corresponding tract level coefficients;

u_{00k} is the random component.

The individual weight is applied for each person level observation; this weight calculation was described in detail in Chapter Four. Again, the weight accounts for the population distribution in the sample and for the odds of household selection conducted by the survey team. All models were tested for normality and the standard errors are robust standard error. Because LNCOMPACT is highly correlated with PERCRURAL, the correlation coefficient is -.75, LNCOMPACT is centered around its grand mean at level 3 to avoid multicollinearity.

Because LNCOMPACT is centered around its grand mean, its regression coefficients in the hierarchical model for each social capital factor can be interpreted as a change of (coefficient for LNCOMPACT/100) in the unit of the social capital factor as a result of one percent higher than the average county compactness index.

4.3. Findings

Table 6.7 present equations for four social capital variables. The intercept of the model corresponds to the mean social capital for a single white female renter who lived in the community for 10 years or more, had high school diploma or received less than high school education, currently not employed, did not live with any children of 17 years old or younger, and whose household income in 1999 was less than $30,000. The models show impacts of county compactness is negatively related to informal social interaction (-0.3), to faith-based social capital (-0.41), and not significant for the other two social capital factors of the above mentioned single white female renter.

Table 6.7 Fixed Effects of the Hierarchical Model

	Social trust	Informal social interaction	Organized group interaction	Faith-based social capital
County mean social capital				
Base	-0.537**	0.821**	-0.031	-0.68**
RURLPERC	-9E-4	-3E-4	-7E-4	-0.003*
LNCOMPACT	-0.185	-0.296**	0.042	-0.406**
LNPOP	-0.025*	5E-4	-0.014	-0.033
INCOMETR	2E-06*	-2E-06**	-3E-06**	4E-6**
COLGRADT	0.004**	3E-4	0.002**	-0.003**
RACDIVER	-0.186**	-0.112*	-0.037	6E-4
Racial differentiation for BLACK				
Base	-0.45**	-0.141**	-0.004	0.227**
LNCOMPACT	0.132	-0.023	-0.271**	-0.137
Racial differentiation for ASIAN				
Base	-0.245**	-0.215**	-0.2**	-0.065
LNCOMPACT	0.318	-0.003	0.124	0.110
Racial differentiation for HISPN				
Base	-0.403**	-0.293**	-0.058	0.0222
LNCOMPACT	0.253*	0.0956	-0.149	0.236
Employment differentiation				
Base	0.02*	-0.123**	-0.012	-0.060**
LNCOMPACT	0.029	0.115	0.067	0.013
Income differentiation for INCOME 30-50K				
Base	0.086**	0.064**	0.088**	0.11**
LNCOMPACT	0.008	0.098*	-0.066	-0.165
Income differentiation for INCOME 50-75K				
INTERCEPT3	0.115**	0.081**	0.118**	0.121**
LNCOMPACT	-0.065	0.190**	-0.071	-0.157**
Income differentiation for INCOME over 75K				
INTERCEPT3	0.108**	0.136**	0.212**	0.164**
LNCOMPACT	-0.042	0.146**	-0.176	-0.248**
Child differentiation				
INTERCEPT3	-0.024*	-0.018	0.123**	0.101**
LNCOMPACT	0.012	0.047	-0.021	0.173**
AGE	0.007**	-0.012**	-0.003**	0.006**
GENDER	-0.073**	-0.047**	-0.024*	-0.107**
OWNER	0.084**	-0.035*	0.02*	0.088**
MARITAL	0.076**	-0.141**	-0.032*	0.143**
SOMECOLL	0.128**	0.084**	0.155**	0.183**
COLLGRAD	0.269**	-0.002	0.29**	0.282**
LIVCOM <1 year	-0.025	-0.09**	-0.122**	-0.163**
LIVCOM 1-5 years	-0.027**	-0.09**	-0.109**	-0.116**
LIVCOM 6-10 years	-0.026*	-0.038*	-0.033*	-0.059**
INCOME0	0.038	0.058**	0.071**	0.104**
KIDS0	0.068	-0.105	-0.128	0.0818

Sprawl's impacts and race

Regarding the effects of race on social capital, the findings indicate that respondents belonging to different racial groups have different degrees of social capital; and urban sprawl can increase the social capital gaps among different racial groups. Compared to Whites, African American participants have higher faith based social capital but they have less social trust and have less informal social interaction. African Americans participate less in organized group activities compared to Whites but more sprawl narrows the gap.

Compared to White, Asian respondents do not perform as well on most examined factors of social capital except for faith-based social capital, which is statistically insignificant. Hispanic respondents share similar patterns of Asian population. Urban sprawl does not have amplifying nor attenuating effects on the relationship between being Asian and social capital. However, Hispanic population has higher social trust in more compact counties (-0.40*(1) + 0.25*LNCOMPACT). Even in the most sprawled county of Jasper (IN) in the dataset (LNCOMPACT = 4.21), Hispanics' social trust index exceeds that of Whites by 0.69.

Sprawl's impacts and employment status

Being employed is positively correlated with social trust. An employed person is more likely to trust others compared to the group of students, retirees, people who are between jobs, and the unemployed. However, the employed person's faith-based social capital and the degree of informal social interaction reduce. Urban compactness does not have impacts on the relationship between being employed and one's social capital.

Sprawl's impacts and income

The relationship between income and social capital is positive for most social capital factors. The role of urban sprawl in their relationship is only statistically significant for some factors of social capital and it tends to widen the gap between income groups. In the case of informal social interaction (playing cards with others, visiting relatives or having them visit, having friends over, socializing with co-workers outside of work, and socializing with friends in public places), more compactness or less sprawl expands the social capital gap between different income groups (0.06*(1) + 0.1*LNCOMPACT for $30-50K, 0.08*(1) + 0.19*LNCOMPACT for $50-70K, and 0.14*(1) + 0.15*LNCOMPACT for above $75K) and the higher income one has, the more informal social interaction one participates in. For example, compared to a person having household income less than $30K living in Jasper County (IN), a person in the same county with household income from $30-50K, 50-75K, and over $75K will have 0.48 unit, 0.88 unit, and 0.77 unit respectively higher. But if they live in San Francisco County of California (LNCOMPACT = 5.34), the social interaction gap due to income is 0.59, 1.09, and 0.92 unit respectively.

Similarly, holding other factors being constant, more compact development widens the gap of income effects on faith-based social capital. When living in counties that have the same degree of urban sprawl as Jasper, a person with household income below $30K has 0.55 unit of faith-based social capital higher than a person with household income within $50-75K, and 0.89 unit higher than a person with household income above $75K. But in counties that are as compact as San

Francisco, the faith-based social capital gap due to income is widened to 0.72 and 1.18 respectively. It is also self evident that the more compact the county is, the less faith-based social capital its residents, especially the more well-off ones, have.

Sprawl's impacts and child presence

The presence of children of 17 years of age or younger in the respondent's household increases his or her organized group social interaction such as community events and discussions of town or school affairs. It also positively affects the respondent's faith-based social capital. In addition, living in less sprawled or more compact counties adds to the difference between those who live with children of 17 or younger and those who do not, when faith-based social capital is concerned. However, the presence of children in the same household is negatively related to the respondent's social trust.

Findings of other variables and controls

Among individual characteristics, education attainment and length of residence in the community have significantly positive association with all nine factors of social capital. As an individual's levels of education and length of residence in the community increase, she has more social interactions with friends and neighbors informally and in group activities and has more religious participation.

Owning a house is positively related to faith-based social capital and social trust. However, homeownership is negatively related to informal social interaction but not significant for organized group interaction. As one becomes older, a person increases his faith-based social capital but his intensity of social interaction as indicated by informal social interaction and organized group interaction declines.

This result is consistent with Putnam's observation of the difference between the number of organizations that one belongs to and the frequency at which one participates in his or her member activities (Putnam 2000).

Females are more likely to be involved in more social interaction activities and in volunteering activities. Females also have higher levels of social trust and of faith-based social capital. Marriage significantly reduces the intensity of informal and organized social interaction activities. This is probably because married couples tend to spend more time together, leaving them less time to devote to visiting friends and clubbing.

Table 6.8 summarizes of relationships between social capital and a person's socio-economic.

Table 6.8 Person's Characteristics and Social Capital

	Social trust	Informal social interaction	Organized group interaction	Faith-based social capital
Age	+	-	-	+
Male (versus female)	-	-	-	-
Married (versus not married)	+	-	-	+
Owning house (versus rent)	+	-	+	+
Having children (versus not having children)	-	Not significant	+	+
Being employed (versus not employed)	+	-	Not significant	-
Education	+	+	+	+
Income	+	+	+	+
Length of residence	+	+	+	+

Compared to those whose household income is under $30K, those who choose not to disclose their household income systematically score higher on most social capital indices. Nevertheless, they score lower on giving and volunteering and there is no statistically significant relationship between this group and social trust or non-electoral political participation.

At the census tract level, mean household income is negatively related to individuals' social interaction variables but is positively related to faith-based social capital and social trust. Another census tract variable, the percentage of college graduates, is positively related to most social capital factors except for faith-based social capital. The remaining census tract variable, racial diversity, is negatively related to informal social interaction and social trust, confirming the findings in previous studies that people coming from one racial group tend not to trust people from other racial groups as they do to those from their own groups.

Chapter VII: Discussion and Conclusion

As city and county planners across the country are seeking better ways to replace shifted jobs and to attract firms in biotech and other high tech industries, they need to have an understanding of the knowledge economy and the innovation process. Most importantly, they need to be informed of how to use their best tool - land use planning to do that job effectively and efficiently. This dissertation pursues that goal by highlighting spatial and social elements in the urban environment that will eventually have deep impacts on economic development policies in the timeframe from 10 to 20 years.

The existing bodies of literature in planning, economic geography, and sociology provide support to the construction of a conceptual model to explain regional innovation by including those spatial and social elements. While a wealth of empirical studies have identified an educated labor force, proximity to research institutions and universities, and agglomeration economies as contributors to innovation, few studies link spatial configuration of the city to innovation. Regarding the social factors, a number of authors such as Knack and Keefer (1997), Saxenian (1997), Tsai and Ghoshal (1998), Putnam (2000), Florida (2002), Dakhli and De Clercq (2004) have started to address the relationship of social capital and innovation at the national, regional, and organizational levels. Their quantitative and qualitative works suggest that trust and connectivity may have positive impact on innovation while faith ties may have either negative or positive impacts on innovation. Built upon those works, the conceptual model extends the original knowledge production function developed by Griliches (1979) in the discussion of innovation.

Based on the conceptual model to explain regional innovation, I then used Hall, Jaffe, and Trajtenberg's (2001) patent data and the inventor file from the US Patent and Trademark Office; the Social Capital Benchmark Survey data (Roper Center 2005); and the county compactness index (Ewing 2003) to analyze the relationship between urban form and social capital, and between urban form, social capital, and innovation. The studied social capital factors including social trust, connectivity, and faith ties often linked by different authors to economic activities. The county compactness index is used to capture urban form while patent and innovator counts to measure innovation. This dissertation therefore provides empirical evidence of whether or not compact urban form influences regional innovation, contributing to the on-going debate about costs of sprawl. In addition, it also explores the extent to which social capital contributes to regional innovation and how urban form also affects social capital.

1. Discussion of Findings

1.1. Impacts of compact urban form and social capital on innovation

To examine the impact of social capital and urban form on innovation, patent counts and innovator counts were used in the extended Griliches-Jaffe's knowledge production function model. Because employment concentration, research and development investment in doctoral universities, the concentration of research employment, and the size of business services sector employment are measured at the metropolitan area while urban form, social capital, innovation, and the number of knowledge workers are measured at the county level, I employed hierarchical modeling. This method allows the researcher to improve standard error estimates of the regression coefficients. The OLS regression models for five major technological categories; Chemical, Computer & Communication, Drug & Medical, Electrical & Electronic, and Mechanical, explained from 79% to 92% of total patent variation across 83 counties. The OLS models for innovator counts also provide similar results. Adding social capital and urban form to the model improves the R-squares of the models by at least three percentage points, after accounting for sample sizes.

With respect to social capital variables, social trust is found to be significantly and positively associated with innovation for all patent types. This confirms what other studies found at the cross-national and organizational level (Knack and Keefer 1997, Tsai and Ghoshal 1998, Saxenian 1997, Cohen and Field 2000, Dakhli and De Clercq 2004). Again, trust functions as the building block for most types of connection and interaction because it reduces transaction costs and increases the effectiveness of team cooperation (Putnam 2000, Patton and Kenney 2004). Higher levels of trust in an urban area where knowledge workers live can facilitate knowledge transfer via off-workplace interaction.

Findings show that the impact of social trust on innovation varies by industry. Social trust appears to be most important for Drugs & Medical and in Chemical and least important for Mechanical. It is noticeable that among five major patent types, Chemical and Drugs & Medical have lowest patent counts during the period of 1990-2002 with 118,612 patents and 103,053 patents respectively. The fact that social trust plays a significant role in the innovation process in Chemical and Drugs & Medical suggests that we are observing unique patenting pattern for Chemical and Drugs &Medical. This issue was raised by Sokoloff and Khan (1990) as they suggest that innovators and firms in some industries might withhold their invention instead of getting it patented due to institutional and cultural factors. As for Chemical and Drugs & Medical, one of those factors is trustworthiness.

Faith-based social capital is found to be negatively and statistically significantly associated with innovation for three out of five patent types. This result is consistent with what Putnam (2000) suggests concerning bonding social capital. He points out that bonding social capital is “exclusive” and good for “mobilizing solidarity” and is provided within dense ethnic enclaves. On the other hand, bridging social capital is "inclusive" and is good for linkage to “external assets” enabling “information spillovers”. As for the relationship between religious participation or faith ties and innovation, faith ties appear to have counterproductive effects for innovation. Despite the fact that those religiously bounded communities do have outreaching activities, the analysis shows that bonding social capital seems to dominate the culture in such communities. This result also supports Florida’s claim that communities with high “traditional social capital” exhibit strong homogeneity and do not support innovation when “traditional social capital” refers to loyalty to certain social and cultural principles and identities is required in faith tied communities (Florida 2002). This loyalty overwhelmingly dominates interactions and does not allow for cross-breeding of different and unconventional ideas and knowledge. Florida also suggests that trust is a component o traditional social capital. However, the findings in this dissertation do not support that. Perhaps, it is not appropriate to label trust as “bridging” or “bonding” social capital as it could appear in both.

The association between urban compactness and innovation is negative and statistically significant in the Computer & Communication, Electrical & Electronic and Mechanical categories, and not significant in the remaining ones for both the OLS and hierarchical models. The innovator regression model shows the association between compactness and the number of innovators is negative and statistically significant for Electrical &Electronic and Mechanical. Those findings indicate that compact urban form at the county level does not, at least directly, encourage innovative activity. However, the negative relationship between the two does not necessarily mean more compactness would depress innovative activity. The failure to find positive coefficient on compactness can be due to one of the following reasons or to a combination of more than one reason: 1) housing preference of innovators in fringe counties of metropolitan areas, 2) possible negative impacts of compact places, 3) decentralization of both people and jobs into suburban areas, and 4) measure of urban form. Those reasons are elaborated in the following section.

The literature on sprawl suggests that sprawl continues for a number of reasons including housing preference (Ewing 1997, Gordon and Richardson 1997, Glaeser and Kahn 2003, Audirac 2005). Scholars have attempted to explain why preference for low density dominates residential choice especially in the US. Despite the possible costs of sprawl (Burchell et al. 1998, 2002; Glaeser and Kahn 2003), as long as those costs are not fully accounted in the costs of living in fringe cities and suburban neighborhoods, people opt to locate their household further away from high density urban areas. The insignificant or even negative coefficient for compactness happens when innovators choose to live in less compact areas.

Results of the analysis of the relationship between urban form and innovation can also be influenced by the actual costs and benefits associated with sprawl and compactness. As discussed in Chapter Two, both sides of the sprawl debate offer evidence and theories to prove and disprove negative impacts of sprawl. Even though they may agree on urban sprawl resulting in longer distance, scholars have not yet agreed so-called “negative impacts” that are associated with longer commute distances. In his recent article, Kahn (2006) compares sprawled and compact cities along the several dimensions of quality of life. His conclusion suggests that among important findings, sprawled cities perform equally well or better than compact cities in terms of average commute time and public safety. However, it is important to note that Kahn does not control for means of transportation in his calculation of commute time, and time spent on waiting at the bus stop was also included. Yet, Kahn’s study might indicate that by living in more sprawling areas, innovators can benefit from improved quality of life in some or all aspects. Similarly, Florida’s work on the Creative Class suggests that an abundance of high quality of life characteristics are necessary to attract and to retain creative workers in the city. If for examples, compact places are associated with more pollution, high crime rates, low quality schools, and high costs of living, those negatives can outweigh the benefits that high population density and improved street accessibility engender on connectivity. Regional innovative productivity could suffer where the negative attributes of compactness reduce the quality of life for knowledge workers, thus making them less productive, or deter their location in the region.

Another reason why for the negative coefficients on compactness for some patent types is the distance between workplace and home. If knowledge workers live close to where they work, i.e. workplace and home in the same county, urban form then affects both the residential environment and workplace in a similar manner. If they live and work in different counties in the metropolitan area, where they choose to have interaction for innovative activities will determine the sign of urban form coefficients in the models. The environment that provides an innovator with stimuli, feedback during the process of innovation, and learning opportunities to improve knowledge may exist around the workplace, not the residence. Both Florida (2002) and Saxenian (1997) suggest that knowledge workers and innovators need formal and informal face-to-face interactions regardless of whether it is inside or outside workplace. Those face-to-face interactions can occur mainly within a relatively small perimeter of the workplace. In that case a compactness measure for residential location of the innovator will not reflect the proper relationship between urban form and innovation.

The literature on deconcentration and decentralization of employment and people in metropolitan areas suggests that subcenters can exist in metropolitan areas (Audirac 2005). Those subcenters can provide similar functionality that a monocentric model of city does; or in other words, they meet with the needs of employment and also provide adequate infrastructure to support face-to-face interaction needed by knowledge workers. As a result, the location decision by knowledge workers will not be necessarily constrained to compact places. They have more options and can choose to move to less compact places that optimize distances to different sub-centers. Such residential location decisions make it more difficult to measure the relationship between innovation and urban form.

The measure of urban form used in the current analysis may not be ideal for the purpose of capturing spatial configuration's impacts on innovative activities. The measure captures population density and street block length and sizes. The length of each side of the block and its size in a more compact urban neighborhood should be smaller than those in a less compact suburban area with less connected cul-de-sacs and fewer alternative routes. However, this measure of compactness does not capture the spatial distribution of employment and residential clusters. The intra-cluster accessibility can be high but inter-cluster accessibility can be low because of the distance among those clusters of workers and residents. Another factor needs to be included in an ideal urban form measure is the degree of land use mix. Higher land use mix is indicative of better work commute for workers.

The dissertation provides further empirical evidence to confirm conclusions in previous studies. For example, the analysis shows results similar to those in prior studies by Black (2004) with respect to the number of scientists and engineers. This number is positively and statistically significantly related to innovation for all patent types, which corroborates Black's findings. Again, they both highlight the role of knowledge workers, those who apply to daily work "ideas, concept, and information rather than manual skill or brawn" (Drucker 1969). However, the dissertation identifies that regions investing in traditional industries such as Chemical and Mechanical tend to generate less innovation, compared to the other three patent types, given the same percentage change in the number knowledge workers.

Firms benefit from being clustered with other firms within the same industry. The findings from the multilevel model for innovation suggest that these localization economies contribute to high innovation in most industrial sectors except Drugs & Medical. However, the relationship between clustered firms and innovation can be bi-directional as well. Innovation can attract firms to locations near innovative sources. Those sources could be other firms, research labs and higher education institutes. Since the current study uses patent counts based on application dates from 1990 through 2002 and the location quotients were estimated based on county business pattern data in 1990. The concentration of industry employment in 1990 is likely to cause more innovation, not the other way around. A recent study by Carlino, Chatterjee, and Hunt (2007) shows a positive impact on patent intensity after controlling for percentage of employment in 2 digit SIC industrial sectors and R&D activities.

Similarly, the concentration of research lab employment and employment size of the business service sector are positively associated with both innovation and innovator counts. However, the associations are not statistically significant for all patent types. The importance of research labs in regional innovation is pronounced in the case of Computer& Communication, Drugs& Medical, and Electrical &Electronics. The business services sector matters in Chemical, Computer &Communication, and Electrical & Electronics.

R&D dollars spent in research universities across the metropolitan area in 1990 is negative and statistically significant for Chemical. The variable is insignificant for the remaining patent types, which could be due to the fact that the

R&D data were collected for 1990 and only a small fraction of the total patents during 1990 -2002 are immediate results of the research activities in this year. In addition, different authors have mentioned research and development investments depend on prior achievements. Firms may invest more in research activities either because they expect the return from successful innovations or because they can demonstrate a history of success. Similarly, firms reduce R&D investment when there are doubts about the research result or because of its past failures. Those issues further add disturbances in the relationship between the R&D dollar amounts and innovation, which could explain why university R&D does not perform as well as expected. However, once the MSA's academic R&D is replaced with the state's academic R&D investment, the coefficients' signs change to positive and its significance become improved. The improvement with the total state R&D may imply cooperation among universities across the state.

1.2. Urban form and determinants of trust, connectivity, and faith ties

By using hierarchical models to analyze the relationship between place characteristics and individual's social capital, this dissertation has set a landmark in empirical literature on social capital. Prior social capital studies do not properly account for the impact of individual, community, and regional conditions on an individual's social capital (Glaeser, Laibson, and, Sacerdote 2000; Leyden 2003; Freeman 2003; Iyer, Kitson, and Toh 2005). By using multilevel modeling techniques, I overcome that weakness and improve standard errors of coefficient estimates. More importantly the multilevel modeling also allows me to examine cross level interaction between urban form and a number of individuals' socio-economic and demographic variables. In the three-level model, county compactness is modeled to impact the general intercept and the slopes for racial dummies, for income group dummies, for employment dummy, and for child presence dummy. Even though urban form and other factors at county and community levels do not have as strong effects as those at the person level on individuals' social capital, the fact that they do have any impacts is critical to planners and researchers of different disciplines.

The study's findings are similar to conclusions of recent studies by Putnam (2000), by Freeman (2003), by Iyer, Kitson, and Toh (2005), and are consistent with the theoretical literature. Socio-economic and demographic characteristics of a person such as her age, marital status, house ownership, education, income, gender, length of residence in community, having children, employment status, and race are important determinants of social capital. The model also indicates that individuals belong to different racial groups also have different levels for each social capital variable, holding other variable constant: American Whites appear to have highest social capital compared to other groups except for faith based social capital where African Americans score highest. Asian individuals score higher than African American and Hispanics in social trust. At the census tract level, median household income is found to be positively correlated with trust and faith-based social capital while negatively correlated with variables of social interaction. The percentage of highly educated people in a census tract is positively correlated with trust and connectivity but negatively correlated with faith based social capital. Racial diversity has negative impacts on individuals' trust and connectivity indices. Population size also has negative impacts on trust.

Unlike the study by Freeman (2001) that uses only one measure for social capital, this current study has revealed complexity in the relationship between urban form and a number of social capital factors. Urban form can have differentiating impacts on social capital depending on the person's socio-economic and demographic group. Specifically, compactness has a positive impact on social trust for Hispanic population. The positive impact of high density compact places for Hispanic population can be explained by the presence of "ethnic enclaves" in metropolitan areas. Guzman and McConnell (2002) report in their study of 1990-2000 change in the Hispanic population that the majority of foreign born in 2000 were from Latin America and undocumented. Howland and Nguyen (2007) suggest that Hispanic immigrants tend to move to where other Hispanics are and the apparel industry followed them. The current study reflects a similar phenomenon about the Hispanic population. By residing in compact metropolitan areas, which often house ethnic enclaves, Hispanic immigrants might enjoy improved opportunities of employment and protection. Therefore, compact places encourage trusting relationship for this group of population.

Compact urban form widens the social capital gap in the case of informal interaction and faith-based social capital. As counties become more compact, individuals tend to participate more in informal social interaction when their household income increases. The social capital literature (Putnam 2000) suggests that higher income may result from high levels of networking activities and vice versa, higher income levels lead to more investment in networking activities. This literature indicates that social capital can generate actual monetary benefits to those who are in the network. Also, as counties become more compact, individuals have less faith based social capital when their household income increases. This phenomenon could be explained by the fact that compact places are likely to offer a multitude of opportunities to participate in various networking activities and these activities may compete with religious activities. In addition, the number of activities available to anyone can increase accordingly to one's levels of income. As a result, less religious participation is associated with more compact places. Individuals who have children in their household are more likely to have higher faith based social capital and compact urban form further increases the social capital gap between those who have children and those do not.

The relationship between urban form and the other measures of social connectivity, organized group interaction, however, is not detected. This is perhaps due to the fact that the measure captures club meetings, community events, and public meetings in which there was a discussion of town or school affairs. Most of those activities are likely to take place locally and therefore relieve the person of commuting. Further more, those activities take place on dates specified in advance and are often important such as town or school meetings, which means they are perceived as obligatory. These are possible reasons why urban form at the county level does not impose any effect on the level of connectivity as captured by participation in organized group activities.

2. Study Limitations

Even though the study has successfully established the first steps for planners to study the relationship between urban built environment and innovation, it has some limitations that planning practitioners and scholars need to overcome to derive convincing results. Among those limitations are the issues of social capital sample size, endogeneity, county aggregation of social capital, and a lack of place of work information for innovators.

The sample size of the Social Capital Community Benchmark survey data creates an issue for obtaining strong and conclusive results for the study. In the analysis of impacts of urban form and social capital on innovation, there are only 81 counties with sample sizes of 25 respondents or higher. Consequently, the according number of metropolitan areas is only 38. Some important metropolitan areas such as New York and Boston metropolitan areas are not included in the study. Therefore, an ideal dataset should have more counties representing a higher number of metropolitan areas as well as more metropolitan areas representing more metropolitan areas across the country.

The endogeneity assumption for social capital in the model to examine impacts of urban form on innovation cannot be satisfactorily addressed by using the current modeling techniques. The problem exists for cross sectional analysis and stems from the location decision of innovative knowledge workers. It is possible that knowledge workers choose to locate in sprawled or compact counties because of some perceived or true benefits that sprawled areas offer. Unfortunately, it is not possible to draw conclusion about whether their living environment makes them become more or less innovative without longitudinal innovation data.

County level social capital measure presents the possible issue of aggregation, in which the individual's social capital might not be related to that of a group of people. The according assumption that underlies the county social capital is as the county social capital increases, so does any of its residents'. This is, however, not true and has been discussed in the social capital literature. Still, scholars have to use this measure when they want to approximate the regional stock of social capital.

Finally, an ideal dataset should have employment density measures and workplace location for innovators. Missing both of them in the analysis and an ability to identify where innovation takes place inhibits planners to have specific strategies targeted innovation with comprehensive land use zoning. Unfortunately, employment density and workplace location for innovators are currently not available in the census and patent data. As a result, it is hard to make policy implications for planners.

3. Synthesis and Implications for Policy

The current research shows that urban form affects social capital and innovative activities. Despite certain limitation, the study has provided planners with an opportunity to examine possible planning tools to impact economic development in the knowledge economy. It is also the first step to construct well established framework for future scholars to build upon in studies of urban spatial configuration, social capital, and innovation.

The study confirms that the number of knowledge workers, the amount of research and development dollars, the concentration of industrial employment, and the size of the supporting business services sector all contribute to innovation. City and county governments need to address the above factors to create knowledge intensive economic activities, including innovation. To have economic growth based on knowledge intensive manufacturing and services, state and local governments tend to create economic incentives in forms of tax abatement and loans. However, there are additional measures that are worth being considered. They include making the working and living environment attractive to knowledge intensive economic activities and more conducive to innovation. This has to be done in accompany with construction of high tech business centers and industrial parks.

The built environment has some impacts on innovation and on social capital; however, there is a need for more studies before planners can make their cities more compact or sprawled to foster innovation. The evidence that compactness can improve innovation via social capital may hint that compactness may have complex relationship with innovation with an existence of both negative and positive signs. This issue is quite possible as compact urban form have both costs and benefits, of which some may not necessarily come from its spatial characteristics. Those issues include quality of the education system, crime rates, and congestion.

Appendices

Table A.1 Descriptive Statistics for County and metropolitan variables

County Level					
Variable	**N**	**Mean**	**Sd**	**Minimum**	**Maximum**
Informal	81	0	0.12	-0.27	0.45
Organized	81	-0.02	0.09	-0.29	0.22
Social_trust	81	0.04	0.16	-0.35	0.39
Faith_based	81	-0.06	0.2	-0.75	0.4
Ln(Kno_workers)	81	9.08	1.3	6.49	12.4
Lnchemical	81	4.94	1.86	0.69	8.26
Lncomputer	81	4.23	2.44	0	9.73
Lndrug	81	4.36	2.23	0	8.18
Lnelectronic	81	4.64	2.06	0.69	9.45
Lnmechanical	81	5.2	1.6	1.95	8.37
Ln(compact)	81	4.63	0.18	4.24	5.34
MSA Level					
LQchemical	38	1.22	0.92	0.31	5.11
LQcomputer	38	1	0.65	0.02	3.02
LQdrug	38	1.28	1.11	0.02	6.01
LQelectronic	38	0.85	0.78	0	2.9
LQmechanical	38	1.04	0.63	0.02	2.47
MSA_academ_R&D	38	143485.5	220331.3	0	837316
LQ(research_emp)	38	1.04	1.28	0.05	7.86
Ln(biz_service)	38	9.75	1.83	6.45	12.87

Table A.2 Basic Model with State Academic R&D

Variable	Chemical	Computer& Communication	Drugs & Medical	Electrical &Electronic	Mechanical
C	**-8.46**** (1.28)	**-15.86**** (1.49)	**-10.36**** (1.60)	**-11.39**** (1.10)	**-6.33***** (0.94)
LN(KNO_WORKERS)	**1.07**** (0.10)	**1.26**** (0.11)	**1.43**** (0.13)	**1.22**** (0.08)	**0.97**** (0.08)
LQ	*0.27** (0.12)	0.28 (0.26)	0.11 (0.10)	**0.47**** 0.15)	**0.59**** (0.16)
LN(STATE_ACA_R&D)	0.08 (0.11)	**0.45**** (0.14)	0.08 (0.16)	**0.28**** (0.10)	0.12 (0.09)
LQ(RESEARCH_EMP)	-0.07 (0.08)	0.14 (0.09)	0.11 (0.09)	0.10 (0.06)	-0.01 (0.06)
LN(BIZ_SERVICE)	**0.23**** (0.09)	*0.24** (0.10)	0.04 (0.11)	0.08 (0.07)	0.05 (0.07)
R-square	0.76	0.81	0.73	0.87	0.82
Adjusted R-square	0.75	0.80	0.72	0.86	0.81

Table A.3. OLS Model with State Academic R&D

	Chemical	Computer & Communication	Drugs &Medical	Electrical &Electronic	Mechanical
C	*-8.02** (3.94)	**-11.11**** (3.76)	**-17.29**** (4.64)	-3.40 (2.77)	2.63 (2.30)
LN(KNO_WORKERS)	**1.26**** (0.14)	**1.54**** (0.13)	**1.45**** (0.17)	**1.58**** (0.09)	**1.31**** (0.08)
LQ	**0.38**** (0.12)	-0.03 (0.23)	0.03 (0.09)	**0.38**** (0.12)	**0.45**** (0.13)
LN(STATE_ACA_R&D)	0.07 (0.11)	**0.54**** (0.11)	0.16 (0.15)	**0.28**** (0.08)	*0.13** (0.07)
LQ(RESEARCH_EMP)	-0.07 (0.07)	0.12 (0.07)	0.09 (0.09)	*0.11** (0.05)	0.00 (0.04)
LN(BIZ_SERVICE)	**0.27**** (0.09)	**0.25**** (0.08)	0.05 (0.10)	*0.12** (0.06)	0.06 (0.05)
LNCOMPACTNESS	-0.61 (0.93)	*-1.82** (0.89)	1.18 (1.13)	**-2.55**** (0.64)	**-2.68**** (0.55)
SOCIAL_TRUST	**2.30**** (0.85)	**2.92**** (0.84)	**3.49**** (0.99)	**1.93**** (0.56)	**1.69**** (0.50)
INFORMAL	0.96 (1.07)	-0.36 (1.08)	0.24 (1.29)	*1.53** (0.71)	0.87 (0.70)
ORGANIZED	-0.78 (1.41)	-0.07 (1.37)	0.43 (1.70)	-0.75 (0.95)	-0.43 (0.86)
FAITH_BASED	-0.59 (0.56)	**-2.40**** (0.52)	-0.88 (0.67)	**-1.08**** (0.38)	**-1.52**** (0.33)
R-square	0.80	0.89	0.79	0.93	0.91
Adjusted R-square	0.77	0.87	0.76	0.92	0.90

Table A.4 OLS Model with Diversity Variables

Variable	**Chemical**	**Computer & Communication**	**Drugs &Medical**	**Electrical &Electronic**	**Mechanical**
C	**-12.388**** 4.333	-2.565 4.833	**-17.903**** 5.217	-1.078 3.223	3.458 2.709
LN(KNO_WORKERS)	**1.244**** 0.139	**1.575**** 0.156	**1.467**** 0.167	**1.636**** 0.103	**1.308**** 0.090
LQ	**0.374**** 0.118	0.455 0.261	0.106 0.085	**0.544**** 0.134	**0.515**** 0.140
MSA_ACADEM_R&D	*-2.0E-06** 8.1E-07	-7.4E-08 9.0E-07	-6.4E-07 9.8E-07	-5.5E-07 6.1E-07	-4.8E-07 5.0E-07
LQ(RESEARCH_EMP)	-0.032 0.076	*0.187** 0.088	0.088 0.091	*0.124** 0.057	0.020 0.048
LN(BIZ_SERVICE)	**0.518**** 0.122	0.346 0.138	0.036 0.152	*0.209** 0.091	*0.155** 0.077
LNCOMPACTNESS	0.319 0.994	-2.642 1.119	1.134 1.213	**-2.680**** 0.741	**-2.639**** 0.620
SOCIAL_TRUST	**2.730**** 0.999	**3.313**** 1.168	**4.577**** 1.211	**2.212**** 0.747	**1.998**** 0.618
INFORMAL	1.148 1.117	-0.383 1.294	0.368 1.370	1.567 0.829	0.989 0.739
ORGANIZED	-1.693 1.443	-0.464 1.625	0.407 1.731	-1.015 1.073	-0.813 0.920
FAITH_BASED	-1.041 0.605	**-2.322**** 0.671	-1.283 0.727	*-1.061** 0.452	**-1.626**** 0.377
IND_DIVERSITY	-1.274 1.178	-0.434 1.436	*3.150** 1.524	0.324 0.928	-0.453 0.740
RAC_DIVERSITY	-0.195 1.017	1.782 1.161	1.576 1.248	0.300 0.766	0.437 0.649
R-square	0.81	0.86	0.81	0.92	0.91
Adjusted R-square	0.78	0.84	0.77	0.90	0.89

Table A.5 OLS - Dependent Variable: Natural Log of Innovator Count

Variable	**Chemical**	**Computer & Communication**	**Drugs &Medical**	**Electrical &Electronic**	**Mechanical**
C	**-11.527**** (3.483)	-7.540 (4.392)	**-15.949**** (4.498)	-2.744 (2.824)	0.628 (2.146)
LN(KNO_WORKERS)	**1.185**** (0.107)	**1.522**** (0.137)	**1.375**** (0.139)	**1.518**** (0.086)	**1.212**** (0.067)
LQ	**0.284**** (0.096)	0.284 (0.231)	0.060 (0.072)	**0.475**** (0.111)	**0.425**** (0.109)
MSA_ACADEM_R&D	*-1.4E-06** *(6.2E-07)*	9.3E-08 (7.9E-07)	-7.5E-07 (8.1E-07)	-5.2E-07 (5.1E-07)	-4.8E-07 (3.9E-07)
LQ(RESEARCH_EMP)	-0.022 (0.059)	0.145 (0.076)	0.060 (0.076)	0.087 (0.048)	0.025 (0.037)
LN(BIZ_SERVICE)	**0.330**** (0.085)	**0.332**** (0.115)	0.159 (0.111)	**0.244**** (0.069)	*0.120** (0.054)
LNCOMPACTNESS	0.276 (0.798)	-1.485 (1.012)	1.121 (1.039)	**-2.217**** (0.651)	**-1.922**** (0.492)
SOCIAL_TRUST	**2.138**** (0.692)	**2.493**** (0.919)	**2.944**** (0.878)	**2.100**** (0.553)	**1.603**** (0.434)
INFORMAL	1.197 (0.850)	-0.982 (1.139)	0.371 (1.109)	1.291 (0.689)	0.802 (0.579)
ORGANIZED	-0.657 (1.125)	-0.423 (1.471)	-0.054 (1.466)	-1.056 (0.918)	-0.649 (0.722)
FAITH_BASED	-0.817 (0.483)	*-1.582** (0.605)	-0.931 (0.621)	-0.650 (0.389)	**-1.148**** (0.297)
R-square	0.84	0.86	0.81	0.92	0.92
Adjusted R-square	0.82	0.84	0.79	0.91	0.91

Table A.6 Multilvel model – Dependent variable: Natural log of innovator count

	Chemical	**Computer & Communication**	**Drugs &Medical**	**Electrical &Electronic**	**Mechanical**
For Level 1 INTERCEPT					
Level 2 INTERCEPT	**-12.184**** (3.358)	**-10.641**** 3.389)	**-15.606**** (3.939)	-1.896 (2.354)	0.311 (1.329)
LQi	**0.591**** (0.139)	0.358 (0.2170	0.192 (0.121)	**0.513**** (0.097)	**0.420**** (0.138)
MSA_ACADEM_R&D	-1E-06 (1E-06)	-1E-06 (1E-06)	0E+00 (1E-06)	0E+00 (0E+00)	0E+00 (0E+00)
LQ(RESEARCH_EMP)	-0.028 (0.071)	**0.170**** (0.035)	0.077* (0.034)	**0.077**** (0.028)	0.026 (0.022)
LN(BIZ_SERVICE)	**0.356**** (0.098)	**0.458**** (0.135)	0.107 (0.149)	**0.205**** (0.076)	0.059 (0.051)
LN(KNO_WORKERS)	**1.335**** (0.100)	**1.466**** (0.058)	**1.522**** (0.139)	**1.502**** (0.064)	**1.211**** (0.051)
LN(COMPACT)	-0.028 (0.735)	-0.987 (0.692)	0.991 (0.929)	**-2.287**** (0.549)	**-1.727**** (0.279)
SOCIAL_TRUST	**2.479**** (0.647)	**2.307**** (0.558)	**3.125**** (0.703)	**1.712**** (0.433)	**1.302**** (0.393)
INFORMAL	1.135 (0.776)	-0.692 (0.911)	-0.463 (1.027)	0.706 (0.675)	0.247 (0.696)
ORGANIZED	-1.047 (0.977)	-0.131 (0.872)	0.096 (1.487)	-0.454 (0.833)	-0.306 (0.772)
FAITH_BASED	-0.846 (0.488)	**-1.606**** (0.579)	-0.585 (0.639)	-0.453 (0.440)	**-0.968**** (0.290)

Table A.7 Descriptive Statistics for County, Census Tract, and Person Level Data

Level-1					
Variable	N	Mean	Sd	Minimum	Maximum
Fblack	22206	0.12	0.33	0	1
Fasian	22206	0.03	0.16	0	1
Fhispn	22206	0.08	0.27	0	1
Age	22206	44.4	16.57	18	118
Gender	22206	0.41	0.49	0	1
Fown	22206	0.69	0.46	0	1
Fmarital	22206	0.5	0.5	0	1
Edsmcoll	22206	0.33	0.47	0	1
Edcollgd	22206	0.35	0.48	0	1
Flivcom1	22206	0.06	0.25	0	1
Flivcom2	22206	0.27	0.44	0	1
Flivcom3	22206	0.15	0.36	0	1
Flabor1	22206	0.67	0.47	0	1
Fincome0	22206	0.13	0.33	0	1
Fincome3	22206	0.23	0.42	0	1
Fincome4	22206	0.18	0.38	0	1
Incom56	22206	0.21	0.41	0	1
Fkids0	22206	0	0.04	0	1
Fkids1	22206	0.39	0.49	0	1
Soctrust	22206	0.04	0.68	-2.54	1.02
Faithba2	22206	-0.07	0.76	-1.03	1.47
Schmooz	22206	0	0.66	-0.97	2.18
Orginter	22206	0.01	0.71	-0.54	5.99
Level-2					
Incometr	6436	34325.56	15005.21	0	150001
Colgradt	6436	15.69	11.89	0	69.16
Racdiver	6436	0.24	0.2	0	0.81
Level-3					
Rurlperc	259	36.63	28.39	0	100
Lncompac	259	4.57	0.2	4.21	5.86
Lnpop	259	11.93	1.3	8.58	16

Table A.8 Examination of Random Effects of Unconditional Models for Social Capital

Random Effect	Social trust	P-value	Informal social interaction	P-value	Organized group interaction	P-value	Faith-based social capital	P-value
level 2 Intercept,R0	0.004	0	0.0002	0.002	0.002	0	0.002	0.004
level-1, E	0.335		0.38		0.457		0.473	
Level 3								
Intercept	0.023	0.006	0.015	0.245	0.024	0.024	0.025	0.027
BLACK	0.005	0.018	0.003	>.500	0.003	0.39	0.01	0.001
ASIAN	0.012	0.37	0.008	0.307	0.003	>.500	0.014	0.093
HISPN	0.012	0.025	0.008	0.026	0.01	0.172	0.009	0.168
AGE	0	0.006	0	>.500	0	0.032	0	0.002
GENDER	0.002	0.348	0.001	0.316	0.002	0.193	0.003	0.041
OWNER	0.001	0.357	0.001	0.16	0.002	0.3	0.002	>.500
MARITAL	0.002	0.065	0.003	0.042	0.001	>.500	0.002	0.336
SOMECOLL	0.004	0.012	0.006	0.001	0.003	0.356	0.001	>.500
COLLGRAD	0.002	>.500	0.006	0.001	0.003	0.124	0.007	0.015
LIVCOM<1 yr	0.006	0.177	0.002	>.500	0.005	0.37	0.003	>.500
LIVCOM 1-5 yrs	0.001	>.500	0.003	0.006	0.002	0.143	0.002	>.500
LIVCOM 6-10 yrs	0.001	>.500	0.002	0.347	0.007	0.003	0.003	>.500
EMPLOYMENT	0.003	0.213	0.0008	>.500	0.001	>.500	0.002	>.500
INCOME30-50K	0.001	>.500	0.0007	>.500	0.002	0.384	0.002	0.086
INCOME50-75K	0.001	>.500	0.002	0.351	0.004	0.135	0.007	>.500
INCOM over 75K	0.001	>.500	0.001	0.443	0.011	0.003	0.006	0.197
KIDS1	0.002	0.194	0.001	0.204	0.005	0.287	0.002	0.395

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