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Knowledge Spillovers, Agglomeration Economies, and the Geography of Innovative Activity: A Spatial Econometric Analysis

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Abstract

This paper investigates the extent to which innovative activity in a metropolitan area is affected by knowledge spillovers in the neighboring metropolitan areas as well as in the metropolitan area itself. The spatial econometric analysis shows that innovative activity in a metropolitan area is positively affected by both specialization and diversity externalities in high technology industries in the metropolitan area, and that there also exist geographic knowledge spillovers across metropolitan boundaries. In addition, this study finds that high technology specialization externalities are more localized than high technology diversity externalities.

Keywords: Knowledge spillovers; Agglomeration economies; Innovative activity; Spatial econometrics

JEL classification: *O31; R12; C31*

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1. INTRODUCTION

During the last decade there has been considerable interest in explaining the endogenous process of technological change in economic growth. As noted in endogenous growth theory, technological knowledge becomes a partly private and partly public good (Grossman and Helpman 1991; Romer 1990). Innovations can be patented by firms, which gives them the exclusive right to produce new goods. But at the same time innovations generate new knowledge that is freely available to all firms. This in turn will enable the receiving firms to use it in their own production and innovation process, again creating new knowledge that can spill over to other firms. As a consequence of this reciprocal and cumulative process, returns to innovation may be non-decreasing or even increasing for the economy as a whole.

The role of knowledge spillovers that generate increasing returns has been a central theme in the new theory of endogenous growth (Grossman and Helpman 1991; Lucas 1988; Romer 1986; Romer 1990). An interesting aspect of this work, from a theoretical as well as an empirical perspective, has been the renewed attention to the geography of knowledge spillovers. 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 activities and uneven economic growth.

For regional scientists, the new growth theory has been of particular interest because it helps overcome the long-lasting divide between convergence approaches of neoclassical theory (Borts and Stein 1964; Solow 1956) and polarization approaches of cumulative causation theory (Hirschman 1958; Kaldor 1970; Myrdal 1957). However, the mechanisms by which knowledge spillovers occur at the regional level are not well understood, especially in terms of their geographic characteristics. As Malecki (1983, p. 95) states, "innovation may be the most important and the least understood aspect of the concept of spatially unbalanced growth."

Although several recent empirical studies have provided evidence on the extent of localized, spatially mediated knowledge spillovers (Acs, Anselin, and Varga 2002; Anselin and Varga 1997; Anselin, Varga, and Acs 2000a; Anselin, Varga, and Acs 2000b; Jaffe, Trajtenberg, and Henderson 1993; Varga 2000), these studies have not established the relative importance of the various forms of knowledge externalities on innovative activity in metropolitan areas. On the other hand, while there have been several important contributions that stress the different roles of those forms of knowledge spillovers (Beardsell and Henderson 1999; Black and Henderson 1999; Glaeser et al. 1992; Henderson, Kuncoro, and Turner 1995), most studies along this line have focused on overall employment growth in metropolitan areas; they do not consider the different roles of knowledge spillovers in explicitly fostering innovative activity. It is preferable to investigate the effects of knowledge externalities on innovative performance through a more direct channel than employment growth.

A further contribution has also been made by Feldman and Audretsch (1999). They attempt to link the extent of knowledge spillovers to the direct measure of innovative output; however, a major shortcoming of their study is that the geographic entities in question have been treated as "isolated islands." Their approach fails to take into account how different regions relate to one another. Despite the fact that knowledge externalities that have been identified as a key mechanism to increasing returns have explicitly geographic components, the role of spatial effects in the knowledge spillover process has been ignored in recent research. In this context, the main objective of this study is to incorporate these issues in an empirical model that explicitly evaluates the extent to which the innovative performance in a metropolitan area is affected by the various forms of high technology-based knowledge externalities not only in the metropolitan area itself, but also in the neighboring metropolitan areas.

This paper is organized into four remaining sections. The main theories and empirical studies on knowledge spillovers and the geography of innovative activity are introduced in Section 2. Section 3 outlines the data and the definition of spatial interaction used in this study and provides the specific models to investigate the extent to which metropolitan innovative activity is related to knowledge externalities from a spatial econometric perspective. In Section 4 the empirical results of the analysis are presented. The paper closes with a summary and concluding remarks in Section 5.

2. KNOWLEDGE SPILLOVERS AND THE GEOGRAPHY OF INNOVATIVE ACTIVITY

2.1 Knowledge Spillovers and Agglomeration Economies

The literature concerning agglomeration of firms can roughly be divided into two camps. One camp argues that knowledge spillovers should not be assumed to be the typical reason for the localization of industries – even in high technology industries themselves (Krugman 1991a; Rauch 1993), while the other camp argues that knowledge spillovers are the prominent reason behind the clustering of high technology firms (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 1989; Jaffe, Trajtenberg, and Henderson 1993).

In the first view, the reasons behind the observed agglomeration of high technology industries are the same as the reasons why industries in general tend to cluster. According to Krugman (1991b), every manufacturing firm tends to locate in the region with larger demand in order to realize economies of scale while minimizing transport costs, but the location of demand itself depends on the distribution of prior manufacturing activity. The basic story of geographic concentration relies on the interaction of three parameters: increasing returns, transportation costs, and demand for manufacturing goods (Krugman 1991b). Although Krugman invokes certain types of Marshallian externalities, he mainly concentrates on "pecuniary" externalities that can be measured and modeled rather than on more "elusive" spillovers of technological knowledge (Acs and Varga, 2002; Martin and Sunley, 1996).

The second group of theorists places greater emphasis on knowledge spillovers. In this literature, it is assumed that despite modern communication technologies, frequent face-to-face contact and intensive interaction is still an important channel of knowledge spillovers due to the tacitness of much innovative knowledge. As Marshall (1920) argued earlier, such knowledge spillovers tend to be geographically bounded within the region where the new technological knowledge was created (Audretsch and Feldman 1996; Feldman and Florida 1994; Jaffe, Trajtenberg, and Henderson 1993). The geographic proximity of people in large cities or in regions with specialized industries, in turn, enables knowledge to circulate more readily, which again generates externalities that enhance innovation and productivity. Thus, there is a self-reinforcing circularity that tends to keep a geographic cluster of innovative activity durable over time. Indeed, these externalities are likely to play a particularly acute role in determining geographic concentration of high technology industries.

The literature also distinguishes between two main sources of externalities. The first concerns specialization externalities, which operate mainly within a specific industry, associated to the contributions by Marshall (1920). Marshall observes that industries specialize geographically because proximity favors the intra-industry transmission of knowledge. The second concerns diversity externalities that favor the creation and transmission of new ideas across industries, as originally suggested by Jacobs (1969). Jacobs believes that the density and variety of local activities plays a major role in the innovation process. With the effects of specialization and diversity externalities, innovating firms have strong incentives to cluster together to take advantage of the various positive agglomeration economies spawned by geographic proximity. This geographic concentration of innovative activity is the consequence of the clustering of these innovative firms. High technology firms, for instance, indicate that they choose locations with proximity to labor, academic institutions, and favorable economic climates. The importance of knowledge spillovers suggests that firms' innovative activities do not proceed in isolation, but are supported by external sources.

2.2 Empirical Findings on Knowledge Externalities and the Geography of Innovative Activity

Based on such theoretical developments, a number of empirical studies have recently attempted to measure the extent to which knowledge spillovers take place and to explore the fundamental question of whether and to what extent knowledge externalities are spatially localized. One contribution in the literature employs a knowledge production function framework. Jaffe, Trajtenberg, and Henderson (1993) find that patent citations tend to occur more frequently within the same state and metropolitan area in which they were patented than outside of the host region and that these effects are particularly significant at the local level. Audretsch and Feldman (1996) examine the extent to which industrial activity clusters geographically and to link this geographic concentration to the existence of knowledge spillovers. Their results suggest that the propensity of innovative activity to cluster geographically tends to be more attributable to the role of knowledge spillovers and not merely the geographic concentration of production.

More recently, Anselin and Varga (1997) and Anselin, Varga, and Acs (2000a; 2000b), using measures of significant innovations for 125 metropolitan areas, investigate the issue of local geographic spillovers between university research and innovative activity by small high technology firms. They measure knowledge spillovers through a set of spatially lagged variables designed to capture the effect of university and private R&D in counties surrounding a metropolitan area within a given distance band from the center of the area. Their results show that spillovers of university research have a positive, significant impact on regional innovation. Varga (2000) also provides formal evidence of a positive effect of agglomeration on local knowledge transfers from universities to high technology innovations, within the knowledge production function framework. He finds that concentration of high technology employment in a region is the most important agglomeration factor promoting knowledge spillovers from universities.

A second strand of empirical research has emerged in the literature focusing on the relationship between economic growth in cities and two key structural elements of knowledge spillovers: the degree of industrial diversity versus specialization and the degree of monopoly versus competitive market structure. Two important papers that empirically test these alternative hypotheses are by Glaeser et al. (1992) and Henderson, Kuncoro, and Turner (1995). These studies use employment data to measure growth but reach different conclusions, particularly regarding effects of specialization versus diversity. Glaeser et al. (1992) find that employment growth is enhanced by diversity across a broad range of industries. Using a more detailed sectoral breakdown, Henderson, Kuncoro, and Turner (1995) find evidence consistent with both specialization and diversity views, depending on whether mature or high technology industries are considered. For mature industries there is evidence for specialization externalities but not for diversity externalities. However, for high technology industries both channels of knowledge externalities are found, suggesting that high technology industries benefit from large, diverse agglomerations; but with maturity production decentralizes to smaller, more specialized cities according to the concept of spatial-temporal product cycles. Using panel data for the contiguous U.S. states, Partridge and Rickman (1999) directly relate measures of externalities to state labor productivity differences, decomposing them into industry mix effects and competitiveness effects. They find that positive static specialization externalities within industry dominate static diversity externalities that result from a diverse range of industries. In addition, Black and Henderson (1999) and Beardsell and Henderson (1999) find faster growth and more innovation when more economic activity is specialized in a single sector.

An important refinement has been made by Feldman and Audretsch (1999). They attempt to link the extent of specialization versus diversity of economic activities to the direct measure of innovative output. In order to test the hypothesis that specialization or diversity is more conducive to innovative output and subsequent economic growth, they estimate a model where the dependent variable is innovative output measured as significant innovations and the explanatory variables are the measures of specialization, science-based diversity, and local competition. By focusing on innovative activity for particular industries at specific locations, they find evidence that specialization does not promote innovative output. The results indicate that diversity across complementary industries sharing a common science base is more conducive to innovation than specialization. In addition, the results indicate that the degree of local competition for new ideas within a city is more conducive to innovative activity than is local monopoly.

While endogenous regional growth theory represents one of the most important advances in regional economics in the past decade, the lack of agreement on the relative importance of specialization and diversity gives an ambiguous message regarding policy choices to promote innovation and economic growth in metropolitan areas. This analysis will join together these strands of empirical research to relate these hypotheses to the crucial issues of spatial patterns of innovation intensity across metropolitan areas.

3. SPATIAL ECONOMETRIC MODEL SPECIFICATIONS

The main purpose of this study is to evaluate empirically the extent to which the innovative performance in a metropolitan area is affected by different channels of knowledge externalities in high technology industries, incorporating a spatial econometric approach. As already noted, it is preferable to test the effects of knowledge externalities on innovative performance rather than indirect effects proxied by employment growth. Therefore, innovative performance, defined as patents per employed worker, is the dependent variable in the models to be presented. As a crucial and new addition to the literature, this study will explicitly deal with the geography of knowledge spillovers by testing for the relationship of spatial interdependence on metropolitan innovative performance.

3.1 Data and Spatial Weights Matrix

Patent statistics are most widely used as an indicator of innovative output of a region. Using patent 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 impacts of patents on actual innovation. 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. The correlation analysis indicates a very tight association ($r = 0.934$) between patents and innovation (Feldman and Florida 1994). In addition, using an exploratory and a regression-based comparison of the innovation count data and data on patent counts, Acs, Anselin, and Varga (2002) find that the measure of patented inventions provides a good representation of innovative activity. Thus, this paper 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.[1]

Despite general agreement on the concept of high technology, there is no general acceptance of precisely which industries to include. This study employs the definition of high technology made in Hecker (1999), which focuses on the proportion of employment in an industry accounted for by scientific, technical, and engineering personnel and on the proportion of employment in an industry accounted for by scientific, technical, and engineering personnel specifically engaged in research and development. Based on these criteria, 31 three-digit industries, 27 in manufacturing and four in services, were selected. Table 1A in the Appendix provides the list of these industries. The data set was based on the 1990 edition of *County Business Patterns* (CBP), produced by the Bureau of the Census. The data set constructed in this study contains the information on employment and number of establishments by three-digit industry for every metropolitan area. In cases where a county-industry has only a few establishments, CBP does not reveal the exact number of employment in that county-industry to maintain confidentiality. Instead, it typically presents the range in which the employment in the county-industry lies. In order to fill in numbers for those censored counties where employment is suppressed, the data set was constructed based on *1990 Comprehensive Employment Data* from the Regional Research Institute at West Virginia University.

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).[2] Although states may be the most relevant policy-making units concerned with fostering innovative activity within their boundaries, they may be regarded as arbitrary economic units. As Krugman (1991a, p. 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 counties among all 3,141 counties in the nation, they 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 that 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

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

[2] Anselin and Varga (1997) made a seminal contribution by utilizing data for 125 metropolitan areas.

easily.[3] Therefore, this study is based on data covering 313 MSAs in the contiguous U.S. states, consisting of all 243 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.

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 or dependence 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 $d_{ij} \leq \delta$, where d_{ij} is the distance between geographic units i and j, and δ 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; Cliff and Ord 1981). This may be related directly to spatial interaction theory and the notion of potential, with $w_{ij} = 1/d_{ij}^{\alpha}$ or $w_{ij} = \exp(-\beta d_{ij})$. 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 1956, 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; Hansen 2001). In general, it is not only geographic proximity that leads to spatial interaction or spatial diffusion between geographic units, but also contacts between geographic units through communication, migration, transactions, and any other type of economic relationship.[4]

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 (Cliff and Ord 1981; Fingleton 2001). In this study, therefore, the measure of spatial interaction of

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

[4] 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. Like Austin, most of these areas are also high technology centers (*Austin American-Statesman*, August 4, 2002).

innovative knowledge between metropolitan areas i and j is extended to accommodate scale and distance effects into the spatial weights matrix via the following specification.

$$(1) \qquad w_{ij} = \frac{Q_i^{\theta} Q_j^{\eta}}{d_{ij}^{\delta}},$$

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 δ^{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 two metropolitan areas increases; however, it increases with innovative intensity of a neighboring metropolitan area. Although the parameters should be estimated, this study *a priori* assumes $\theta = \eta = 1$ and $\delta = 2$ for a standard gravity effect based on the Newtonian analogy (Sen and Smith 1995). In empirical analysis, however, the scale parameters θ and η and the distance decay parameter δ are generally interpreted as the responsiveness of spatial interaction to scale and distance effects, respectively, and are expected to vary in terms of socio-economic context (Haynes and Fotheringham 1984). In this study, sensitivity analysis is employed to determine how sensitive a model is to changes in the values of the parameters of the spatial weights.

3.2 Base Model

To reflect the extent to which the high technology industry sector within a metropolitan area is specialized, this study includes as an explanatory variable a measure of specialization for high technology employment. This measure is defined as the share of total employment in the metropolitan area accounted for by high technology employment in the area relative to the share of total employment accounted for by that high technology industry sector in the United States. A higher value of this measure indicates a greater-than-average degree of specialization of the high technology industry sector in that particular metropolitan area. Thus, a positive coefficient of this variable would indicate that increased specialization of the high technology industry sector within a metropolitan area is conducive to greater innovative activity.

To address Jacobs' theory, we need a measure of the diversity of industries in a metropolitan area. A common measure of diversity is the inverse of a Hirschman-Herfindahl index or the Herfindahl equivalent index (Ellison and Glaeser 1997; Henderson, Kuncoro, and Turner 1995). However, an interesting extension is the assessment of the impact of high technology diversification versus general industrial diversity

(Cortright and Mayer 2001; Chapple et al. 2004). Metropolitan areas that are more diversified within high technology industries may find themselves better positioned in performing innovative activity. Various sources of innovation, cross-fertilization of different ideas, local backward-forward linkages, and interfirm networks within more diversified high technology industries may produce continuing innovative capacity in a metropolitan area, which may generate a higher rate of innovation in the metropolitan area. In order to identify the impact of diversification within the high technology industry sector, the presence of diversity in the high technology industries is included. In this study, therefore, the diversity measure is given by $DIV = 1/ \Sigma_j s_j^2$, where s_j denotes the share of total high technology employment in a metropolitan area attributable to high technology industry j in the metropolitan area. If a metropolitan area is fully concentrated in a single high technology industry, we find $DIV = 1$; this index increases as high technology activities in this metropolitan area become more diverse. This indicator reflects the sectoral diversity within the high technology industries in a metropolitan area. Therefore, it is not necessarily negatively associated with the high technology specialization in the metropolitan area. A positive coefficient of this variable would indicate that a greater diversity among high technology industries is conducive to greater innovative activity.

In measuring the extent of localized high technology competition, this study employs a measure used by Glaeser et al. (1992), which is defined as the number of establishments per worker in the metropolitan high technology industries divided by the number of establishments per worker in the high technology industries in the United States. A higher value of this indicator means that the high technology industry sector has more establishments relative to its employment size in this metropolitan area than it does in the United States. Following Porter (1990), a positive coefficient of this variable would indicate that increased localized high technology competition within a metropolitan area is conducive to greater innovative activity. However, the impact of local competition in high technology industries on innovative activity might be ambiguous. Indeed, as Schumpeterian innovation models emphasize, competition gives firms incentives for devoting resources to R&D investment; but if the diffusion of innovations or geographic knowledge spillovers are too fast, economic profit from R&D investment decreases, which reduces the incentives for R&D investment. In this way, competitive market structure might have a negative impact on innovations.

As a result, the base model to be estimated in this study can be expressed as:

(2) $$INNOV = \beta_0 + \beta_1\, SPEC + \beta_2\, DIV + \beta_3\, COMP + \varepsilon,$$

where *INNOV* is an $(n \times 1)$ vector of a proxy for innovative intensity (i.e., innovative output per worker), *SPEC* a vector of high technology specialization, *DIV* a vector of high technology diversity, *COMP* a vector of local competition in high technology industries, and ε a vector of error terms.[5] However, when models are estimated for cross-sectional data on spatial units, ignoring lack of independence across these units can cause serous problems of model misspecification (Anselin 1988). Also theories of innovation and empirical evidence suggest that urban proximity and neighborhood spillover effects are likely to be significant. Three kinds of spatial econometric models can be used to deal with spatial dependence of observations: the spatial lag model, the spatial error model, and the spatial cross-regressive model (Anselin 1988; Anselin and Bera 1998; Florax and Folmer 1992).

3.3 Spatial Lag Model

In the spatial lag model, spatial autocorrelation of observations is treated by incorporating an endogenous spatial lag variable. The structural model is written in the following form.

$$(3) \qquad y = \rho Wy + X\beta + \varepsilon, \qquad \varepsilon \sim N(0, \sigma^2 I),$$

where y is an $(n \times 1)$ vector of observations on a dependent variable, Wy an $(n \times 1)$ vector of observations on a spatially lagged dependent variable for an $(n \times n)$ spatial weights matrix W, ρ a spatial autoregressive coefficient, X an $(n \times k)$ matrix with observations on the exogenous explanatory variables, β a $(k \times 1)$ vector of corresponding coefficients, and ε an $(n \times 1)$ vector of independent disturbances. The resulting endogenous spatial lag Wy can be considered to be a spatially weighted average of the observations at neighboring locations. Hence, the corresponding spatial lag model to be estimated in this study is given by:

$$(4) \qquad INNOV = \rho WINNOV + \beta_0 + \beta_1\, SPEC + \beta_2\, DIV + \beta_3\, COMP + \varepsilon, \qquad \varepsilon \sim N(0, \sigma^2 I),$$

where $WINNOV$ is a spatially lagged dependent variable for a spatial weights matrix W, ρ a spatial autoregressive parameter, and ε a vector of spherical error terms.

From a spatial filtering perspective (Anselin and Bera 1998), the spatial lag model may be expressed as:

$$(5) \qquad (I - \rho W)y = X\beta + \varepsilon,$$

where $(I - \rho W)y$ is a spatially filtered dependent variable, i.e., with the effect of spatial autocorrelation filtered out. More specifically, the spatial regression model (4) can be expressed as:

$$(6) \qquad (I - \rho W)INNOV = \beta_0 + \beta_1\, SPEC + \beta_2\, DIV + \beta_3\, COMP + \varepsilon, \qquad \varepsilon \sim N(0, \sigma^2 I).$$

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[5] This study includes a human capital variable as a control in the regression. This is further discussed in the next section.

From equation (6), the spatial lag model allows for the proper interpretation of the significance of the exogenous variables, after the spatial effects have been corrected for or filtered out.

The presence of the spatially lagged dependent variable Wy on the right-hand side of equation (3) will induce a nonzero correlation with the error term. $[Wy]_i$ is always correlated with ε_i, irrespective of the correlation structure of the errors. The spatial lag for a given observation i is not only correlated with the error term at i, but also with the error terms at all other locations. Therefore, ordinary least squares (OLS) estimation of the spatial lag model specification yields biased and inconsistent estimates for the coefficients due to the simultaneity between the error terms and the spatially lagged dependent variable. Instead, alternative estimators based on maximum likelihood (ML) and instrumental variables (IV) have been suggested to provide consistent estimators (Anselin 1988; Anselin and Bera 1998; Conley 1999; Kelejian and Prucha 1998; Kelejian and Robinson 1993).

3.4 Spatial Error Model

The second form of spatial dependence is relevant when the spatial dependence works through the error process rather than endogenously through the dependent variable. Spatial error dependence may be interpreted as a nuisance since it reflects spatial autocorrelation in measurement errors. It can also be interpreted as spatial autocorrelation in variables that are otherwise not crucial to the model in the sense that the ignored variables spillover across the spatial unit of observation (Anselin and Bera 1998). Spatial error autocorrelation is modeled as:

$$\text{(7)} \quad \begin{aligned} y &= X\beta + \varepsilon \\ \varepsilon &= \lambda W\varepsilon + \xi, \qquad \xi \sim N(0, \sigma_\xi^2 I), \end{aligned}$$

where λ is the coefficient of spatially lagged autoregressive errors $W\varepsilon$ and ξ is an $(n \times 1)$ vector of spherical error terms (Anselin 1988). Taking into account the spatial autocorrelation of the error term, the regression model to be estimated in this study becomes:

$$\text{(8)} \quad \begin{aligned} INNOV &= \beta_0 + \beta_1\, SPEC + \beta_2\, DIV + \beta_3\, COMP + \varepsilon \\ \varepsilon &= \lambda W\varepsilon + \xi, \qquad \xi \sim N(0, \sigma_\xi^2 I). \end{aligned}$$

Alternatively, from a spatial process perspective, the spatial error specification (7) may be expressed as:

$$\text{(9)} \quad y = X\beta + (I - \lambda W)^{-1}\xi, \qquad \xi \sim N(0, \sigma_\xi^2 I),$$

and the corresponding spatial regression model (7) can be re-expressed as:

$$\text{(10)} \quad INNOV = \beta_0 + \beta_1\, SPEC + \beta_2\, DIV + \beta_3\, COMP + (I - \lambda W)^{-1}\xi, \qquad \xi \sim N(0, \sigma_\xi^2 I).$$

From equation (10), it is evident that a random shock introduced into a specific metropolitan area will not only affect the innovative activity in that metropolitan area, but also will affect the innovative performance of other metropolitan areas through the inverse spatial transformation $(I - \lambda W)^{-1}$. The effects of the random shock will diffuse throughout the entire regional system through the spatial multiplier effect, which yields a Leontief expansion: $(I - \lambda W)^{-1} = I + \lambda W + \lambda^2 W^2 + \lambda^3 W^3 + \cdots$ (Anselin and Bera 1998).

OLS estimation in the presence of non-spherical errors yields unbiased estimates, but a biased estimate of the parameter's variance. Thus, inference based on the OLS estimates may be misleading. Instead, inferences should be based on the spatial error model estimated by ML or generalized method of moments (GMM) (Anselin 1988; Anselin and Bera 1998; Conley 1999; Kelejian and Prucha 1999).

3.5 Spatial Cross-Regressive Model

In addition, we can also construct spatially lagged exogenous variables that are designed to explicitly capture the substantive spillover effects that flow across metropolitan boundaries. Such a spatial lag of an explanatory variable is a spatially weighted average of the values in neighboring metropolitan areas. The structural form of the spatial cross-regressive model is written as:

(11) $y = X\beta + WX^*\gamma + \varepsilon, \qquad \varepsilon \sim N(0, \sigma^2 I),$

where X^* is an $(n \times (k-1))$ matrix of explanatory variables with the constant term deleted, and γ is a $((k-1) \times 1)$ vector of respective coefficients. The spatial cross-regressive model to be estimated in this study is expressed as:

(12) $$INNOV = \beta_0 + \beta_1 SPEC + \beta_2 DIV + \beta_3 COMP + \gamma_1 WSPEC + \gamma_2 WDIV + \gamma_3 WCOMP + \varepsilon$$
$$\varepsilon \sim N(0, \sigma^2 I),$$

where *WSPEC*, *WDIV*, and *WCOMP* are spatially lagged variables of *SPEC*, *DIV*, and *COMP*, respectively, for a spatial weights matrix W. Whereas the spatially lagged endogenous variable in equation (4) might cover all forms of spillovers, the spatially lagged explanatory variables in equation (12) are limited to the spatial effects via the three mechanisms of knowledge spillovers. Thus, equation (12) allows more specific results of knowledge spillover mechanisms, i.e., it gives estimates of both direct effects and spatial lagged effects of the three mechanisms in the process of knowledge spillovers. Because the original explanatory variables and the spatially lagged explanatory variables are exogenous, estimation of the spatial cross-regressive model can be based on OLS.

This study proceeds by first estimating β by means of OLS regression of equation (2). Based on the OLS residuals and a series of diagnostics for spatial effects, a spatial dependence model is implemented where appropriate.

4. ESTIMATION RESULTS

Table 1 presents the estimation results for the alternative models of metropolitan innovative intensity (i.e., number of patents per 100,000 workers) in metropolitan areas, using a database of 313 observations.[6] Column (1) of Table 1 contains the simple descriptive statistics. One concern regarding the estimation of the model is that metropolitan areas with proportionately more knowledgeable people might be expected to generate a greater intensity of innovative activity, *ceteris paribus*, because knowledge spillovers are geographically limited to the metropolitan area and much knowledge is most productive in the metropolitan area within which it is acquired (Black and Henderson 1999; Glaeser, Scheinkman, and Shleifer 1995; Lucas 1988; Rauch 1993; Simon 1998; Simon and Nardinelli 2002). Thus, this study includes as a control in the regressions a human capital variable, measured by the percentage of college graduates as a share of population over 25 years old. Including the human capital variable is expected to have a positive sign because a high proportion of more educated people leads to greater intensity of innovative activity in metropolitan areas.

The base model confirms the significance of the two channels of knowledge spillovers, specialization and diversity, on the intensity of innovative activity in a metropolitan area. As shown in Column (2) of Table 1, the coefficients on the high technology specialization and diversity are positive and highly significant ($p < 0.001$); however, the local competition in high technology industries has a negative but insignificant effect on innovative activity. The result on specialization differs from Feldman and Audretsch (1999). They obtained a negative impact of specialization on innovative activity. However, the measures used in this paper are slightly different from those used in their study. In order to evaluate the extent to which metropolitan innovative performance is affected by the various forms of high technology-based knowledge externalities, this study uses a measure of specialization for high technology employment and a measure of diversification within the high technology industry sector. However, the result in this analysis is consistent with Henderson, Kuncoro, and Turner (1995), although they observe the effects of knowledge externalities indirectly through examination of employment growth. For high technology industries both channels of knowledge externalities are found to be significant. High technology specialization in a metropolitan area facilitates innovation in the metropolitan area. In addition, various sources of innovation, cross-fertilization of different ideas, local backward-forward linkages, and interfirm networks within more diversified high technology industries produce continuing innovative capacity in a metropolitan area, which generates a higher rate of innovation in the metropolitan area. As expected, the coefficient on the human capital variable is positive and highly significant ($p < 0.001$), indicating that a higher level of human capital generates a greater intensity of innovative activity through more localized spillovers in a metropolitan area.

[6] As there is no compelling *a priori* functional form, this study implements a log specification, which allowed us to correct for non-normality of error terms in the starting linear specification.

TABLE 1

Regression Results for Metropolitan Innovative Activity 1990 ($\theta = \eta = 1$, $\delta = 2$)

Model	(1) Descriptive Statistics	(2) Base Model	(3) Spatial Lag Model		(4) Spatial Cross-Regressive Model
Estimation	Means (Std. dev.)	OLS Robust	ML	Robust IV (2SLS)	OLS Robust
Constant		1.257^{**}	0.696^{**}	0.696^{*}	0.522
		(0.199)	(0.259)	(0.322)	(0.320)
ρ			0.199^{**}	0.231^{*}	
			(0.070)	(0.095)	
Specialization	0.714	0.977^{**}	0.935^{**}	0.920^{**}	0.959^{**}
	(0.481)	(0.134)	(0.109)	(0.129)	(0.129)
Diversity	6.386	0.063^{**}	0.060^{**}	0.058^{**}	0.057^{**}
	(3.127)	(0.010)	(0.012)	(0.010)	(0.010)
Competition	1.276	−0.008	−0.015	−0.015	−0.028
	(0.788)	(0.071)	(0.064)	(0.068)	(0.070)
Human capital	19.667	0.036^{**}	0.035^{**}	0.031^{**}	0.035^{**}
	(6.205)	(0.007)	(0.007)	(0.006)	(0.007)
Specialization – spatial lag					0.235 (0.159)
Diversity – spatial lag					0.074^{**} (0.025)
Competition – spatial lag					0.143 (0.118)
R^2-adjusted		0.448		0.473	0.461
AIC		645.728	640.015		641.322
Breusch-Pagan			27.990^{**}		
LM-ERR		7.994^{**}	0.413		4.117^{*}
Robust *LM-ERR*		0.881			0.517
LM-LAG		8.147^{**}			3.610
Robust *LM-LAG*		1.034			0.010

Notes: Estimated standard errors are in parentheses; for the base model and the spatial cross-regressive model, White heteroskedasticity consistent standard errors are in parentheses; ** $p < 0.01$ and * $p < 0.05$.

For the base model, specification tests for spatial dependence are carried out using the Lagrange multiplier tests for spatial error dependence (*LM-ERR*) and spatial lag dependence (*LM-LAG*). As evidenced in a large number of Monte Carlo simulation experiments (Anselin and Rey 1991), the joint use of the Lagrange multiplier tests for spatial lag dependence and spatial error dependence provides the best guidance for model specification. If *LM-LAG* is significant while *LM-ERR* is not, then a spatial lag dependence model is the likely alternative and vice versa. However, when both *LM* test statistics have high values indicating significant spatial dependence, the one with the higher robust *LM* test statistic tends to indicate the correct alternative. In this model, the robust *LM* tests for spatial dependence show that there is an indication of misspecification in the form of spatial lag dependence. OLS estimation of the spatial lag model specification yields biased and inconsistent estimates for the coefficients due to the simultaneity between the error terms and the spatially lagged dependent variable. Instead, alternative estimators based on ML and IV have been suggested to provide consistent estimators (Anselin 1988; Anselin and Bera 1998).

Column (3) of Table 1 displays the results for the model that incorporates a spatially lagged dependent variable. Note that with the exception of the coefficient for high technology local competition, all coefficients are highly significant ($p < 0.001$), including the parameter estimate associated with the spatially lagged dependent variable. Compared with the OLS results in the base model, the spatial lag model exhibits a better overall fit to the data, as indicated by a decrease in the Akaike information criterion (*AIC*) from 645.7 to 640.0. In the spatial lag model, there is no evidence of spatial autocorrelation remaining in the residuals ($p = 0.520$). This result clearly suggests that spatial dependence has been adequately dealt with by incorporating the spatially lagged dependent variable.

The results of the regression estimation can be interpreted in two ways (Anselin and Bera 1998). On the one hand, it yields some information on the relationship between innovative activity and knowledge externalities in a metropolitan area through the parameters of the explanatory variables having controlled for spatial effects. On the other hand, it may help to highlight the pathway whereby geographic knowledge spillover effects take place since it indicates how innovative activity in a metropolitan area is affected by that of neighboring metropolitan areas through the ρ parameter of the spatially lagged dependent variable, after controlling for the levels of high technology specialization, diversity, and local competition in the metropolitan area. The highly significant coefficient for the spatially lagged dependent variable ($p = 0.004$) indicates that the geographic area of the effects of knowledge spillovers exceeds metropolitan boundaries. The fact that innovative activity in a metropolitan area is positively related to the spatially weighted average level of innovative activity in neighboring metropolitan areas suggests that in addition to knowledge externalities originating in the same location, geographic knowledge spillovers from neighboring metropolitan areas have also substantial effects on innovative activity in the metropolitan area.

In the spatial lag model, it is apparent that the spatial Breusch-Pagan test statistic indicates a strikingly significant presence of remaining heteroskedasticity ($p < 0.001$). To mitigate this problem, this study re-estimates the spatial lag model via a heteroskedasticity-robust IV or two stage least squares (2SLS) estimation.[7] Neither the size of the estimated parameters nor their significance differs meaningfully from those of the previous model. The robust IV (2SLS) spatial lag estimates continue to support the

[7] It has been shown that in instrumental variables estimation of the spatial lag model a series of spatially lagged exogenous variables are the proper set of instruments for the spatially lagged dependent variable (Kelejian and Robinson 1993). In this study, instruments for the spatially lagged dependent variable (*WLNINNOV*) are *WSPEC*, *WDIV*, *WCOMP*, and *WHK*.

importance of the effects of knowledge spillovers of high technology specialization and diversity on innovative performance.

Given the indication that spatial interaction extends beyond a given metropolitan area, this study constructs three spatial lag variables to explicitly account for exogenous spatial effects of knowledge spillovers. The explanatory variables in the spatial cross-regressive model are designed to capture the effect of specialization, diversity, and local competition, respectively, in high technology industries in neighboring metropolitan areas. Specifically, for any metropolitan area i, the spatial lags $[WSPEC]_i$, $[WDIV]_i$, and $[WCOMP]_i$ represent the weighted average of specialization, diversity, and local competition in high technology industries in the neighboring metropolitan areas.[8] In fact, by explicitly including the levels of the three sources of knowledge spillovers at the neighboring metropolitan areas as well as for the metropolitan area, we are able to get more precise insights into the spatial extent of geographic knowledge spillovers. Whereas the spatially lagged dependent variable in the spatial lag model might cover all forms of spillovers, the result of the spatial cross-regressive model regression result may provide some evidence on the relative significance of different forms of geographic knowledge spillovers.

As shown in Column (4) of Table 1, when the spatial lag variables are added to the base model specification, the overall model fit improves slightly, as measured by a decrease in the *AIC* from 645.7 to 641.3, but with marginally significant spatial dependence remaining ($p = 0.042$). While local high technology competition in a metropolitan area does not have a significant effect on metropolitan innovative activity, specialization and diversity in high technology industries have positive, significant effects on innovative activity in the metropolitan area. In addition, high technology diversity in its neighboring metropolitan areas has a positive, significant effect on innovative activity in the metropolitan area ($p = 0.003$). Interestingly, however, there is no evidence that the effects of high technology specialization on metropolitan innovative activity spill over from outside the metropolitan area. In contrast to high technology diversity, the effects of high technology specialization seem to be contained within metropolitan areas.

These results suggest that high technology specialization externalities are more localized than high technology diversity externalities, and they work only in a bounded metropolitan area, which may correspond to a self-contained regional system of innovation. On the other hand, it would be particularly advantageous to have the opportunity to explore diverse innovative technological possibilities potentially available from neighboring regions. It seems reasonable to assume that a specific region would benefit more from neighbors that have diverse high technology strengths. This could be simply a "search and matching" and "learning-by-searching" phenomenon (Dosi 1988; Nelson and Winter 1982). There would be a higher probability that specialized producers would be able to acquire useful knowledge and innovations from neighboring regions with a larger number of potentially unique sources. More generally, specialized producers in one

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[8] Formally, the spatial lag $[Wx]_i$ can be obtained as: $[Wx]_i = \Sigma_j w_{ij} x_j$, where w_{ij} is an (i, j) element of the spatial weights matrix W.

region might more readily make up for gaps in the local knowledge or skill base by acquiring knowledge or services from neighboring regions with diverse innovative strength and service offerings.

One concern regarding the estimation of the model is the way in which spatial knowledge spillovers between metropolitan areas are modeled into a spatial weights matrix. As explained earlier, this study *a priori* assumed $\theta = \eta = 1$ and $\delta = 2$ for a standard gravity effect based on the Newtonian analogy. However, the scale parameters θ and η and the distance decay parameter δ could vary in terms of socio-economic context. In order to determine how sensitive the model is to changes in the values of the parameters, this study re-estimates the models by using alternative assumptions about the scale parameters and the distance decay parameter. As shown in Tables 2 and 3, it is apparent that different parameter assumptions produce similar results. In terms of the explanatory power of regression equation, the form of spatial dependence, and the sensitivity of regression coefficients to changes in the parameters of spatial weights, different parameter assumptions provide very similar estimation results. Regression fits of the models are similar, and the structure of spatial dependence is also very similar as alternative models exhibit significant spatial lag dependence except for the assumption of $\theta = \eta = 2$ and $\delta = 2$. In addition, the signs and significance of the explanatory variables representing the channels of knowledge spillovers follow similar patterns for alternative models.[9]

5. SUMMARY AND CONCLUSION

Although several recent empirical studies have provided evidence on the extent of localized, spatially mediated knowledge spillovers, these studies have not established the relative importance of the various mechanisms of knowledge externalities on innovative activity at the level of metropolitan areas. In light of this, this paper has investigated the extent to which innovative activity in a metropolitan area is affected by knowledge spillovers from neighboring metropolitan areas as well as in the metropolitan area itself, and it does so by considering a set of potential mechanisms whereby knowledge is spatially diffused.

The main result of the analysis is that innovative activity in a metropolitan area is positively affected by both specialization externalities and diversity externalities in high technology industries. A second important issue addressed in the analysis is the presence of geographic knowledge spillovers across metropolitan boundaries. More precisely, the

[9] Based on the assumption of $\theta = \eta = 1$ and $\delta = 3$, high technology specialization in its neighboring metropolitan areas has a marginally significant effect on innovative activity in the metropolitan area ($p = 0.050$). The spatial weights based the assumption of zero weight attributed to scale (i.e., $\theta = \eta = 0$ and $\delta = 2$) produce a positive, significant coefficient on the spatial lag of high technology specialization; however, there is a significant presence of remaining spatial dependence.

TABLE 2

Sensitivity Analysis: Distance Effects

	(1) $\theta = \eta = 1$ and $\delta = 1$			(2) $\theta = \eta = 1$ and $\delta = 3$		
Model	Spatial Lag Model		Spatial Cross-Regressive Model	Spatial Lag Model		Spatial Cross-Regressive Model
Estimation	ML	Robust IV (2SLS)	OLS Robust	ML	Robust IV (2SLS)	OLS Robust
Constant	−0.505	−1.059	−0.517	0.902**	0.878*	0.736
	(0.423)	(0.733)	(0.616)	(0.222)	(0.272)	(0.280)
ρ	0.572**	0.783**		0.134*	0.171*	
	(0.139)	(0.236)		(0.052)	(0.075)	
Specialization	0.943**	0.904**	0.974**	0.935**	0.917**	0.951**
	(0.108)	(0.129)	(0.133)	(0.109)	(0.130)	(0.129)
Diversity	0.058**	0.055**	0.053**	0.060**	0.058**	0.059**
	(0.012)	(0.011)	(0.010)	(0.012)	(0.010)	(0.010)
Competition	−0.012	−0.015	0.005	−0.015	−0.021	−0.034
	(0.064)	(0.068)	(0.073)	(0.064)	(0.068)	(0.070)
Human capital	0.035**	0.032**	0.037**	0.035**	0.033**	0.034**
	(0.007)	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)
Specialization – spatial lag			0.147			0.240*
			(0.476)			(0.122)
Diversity – spatial lag			0.255**			0.042*
			(0.061)			(0.018)
Competition – spatial lag			0.057			0.141
			(0.202)			(0.094)
R^2-adj. / *Sq.Corr.*		0.479	0.474		0.470	0.457
AIC	637.707		633.602	641.314		643.711
Breusch-Pagan	28.576**			27.605**		
LM-ERR	0.916		0.901	0.127		3.522
LM-LAG			1.298			2.867

Notes: Estimated standard errors are in parentheses; for the spatial cross-regressive model, White heteroskedasticity consistent standard errors are in parentheses; ** $p < 0.01$ and * $p < 0.05$.

TABLE 3

Sensitivity Analysis: Scale Effects

	(1) $\theta = \eta = 0$ and $\delta = 2$			(2) $\theta = \eta = 2$ and $\delta = 2$		
Model	Spatial Lag Model		Spatial Cross-Regressive model	Spatial Error Model		Spatial Cross-Regressive Model
Estimation	ML	Robust IV (2SLS)	OLS Robust	ML	GMM (Iterated)	OLS Robust
Constant	0.545*	0.241	0.452	1.252**	1.252**	0.589
	(0.254)	(0.348)	(0.316)	(0.180)	(0.180)	(0.342)
ρ	0.264**	0.394**				
	(0.070)	(0.095)				
Specialization	0.927**	0.864**	0.940**	0.940**	0.941**	0.982**
	(0.107)	(0.128)	(0.130)	(0.108)	(0.108)	(0.132)
Diversity	0.057**	0.053**	0.057**	0.057**	0.057**	0.056**
	(0.012)	(0.010)	(0.010)	(0.012)	(0.012)	(0.010)
Competition	−0.013	−0.024	−0.031	−0.026	−0.025	−0.014
	(0.063)	(0.068)	(0.072)	(0.066)	(0.066)	(0.069)
Human capital	0.034**	0.034**	0.033**	0.038**	0.038**	0.037**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Specialization – spatial lag			0.502*			0.073
			(0.205)			(0.159)
Diversity – spatial lag			0.058*			0.079**
			(0.024)			(0.024)
Competition – spatial lag			0.172			0.116
			(0.115)			(0.119)
λ				0.220*	0.217	
				(0.086)	–	
R^2-adj. / *Sq.Corr.*		0.488	0.462		0.455	0.462
AIC	633.947		640.831	641.042		640.687
Breusch-Pagan	27.521**			27.203**		
LM-ERR	0.003		7.821**			1.113
LM-LAG			6.397*	0.388		1.527

Notes: Estimated standard errors are in parentheses; for the spatial cross-regressive model, White heteroskedasticity consistent standard errors are in parentheses; ** $p < 0.01$ and * $p < 0.05$.

spatial dependence model specifications show that there also exist geographic knowledge externalities across boundaries, which implies that innovative activity in a metropolitan area is positively influenced by the level of innovativeness of neighboring metropolitan areas. Given the indication of spatial dependence in innovative activity in metropolitan areas, this study also constructs three spatial lag variables to explicitly account for the spatial effects of the three different channels of knowledge spillovers. Interestingly, high technology diversity externalities in neighboring metropolitan areas have significant effects on innovative activity in a given metropolitan area, whereas there is no evidence that the effects of high technology specialization externalities on metropolitan innovative activity spill over from outside metropolitan areas. This suggests that the effects of high technology specialization seem to be contained within metropolitan areas; in other words, high technology specialization externalities are more localized than high technology diversity externalities.

In conclusion, the results of this study shed some light on the relationship between the process of knowledge spillovers and the industrial characteristics of the neighboring metropolitan areas as well as within a metropolitan area. From the viewpoint of national innovation systems, what matters is not only the distribution of innovative activities across regions, but also the way in which regions interact with each other as elements of an innovation system (Edquist 1997; Lundvall 1988; Nelson and Rosenberg 1993). Insights into spatial dependence of innovative activity allow for more effective implementation of regional policies and for the possibility of regional cooperation. In this respect, these findings have an important consequence for regional economic policies. They suggest that regional economic policy makers consider the specific geographies of such knowledge spillovers, and give helpful hints on how regional policy coordination might promote a virtuous circle of regional economic growth.

APPENDIX

TABLE 1A High Technology Industries

SIC	Industry
281	Industrial inorganic chemicals
282	Plastics materials and synthetics
283	Drugs
284	Soap, cleaners, and toilet goods
285	Paints and allied products
286	Industrial organic chemicals
287	Agricultural chemicals
289	Miscellaneous chemical products
291	Petroleum refining
348	Ordnance and accessories, nec
351	Engines and turbines
353	Construction and related machinery
355	Special industry machinery
356	General industrial machinery
357	Computer and office equipment
361	Electric distribution equipment
362	Electrical industrial apparatus
365	Household audio and video equipment
366	Communications equipment
367	Electronic components and accessories
371	Motor vehicles and equipment
372	Aircraft and parts
376	Guided missiles, space vehicles, parts
381	Search and navigation equipment
382	Measuring and controlling devices
384	Medical instruments and supplies
386	Photographic equipment and supplies
737	Computer and data processing services
871	Engineering & architectural services
873	Research and testing services
874	Management and public relations

Source: Adopted from Hecker (1999).

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