REGIONAL ECONOMIC DEVELOPMENT RESEARCH LABORATORY

Research Report 05-2006-01

May 2006

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I. Introduction

Innovation, supported by a developed and active entrepreneurial system, has long been recognized as critical to regional economic competitiveness (for a review see Chesire and Malecki, 2004). According to Porter (1990, 1996, 1998), regional competitiveness is driven by gains in productivity, and advances in productivity result from sustained innovative activity. This view is consistent with the new growth theory (Romer 1986, 1990) and the new economics of innovation and technological change (Nelson, 1993).

The innovation -- economic development relationship is good economic news for regions with significant innovative capacity (e.g., the Research Triangle in North Carolina) or the resources to attract a major research and development center (e.g., Florida and the Scripps Institute). Unfortunately, for many local economies, however, innovative capacity and activity are distributed very unevenly across space. For example, among the 1,343 counties in the 13 Southern states, 26 counties had an average of 100 or more utility patents a year from 1990 to 1999 while 681 counties averaged less than one utility patent per year for the same period. A clustering of patenting activity would not necessarily be detrimental to the economic development prospects of areas with little

**Presented paper at the 2006 Annual Meetings of the Canadian Economics Association and Canadian Agricultural Economics Society, Montreal, May 2006. Please do not quote without permission of the authors.*

innovative activity if there existed the spillovers of jobs and income from the innovation centers to other areas. Evidence of such spillovers is relatively limited. Acs (2002, p. 165) for example, concluded that "We have established a striking correlation between local R&D and subsequent high-technology employment in the same MSA and three-digit industry cluster. There is apparently no spillover relationship from R&D in other industry groups." These findings were duplicated by Shapira (2004) who noted that Georgia's innovation and technology development initiatives had little "trickle down" impact outside the Atlanta metropolitan region.

The absence of strong and widespread spillover effects from the clusters of innovative activity may contribute to a divergence of economic development trends between metropolitan and rural areas. Yet many nonmetropolitan counties have a history of innovative activity, and this base of innovation may serve as the foundation for an endogenous development strategy for these areas. The goal of this research is to identify the local and regional characteristics associated with innovative activity in nonmetropolitan counties in the South. Innovative activity will be measured by utility patent counts for the ten-year period 1990 through 1999. Of special interest are the determinants of innovation in nonmetropolitan counties near metropolitan clusters of innovation. Specifically, is patenting activity in nonmetro counties associated with activity in the metro core, and if so, what characteristics of rural counties contribute to increased innovation?

The paper is organized as follows. First, we review recent research on the association between innovative activity and local economic development. Next, we provide an overview of innovative activity in the metro and nonmetro South from 1990 to

1999. Local indicators of spatial association (Local Moran I) are used to identify the cores of clusters of innovation among Southern counties. Third, knowledge production functions are estimated for the 591 nonmetropolitan counties in labor market areas with a metropolitan core. The principal goal of these estimations is to determine the influence of metro innovative activity on nonmetro counties in the metro area's LMA. Our findings indicate that patent activity in metro areas had a small but statistically significant association with patent totals for nearby nonmetro economies. We did not find, however, any relationship between university research and development expenditures in the metro core and patenting activity in the remaining counties of the LMAs. Policy recommendations are provided in the conclusions section of the paper.

II. Innovation and Local Economic Development

Empirical support for the role of innovation in regional economic growth is provided in a study of county level differences in 2002 per capita incomes and 1997 to 2002 per capita income growth (Schunk, Woodward, and Hefner, 2005). The authors used county-level utility patents and university research and development expenditures as measures of local innovation and innovative capacity. Their findings indicate that "Roughly two-thirds of the variation in county-level per capita income across the U.S. can be explained by variations in these measures of innovation and innovative capacity (p. 9)," and . . . "counties with higher levels of patents and university research and development also appear to see faster rates of growth (p. 11)."

Barkley, Henry and Nair (2006) also found a strong correlation between local indicators of innovation and innovative capacity and measures of economic growth and

development for metropolitan areas in the South. In this research, cluster analysis was used to divide the 107 metro areas in the South according to 16 indicators of innovative activity (e.g., patents, university R&D expenditures); innovative capacity (e.g., employment in high-technology manufacturing, employment in scientific and technical occupations); and entrepreneurial environment (e.g., venture capital investments, employment in business services). The cluster analysis identified six groupings of metropolitan areas that the authors labeled Outliers, High, College Towns, Medium, Below Average, and Low based on the magnitude of the area's innovative activity and capacity. Only 21 of the metropolitan areas were classified as "Regional Innovative Systems" based on relatively high levels for the selected measures of innovation (Outliers: 4, High: 12, and College Towns: 5). The "Outliers" cluster exhibited markedly higher 1990 to 2000 growth rates in population, employment and earnings than any of the remaining 5 cluster groupings. In addition, the metro areas in the "High" and "College Town" clusters outperformed the cities in the "Medium" cluster which in turn outperformed the metro areas in the "Below Average" and "Low" clusters.

Eberts, Erickcek, and Kleinhenz (2006) used factor analysis on 40 community characteristics to "distill" the principal "growth factors" associated with economic growth in 118 metropolitan areas. The eight growth factors identified in the study were: skilled workforce, urban assimilation, racial inclusion, legacy of place, income inequality, locational amenities, business dynamics, and urbanization/metro structure. Among these factors, however, the authors (p. ii) suggested that "a skilled workforce is the primary driver of economic growth." The "skilled workforce" was a proxy for the innovative capacity of the metropolitan economies as represented by seven variables: productivity

in the information sector, patents per employee, graduate degrees, bachelors degrees, labor force occupations and skills, and percent of population between 16 and 64. Among these seven variables, the authors noted (p. 42) that the percentage of the workforce with a bachelor's degree and the number of patents per employee stood out in their correlation with area output and productivity growth.

III. Overview of Nonmetropolitan Patenting Activity

Patents as Proxy for Innovation. Previous measures of the innovative process in a region generally focused on: (1) inputs into the process such as public and private expenditures for research and development or employment in scientific and technical occupations; (2) an intermediate output measure such as patents; or (3) proxy measures for innovative output and capacity as reflected in employment in high technology and information technology industries, new product development as reflected in trade and technical publications, or venture capital funding for new enterprises (Barkley, Henry, and Nair, 2006). Among these alternatives, patents have become a popular measure for innovative activity at the local level (e.g., county or metropolitan area) because annual data are readily available from the U.S. Patent and Trademark Office. Alternatively, innovation measures such as new products, private research and development expenditures, and employment in high tech industries may not be available for many nonmetropolitan counties because of data collection costs or data disclosure regulations.

Patent counts are not without shortcomings when used to represent innovation. First, all inventions are not patented and all patented inventions are not of equal consequence with respect to new products or production processes (Griliches, 1984).

Gordan and McCann (2005) suggest that there are three common features of all innovations: newness, improvement, and the overcoming of uncertainty. It is unlikely that all patents equally provide the three features of innovation. Second, Zucker and Darby (2006) claim that the key to new high-technology industries is the presence of "star scientists" and not the scientists' "disembodied discoveries." The authors note that patents tend to diffuse over time while the science and engineering stars become more concentrated. Third, patenting activity is concentrated in manufacturing. Activities in trade and service industries that provide "newness, improvement, and overcoming of uncertainty" are less likely to be patented. Thus the use of patent data may over-represent the relative innovative activity of counties with significant manufacturing sectors. Finally, patents are credited to the home address of the lead scientist on the patent. This location may not be the same county where the research and development occurred or where the new product/process was implemented. Acs, Anselin, and Varga (2000) recognize the shortcomings of patent data, but their research finds a reasonably high (.79) correlation between patent and SBA innovation counts at the metropolitan level, plus patent and innovation counts are associated in a similar manner to explanatory variables included in regional knowledge production functions. The authors (p. 28) conclude that "The empirical evidence suggests that patents provide a fairly reliable measure of innovative activity."

Patents 1990-1999. The innovation activity in Southern nonmetropolitan counties (as reflected in utility patents 1990-99) varied markedly across the 965 counties (1990 nonmetro designation). One-hundred and fifteen nonmetro counties (11.9%) reported no patents for the 10 year period (see figure 1). Another 534 counties (55.3%) averaged less

than one patent per year for the time period. In sum, over two-thirds (67.2%) of the Southern nonmetropolitan counties had fewer than 10 patents over the 10 year period. Alternatively, a relatively small number of nonmetro counties were very active in innovation. Seventeen nonmetro counties (table 1) averaged more than 10 patents per year from 1990 to 1999. These 17 counties accounted for 3,255 patents or 25.7% of the all patenting activity among the 965 Southern nonmetro counties. Among the most innovative nonmetropolitan areas are counties with major research universities (Oktibbeha, MS and Payne, OK); counties near major federal research centers (Roane, TN and Indian River, FL); counties with large employment in the oil industry (Washington and Stephens, OK): and counties near metropolitan areas (Hall, GA and Bradley, TN).

Metropolitan areas, as expected, had significantly more patenting activity than nonmetro counties (table 2). The average metropolitan county had 287.4 patents from 1990 to 1999 for an average of 18.7 patents per 10,000 residents. Nonmetro counties averaged only a total of 13.1 patents and 5.1 patents per 10,000 population. Proximity to a metro area did not necessarily result in greater patenting activity for the nonmetro county. The average number of patents (13) and patents per 10,000 residents (5) were almost identical for the 591 nonmetro counties in Labor Market Areas (LMAs) with a metro core versus the 374 nonmetro counties in LMAs consisting entirely of nonmetro counties.

Spatial Concentrations. Previous research indicates that innovative activity is positively associated with the availability of localization and urbanization economies (see, for example, Gordon and McCann, 2005 and Anderson, Quigley, and Wilhelmsson,

2005). In addition, the existence of limited geographic spillovers from innovative activity (Acs, 2002) suggests that patenting activity in the South may be clustered in locations with significant R&D inputs plus supportive environments. Of particular interest to this study are the identification of innovation clusters in the South and the role of nonmetro areas in these clusters.

The Local Moran I was selected as the local indicator of spatial association (see equation 1). The selected spatial weights matrix (*W)* is a contiguity matrix where $w_{ij}=0$ if counties *i* and *j* are not contiguous and $1/\eta$ if the counties share a boundary (η = number of counties contiguous to county *i)*. The county attributes are total patents 1990-1999 and total patents per 10,000 people, 1990-1999.

$$(1) \qquad I_i = Z_i \left[\sum W_{ij} Z_j \right]$$

$$\begin{aligned} \text{where } I_i &= \text{Local Moran for county } i \\ Z_i &= \text{standardized value of patent counts (density) for county } i \\ Z_j &= \text{standardized value of patent counts (density) for county } j \\ W_{ij} &= 1/n \text{ if } i \text{ and } j \text{ are contigious, } 0 \text{ otherwise} \end{aligned}$$

Figure 2 provides the LISA results for total patents. Clusters of high patenting activity (46 counties) are evident in Texas (Houston, Austin, Dallas); Atlanta; South Florida; Raleigh-Durham, North Carolina; Northern Virginia; and Washington County, Oklahoma (home of Phillips Petroleum). Also evident are numerous clusters of low innovative activity. These agglomerations of counties with few patents occur in Appalachian Kentucky, the Mississippi Delta, the Deep South Cotton Belt, and Western Texas and Oklahoma.

The LISA clusters of high total patents may understate innovative activity in the South because the Local Moran I identifies only the cores of the high-high clusters. Missing from Figure 2 are the fringe counties to the high-high clusters that have high patent values but lack high-patent neighbors in most directions. Also missing are "hot spots" of patenting activity. These counties have high total patents, but the patenting activity in their neighboring counties is insufficient for inclusion as a core in a high-high cluster. To help identify the "fringe" and "hot spot" counties, we added all counties with 89 or more patents from 1990 to 1999 (89 was the fewest number of patents for a county included in a high-high cluster). One-hundred and fifty additional counties were identified using the modified selection criteria - - 18 nonmetro and 132 metro counties (figure 4). Some of these 150 counties are fringe counties of the high-high clusters, especially in the case of Florida and the Raleigh-Durham area of North Carolina. In general, however, the additional counties represent "hot spots" -- counties with high patent totals surrounded by counties with a mix of patenting activity. These areas may represent "emerging" clusters of innovation if spillovers to nearby counties are significant.

Table 4 provides the LISA results for patent density (patents 1990-99 per 10,000 population). These findings (38 counties in high-high clusters) are similar to those for total patents except that the Atlanta and Florida clusters disappear and clusters in the oil/gas rich areas of Texas and Oklahoma become more prominent (especially the Tulsa-Bartlesville area). Patent density is high in these nonmetro Southwest counties more because of sparse population than high patent output.

The fringe and "hot spot" counties missed by the LISA were identified by including all counties with more than 10 patents per 10,000 population (the minimum patent density among the 38 counties in the high-high clusters). In addition, we included only counties with 10 or more total patents for 1990-1999. Two-hundred and thirty seven counties met the selected criteria for fringe and hot spots (78 nonmetro and 159 metro). Most metropolitan areas in the South were represented as hot spots based on the relatively low cut-off of 10 patents from 1990 to 1999 per 10,000 residents. In addition, many of the identified nonmetro counties were fringe counties of the identified metropolitan areas. In sum, it appears that the LISA for total patents is more discriminating than that for patent density.

IV. Estimating Nonmetropolitan Knowledge Production Functions

Following Griliches (1979) and others (e.g., Jaffe, Trajtenberg, and Henderson, 1993; Fritsch, 2002; and Acs, 2002), the concept of a knowledge production function is used to identify the contributing factors to a county's innovative activity. This function assumes that output of the innovative process is a result of inputs into the process (e.g., private and university R&D). For this study, innovative output is represented by utility patents in the county from 1990 to 1999 (USTPO).

The knowledge production function may be expressed in Cobb-Douglas form as:

$$(2)\ log(I) = \beta_0 + \beta_1 log(PR) + \beta_2 log(UR) + \beta_3 Z + e$$

Where *I* is a proxy for innovation output (e.g., patents), *PR* is industry R&D, *UR* is university R&D, and Z is a vector of county and regional characteristics. Measures of private and university R&D expenditures for nonmetropolitan counties are not available.[1]

The proxy variable selected for *PR* is percent of county employment in scientific and technical occupations, and the proxy variable for *UR* is the number of individuals in the county enrolled in college. County and regional characteristics found in earlier research to be associated with innovative activity are the structure of the local economy, characteristics of the local labor market, and innovative activity in nearby communities (spillovers). More specifically, research on innovative activity in states and metropolitan areas indicates a positive association between area patent numbers and (a) employment in high-tech industries (Riddel and Schwer, 2003); (b) size, density, and diversity of the local economy (Anderson, Quigley, and Wilhelmsson, 2005); (c) proportion of small and large firms in the area (Gordon and McCann, 2005); and (d) the presence of patenting activity in nearby locations (Lim, 2004; Acs, 2002).

Of particular interest to this study is the association between innovative activity in metropolitan areas (MSAs) and patent counts in nonmetro counties in the labor market areas (LMAs) of the MSA. The following model was estimated for the 591 Southern nonmetropolitan counties in LMAs with a metro core area.

$$(3)\quad I = \beta_0 + \beta_1 PR + \beta_2 UR + \beta_3 EMP + \beta_4 MFG + \beta_5 HTECH + \beta_6 DIV + \beta_7 MET + \beta_8 COMP + \beta_9 COMP^2 + \beta_{10} WI + \beta_{11} DIST + \beta_{12} AMTY + e$$

Where *I* is total patents in county 1990-1999, and *PR* and *UR* are as defined earlier. *EMP* (total county employment, 1990) is a proxy for the scale and density of the county economy. *EMP* is hypothesized to be positively associated with patenting activity. *MFG* and *HTECH* are the percentage of total employment in manufacturing and high-technology manufacturing industries, respectively.[2] The coefficient on *HTECH* is hypothesized to be positive while the coefficient on *MFG* is uncertain. Patenting among

manufacturers is high relative to other sectors, but Glaeser and Saiz (2003) found that innovative firms avoided traditional manufacturing areas. The industrial diversity of the county economy (*DIV*) is represented by the inverse of the Hirshman-Herfindahl Index, and a positive association is anticipated between *DIV* and *I*. The influence of establishment size on innovation is estimated through the Glaeser competitiveness measure (*COMP* = number of establishments/employment). A U-shaped relationship between *COMP* and patents is consistent with innovation occurring primarily in the largest and smallest establishments. A negative coefficient on *COMP* and a positive coefficient on $COMP^2$ are consistent with earlier findings. *MET* represents one of four alternative measures of innovative activity in the core MSA of the county's LMA. Innovative activity in the metro area is measured by total patents 1990-1999; patents per 10,000 residents; total academic R&D expenditures 1997-1999; and percentage of employment in scientific and technical occupations in 1990.[3] A positive coefficient for *MET* supports the hypothesis of a spillover of innovative activity from metro to nonmetro areas. Finally, some patenting activity in nonmetro counties may reflect the residential choices of scientists and not the location of the patenting activity. The variables *DIST* (miles from county's largest city to MSA core city) and *AMTY* (the McGranahan (1999) natural amenity rank for the county) were included to partially control for county patent activity that may be associated with population spillovers. A list of the variables and data sources is provided in table 3. All explanatory variables except metro patents and metro university R&D expenditures used 1990 values to control for possible endogeneity issues. In addition, all variables were expressed in log form so that the estimated coefficients are elasticities.[4]

V. Summary of Findings

Nonmetro Counties Only. The dependent variable in the knowledge production functions, nonmetro county patents 1990-1999, is count data with an over dispersion of observations of zero or near zero. Following Wooldridge (1991), the poisson estimation method with robust standard errors was selected to account for this over dispersion of count data. Five models were estimated to determine the role of nonmetro county characteristics on county patent totals and the sensitivity of the initial estimations' findings to the inclusion of four measures of innovative activity in the metro core of the nonmetro county's labor market area. The selected measures of MSA innovative activity and capacity are MSA patent totals, MSA patents per 10,000 population (patent density), MSA university R&D expenditures, and MSA employment in scientific and technological professions. University R&D expenditures is our proxy variable for university-based innovative activity and scientific and technical employment is our measure of inputs in industry related innovation.

The findings for the five estimations are presented in tables 4a and 4b. The associations between nonmetro county characteristics and county patent totals are similar to those found in earlier studies using state-level and metro-level data. Nonmetro patent totals were positively associated with the size (employment) and industrial diversity of the local economy. A relatively large manufacturing sector was not significantly related to patenting activity, and no significant relationship was found between high-technology employment in nonmetro counties and patents. Acs (2002) found that the presence of high technology industries facilitated the spillover of innovation. A base of high-tech firms in a nonmetro area appears to offer little advantage in terms of increased patenting

activity. This is consistent with earlier findings by Barkley, Dahlgren, and Smith (1988) that nonmetro high-tech firms differed little from firms in traditional nonmetro manufacturing industries.

The competitiveness of the local industry structure (COMP = number of establishments/total employment) was not statistically correlated with innovative activity in the nonmetro counties. This finding is inconsistent with earlier research indicating that relatively high levels of innovation are associated with both a small number of large establishments as well as a large number of small establishments. The percentage of the labor force in science and technology professions (our proxy for industry R&D) was positively related to county patent totals. Our proxy variable for university R&D (college enrollment in county) also was positively associated with county innovative activity. The college enrollment variable is, however, correlated with county size as measured by the total employment variable (.65). Thus, college enrollment may be reflecting agglomeration economies in addition to (or instead of) local university research and development activity.

The availability of local amenities (as reflected in the McGranahan index) and proximity to metro areas were positively associated with nonmetro patent totals. This finding may indicate that the more innovative firms in nonmetro areas are located in counties with higher amenities and access to metro areas. Alternatively, the lead scientists on patents may reside in adjacent, high amenity nonmetro counties but work in metro areas. Thus, these findings may reflect residential instead of production location choices.

Of principal interest to this study is the role of spillovers in nonmetro county patent activity. The spatially lagged dependent variable (W • Patents) indicates a positive association between patent total in a county and patent activity in surrounding counties. That is, counties with low patent totals tend to cluster and counties with high patent totals tend to locate near similar counties. Alternatively, patent and R&D activity in metro areas of the LMAs had relatively little influence on patent totals in the nonmetro counties. MSA patent totals and MSA patent density were positively associated with nonmetro patent activity, but neither of the coefficients were close to statistically significant (at the .10 level). Metro inputs for the innovation process (university R&D and private R & D as reflected in scientific and technical employment) were negatively related to nonmetro patent counts but not at high levels of statistical significance. The absence of a strong correlation between MSA innovation measures and patent counts in nearby nonmetro counties was not unexpected. Recent research finds evidence of technology spillovers within metropolitan areas (Fischer and Varga, 2003; Lim, 2004; and Acs, 2002); however, this research also notes that these spillovers dissipate with distance. For example, Fischer and Varga (2003, p. 315) concluded that "Our empirical results confirm the presence of geographically mediated knowledge spillovers . . . The results also demonstrate that such spillovers follow a distinct distance decay pattern." The findings for Southern nonmetropolitan counties appear to indicate that these counties are too distant from the metro innovation centers to benefit greatly from available spillovers.

Nonmetro Counties Plus. One interpretation to the findings provided in Table 4 is that metropolitan areas are defined so broadly as to internalize most of the spillovers

resulting from innovative activity concentrated in the core counties. Isserman (2005) suggested an alternative to the metro-nonmetro designations of counties based on population density and percent of the population that resides in rural areas. Four county classifications resulted from Isserman's criteria: rural, mixed, rural, mixed urban, and urban. Of special interest to this paper are the rural counties, counties defined by Isserman as having (1) a population density less than 500 per square mile, and (2) 90 percent of the county's population is in rural areas or the county has no urban area with a population of 10,000 or more (p. 475). Fifty-six "rural" counties were contained within the metropolitan areas of the South in 1990. Innovative activity in these rural counties would be consistent with urban-rural knowledge spillovers, yet this activity was not captured in our analysis of nonmetro county patent counts.

The knowledge production functions expressed in equation (2) were re-estimated for the 591 nonmetro counties plus the 56 rural counties in the Southern MSAs. The MSA characteristics in each LMA were re-calculated to reflect the exclusion of the rural counties from the MSA. As before, the production functions were estimated using the Woolridge (1991) poisson estimation procedure with robust standard errors to account for over dispersion of the count (patent totals) data.

The regression results for the 647 counties are presented in Table 5. The findings are similar to those in Table 4 with two principal exceptions. First, patent counts in nonmetro plus rural counties were positively related to MSA patent totals and MSA patent density. The expansion of the data set from nonmetro (591 counties) to nonmetro plus rural (647 counties) resulted in both an increase in the size of the coefficients and the significance levels. These findings support earlier research indicating that a county's

innovative activity is associated with innovation in nearby locations. However, the sensitivity of the association to the inclusion of 56 rural counties in MSAs also is consistent with an earlier findings of a limited spatial dimension to innovation spillovers. MSA fringe counties appear to "benefit" from patent activity in the urban MSA counties, but patent numbers in nonmetro counties in the MSA's LMA have little correlation to patent activity in the core counties. In sum, innovation spillovers from patents are evident but spatially limited.

Second, patent totals in nonmetro plus rural counties are negatively related to expenditures for academic R&D in the urban metro counties. This finding indicates a "backwash" effect between university research in the MSA and innovative activity in the remaining counties of the LMA. University research and development activities may be attracting knowledge resources away from the hinterland areas. This relationship for Southern counties also is consistent with previous research. For example, McCann and Simonen (2005, p. 18) found in a study of innovation in Finland . . . "very little support for the argument that cooperation with universities, research institutes, or consultants plays any role in promoting innovation." Andersson, Quigley, and Wilhelmson (2004), on the other hand, found a positive relationship between university-based research in Sweden and the productivity of labor in the community, but they concluded that the external benefits were highly concentrated geographically. Finally, Zucker and Darby (2005) proposed that star scientists are becoming more concentrated over time as they move to areas with many in their discipline. This concentration of "stars" may further limit the possibility of knowledge spillovers to nonmetro counties not near these centers of science and technology.

Differences Within LMAs. The previous analysis indicates that, on average, 1990-1999 patenting activity in nonmetro and rural counties was not highly correlated with 1990-1999 patenting activity in the labor market area's MSA counties. These findings obscure the differences in patenting activity that exist among the nonmetro and rural counties in an LMA. In the Raleigh-Durham (NC) LMA, for example, there were eight nonmetro-rural counties in 1990, and the 1990-1999 patent totals for these eight counties were 0, 9, 11, 15, 16, 23, 33, and 81. Thus, some counties benefited greatly from proximity to innovative activity in the MSA while other counties realized only limited benefits. The goal of this section is to identify county characteristics associated with metro-to-nonmetro linkages in patent activity within an LMA.

Metro-to-nonmetro linkages were estimated by the ratio of patent totals (1990 to 1999) in the nonmetro (rural) county to the patent totals in the metro urban counties in the LMA. Based on earlier results, we hypothesized that this ratio will be associated with county size (Employment 1990); distanced to MSA core county; industry structure of the county (% Mfg. Employment, % High-Tech Employment, % Employment in Small Establishments (fewer than 20 employees), Industrial Diversity); and quality of local human capital (% College Graduates, % Occupations). The following model was estimated using a *ln-ln* transformation.

$$(4)\quad R = \beta_0 + \beta_1 EMP + \beta_2 DIST + \beta_3 MFG + \beta_4 HTECH + \beta_5 SMALL + \beta_6 DIV + \beta_7 TECHEMP + \beta_8 COLLEGE + \beta_9 METPATDEN + \beta_{10} W \bullet R$$

Where R is the ratio of patents in the county to patents in the MSA urban counties, and the remaining variables are as defined earlier in Table 3. Equation 4 also contains a spatially lagged dependent variable $(W \bullet R)$ to control for spatial auto-correlation and the

variable MetPatentDensity to account for patent intensity differences among the Southern metro areas. Model (4) was estimated for the 212 nonmetro and rural counties in the LMAs of metro areas with 500 or more patents for 1990-1999. Only MSAs with high patent counts were selected because these are the areas from which urban-to-rural innovation spillovers are most likely to be present.

Table 6 provides the OLS regression results for Equation 4. A log transformation of all variables was used, thus the estimated coefficients are elasticities. The findings indicate that the urban-to-rural innovation linkages (as represented by the ratio of county patents to metro area patents) was positively related to county size and proximity to the metro core city. High linkage counties also were characterized by a highly educated population (percent college grads), a diverse industrial base, and a relatively large share of small establishments (employment less than 20). Relatively large shares of manufacturing employment, high-tech employment, and scientific and technical occupations were not significantly related to the linkage measure. The above findings are consistent with recent research (Andersson, Quigley, and Wilhelmsson, 2005) indicating that the level of innovation is sensitive to (1) the density of employment and establishments and (2) the diversity of the area economy.

VI. Conclusions

The findings of this research indicate only a limited association between innovative activity in the MSA urban counties and patent levels in the nonmetro and rural counties in the MSA's labor market area. In addition, the nonmetro and rural counties with the strongest urban-to-rural spillovers have large and diverse employment bases,

well educated labor forces, and proximity to the MSAs. As such, we conclude that most nonmetro areas will benefit little from state and local policies that promote systems of innovation in metropolitan areas. Among the relatively few nonmetro counties that do benefit from metro innovative activity, the benefits will be concentrated in the counties that least need economic assistance.

In summary, programs to encourage innovation likely will lead to further concentration of economic activity in a relatively small number of metro areas and a few fortunate nonmetro and rural counties near these metro centers of innovation. For most nonmetro counties in the South, centers of innovation in metro areas will be benign at best or detrimental if significant backwash effects exist. Therefore, programs and policies targeted at innovation and entrepreneurship in nonmetro areas will be needed if the nonmetro counties are to participate in the knowledge economy. Increased R&D expenditures at universities and government research centers in nonmetro counties may be helpful in stimulating innovation in these areas. Yet, the quality of the local labor force and the entrepreneurial environment must improve if any increases in innovative activity are to ultimately lead to new economic activity.

Endnotes

(1) Total R&D expenditures at universities and colleges is available from the National Science Foundation; however, only seven Southern nonmetro colleges and universities were included on the NSF data base. Thus, we substituted number of college students as the measure for university R&D. Scientific and technical professions are defined as computer science; engineering except civil; and natural, physical, and social sciences.

(2) The classifications for high-technology industries followed that of Markusen et al. (2001).

(3) For the metropolitan areas, total patents 1990-1999 is a proxy for innovation outputs while total academic R&D expenditures measures university innovation inputs and total employment in scientific and technical occupations is a proxy for industry R&D inputs.

(6) For 115 nonmetro counties the 1990 to 1999 patent total equaled zero. These counties were assigned a patent total equal to one so that the log of the dependent variable was defined *(ln (1) = 0).*

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Table 1. Southern Nonmetropolitan Counties That Averaged More Than 10 Patents Per Year, 1990-1999.

County	State	Patents
Washington	Oklahoma	554
Stephens	Oklahoma	480
Montgomery	Virginia	327
Hall	Georgia	193
Roane	Tennessee	188
Henderson	North Carolina	174
Iredell	North Carolina	148
Indian River	Florida	145
Payne	Oklahoma	143
Franklin	Texas	128
Bradley	Tennessee	127
Kay	Oklahoma	121
Monroe	Florida	113
Kleberg	Texas	108
Oktibbeha	Mississippi	107
Oconee	South Carolina	105
Beaufort	South Carolina	104

Table 2. Mean Values of Patenting Activity 1990-1999 by County Type, Selected Counties

County Type	Mean Total Patents	Mean Patents Per 10,000 Population
Metropolitan (393)[a]	287.4	18.7
Nonmetropolitan (965)	13.1	5.1
<u>Nonmetro Subgroups</u>		
Metro LMA (591)	13.1	5.1
Nonmetro LMA (374)	13.0	5.1
<u>Regional Innovation Systems</u>		
<u>Nonmetro Subgroups</u>		
Outliers (31)	16.7	6.2
High (44)	19.3	7.4
College Towns (24)	7.1	3.9
Medium (135)	15.2	5.2
Below Average (320)	10.7	4.4
Low (36)	18.1	8.2

[a] Number of Southern counties in the category

Table 3. Variable Descriptions and Data Sources

Variable	Description
% Mfg Emp	Percent of total county employment in manufacturing, 1990 (CBF)
% High-Tech Emp	Percent of total county employment in high-technology manufacturing, 1992 (Census of Manufacturers)
Total Emp	Total county employment, 1990 (CBP)
Distance	Miles from largest city in county to core city in LMA's MSA
% Tech Occup.	Percent of employment in technical professions – computer science; engineering; natural, physical and social sciences (BLS, 1990)
% College Enrol	Number of individuals in county enrolled in college (Census, 1990)
Ind Diversity	Inverse of Hirschman-Herfindahl Index, two-digit SIC, 1990 (CBP)
Comp	Number of establishments/total employment (CBP, 1990)
Amenities	McGranahan Index of natural amenities (ERS, USDA, 1999)
% Small Estab	Percent of county establishments with fewer than 20 employees
W • Patents	Spatially lagged dependent variable, W = contiguity matrix
MSA Patents	MSA patent totals, 1990-1999 (USTPO)
MSA Patent Density	MSA patents per 10,000 population, 1990-1999 (USTPO)
MSA Univ R & D	MSA University expenditures for research and development, 1997-1999 (NSF)
MSA Tech Emp	MSA technical employment as percent of total employment (BLS, 1990)

Table 4a. Regression Results for Total Patents in 591 Nonmetro County, 1990-1999, Poisson Estimations.[a]

Dependent Variables	Model 1 No MSA Term	Model 2 MSA PAT Total	Model 3 MSA PAT Density
% Mfg. Emp	.110	.109	.106
	(1.33)[b]	(1.30)	(1.25)
% High Tech Emp	.020	.021	.020
	(1.00)	(1.01)	(1.00)
Total Emp	.56e-4	.56e-4	.56e-4
	(10.56)	(10.20)	(10.67)
Distance	-.005	-.006	-.005
	(-2.08)	(-2.21)	(-2.05)
Amenities	.386	.385	.376
	(5.12)	(5.08)	(4.64)
% Tech Occup.	.141	.137	.139
	(2.49)	(2.36)	(2.43)
College Enrol.	.68e-4	.69e-4	.68e-4
	(5.43)	(5.22)	(5.48)
Indust. Diversity	.168	.168	.169
	(3.28)	(3.22)	(3.29)
Comp	18.809	18.661	20.302
	(.51)	(.50)	(.55)
$Comp^2$	-274.988	-269.715	-289.868
	(-.83)	(-.81)	(-.88)
W. PATENTS	.140	.139	.136
	(4.57)	(4.53)	(4.39)
MSA PATENTS		.08e-4	
		(.43)	
MSA PAT DEN			.004
			(.72)
MSA UNIV R & D			
MSA Tech Emp			
Intercept	-1.213	-1.190	-1.248
	(-1.16)	(-1.12)	(-1.21)
R^2 (Psuedo)	.526	.527	.527
Chi Sq	1230.1	1256.7	1253.7
Number	591	591	591

[a] The analysis followed the Woolridge (1991) poisson estimation method with robust standard errors. Estimations were made using STATA 9.2 (www.state.com)
[b] t-values for the coefficients are provided in parentheses.

Table 4b. Regression Results for Total Patents in 591 Nonmetro Counties, 1990-1999, Poisson Estimations.

Dependent Variables	Model 4 UNIV R & D	Model 5 MSA SC & Tech
% Mfg. Emp	.107	.097
	(1.30)	(1.44)
% High Tech Emp	.022	.020
	(1.09)	(.96)
Total Emp	.56e-4	.56e-4
	(10.46)	(10.65)
Distance	-.006	-.005
	(-2.05)	(-2.32)
Amenities	.382	.393
	(5.10)	(4.91)
% Tech Occup.	.144	.147
	(2.55)	(2.37)
College Enrol.	.67e-4	.69e-4
	(5.31)	(5.73)
Indust. Diversity	.166	.169
	(3.26)	(3.29)
Comp	17.673	16.558
	(.49)	(.48)
$Comp^2$	-267.041	-252.36
	(-.83)	(-.83)
W. PATENTS	.139	.143
	(4.52)	(4.54)
MSA PATENTS		
MSA PAT DEN		
MSA UNIV R & D	-.001	
	(-1.50)	
MSA Tech Emp		-.084
		(-.55)
Intercept	-1.132	
	(-1.12)	
R^2 (Psuedo)	.528	.528
Chi Sq	1310.2	1233.0
Number	591	591

Table 5a. Regression Results for Total Patents in 647 Southern Counties, 1990-1999, Poisson Estimations. [a]

Dependent Variables	Model 1 No MSA Term	Model 2 MSA PAT Total	Model 3 MSA PAT Density
% Mfg. Emp	-.035	-.050	-.050
	(-.28)	(-.40)	(-.39)
% High Tech Emp	-.001[b]	.002	-.000
	(-.06)	(.07)	(-.02)
Total Emp	.56e-4	.56e-4	.56e-4
	(8.04)	(8.07)	(8.22)
Distance	-.012	-.016	-.012
	(-1.92)	(-2.15)	(-1.87)
Amenities	.493	.476	.465
	(5.57)	(5.63)	(5.13)
% Tech Occup.	.238	.232	.238
	(5.55)	(5.52)	(5.74)
College Enrol.	.52e-4	.56e-4	.51e-4
	(3.66)	(3.90)	(3.60)
Indust. Diversity	.125	.096	.120
	(2.61)	(1.80)	(2.44)
Comp	42.758	40.611	46.037
	(1.14)	(1.13)	(1.19)
$Comp^2$	-805.841	-743.787	-840.865
	(-1.82)	(-1.77)	(-1.84)
W. PATENTS	.247	.246	.238
	(3.92)	(3.76)	(3.75)
MSA PATENTS		.70e-4	
		(2.51)	
MSA PAT DEN			.010
			(2.64)
MSA UNIV R & D			
MSA Tech Emp			
Intercept	-1.238	-1.029	-1.337
	(-1.41)	(-1.14)	(-1.50)
R^2 (Psuedo)	.503	.516	.511
Chi Sq	1326.6	1363.1	1330.2
Number	647	647	647

a The analysis followed the Woolridge (1991) poisson estimation procedure with robust standard errors.

[b] values for the coefficients are provided in parentheses.

Table 5b. Regression Results for Total Patents in 647 Southern Counties, 1990-1999, Poisson Estimations.[a]

Dependent Variables	Model 4 UNIV R & D	Model 5 MSA SCI & Tech
% Mfg. Emp	-.038	-.026
	(-1.89)[b]	(-.23)
% High Tech Emp	.002	-.001
	(.10)	(-.06)
Total Emp	.56e-4	.57e-4
	(8.17)	(7.53)
Distance	-.013	-.013
	(-1.95)	(-1.85)
Amenities	.476	.494
	(5.73)	(5.45)
% Tech Occup.	.238	.239
	(5.56)	(5.45)
College Enrol.	.51e-4	.50e-4
	(3.62)	(3.03)
Indust. Diversity	.120	.124
	(2.54)	(2.51)
Comp	38.319	47.887
	(1.10)	(1.17)
$Comp^2$	-749.638	-871.286
	(-1.85)	(-1.67)
W. PATENTS	.243	.244
	(3.92)	(4.01)
MSA PATENTS		
MSA PAT DEN		
MSA UNIV R & D	-.002	
	(-2.00)	
MSA Tech Emp		.085
		(.52)
Intercept	-1.015	-1.754
	(-1.22)	(-1.52)
R^2 (Psuedo)	.506	.504
Chi Sq	1339.9	1334.5
Number	647	647

a The analysis followed the Woolridge (1991) poisson estimation procedure with robust standard errors.

[b] values for the coefficients are provided in parentheses.

Table 6. OLS Regression Results for Ratio of Patents in Nonmetro and Rural Counties To Patents in MSAs, 1990-1999

Dependent Variables	Estimated Coefficients
% Mfg. Emp	.130
	(1.41)[a]
% High Tech Emp	.005
	(.13)
Total Emp	.977
	(7.36)
Distance	-1.129
	(-7.51)
% Tech Occup.	.019
	(.09)
% College Grad	.645
	(2.76)
Indust. Diversity	.342
	(1.73)
% Small Est	4.73
	(1.91)
W. Ratio	.292
	(4.89)
MSA Pat Den	-8.42
	(-6.84)
Intercept	-25.716
	(-2.42)
R^2 (Psuedo)	.631
F (10,202)	37.18
Number	212

[a] t-values for the coefficients are provided in parentheses.

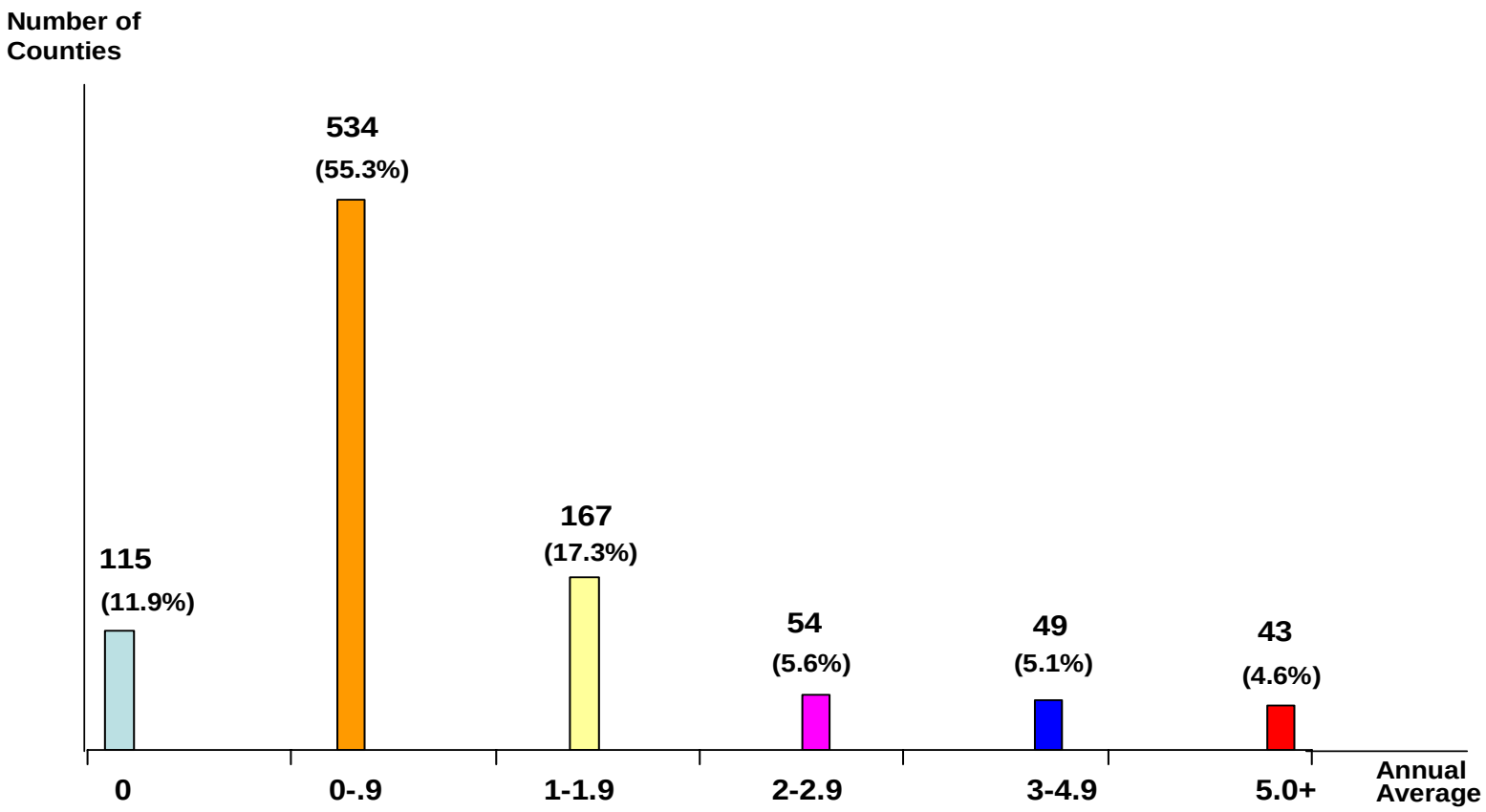


Figure 1. Distribution of Patenting Activity Among Southern Nonmetropolitan Counties, 1990-1999.

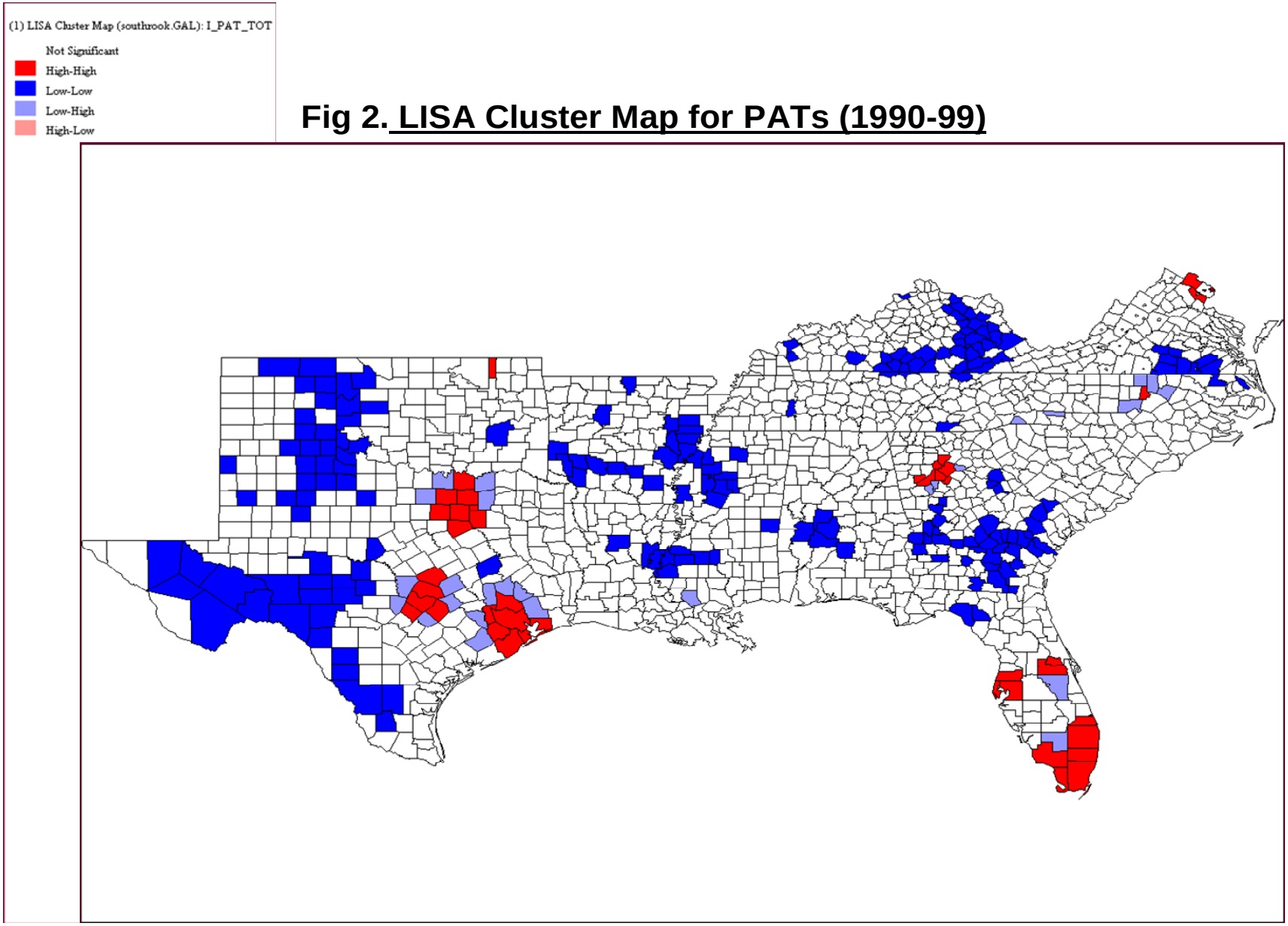
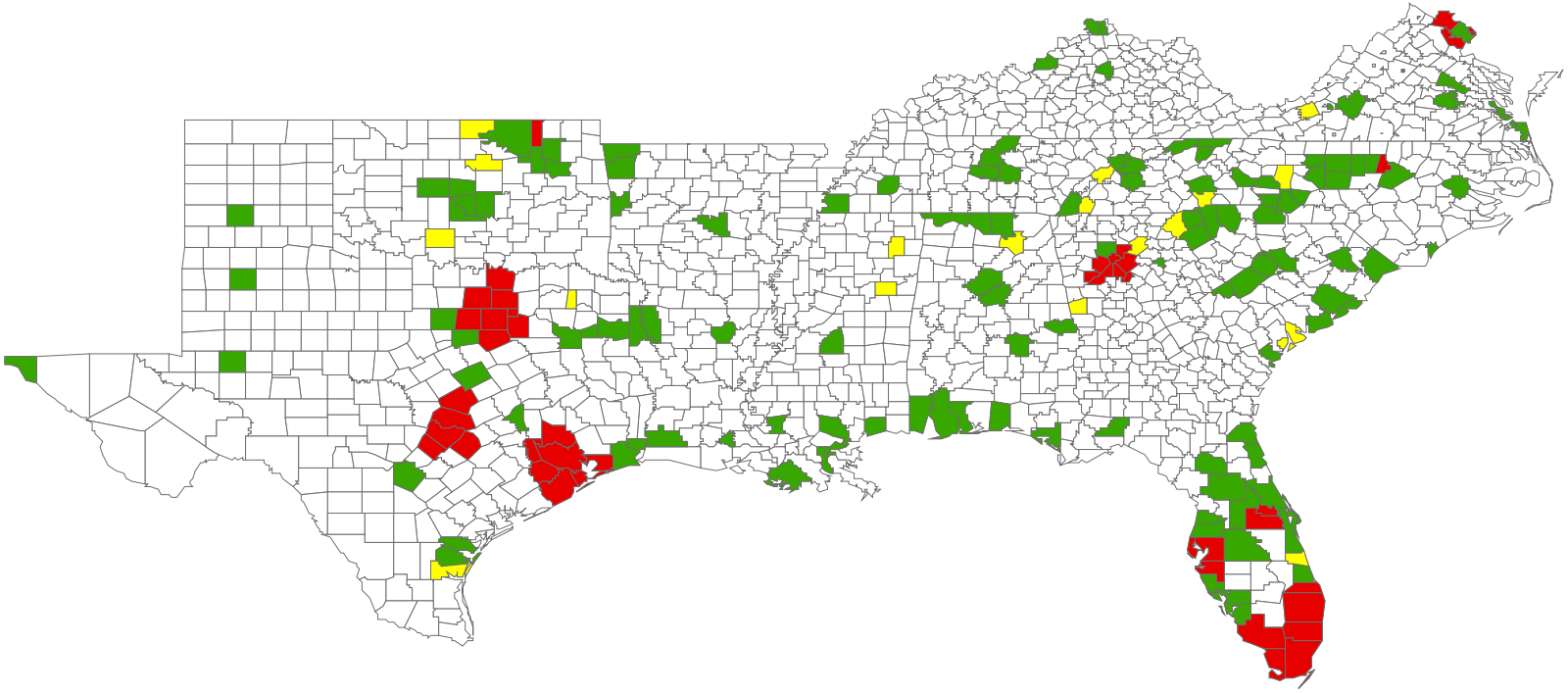


Fig 2. LISA Cluster Map for PATs (1990-99)

Fig 3. LISA Results Based on Total PATs in MSA and Non-MSA Counties



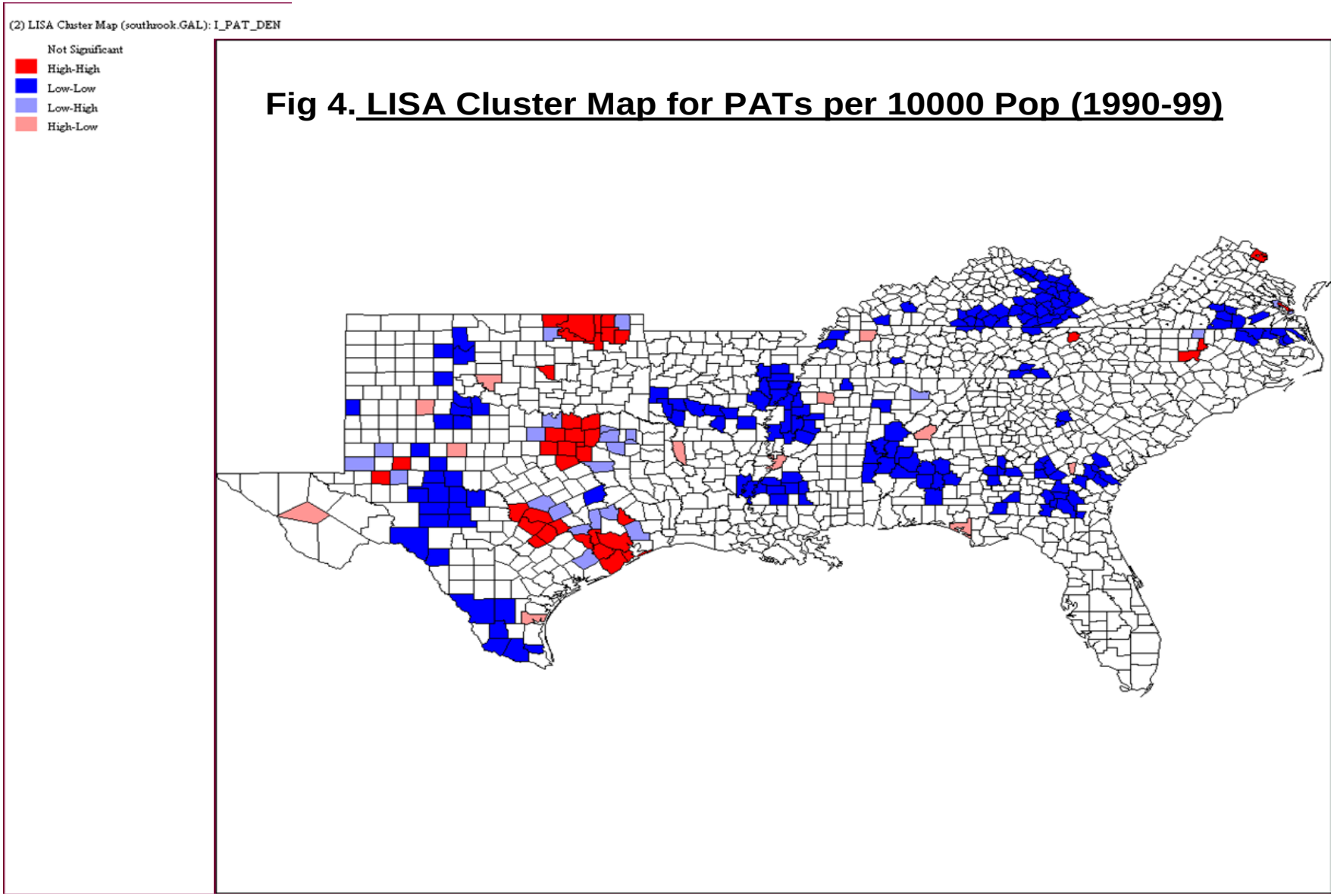


Fig 4. LISA Cluster Map for PATs per 10000 Pop (1990-99)

Fig 5. LISA Results Based on PATs per 10000 Pop in MSA and Non-MSA Counties with 10 or more