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# The Spatial Distribution of Innovative Activity in U.S. Metropolitan Areas: Evidence from Patent Data*

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**Abstract.** Despite the fact that knowledge spillovers have explicitly geographic components, the role of spatial effects in the knowledge spillover process has been ignored. In this context, the objective of this paper is to observe differences in the spatial distribution of innovative activity across U.S. metropolitan areas, and thereby to examine whether the concentration of innovative activity in a metropolitan area is spatially correlated to the concentration of neighboring metropolitan areas' innovative activity. Based on a data set of patents, this paper presents the recent space-time patterns of metropolitan innovative activity for the period 1990-1999.

## 1. Introduction

The fact that knowledge spillovers lead to increasing returns which in turn may be bounded for a time within the geographic limits, suggests that regions may realize different growth trajectories. However, the general analyses in the new endogenous growth theories have not explicitly considered the space in which economic relationships take place (Grossman and Helpman 1991; Lucas 1988; Romer 1986; Romer 1990). These studies have not established whether regions showing high or low values of productivity are randomly distributed across space or, on the contrary, are clearly concentrated in particular territories. Nor have they tested the spatial patterns of regional growth dynamics.

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Beginning in the early 1990s, there have been a number of empirical studies to explore the geographic aspects of knowledge externalities and the localized relationships between private and university Research and Development and innovative firms (Acs, Anselin, and Varga 2002; Anselin and Varga 1997; Anselin, Varga, and Acs 2000a; Anselin, Varga, and Acs 2000b; Audretsch and Feldman 1996; Feldman 1994; Feldman and Florida 1994; Jaffe, Trajtenberg, and Henderson 1993). However, as Malecki (1983:95) states that "innovation may be the most important and the least understood aspect of the concept of spatially unbalanced growth," we have still a limited understanding of the sources of technological progress and of why the pace of progress varies over time and space.

If technological knowledge is not easily accessible at every point in space, the location of knowledge creation and the characteristics of knowledge diffusion become a crucial issue in understanding the creation of technological enclaves and the spatial patterns of regional growth dynamics. This explains why the extent to which knowledge spillovers are indeed bounded within geographic limits has received particular attention in the growing literature. In this context, the first objective of this study is to observe differences in the spatial distribution of innovative activity across metropolitan areas, and thereby to introduce the consideration of the geography of innovative activity as an important requirement for the analysis of uneven regional growth. The second objective of this paper is to examine whether the concentration of innovative activity in a metropolitan area is spatially correlated to the concentration of neighboring metropolitan areas' innovative activity, and thereby to further investigate if spatial clusters of innovative activity can be isolated across metropolitan areas.

Based on a data set of patents, this paper presents the spatially detailed analysis of recent trends of innovative activity. This study applies exploratory spatial data analysis methods and concentrates on recent space-time patterns of innovative activity at the level of metropolitan areas. Particular emphasis is paid to the spatial dimensions of changing metropolitan innovativeness.

This paper is organized as follows. The following section briefly summarizes the literature which provides a theoretical rationale for why innovative activity tends to be spatially concentrated. Section 3 deals with a methodological issue on the specification of spatial interaction relationship, followed by exploratory spatial data analysis methods. The empirical results of the analysis at the metropolitan level are discussed in Section 4. This paper closes with summary and concluding remarks in Section 5.

## 2. The Evolutionary Nature of Technological Change and Its Economic Geography

In the last decade, there has been a widespread resurgence of interest in innovative activity. It is increasingly seen as an essential basis for economic growth in the advanced economies (Dosi et al. 1988; Grossman and Helpman 1991; Lucas 1988; Nelson and Winter 1982; Romer 1986; Romer 1990). Along with this renewed interest in innovative activity, has come a concern about why the distribution of innovative activity is geographically concentrated (Acs, Anselin, and Varga 2002; Anselin and Varga 1997; Anselin, Varga, and Acs 2000a; Anselin, Varga, and Acs 2000b; Audretsch and Feldman 1996; Feldman 1994; Feldman and Florida 1994; Jaffe, Trajtenberg, and Henderson 1993). Such attention to the issue of geography rests ultimately upon the recognition of the essential importance of knowledge spillovers and spatially bounded increasing returns in promoting the geographic concentration of innovative activity and economic growth. This section briefly summarizes the literature which provides a theoretical rationale for why innovative activity tends to be spatially concentrated.

### *The nature of knowledge as an input of innovation*

Knowledge as an input in generating innovation is inherently different from the more traditional inputs of labor and capital. Knowledge created by one firm can be transmitted to other firms without any compensation or with compensation less than the value of the knowledge. Knowledge spillovers arise because knowledge is a partially excludable and non-rivalrous good (Romer 1990). The lack of excludability implies that knowledge producers have difficulty in fully appropriating the returns because they cannot prevent other firms from utilizing a part of the knowledge without compensation.[2]

The process of innovation combines two types of knowledge: codified knowledge and tacit knowledge. According to Polanyi (1966), codified knowledge involves know-how that is transmittable in a formal, systematic way and does not require direct experience of the knowledge that is being acquired. By contrast, tacit knowledge is context-dependent and difficult to codify. Von Hippel (1994) persuasively demonstrates that highly contextual and uncertain knowledge, what he refers to as “sticky knowledge,” can only be communicated or transferred through face-to-face contacts and network types of relationships, which require spatial proximity.

[2] Various forms of proprietary control mechanism, such as patent systems and copyright, grant inventors temporary monopoly power in order to allow them to reap a return from their inventions.

When one combines these two features of knowledge in the process of innovation – the centrality of sticky tacit knowledge and the growing importance of learning-through-interacting – it becomes apparent why geography matters in the distribution of innovative activity. Spatial proximity matters in transferring knowledge, because such tacit knowledge can easily spill over within a spatial network, which consists of a set of nodes and links (Karlsson and Manduchi 2001; Simmie 1997). The nodes can be represented by human settlements such as metropolitan areas, and characterized by their unique endowments of innovative capacity and related activities, including human capital and knowledge infrastructure. The links can be represented by communication channels as well as transportation.

### *The nature of innovation and its geographic context*

The spatial concentration of innovative activity stems also from the fundamental nature of the innovation process. Feldman (1994) develops this argument by sketching out five stylized facts about the innovation process presented by Dosi (1988), which are: (i) the uncertainty of the innovation process, (ii) the reliance on advances in scientific knowledge, (iii) the complexity of the innovation process, (iv) the importance of learning-by-doing and learning-by-using, and (v) the cumulativeness of innovative activity.

The process of innovation is an intrinsically uncertain, complex learning process that produces new products, processes, or organizational practices. The uncertainty of the innovation process provides an incentive for innovative firms to locate together. A geographic concentration of firms may facilitate networking and problem-solving, and can be thought of as an approach to minimize uncertainty and complexity. Being a part of a localized network enables a firm to exploit technological developments in a timely manner and to facilitate problem-solving through sharing experiences with similar technologies (Lundvall 1988).

Most major new technological opportunities stem from scientific advances, and technological innovations rely heavily upon sources of basic scientific knowledge such as universities, research institutions, and R&D activities. Spatial proximity of a knowledge-intensive industry to universities and knowledge infrastructure gives direct access to individuals that can turn information into usable knowledge in a timely manner.

Another stylized fact about innovative activity is the importance of learning-by-doing and learning-by-using. Some aspects of knowledge have a tacit nature which cannot be communicated and transferred in a direct, codified way. This knowledge is learned through learning-by-doing and learning-by-using (Nelson and Winter 1982), which result in geographically localized relationships.

Finally, the cumulative nature of innovative activity suggests that the firms located in innovative regions will find themselves in a more favorable position for the next round of innovation as compared with firms located in less innovative regions. This implies a virtuous and self-reinforcing process by which past innovation breeds future location of innovative activity within selected regions, eventually leading to the spatial clustering of innovative activity (Arthur 1990).

### *The nature of technological regimes and its geographic context*

Another approach to analyze the spatial patterns of innovative activity is the concept of technological regimes, which dates back to the contribution of Nelson and Winter (1982). In broad terms, a technological regime can be defined by the particular combination of four fundamental factors: (i) technological opportunity, (ii) appropriability, (iii) cumulativeness of technological knowledge, and (iv) knowledge base (Breschi 1999). It seems reasonable to claim that there is a spatial dimension to technological regimes, and that the basic features defining a firm's technological regime will have consequences for its geographic location and for the spatial distribution of innovative activity.

Opportunity conditions reflect the probability of innovation for any given amount of resources. Technological regimes marked by high levels of innovative opportunities are expected to exhibit a strong tendency toward sectoral concentration. This results in a small number of innovators, and therefore a relatively higher level of concentration of innovative activities. The sources of technological opportunities, such as universities, research institutions, and R&D activities, strongly affect where such opportunities are available, and therefore it drives the spatial concentration of innovative activity.

Appropriability conditions reflect the possibility of protecting innovations from imitation, and therefore gaining a larger share of profits from innovations. Cumulativeness of technological knowledge represents the probability of innovation for any given amount of innovations produced in previous periods. By limiting the extent of knowledge spillovers and allowing successful innovators to acquire high levels of market power, industries with a high level of appropriability and technological cumulativeness are expected to result in a small number of innovators, and therefore a relatively higher level of spatial concentration of innovative activity.

Finally, knowledge base conditions characterize the properties of the knowledge on which the firms' innovative activity is based. Some aspects of knowledge have a tacit nature which cannot be completely codified and transferred through blueprints and instructions. This type of knowledge can only be learned through everyday practice and practical example. This is relevant when a technology is on the early stages of its life cycle (Nelson and Winter 1982). Due to these features, knowledge can only be effectively transmitted through face-to-face contacts and inter-firm mobility of workers, both of which are eased by close geographic and cultural proximity

(Saxenian 1996). Spatial proximity facilitates the transmission of complex, tacit knowledge across agents, and it is expected to result in the creation of technological enclaves.

***The discontinuous nature of technological change and its geographic context***

Within the evolutionary framework, technologies are thought to evolve along specific paths or trajectories; however, major innovative breakthroughs represent dramatic breaks in the direction of technological development (Boschma and van der Knaap 1997). It is not always likely that technological knowledge accumulated along trajectories determines the appearance of innovation. It is even very likely that prevailing routines and institutions act as impediments for the adoption of major innovations.

Chance events and spatial accidents are involved in this case because it is impossible to predict where a specific potential source of major technological innovations will induce the rise of a new industry. In this view, small, fortuitous events may determine the location of a new industry, and the impact of the local environment is expected to be of minor importance for the location of a new industry (Boschma and van der Knaap 1997).

Consequently, the discontinuous nature of technological change might imply that the spatial formation of a new industry involves spatial indeterminacy and spatial leapfrogging (Brezis, Krugman, and Tsiddon 1993; Boschma and Lambooy 1999). Due to a mismatch with the new requirements on the local environment, spatial practices that have been accumulated in the past might not provide any stimuli to the development of a newly emerging industry, and this produces the spatial leapfrogging pattern of the new industry.

Human agencies and institutions also play an essential role in determining the location of a newly emerging industry (Boschma and Lambooy 1999). As noted, there is likely to be a wide gap between the requirements of major new technologies and their local environment. Therefore, newly emerging firms depend on their capacity to locally produce their own necessary conditions of growth, such as specific knowledge bases, technological interdependencies, entrenched network relations, etc. (Rigby et al. 1997). In this perspective, firms and other organizations (including competitors, users/customers, suppliers, and regulating institutions) should not only adapt their behavior to the external environment, but also adapt their environment in accordance with their own needs (Saviotti 1996). In short, the discontinuous nature of radical innovations provides an explanation for the patterns of spatial leapfrogging as a response to occasional major changes in technology.

# 3. Research Methods: Exploratory Spatial Data Analysis

***The spatial weights matrix***

Exploratory spatial data analysis is a set of techniques that aims to describe spatial distributions, to discover patterns of spatial association, to suggest different spatial regimes or other forms of spatial instability, and to identify atypical observations (Anselin 1996). For specifying spatial relationship in a set of geographic units, the concept of neighborhood has to be quantified. Given any predefined method to determine the neighborhood relation for $n$ geographic units, we have an $(n \times n)$ matrix to capture the spatial relationship among the $n$ geographic units. This matrix is called a spatial weights matrix **W**, which indicates the form of spatial interaction that is assumed to hold. The traditional approach relies on the geography or spatial arrangement of the units, designating geographic units as neighbors when they share a common border (simple binary contiguity) or are within a given distance of each other, i.e., $w_{ij} = 1$ for $d_{ij} \leq d$, where $d_{ij}$ is the distance between geographic units $i$ and $j$, and $d$ is a distance cutoff value (distance-based binary contiguity). More generally, the spatial weights may be specified to express any measure of potential interaction between geographic units $i$ and $j$ (Anselin 1988). This may be related directly to spatial interaction theory and the notion of potential, with $w_{ij} = 1/d_{ij}^{a}$ or $w_{ij} = \exp(-ßd_{ij})$. In these spatial weights, the strength of spatial interaction between two geographic units is inversely proportional to the distance between the units.

However, these spatial weighting schemes do not consider the masses of geographic units. It is reasonable to assume that regions with large economies will be influential, having an effect on remote regions because of extensive trade, capital, and labor market linkages (Isard 1998). For example, innovative activity in a metropolitan area ranked in the lower hierarchy of knowledge accumulation will depend on innovative activity in metropolitan areas with larger accumulation of knowledge (Echeverri-Carroll and Brennan 1999). In general, it is not only geographic proximity that leads to spatial interaction or spatial diffusion of knowledge between geographic units, but also contacts between geographic units through communication, migration, transactions, and any other type of economic relationship.[3]

[3] An analysis of Internal Revenue Service data reveals that metropolitan areas are increasingly linked by common knowledge and industries. For example, the top ten metropolitan areas contributing people to Austin TX from 1992 through 2000 are Los Angeles-Long Beach CA, San Jose CA, Chicago IL, Phoenix-Mesa AZ, Washington DC-MD-VA-WV, San Diego CA, Orange County CA, Boston MA-NH, Denver CO, and Atlanta GA, and most of them also are high technology centers (Austin American-Statesman August 4, 2002).

In order to capture these phenomena, different approaches have to be suggested to generalize the concept of spatial interaction or spatial diffusion of knowledge and thus to allow for economically viable interpretations of spatial interaction matrices (Fingleton 2001). In this study, therefore, the measure of spatial interaction of innovative knowledge between metropolitan areas *i* and *j* is extended to accommodate both size and proximity effects into the spatial weights matrix via the following specification:

$$w_{ij} = \frac{Q_i^q Q_j^h}{d_{ij}^d}, \tag{1}$$

where $Q_i$ and $Q_j$ are the size proxies for innovative intensity of metropolitan areas *i* and *j*, respectively, and $d_{ij}$ is the distance between metropolitan areas *i* and *j*. Given the size of innovative intensity of metropolitan area *i*, the spatial interaction with metropolitan area *j* is likely to be stronger if metropolitan area *j* possesses a larger innovative intensity. The spatial weight $w_{ij}$ between two metropolitan areas *i* and *j* is proportional to innovative forces between these metropolitan areas, as proxied by the product of their average patents per 100,000 workers (1990-1999), divided by the *d*-th power of the distance $d_{ij}$ between two metropolitan areas. This weighting scheme of spatial interaction says that spatial interaction of innovative activity between two metropolitan areas declines as the distance between the areal units increases; however, it increases with innovative intensity of a neighboring metropolitan area. Although the parameters should be estimated, this study a priori assumes *?* = *?* = 1 and *d* = 2 for a gravity effect.

***Moran's I statistic***

Spatial autocorrelation can be defined as the coincidence of value similarity with locational similarity (Anselin and Bera 1998). Several indexes have been proposed in the spatial data analysis literature to assess the presence of spatial autocorrelation. This study employs the Moran's *I* statistic, which is the most widely known measure of spatial autocorrelation. The Moran's *I* statistic gives a formal indication of the degree of linear association between the observed values and a spatially weighted average of the neighboring values.

Formally, the Moran's *I* statistic for *n* observations on a variable *x*, with observation $x_i$ at location *i*, is expressed as:

$$I = \left(\frac{n}{s_0}\right) \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\, x_i\, x_j}{\sum_{i=1}^{n} x_i^2}, \tag{2}$$

where $n$ is the number of observations, $w_{ij}$ is the element in the spatial weights matrix W corresponding to the geographic units $(i, j)$, the observations $x_i$ and $x_j$ are in deviations from the mean of the variable for units $i$ and $j$, respectively, and $s_0$ is a normalizing factor equal to the sum of the elements of the spatial weights matrix, i.e., $s_0 = \Sigma_i \Sigma_j w_{ij}$ (Anselin 1992). When the spatial weights matrix is row-standardized such that the elements in each row sum to 1, the expression (2) simplifies to:

$$I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} x_i x_j}{\sum_{i=1}^{n} x_i^2}, \tag{3}$$

or, in matrix notation:

$$I = \frac{\mathbf{x}'\mathbf{W}\mathbf{x}}{\mathbf{x}'\mathbf{x}}, \tag{4}$$

where W is a spatial weights matrix whose characteristic element, $w_{ij}$, summarizes the spatial interaction between areas $i$ and $j$, $x$ is a vector of the observed values $x_i$, in deviations from the mean. The value of Moran's $I$ statistic ranges from –1 for negative spatial autocorrelation to 1 for positive spatial autocorrelation. Over the entire geographic units, if similar values are more likely than dissimilar values between neighbors, the Moran's $I$ statistic tends to be positive, and vice versa. Comparing the change in spatial autocorrelation for different time points, this study will trace the trajectory of dynamic spatial distribution patterns of metropolitan innovative activity over time.

***Moran scatterplot***

From a more disaggregated view of the nature of spatial association, the Moran scatterplot, suggested by Anselin (1996), is employed to capture the local structure of spatial association. Since the elements in the vector x in (4) are in deviations from the mean, the Moran's $I$ statistic is formally equivalent to the slope coefficient in the linear regression of the spatial lag Wx on x. This interpretation of the Moran's $I$ statistic provides a way to visualize the linear association between x and the spatially weighted average of the neighboring values, or spatial lag Wx, in the form of a bivariate scatterplot of Wx against x.

The Moran scatterplot decomposes global spatial association into the four different quadrants, which correspond to the four types of local spatial association between a metropolitan area and its neighbors: (i) *HH*: a high innovation area surrounded by high innovation neighbors (quadrant I); (ii) *LH*: a low innovation area surrounded by high innovation neighbors (quadrant II); (iii) *LL*: a low innovation area surrounded by low innovation neighbors (quadrant III); (iv) *HL*: a high innovation area surrounded by low innovation neighbors (quadrant IV). Quadrants I and III represent positive spatial association indicating spatial clustering of similar values while quadrants II and IV refer to negative spatial association.

# 4. Empirical Results

### *Data*

Previous empirical studies of the spatial distribution of innovation use states as their observational units (Audretsch and Feldman 1996; Feldman 1994; Feldman and Florida 1994). Although states may be the most relevant policymaking units concerned with fostering innovative activity within their boundaries, they may be regarded as arbitrary economic units. As Krugman (1991:57) emphasizes, “states aren’t really the right geographical units,” because of the lack of concordance between economic market and political units. When data are aggregated to the state levels, the high degree of spatial aggregation might mask the existence of different economic trajectories below the state level.

Even if Metropolitan Statistical Areas (MSAs) cover only 836 metropolitan counties among all 3,141 counties in the nation, excluding 2,305 nonmetropolitan counties, MSAs are less arbitrary economic units than states.

In many respects, the U.S. economy is really a collection of metropolitan economies linked to a national system. In the theoretical context that spatial processes occur within the boundaries of geographic areas characterized by functional linkages and dependencies, spatial units which are more disaggregated than states are likely to be more appropriate to study the nature of knowledge spillovers that are supposed to be locally bounded (Varga 1998). If knowledge spillovers are important to innovative activity, they should be more easily identified in metropolitan areas where many people are concentrated into a relatively small geographic space so that knowledge can be transmitted between them more easily.[4] Therefore, this study is based on data covering all 313 MSAs in the contiguous U.S. states, consisting of all 243 Metropolitan Statistical Areas (MSAs), 59 Primary Metropolitan Statistical Areas (PMSAs) and 11 New England Consolidated Metropolitan Areas (NECMAs), as defined by the Office of Management and Budget as of July 1996.

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[4] Innovative activity measured by patent counts is highly concentrated in metropolitan areas. More than 90 percent of the total number of patents (1990-1999) has been granted within metropolitan areas (U.S. Patent and Trademark Office).

Patent statistics are most widely used as an indicator of innovative output of a region. Using patents statistics as a proxy for innovative output has several disadvantages (Griliches 1990). The main disadvantage of patent statistics lies in the problem that simple patent counts do not take into account differences in the quality and economic impact of innovations. However, these differences do not form a major concern since the spatial distribution of patents still gives valuable information about the degree of innovativeness of a region. In addition, the correlation analysis indicates a very tight association ($r$ = 0.934) between patents and innovation (Feldman and Florida 1994). Thus, this study employs patent statistics to analyze metropolitan differences in innovative performance. The data on patents are obtained from the *United States Patent Grants by State, County, and Metropolitan Area (1990-1999)*, reported by the U.S. Patent and Trademark Office.[5] The amount of data available depends on the geographic region and the level of classification detail. However, this report does not include classifications of patents; this study could not present the industrially detailed analysis of innovative activity.

***The spatial distribution of innovative activity***

The analysis in this section begins with an overview of the spatial distribution of patents in all metropolitan areas over the years 1990-1999. It has been previously recognized by Feldman and Florida (1994) and Audretsch and Feldman (1996) that, at the level of states, innovative activity exhibits a remarkably strong tendency to cluster spatially. According to these studies, the most active states in innovative activity are California, New York, New Jersey, Massachusetts, Pennsylvania, Illinois, Ohio, Texas, Connecticut, Michigan, and Minnesota.

Figures 1 and 2 provide a clear description of the spatial distribution of innovative activity across metropolitan areas based on patents in 1990 and 1999, respectively. From Figures 1 and 2, it is clear that the distribution of innovative activity tends to follow an explicit spatial pattern. A particularly striking feature shown in Figures 1 and 2 is that the bulk of innovative activity in the United States occurs in the metropolitan areas on the coasts, and especially in California and in New England-Middle Atlantic. There appear some quite large spatial clusters around the main metropolitan areas in those regions. Moreover, some other relatively isolated spatial clusters emerge in the South.

[5] For more detailed description on patent data, see Worgan and Nunn (2002).

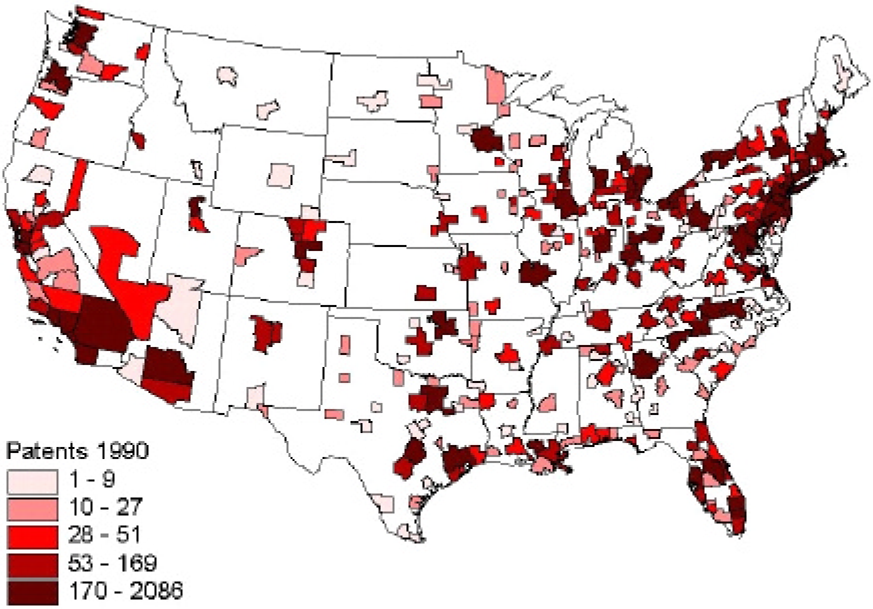


**Figure 1.** Number of patents, 1990

The major innovation concentrations are the California and the New England-Middle Atlantic clusters. The California cluster exhibits a center in the north (around San Jose and San Francisco metropolitan areas) and a center in the south (around Los Angeles and San Diego metropolitan areas). The New England-Middle Atlantic cluster is centered around Boston, Philadelphia, and New York metropolitan areas. It is also possible to recognize some medium-sized clusters, such as metropolitan areas around Seattle, Chicago, Detroit, Minneapolis, Dallas, and Houston.

Table 1 provides the distribution of innovative activity among metropolitan areas. The geographic distribution of innovative activity is highly concentrated in a relatively small number of metropolitan areas. Almost 75 percent of the total number patents in the period 1990-1999 were recorded in the top 50 metropolitan areas. The top 30 centers of innovative activity accounted for 61.0 percent of the total number of patents in the period 1990-1999. Furthermore, the top 10 centers of innovative activity produced over 30 percent of the total number of patents, suggesting the existence of a strong concentration of innovative activity among a limited number of metropolitan areas.

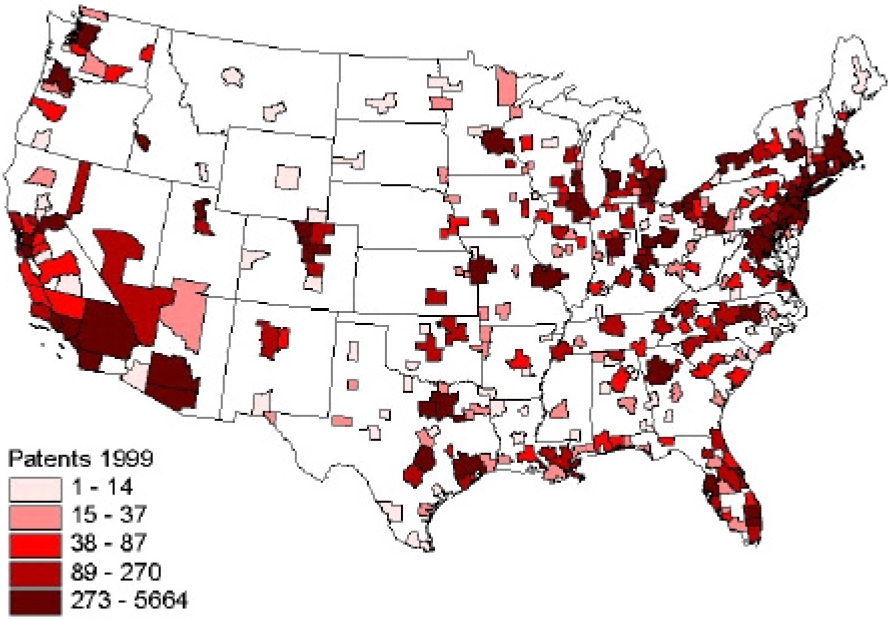


**Figure 2.** Number of patents, 1999

***The spatial concentration and cumulativeness of innovative intensity***

A simple comparison of the absolute amount of patents across metropolitan areas would ignore the size of metropolitan employment. To normalize for differences in metropolitan employment size, innovative activity may be measured on a per worker basis (Audretsch and Feldman 1996; Feldman 1994; Feldman and Florida 1994). When the absolute distribution of innovative activity is converted to a ratio of patents per 100,000 workers, geographic concentration of innovative activity persists. As Figures 3 and 4 demonstrate, even after controlling for metropolitan employment, innovative activity is geographically concentrated in the metropolitan areas in California and on the east coast in New England-Middle Atlantic. Also, there is a higher incidence of patenting in the metropolitan areas in the Sunbelt as well as in the traditional manufacturing belt.

**Table 1.** Total patents (PAT), 1990-1999

| MSA / PMSA | PAT | %PAT | CUM% |
|---|---|---|---|
| San Jose, CA | 27,617 | 4.97 | 4.97 |
| Boston-Worcester-Lawrence-Lowell-Brockton, MA-NH | 26,419 | 4.75 | 9.71 |
| Chicago, IL | 24,286 | 4.37 | 14.08 |
| Los Angeles-Long Beach, CA | 18,538 | 3.33 | 17.41 |
| Detroit, MI | 15,932 | 2.86 | 20.28 |
| Minneapolis-St. Paul, MN-WI | 15,209 | 2.73 | 23.01 |
| Philadelphia, PA-NJ | 14,496 | 2.61 | 25.62 |
| Rochester, NY | 13,330 | 2.40 | 28.02 |
| New York, NY | 12,748 | 2.29 | 30.31 |
| Houston, TX | 12,121 | 2.18 | 32.49 |
| Orange County, CA | 11,248 | 2.02 | 34.51 |
| San Diego, CA | 10,981 | 1.97 | 36.48 |
| Dallas, TX | 10,795 | 1.94 | 38.42 |
| Washington, DC-MD-VA-WV | 9,498 | 1.71 | 40.13 |
| San Francisco, CA | 9,492 | 1.71 | 41.84 |
| Oakland, CA | 9,315 | 1.67 | 43.51 |
| New Haven-Bridgeport-Stamford-Danbury-Waterbury, CT | 8,844 | 1.59 | 45.10 |
| Newark, NJ | 8,585 | 1.54 | 46.65 |
| Middlesex-Somerset-Hunterdon, NJ | 8,291 | 1.49 | 48.14 |
| Seattle-Bellevue-Everett, WA | 8,010 | 1.44 | 49.58 |
| Phoenix-Mesa, AZ | 7,794 | 1.40 | 50.98 |
| Austin-San Marcos, TX | 7,761 | 1.40 | 52.37 |
| Pittsburgh, PA | 6,786 | 1.22 | 53.59 |
| Atlanta, GA | 6,744 | 1.21 | 54.81 |
| Cleveland-Lorain-Elyria, OH | 6,376 | 1.15 | 55.95 |
| Nassau-Suffolk, NY | 6,004 | 1.08 | 57.03 |
| Cincinnati, OH-KY-IN | 5,815 | 1.05 | 58.08 |
| St. Louis, MO-IL | 5,761 | 1.04 | 59.11 |
| Portland-Vancouver, OR-WA | 5,548 | 1.00 | 60.11 |
| Baltimore, MD | 4,886 | 0.88 | 60.99 |
| Albany-Schenectady-Troy, NY | 4,784 | 0.86 | 61.85 |
| Raleigh-Durham-Chapel Hill, NC | 4,759 | 0.86 | 62.70 |
| Wilmington-Newark, DE-MD | 4,459 | 0.80 | 63.51 |
| Milwaukee-Waukesha, WI | 4,369 | 0.79 | 64.29 |
| Hartford, CT | 4,304 | 0.77 | 65.07 |
| Indianapolis, IN | 4,291 | 0.77 | 65.84 |
| Denver, CO P | 4,290 | 0.77 | 66.61 |
| Monmouth-Ocean, NJ | 4,013 | 0.72 | 67.33 |
| Bergen-Passaic, NJ | 3,872 | 0.70 | 68.03 |
| Boise City, ID | 3,651 | 0.66 | 68.68 |

Table 1. Continued

| MSA / PMSA | PAT | %PAT | CUM% |
|---|---|---|---|
| Salt Lake City-Ogden, UT | 3,491 | 0.63 | 69.31 |
| Trenton, NJ | 3,453 | 0.62 | 69.93 |
| West Palm Beach-Boca Raton, FL | 3,266 | 0.59 | 70.52 |
| Ann Arbor, MI | 3,252 | 0.58 | 71.10 |
| Fort Lauderdale, FL | 3,050 | 0.55 | 71.65 |
| Grand Rapids-Muskegon-Holland, MI | 2,865 | 0.52 | 72.17 |
| Tampa-St. Petersburg-Clearwater, FL | 2,858 | 0.51 | 72.68 |
| Dayton-Springfield, OH | 2,829 | 0.51 | 73.19 |
| Buffalo-Niagara Falls, NY | 2,821 | 0.51 | 73.70 |
| Boulder-Longmont, CO | 2,798 | 0.50 | 74.20 |

*Source*: Computed from *United States Patent Grants by State, County, and Metropolitan Area (1990-1999)*, U.S. Patent and Trademark Office.

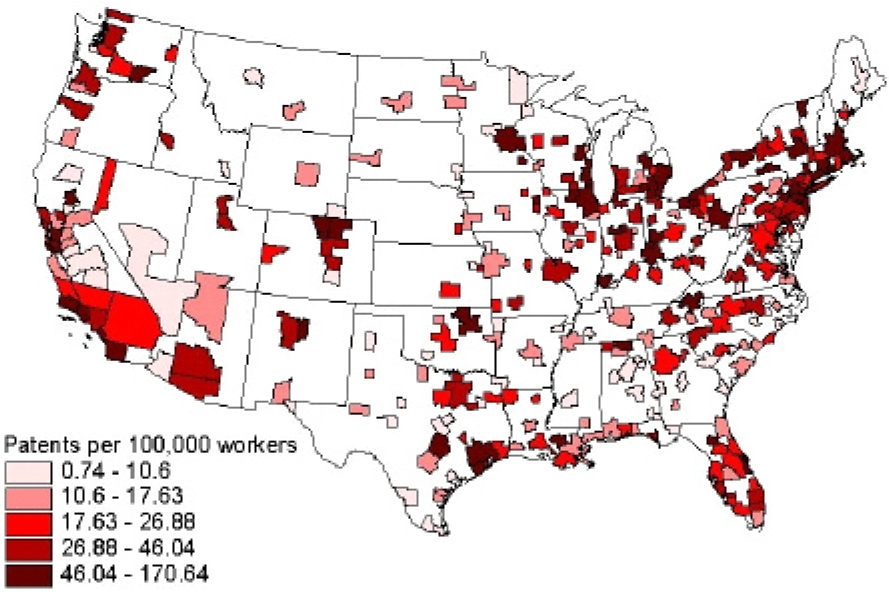


**Figure 3.** Number of patents per 100,000 workers, 1990

The Spearman's rank order correlation coefficient ($r_s$ = 0.866) of innovative intensities between 1990 and 1999 suggests the existence of a very high stability over time in the hierarchy of innovative intensity in all metropolitan areas. However, it is worth highlighting several upward and downward movements in the leading group. For the years 1990 and 1999, Table 2 lists the top 30 metropolitan areas along with measures of innovative intensity, expressed by the number of patents per 100,000 workers and rankings based on patenting activities. Over the past decade, innovative intensity among leading metropolitan areas has changed considerably, making it a spatially-dynamic phenomenon.

The most obvious change has been a rise of the metropolitan innovation potential in new high technology centers (e.g., San Francisco-Oakland-San Jose, Boise City, Denver-Boulder-Greeley, Austin, San Diego, and Raleigh metropolitan areas), which have built up very competitive systems of regional innovation. On the other hand, all of the eight metropolitan areas that have experienced downward movement belong to traditionally dominant metropolitan areas in the New England-Middle Atlantic cluster, although they are still among the leaders in terms of the level of innovative intensity. These metropolitan areas seem to have suffered some losses with respect to their regional competitive advantage.

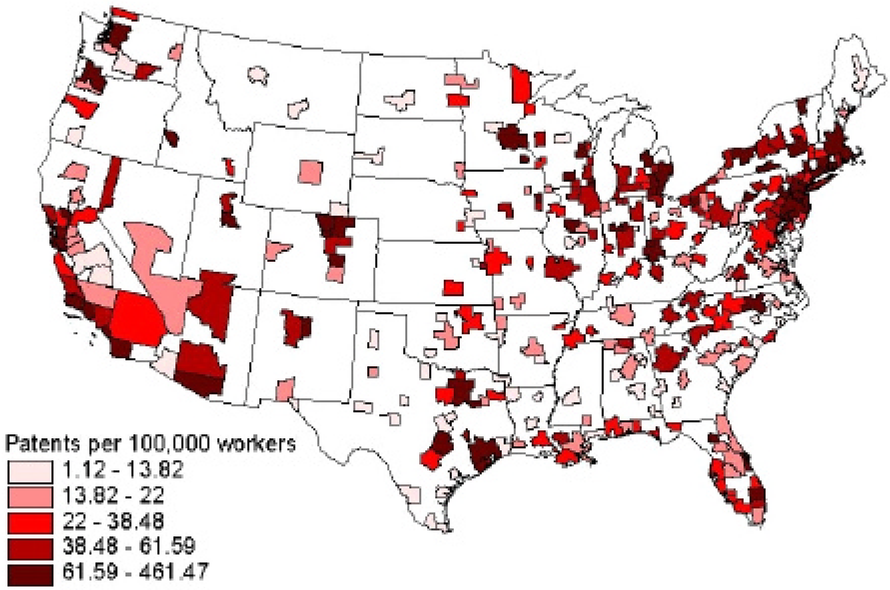


**Figure 4.** Number of patents per 100,000 workers, 1999

The measures of concentration of innovative activity across the metropolitan areas corroborate these initial evaluations. To measure the extent to which innovative activity is concentrated geographically, this study follows Krugman's (1991) example and calculates the locational Gini coefficients for the geographic concentration of innovative activity across the metropolitan area.[6] The Gini coefficient *G*, which is a summary statistic of the Lorenz

[6] This study presents the result based on the locational Gini coefficient because other measures of spatial concentration, the spatial Herfindahl index and the coefficient of variation, produce the same results as the locational Gini coefficient.

curve, is defined as the ratio of the mean absolute difference between all pairs $(x_i, x_j)$ to twice the mean level of the variable $x_i$:

$$G = \frac{1}{2n^2 \bar{x}} \sum_{i=1}^{n} \sum_{j=1}^{n} \left| x_i - x_j \right|, \qquad (5)$$

where $n$ is the total number of regions and $\bar{x}$ is the average value of the variable $x_i$ (Coulter 1989). The locational Gini coefficient ranges from a minimum value of 0 when all metropolitan areas are equal, to a maximum value of 1 when every metropolitan area except one has a size of zero. The closer the coefficient is to 1, the more geographically concentrated the variable would be.

**Table 2.** Patents per 100,000 workers (PWP)

| MSA / PMSA | PWP90 | PWP99 | RANK90 | RANK99 | ?RANK |
|---|---|---|---|---|---|
| San Jose, CA | 123.93 | 461.47 | 6 | 1 | 5 |
| Boise City, ID | 44.87 | 391.80 | 68 | 2 | 66 |
| Dutchess County, NY | 77.07 | 262.19 | 15 | 3 | 12 |
| Rochester, NY | 148.89 | 238.38 | 4 | 4 | 0 |
| Rochester, MN | 63.91 | 233.86 | 27 | 5 | 22 |
| Boulder-Longmont, CO | 99.31 | 210.87 | 9 | 6 | 3 |
| Austin-San Marcos, TX | 68.51 | 193.15 | 22 | 7 | 15 |
| Burlington, VT | 59.73 | 179.48 | 31 | 8 | 23 |
| Fort Collins-Loveland, CO | 57.50 | 174.06 | 40 | 9 | 31 |
| Santa Cruz-Watsonville, CA | 59.51 | 167.64 | 33 | 10 | 23 |
| Middlesex-Somerset-Hunterdon, NJ | 110.32 | 146.60 | 7 | 11 | -4 |
| Trenton, NJ | 170.64 | 145.44 | 1 | 12 | -11 |
| Ann Arbor, MI | 79.93 | 136.68 | 12 | 13 | -1 |
| Binghamton, NY | 73.88 | 134.24 | 16 | 14 | 2 |
| San Francisco, CA | 44.17 | 120.70 | 74 | 15 | 59 |
| Oakland, CA | 54.26 | 119.47 | 45 | 16 | 29 |
| Raleigh-Durham-Chapel Hill, NC | 39.79 | 114.76 | 87 | 17 | 70 |
| Wilmington-Newark, DE-MD | 124.28 | 110.61 | 5 | 18 | -13 |
| Monmouth-Ocean, NJ | 69.18 | 108.90 | 21 | 19 | 2 |
| Hamilton-Middletown, OH | 58.50 | 106.27 | 37 | 20 | 17 |
| San Diego, CA | 52.92 | 105.00 | 47 | 21 | 26 |
| Saginaw-Bay City-Midland, MI | 162.73 | 104.84 | 3 | 22 | -19 |
| Minneapolis-St.Paul, MN-WI | 67.53 | 104.48 | 24 | 23 | 1 |
| Greeley, CO | 55.15 | 101.13 | 44 | 24 | 20 |
| New Haven-Bridgeport-Stamford-, CT | 78.98 | 99.99 | 13 | 25 | -12 |
| Boston-Worcester-Lawrence-, MA-NH | 58.64 | 97.60 | 36 | 26 | 10 |
| Cedar Rapids, IA | 58.66 | 97.18 | 35 | 27 | 8 |
| Newark, NJ | 73.34 | 96.57 | 18 | 28 | -10 |
| Yolo, CA | 32.45 | 95.96 | 110 | 29 | 81 |
| Racine, WI | 67.47 | 95.65 | 25 | 30 | -5 |

*Source*: Computed from *United States Patent Grants by State, County, and Metropolitan Area (1990-1999)*, U.S. Patent and Trademark Office.

The locational Gini coefficients are calculated for two different variables: patents and income. Comparing patents and income, we can see that innovative activities display much higher levels of spatial concentration than economic activity across all metropolitan areas. The locational Gini coefficients for innovative activity are based on patents granted per 100,000 workers in a metropolitan area. The locational Gini coefficients for economic activity are based on income per worker in a metropolitan area and are calculated in a similar way.

Figure 5 provides the locational Gini coefficients for innovative activity and economic activity for the period 1990-1999. As previous studies observe strong spatial concentration of innovations at the state level (Audretsch and Feldman 1996; Feldman 1994; Feldman and Florida 1994), Figure 5 shows that innovative activity displays much higher level of spatial concentration than economic activity for every year. The spatial distribution of innovative activity in the metropolitan areas appears to be highly concentrated mainly because of the substantial differences in innovative intensity as shown in Figures 3 and 4.

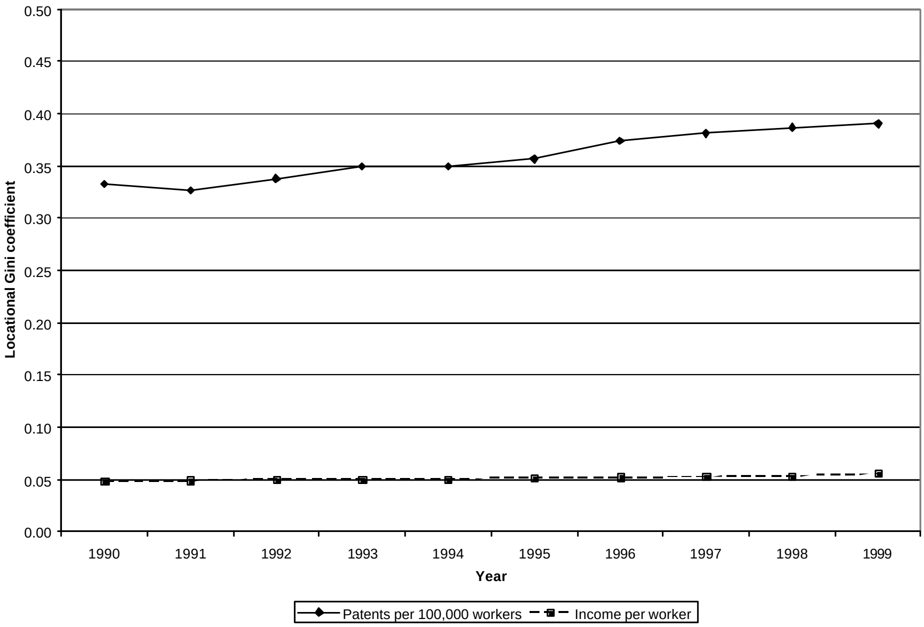


**Figure 5.** Locational Gini coefficients, 1990-1999

The degree of spatial concentration of economic activity (*G* = 0.049 in 1990 and *G* = 0.056 in 1999) is remarkably lower than that of innovative activity. Another interesting point to be noted is the presence of a steady increasing trend in the spatial concentration of innovative activity over the past decade (from *G* = 0.333 in 1990 to *G* = 0.390 in 1999). This suggests that there is no indication of convergence in innovative intensity across metropolitan areas. The difference in the spatial concentration can be ascribed to the fact that spatially bounded increasing returns and geographically localized knowledge spillovers are more important for innovative activity rather than for overall economic activity.

### *Exploratory spatial data analysis results*

The locational Gini coefficient only shows the degree of geographic concentration of a variable. It provides no information about the way in which the value in one region is spatially structured with the value in neighboring regions. However, a given value of spatial concentration can indeed correspond to different spatial configurations of a variable. Hence, this study also employs spatial autocorrelation technique which enables us to identify a significant nonrandom arrangement in an areal pattern of a certain variable (Anselin 1996; Rey 2001; Rey and Montouri 1999). The advantage of the concept of spatial autocorrelation over the locational Gini coefficient is that it allows us to identify clustering patterns which spread out over the regional borders. If it is the case that geographic distance still matters for the spatial diffusion of knowledge, we would expect to find significant regional clustering, which is indicated by the presence of significant spatial autocorrelation. This study tests overall spatial autocorrelation by means of the Moran's *I* statistics.

The statistical significance of the Moran's *I* statistic is calculated by applying a randomization assumption, given non-normality for distributions of patents per 100,000 workers. Table 3 presents the result of spatial autocorrelation for innovative intensity for the period 1990-1999. The analysis of metropolitan patent grants per 100,000 workers by means of the Moran's *I* statistic provides strong evidence of positive spatial autocorrelation with $p < 0.001$ for every year. This result indicates that the hypothesis of spatial randomness is rejected and hence, the spatial distribution of innovative intensity is by nature clustered over the whole period. The metropolitan areas with relatively high innovative intensity tend to be close to other metropolitan areas with high innovative intensity, and vice versa. This suggests that the metropolitan innovative intensity is spatially related and therefore should not be assumed to be independent observations.

Figure 6 compares the values of the Moran's *I* statistic for per worker income with those for patents per 100,000 workers for the period 1990-1999. These results show that the values of the Moran's *I* statistic for innovative activity are lower than those of economic activity for every year. When this result is combined with the previous result of the locational Gini coefficients for innovative activity, it can be concluded that although the metropolitan areas with relatively high innovative intensity tend to be spatially associated with other metropolitan areas with high innovative intensity, innovative activity takes place in a more spatially scattered or spatially leapfrogging way than economic activity, but once it takes place in that way it is more spatially concentrated than economic activity.

**Table 3.** Moran's *I* statistic for patents per 100,000 workers, 1990-1999

| Year | Moran's *I* | *z*-value |
|---|---|---|
| 1990 | 0.164 | 5.022 |
| 1991 | 0.196 | 5.990 |
| 1992 | 0.180 | 5.511 |
| 1993 | 0.188 | 5.749 |
| 1994 | 0.184 | 5.629 |
| 1995 | 0.191 | 5.843 |
| 1996 | 0.205 | 6.274 |
| 1997 | 0.189 | 5.788 |
| 1998 | 0.189 | 5.793 |
| 1999 | 0.179 | 5.490 |

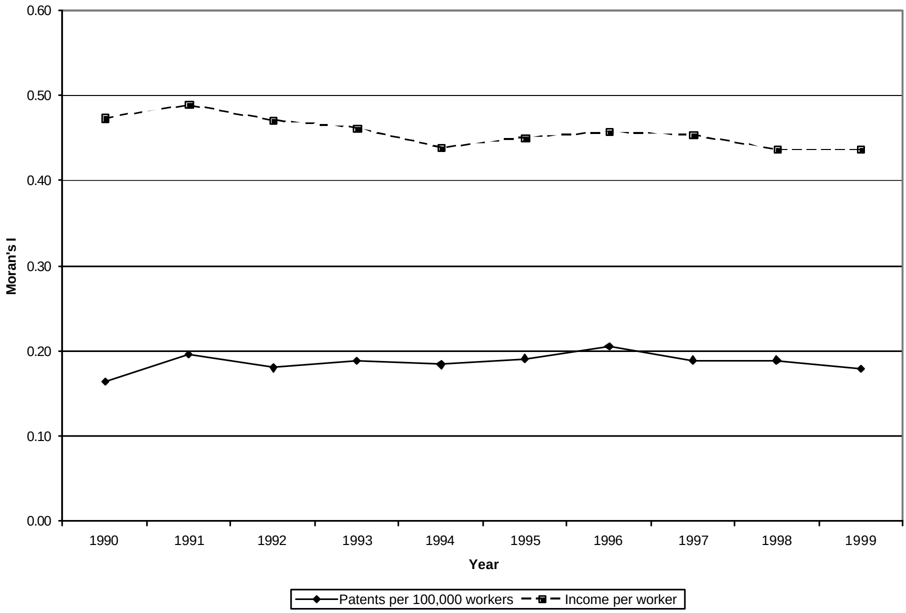


**Figure 6.** Moran's *I* statistic, 1990-1999

Figures 7 and 8 display the Moran scatterplots for the initial year and final years. In 1990, 65.5 percent of the metropolitan areas exhibit association of similar values (i.e., 20.4 percent in quadrant I (*HH*: high innovative intensity – high spatial lag) and 45.0 percent in quadrant III (*LL*: low innovative intensity – low spatial lag)) and in 1999, 64.2 percent of all the metropolitan areas exhibit the same positive association (i.e., 17.9 percent in quadrant I (*HH*) and 46.3 percent in quadrant III (*LL*)).

Furthermore, the Moran scatterplots can help to identify spatial instability and atypical regions, i.e., regions deviating from the global pattern of positive spatial autocorrelation. In 1990, 108 metropolitan areas (34.5 percent) display association of dissimilar values: 53 metropolitan areas in quadrant II (*LH*: low innovative intensity – high spatial lag) and 55 metropolitan areas in quadrant IV (*HL*: high innovative intensity – low spatial lag). In 1999, there are 112 atypical metropolitan areas (35.8 percent): 46 metropolitan areas in quadrant II (*LH*) and 66 metropolitan areas in quadrant IV (*HL*).

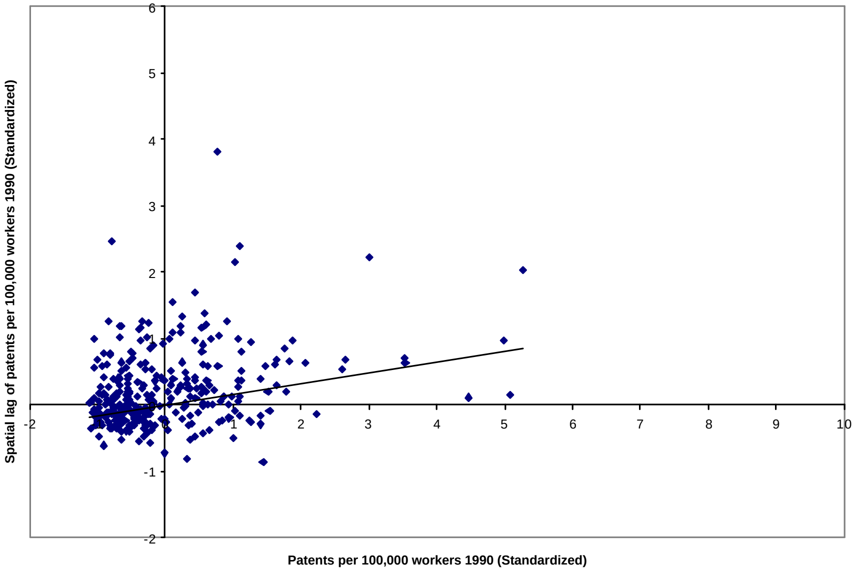


**Figure 7.** Moran scatterplot for patents per 100,000 workers, 1990

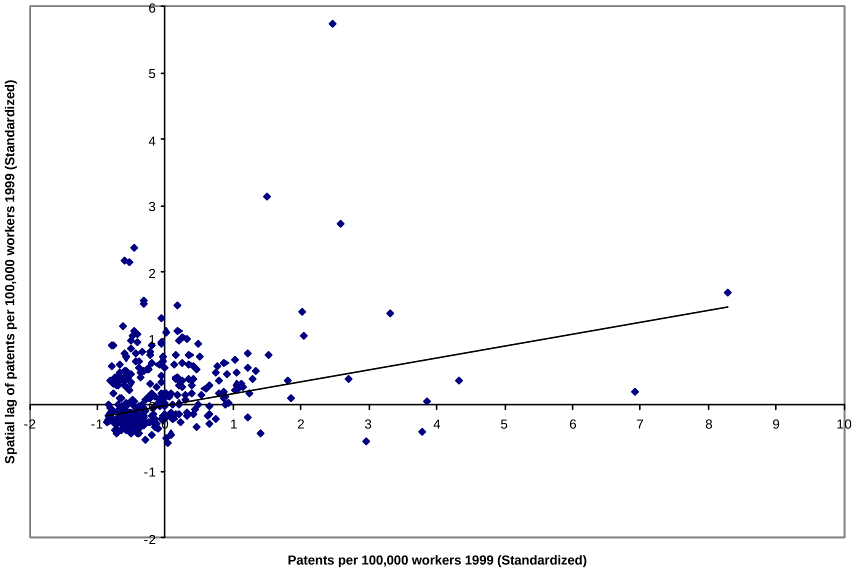


**Figure 8.** Moran scatterplot for patents per 100,000 workers, 1999

Figures 9 and 10 show the interpretation of the local Moran statistic in the form of Moran scatterplot maps. The black areas (*HH*: high innovative intensity – high spatial lag) represent a highly innovative metropolitan area which is surrounded by highly innovative neighboring metropolitan areas; the dark gray areas (*LL*: low innovative intensity – low spatial lag) are metropolitan areas of low innovation clusters. Gray areas (*HL*: high innovative intensity – low spatial lag) show a highly innovative metropolitan area surrounded by low innovative metropolitan areas. White areas (*LH*: low innovative intensity – high spatial lag) exhibit a low innovative metropolitan area surrounded by highly innovative metropolitan areas.

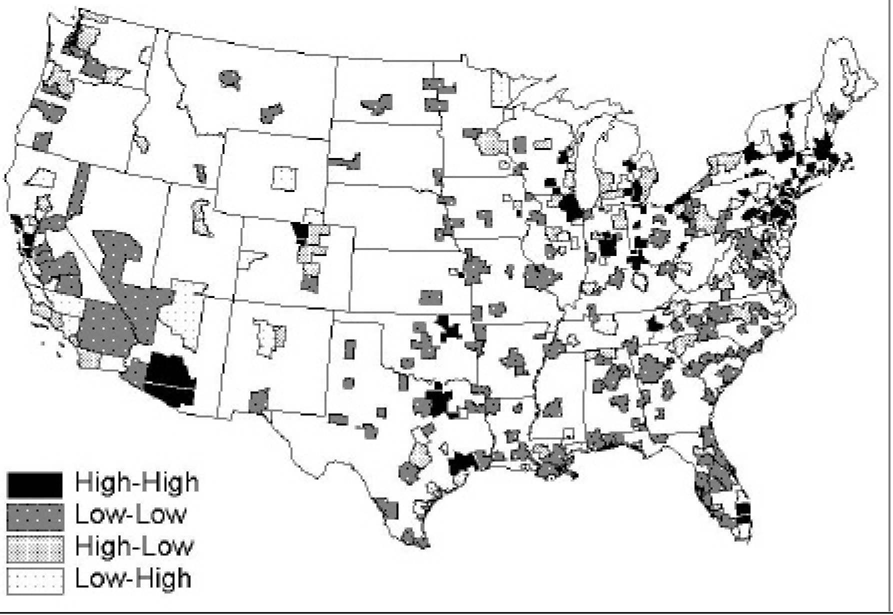


**Figure 9.** Moran scatterplot map, 1990

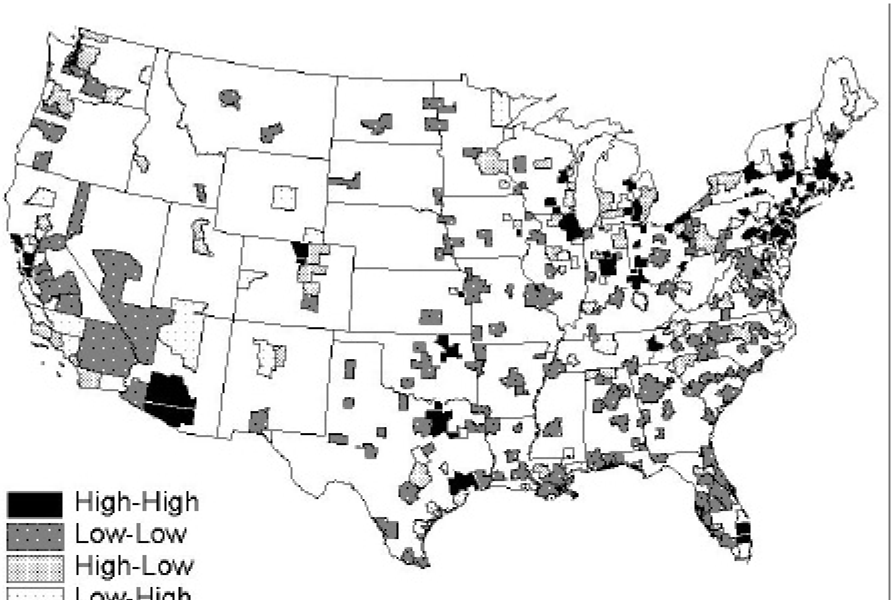


**Figure 10.** Moran scatterplot map, 1999

As indicated in Figures 9 and 10, for the levels of patents per 100,000 workers in 1990 and 1999, the traditionally dominant high technology metropolitan areas in the California clusters and the New England-Middle Atlantic clusters tend to be located in quadrant I (*HH*: high innovative intensity – high spatial lag), which is characterized by a high level of innovative intensity, positively related with neighboring metropolitan areas. On the other hand, the new medium-sized high technology clusters, such as Austin, Boise City, Dallas, Raleigh, and Seattle metropolitan areas, tend to be located in quadrant IV (*HL*: high innovative intensity – low spatial lag) (see Table A). These results suggest that the new high technology metropolitan areas have grown up outside existing major high technology centers and in a more spatially scattered or spatially leapfrogging way than the traditionally dominant high technology metropolitan areas.

More insight into the evolution of Moran scatterplots over time is provided by a measure of space-time transitions (Rey 2001). These space-time transitions can be broken down into four groups: Type I, Type II, Type III, and Type 0. Type I transition involves the transitions with a relative move of only the metropolitan area: $HH_t \rightarrow LH_{t+1}$, $HL_t \rightarrow LL_{t+1}$, $LH_t \rightarrow HH_{t+1}$, and $LL_t \rightarrow HL_{t+1}$. Type II transition contains transitions of only the neighboring metropolitan areas in relative space: $HH_t \rightarrow HL_{t+1}$, $HL_t \rightarrow HH_{t+1}$, $LH_t \rightarrow LL_{t+1}$, and $LL_t \rightarrow LH_{t+1}$. Type III transition includes transitions of both a metropolitan area and its neighbors to different states: $HH_t \rightarrow LL_{t+1}$, $HL_t \rightarrow LH_{t+1}$, $LH_t \rightarrow HL_{t+1}$, and $LL_t \rightarrow HH_{t+1}$. Finally, the four cases in which a metropolitan area and its neighbors remain at the same level are referred to as Type 0 transitions: $HH_t \rightarrow HH_{t+1}$, $HL_t \rightarrow HL_{t+1}$, $LH_t \rightarrow LH_{t+1}$, and $LL_t \rightarrow LL_{t+1}$.

The detection of spatial clusters of high and low values of innovative intensity at the beginning and at the end of the period will be seen as evidence of persistence in the spatial inequality. In contrast, the disappearance of significant agglomerations would be a sign of spatial diffusion of innovative activity. A measure of the stability in the transition types can be measured by the ratio of the number of observations experiencing a Type 0 transition to the number of all observations. For the period 1990-1999, the most common type of transition is a Type 0 transition in which a metropolitan area and its neighbors remain at the same level, with spatial stability of 70.0 percent. In contrast, the Type I and II transitions for the period are less common than the Type 0 transition, with 8.6 percent and 18.2 percent, respectively. The Type III transitions which contain a move of both a metropolitan area and its neighbors are least common for the period, with 3.2 percent. These results suggest the high stability of both a metropolitan area and its neighbors, but the relative higher mobility of the individual metropolitan area compared to its neighboring metropolitan areas. From these results, the lack of evidence of significant movements in the composition of the detected spatial clusters for the period suggests that these metropolitan areas had difficulties in leaving their clusters of high/low values. In other words, high stability and persistence in the spatial characterization seems to exist despite the loss of relative competitiveness of the traditionally dominant high technology clusters.

# 5. Conclusions

This paper has addressed the spatial distribution of innovative activity across metropolitan areas for the period 1990-1999, and examined the issue that the concentration of innovative activity in a metropolitan area is spatially correlated to the concentration of neighboring metropolitan areas' innovative activity. This issue has been approached from exploratory spatial data analysis techniques. The results provide new insights into the spatial dimension of innovative activity across metropolitan areas. The main conclusions reached by this exploratory analysis can be summarized as follows:

- The spatial distribution of innovative activity is highly concentrated in a relatively small number of metropolitan areas. The bulk of innovative activity occurs in the metropolitan areas on the coasts, especially in California and in New England-Middle Atlantic, and some other relatively isolated spatial clusters emerge in the South.
- Over the past decade, innovative intensity among leading metropolitan areas has changed considerably, making it a spatially-dynamic phenomenon. The most obvious change has been a rise of the metropolitan innovation potential in new high technology centers (e.g., San Francisco-Oakland-San Jose, Boise City, Denver-Boulder-Greeley, Austin, San Diego, and Raleigh metropolitan areas). On the other hand, all the 8 metropolitan areas that have experienced downward movement among the top 30 innovative centers belong to traditionally dominant metropolitan areas in the New England-Middle Atlantic cluster.
- The locational Gini coefficients for innovative activity and economic activity for the period 1990-1999 shows that innovative activity displays much higher level of spatial concentration than economic activity for every year. In addition, it is noted the presence of a steady increasing trend in the spatial concentration of innovative activity over the past decade. This suggests that there is no indication of convergence in innovative intensity across metropolitan areas. The difference in the spatial concentration can be ascribed to the fact that spatially bounded increasing returns and localized knowledge spillovers are more important for innovative activity rather than for overall economic activity.
- The analysis of metropolitan patent grants per 100,000 workers by means of the Moran's *I* statistic provides strong evidence of positive spatial autocorrelation for the period 1990-1999. The metropolitan

areas with relatively high innovative intensity tend to be close to other metropolitan areas with high innovative intensity, and vice versa. This suggests that the metropolitan innovative intensity is spatially correlated and therefore should not be assumed to be independent observations. When this result is combined with the previous result of the locational Gini coefficients for innovative activity, it can be concluded that although the metropolitan areas with relatively high innovative intensity tend to be spatially associated with other metropolitan areas with high innovative intensity, innovative activities take place in a more spatially scattered or spatially leapfrogging way than economic activity, but once it takes place in that way it is more spatially concentrated than economic activity.

- For the levels of patents per 100,000 workers in 1990 and 1999, the traditionally dominant high technology metropolitan areas in the California clusters and the New England-Middle Atlantic clusters are characterized as a region with a high level of innovative intensity, surrounded by neighbors with high values of innovative intensity. On the other hand, the new medium-sized high technology clusters, such as Austin, Boise City, Dallas, Raleigh, and Seattle metropolitan areas, are characterized as a highly innovative region surrounded by neighbors with low values of innovative intensity. These results suggest that the new high technology metropolitan areas have grown up outside existing major high technology centers and in a more spatially scattered or spatially leapfrogging way than the traditionally dominant high-technology metropolitan areas.
- For the period 1990-1999, the most common type of spatial transition is a Type 0 transition in which a metropolitan area and its neighbors remain at the same level. In contrast, the Type I and II transitions in which either a metropolitan area or its neighbors move to different states are less common than the Type 0 transition. The Type III transitions which contain a move of both a metropolitan area and its neighbors are least common for the period. These results suggest the high stability of both a metropolitan area and its neighbors, but the relative higher mobility of the individual metropolitan area compared to its neighboring metropolitan areas. From these results, the lack of evidence of significant movements in the composition of the detected spatial clusters for the period suggests that these metropolitan areas had difficulties in leaving their clusters of high / low values.

This study has been mainly exploratory and it leaves open several directions for further research. First, more empirical work should be done in order to better assess differences in the spatial distribution of innovative activity across metropolitan areas. In particular, knowledge externalities as a key mechanism to spatially bounded increasing returns should be investigated to examine the differences in innovative performance across metropolitan areas. Second, the extent to which innovative performance in a metropolitan area is affected by different channels of knowledge externalities (i.e., specialization, diversity, and local competition) should be evaluated. Finally, despite the fact that knowledge spillovers have explicitly geographic components, the role of spatial effects in the knowledge spillover process has been ignored. In this context, we should explicitly deal with the geography of knowledge spillovers by testing for the relationship of spatial interdependence on metropolitan innovative performance.

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