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REGIONAL INNOVATION SYSTEMS (RIS) IN THE U.S. SOUTH: THE ROLE OF LOCAL CHARACTERISTICS OF RIS IN RURAL DEVELOPMENT

Doohee Lee
Clemson University, dooheel@clemson.edu

REGIONAL INNOVATION SYSTEMS (RIS) IN THE U.S. SOUTH:
THE ROLE OF LOCAL CHARACTERISTICS OF RIS IN RURAL DEVELOPMENT

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Doohee Lee
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Dr. David L. Barkley, Committee Chair
Dr. Mark S. Henry
Dr. Michael D. Hammig
Dr. John T. Warner

ABSTRACT

Regional innovation systems (RIS) and innovative activity are now recognized as having important roles to play in regional economic development policy. The goal of this study is to expand our understanding of the relationship between regional economic growth and the local characteristics of RIS. The research identified the existence and importance of sources of innovation, knowledge spillovers, and regional spillovers as the principal characteristics of RIS in the South. A knowledge production function approach was used to estimate the determinants of innovative activity in rural counties. A zero inflated negative binomial model was estimated to capture the influence of local characteristics of the county on the existence and volume of innovative activity in the county.

The findings of this research indicate that local innovative activity and characteristics of RIS matter in regional economic growth. Patenting activities in metro areas had a positive and statistically significant association with patent totals for nearby rural areas. However, the results of the OLS models and the simultaneous system of equations for the extended Carlino-Mills model found a negative association between metro patenting activity and economic growth of neighboring rural areas, indicating "backwash" effects. Thus, the implication from these findings is that regional policymakers should be careful of investments in metro RIS if the goal is economic development in nearby rural areas.

DEDICATION

To **JEHOVAH JIREH**.

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I would like to express my gratitude to: Sangsoo and Ahnja P. Lee, my parents, without whom I could not have started; Dr. L. David Barkley, my adviser, without whom I would not have continued; and Kyungmi J., Jubilee D., and Yobel S. Lee, my family, without whom I could not have finished.

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CHAPTER 1

INTRODUCTION

This study examines the role of Regional Innovation Systems (RIS) on county innovative activity and regional economic growth in the South[1]. Cooke and Morgan (1998, p. 71) defined RIS as "regions that possess the full panoply of innovation organizations set in an institutional milieu, where systemic linkage and interactive communication among the innovation actors is normal." The popularity of RIS is closely related to the apparent shortcomings of traditional regional development models and policies, the emergence of identifiable and successful clusters of innovative activity in many regions, and the increased use of regional development policy for stimulating innovative activity at the local level (Enright, 2001; Asheim and Isaksen, 1997).

California's Silicon Valley, Massachusetts' Route 128, North Carolina's Research Triangle, and Florida's Scripps Institute are considered as the intensely productive regions with innovative activities. Policymakers, particularly at the local level, increasingly are interested in growing their own regional clusters of innovation. Thus, innovative activity and RIS are now recognized as having important roles to play in regional economic development policy (Black, 2004; Acs *et al.*, 1994). By determining what local characteristics of RIS are associated with the spread of innovative activities at the local level, we can develop policies and programs to enhance the regional economic development benefits related to RIS.

[1] The South is 13 Southern states in the U.S. included in this analysis are: Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, and Virginia.

Most research on innovation and RIS focused on high-tech industries in large metropolitan areas. The findings from such studies of centers of high technology industries provided only limited insights into innovation systems in less technologically-advanced regions. Thus, a potential shortcoming to the strategy of promoting RIS is that innovative activity tends to concentrate in the larger metropolitan areas, and a regional innovation system may overlook the endogenous capabilities of less-developed regions (Wiig and Wood, 1995). For example, the role of nonmetropolitan or rural areas in RIS has received relatively little attention. If a metropolitan area's innovative activity generates "spread" effects on surrounding nonmetropolitan areas, these nonmetropolitan areas will benefit from the development of RIS in the metro core. On the other hand, metropolitan growth may generate "backwash" effects on surrounding nonmetropolitan areas.

The goal of this study is to identify the local characteristics of RIS associated with innovative activity in rural counties in the labor market areas (LMA) of the South. In addition, the research will attempt to determine whether innovative activities in the RIS of metropolitan areas are associated with innovation in nearby nonmetro or rural areas. Innovative activity will be measured by utility patent[2] counts for the ten-year period 1990 through 1999. Of special interest are the determinants of RIS in nonmetro or rural counties near metropolitan clusters of innovative activities. Specifically, is patenting activity in nonmetro or rural counties associated with innovative activity in the metro core, and if so, what characteristics of the metro and rural counties contribute to increased rural innovative activities? A second purpose of the research is to develop and estimate an empirical framework to test for the importance of RIS on regional economic growth. Of special

[2] Among three kinds of patents (utility patents, plant patents, and design patents), utility patents were granted to the inventor or discover of any new and useful method, process, machine, device, manufactured item, chemical compound, or improvement to the same (USPTO, 2005).

interest are the local characteristics of RIS as identified by knowledge production function (KPF) models for Southern rural areas.

The research that follows makes three principal contributions. First, the research extends the framework initiated by Griliches (1979, 1984) to account for the local characteristics of RIS in the South such as innovation sources, knowledge spillovers, and regional spillovers effects. Second, a novel empirical framework is developed to test the relationship between the local characteristics of RIS and rural patent activity at the local level. Third, the paper tests the hypothesis that the contribution of innovative activity to regional economic growth depends on the local characteristics of RIS.

The econometric technique employed in this research (a zero inflated negative binomial model) more accurately accounts for the distributional characteristics of innovation data than previous work that used count data, such as Poisson and negative binomial models. The findings of this research indicated that the innovative performance of regions is improved when firms became better innovators by interacting with various support organizations within their region. This study also confirmed that local innovation activity and regional spillovers mattered in regional economic growth. Patenting activities in metro areas had a small but statistically significant association with patent totals for nearby rural economies. However, the results did not show any relationship between university R&D expenditures in metro cores and patenting activity in the rural remaining counties of the core's LMA. Furthermore, the results of the OLS models and the simultaneous equation for the extended Carlino-Mills model found a negative association between metro patenting activity and economic growth of neighboring rural areas, indicating 'backwash' effects.

This paper is organized as follows. Chapter 2 provides a brief background of studies of RIS at the regional level. These earlier works provide both the empirical and conceptual bases for the research on the South. This chapter includes an overview of innovative activities in the South and a brief survey of the role of the extended KPF models for research on RIS.

Chapter 3 develops an empirical model based on a KPF to evaluate the local characteristics of RIS at the nonmetro or rural county level for the South during 1990-99. The chapter includes a description of the data set for the empirical analyses, followed by discussion of the econometric techniques adopted to examine the spillovers effects of patenting activity. This is followed by a more analytical discussion of technology-related issues associated with the RIS, including an investigation of the region as the base for regional innovation activities and the capabilities of firms located there. Specific regional factors that affect innovation activities are also examined. Chapter 3 concludes with empirical analysis of the determinants of innovative activity in the nonmetro and rural counties of the South.

Chapter 4 develops an empirical model based on the OLS models and the extended Carlino-Mills model to evaluate the relationship between innovative activity and economic growth at the rural county level of the South during 1990-2000. The chapter includes a description of the data set for the empirical analysis, followed by a discussion of the econometric technique adopted to examine the determinants of county economic growth rates. Lastly, Chapter 5 summarizes the empirical findings and focuses on the policy implications emanating from this body of work.

CHAPTER 2

RIS AND REGIONAL DEVELOPMENT

2.1 Introduction

The concept of RIS has received much attention from policy makers and academic researchers as a framework for innovation policy making in recent years (Asheim *et al.*, 2003; Cooke *et al.,* 2002). The popularity of the concept of RIS is closely related to the emergence of regionally identifiable clusters of industrial activity as well as the surge in regional development policies to sustain innovation-based learning economies. A major issue is the development of an adequate empirical basis for conceptual work focusing on RIS. The goal of this chapter is to review and summarize the recent literature on RIS, and to present a summary of the shortcomings and challenges in this research. Furthermore, this chapter will suggest a research methodology that may be used to determine the local characteristics of RIS.

The remainder of this chapter is organized as follows. First, RIS at the regional level are defined based on local characteristics identified in the literature. The literature reviews provide both the empirical and conceptual bases for the research on RIS in the South. Second, I review recent research on the association between the local characteristics of RIS and regional economic development. Third, this study provides an overview of innovative activity in the 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 and the spatial spillovers of innovative activity from the RIS. In the final section, the summary of findings is provided.

2.2 Studies of RIS

The concept of RIS as an economic development policy is relatively new though RIS have in the literature since the early 1990s (Cooke, 1992, 2001). This section reviews some of the conceptual thoughts and local characteristics of RIS and the role of RIS in regional economic growth.

2.2.1 Identification of RIS

The concept of RIS has no commonly accepted definitions. According to Doloreux and Parto (2004), the origin of the concept was from two main bodies of theory and research. The first is systems of innovation. The systems of innovation literature conceptualized innovation as a social process (Doloreux and Parto, 2004). Freeman (1987) defined a regional innovation system as a network of public and private institutions that through its activity and interaction creates, brings, modifies, and spreads new technologies. The second is regional science. From a regional point of view, innovation is a localized process, suggesting that the benefits deriving from localization advantages and spatial concentration through which the process of knowledge creation and dissemination occurred (Doloreux and Parto, 2004). Andersson and Karlsson (2002) suggested that a regional innovation system consisted of two key actors, regional knowledge spillovers and sources of innovation.

Conceptualizations of RIS are provided by Cooke *et al.* (2000) and others (Asheim and Isaksen, 2002; Wolfe, 2003; Enright, 2001). According to these studies, all regions have some kind of RIS, including not only regions with strong preconditions to innovation, but also old industrial regions, peripheral regions, and rural regions (Wigg, 1999). Cooke (2001) and Cooke *et al.*(1998) ranked RIS at different points on a scale from strong to weak, and

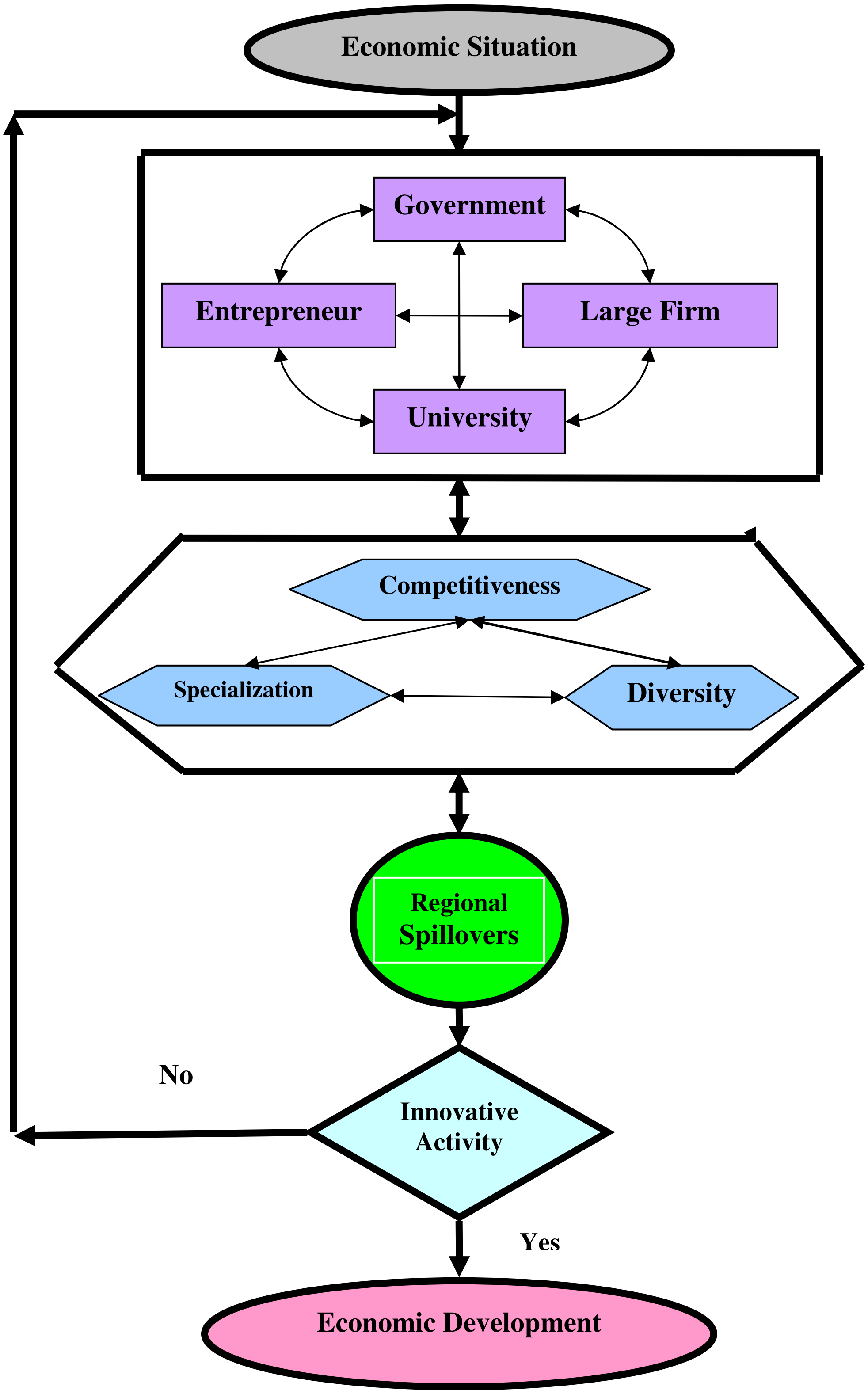
Asheim and Isaksen (2002) distinguished between different types of RIS in order to capture some conceptual variety. Based on this earlier research, Niosi (2000, p.8) defined RIS as "regions in which innovative activities take place. Innovative activities must be measurable by some universally acceptable indicator, such as the granting of patents to locally-based inventors or the launching of new products designed and developed in the area."

Wigg and Wood (1995), however, argued that there had been an overemphasis on core regions and high-tech industries in the literature. This early focus also created difficulties for the application of findings from the studies of core RIS to RIS in less technologically-advanced regions. Thus, studies on RIS often cited the lessons that might be learned from successful, usually geographically core regions, without fully understanding on the endogenous capabilities of less-developed regions (Wigg and Wood, 1995, p.4).

Three broad dimensions of the local characteristics of RIS are emphasized in this paper. First are the interactions among different sources of innovation in the RIS such as small firms, large firms, and the wider research community. Second is the role of knowledge spillovers to which innovation processes are institutionally embedded in the regional setting of systems of production. Third are regional spillovers, which are related to regional characteristics and may embody localized interactive learning. Accordingly, policy strategies could be oriented towards the promotion of accessibility in the development of a RIS (Andersson and Karlsson, 2002) and the development of local comparative advantages linked to specific local resources.

The context within which firms conduct innovative activities is highly important and may be modeled by analyzing the interrelationships between economic and technological systems at various scales. The RIS are comprised of the elements (small and large firms, universities and government agencies) and relationships (knowledge spillovers and regional spillovers) that interact in the production, diffusion, and use of new knowledge. Figure 2.1 summarizes the concepts, and the following sections discuss the components of RIS in more detail.

Figure 2.1 The Flow Chart of Regional Innovation System



2.2.2 Sources of Innovation

The systemic approach to innovation is founded upon the interactive model of innovation. It is important to promote interactions between different innovative actors that have reasons to interact, such as interactions among small start-up firms, larger firms, universities and government agencies (Cooke, 2001). Baumol (2004) argued that there were four principal sources of innovation (small firms, large firms, government and universities R&D), and each source specialized in a part of the innovation process: revolutionary breakthroughs (small firms), incremental improvements (large firms) and basic research (government agencies and universities).

Role of Entrepreneurs and Small Firms in Innovation

Two recent studies (CHI Research, 2003, 2004) by the U.S. Small Business Administration (SBA) provided support for small firms as important sources of innovation. These reports examined technological change. The entrepreneur is naturally associated with the small startup-firm, and these reports found that small firms were more innovative per employee than larger firms. The study from CHI Research (2003)[3] reported that:

> "The small firm share of U.S. patenting is similar to their share of manufacturing employment, 41%. Small firms produce more highly cited patents than large firms on average. Small firm patents are twice as likely as large firm patents to be among the 1% most cited patents. That is, small firm patents are on average more technically important than large firm patents. Small patenting firms produce 13-14 times more patents per employee as large patenting firms. The small firms are younger than the large firms, but are not new startups. Persistence distinguishes these patenting small firms from innovative small firms in general. We think of

[3] The scope of the research was that a total of 1,071 firms with 15 or more patents issued between 1996 and 2000 were examined. A total of 193,976 patents were analyzed. CHI created a database of these firms and their patents. This list excluded foreign-owned firms, universities, government laboratories, and nonprofit institutions (CHI Research, 2003).

> these small firms the "serial innovators," a term suggested by Leigh Buchanan at *Inc* magazine. Small firm patenting is very strong in health technologies and gaming, and there are a large number of small firm innovators in parts of information technology. Small firm innovation is twice as closely linked to scientific research as large firm innovation on average, and so substantially more high-tech or leading edge. Small firm innovation is more extensively linked to outside technology while large firms build more their own technology. Small firm innovators are more dependent on local technology." [CHI Research, 2003, p. 3]

Moreover, the more recent study (CHI Research, 2004, p. ii) found that, "The technological influence of small firms is increasing. The percentage of highly innovative U.S. firms (those with more than 15 U.S. patents in the last five years) that are defined as small firms increased from 33 percent in the 2000 database to 40 percent in the 2002 database…Small companies represent 65 percent of the new companies in the list of most highly innovative companies in 2002."

Koo (2005) argued that a cluster of small firms could achieve economies of scale and flexible specialization through close cooperation among themselves. Many researchers hypothesized that a local economy's performance is linked to entrepreneurial activity if the entrepreneurs serve as a mechanism for knowledge spillovers (Audretsch and Fritsch, 1996; Malecki, 1994). A rich empirical work also linked entrepreneurship to RIS. Feldman (2001) examined the formation of innovative clusters around Washington, D.C. and found that clusters formed not because resources were initially located in a particular region, but through entrepreneurial activity. Feldman notes that large firms have made important contributions to RIS, however, the smaller enterprises have specialized in the breakthroughs.

Role of Large Firms in Innovation

Schumpeter (1947) argued that innovation increased more than proportionately with firm's size, and that large firms had a natural advantage in innovation because there were scale and scope economies in the production of innovations. Firms with greater market power can more easily appropriate the returns from innovation and hence have better incentives to innovate. Of particular significance in innovation is competitiveness and rivalry among oligopolistic firms (Baumol, 2004). According to data provided by the National Science Foundation (National Science Board, 2000), 46 percent of total U.S. industrial R&D funds was spent by 167 companies that employed 25,000 or more workers; 60 percent of these funds was spent by 366 companies with at least 10,000 employees; and 80 percent was spent by 1,990 firms of 1,000 or more employees. Alternatively, about 15 percent of total U.S. industrial R&D funds was spent by the 32,000 companies that employed fewer than 500 workers.

Acs *et al*. (1994) pointed out that the innovation output of all firms increased along with an increase in R&D expenditures, both in private enterprises and in university laboratories. Private enterprises' R&D expenditures played a particularly important role in generating innovation for large firms, while expenditures on government and university R&D played an important role in generating innovative activity for small firms (Audretsch and Feldman, 2003).

Role of Universities and Government Agencies

The last two key developers of innovation are universities and government agencies. Baumol (2004) argued that basic research was difficult for a small or large firm to conduct because it was considered a wasteful investment:

> "From the point of view of the unthinking market mechanism, expenditure on basic research is a 'wasteful' expenditure, because the outlay promises no addition to the profits of the firm. By its very nature, it is nearly impossible to predict whether basic research will yield any financial benefit at

> all and, if so, who will ultimately be the beneficiary. Certainly, it need not be the enterprise that carried it out. That is why governments and universities have had to step in, if basic research of any magnitude was to be carried out. It is important for growth in the long run that this be done, for so much of applied innovation is made possible or is at least stimulated by its results." [Baumol, 2004, p. 330]

An additional contribution of universities and the public institutions to innovation includes the education of the innovator, and also one of the major purposes of research in the academy is the training of the researchers of the future (Baumol, 2004).

University research spillovers were investigated in several empirical studies. Jaffe (1989) and Jaffe *et al.* (1993) provided empirical evidence that university research had a significant effect on innovative activity at the state level. Acs (2002) found that academic research had a high-tech employment spillover at the city level. His results also suggested that spillovers from university research were greater than those from the private industrial R&D. Varga (2000) provided evidence of a positive effect of agglomerations of universities on high technology innovations. Anselin *et al.* (1997) found that regional university research stimulated regional high technology firms' innovative activities in the U.S. Black (2004) concluded that greater R&D activity in the local academic sector also contributed to more innovative activities for small firms, supporting previous evidence that small firms generated innovations from R&D at local universities.

Woodward *et al.* (2006) analyzed the connection between university proximity and the location of new-technology intensive plants. They used a conditional logit model for all counties in the U.S. for 1996. They found that a university's R&D impact on firm location choices varied by industry. These findings were supported by other research indicating that government and university research laboratories provided an important source of innovation to private enterprises (Jaffe, 1989; Feldman and Audretsch, 1998).

2.2.3 Knowledge Spillovers in RIS

There are three regional factors related to the availability and diffusion of knowledge spillovers: industrial specialization, industrial diversity, and regional competitiveness.

Industrial Specialization and Spillovers

The first theory of external economies was developed by Marshall, 1890; Arrow, 1962; and Romer, 1986, hereafter MAR. MAR assumed that for a given region, specialization in a limited number of economic activities would contribute to spillovers and growth (Van Stel and Nieuwenhuijsen, 2004). In a regional innovation system, industrial specialization in a region refers to the geographic concentration of a particular industry within a specific region and may result from the interaction of increasing returns to scale, transportation costs savings, labor pooling, and local demand, generating additional externalities that enhance industry innovation and growth (Krugman, 1991). In the MAR theory, regional specific industry growth is maximized if an industry is dominant in the region, and if local competitiveness is not too strong (Koo, 2005).

Much empirical research focused on the effects of an economy's industrial structure on innovation and growth. Henderson *et al.* (1995) examined employment growth rates between 1970 and 1987 in five traditional capital goods industries located in 224 cities. They found that employment growth in these sectors was positively correlated with a high past concentration in the same industry, supporting the industrial concentration, or MAR view.

Regional Competitiveness and Spillovers

A second theory of knowledge spillovers was proposed by Porter (1990). Porter assumed that local competitiveness accelerated imitation and upgraded innovation. Although competition decreased the relative benefits for the innovator due to large spillovers to competitors, the amount of innovative activity increased because competition forced enterprises to innovate (Van Stel and Nieuwenhuijsen, 2004). Gleaser *et al.* (1992) provided an evidence of fierce competition to innovate, resulting in growth, from the Italian ceramics industries. Thus, while MAR emphasized the negative effect of local competitiveness on the amount of innovative activity, Porter assumed that the positive effects dominated (Van Stel and Nieuwenhuijsen, 2004). The empirical research tends to favor the competitiveness view over the MAR view. Following Glaeser, *et al.* (1992), much of the empirical research found that local competitiveness was more conducive to city growth than was local monopoly. Feldman and Audretsch (1999) also found that local competitiveness was more beneficial to innovative activity than was local monopoly.

Industry Diversity and Spillovers

The third explanation on the availability and significance of local knowledge spillovers was developed by Jacobs (1969). Jacobs believed that the variety of local economic activities played a major role in the innovation process. In her theory, industry variety rather than specialization in the region promoted innovation and industry growth because many knowledge transfers occurred across industries. The availability of Jacobs externalities (*i.e.* spillovers) provided innovating firms with strong incentives to cluster together to take advantage of the various positive agglomeration economies resulting from cross-industry networking (Koo, 2005).

Glaeser *et al.* (1992), Feldman and Audretsch (1999), and Acs et *al.* (2002) examined the role of externalities associated with knowledge spillovers as an engine of regional economic growth. They tested models of knowledge externalities and found that local competitiveness and industrial diversity, rather than regional specialization and monopoly, encouraged employment growth, innovative activities and economic development. Their evidence suggested that knowledge spillovers might occur predominately between, rather than within, industries, consistent with the theories of Jacobs (1969). Alternatively, Henderson *et al.* (1995) showed that either diversity or specialization might create external economies, depending on the industry.

2.2.4 Regional Spillovers in RIS

If knowledge spillovers are important, it follows that they will influence firms' location decisions. In particular, when knowledge is not easily exchanged due to a distance, firms tend to locate in the industry cluster to capitalize on the innovations (*e.g.* patents) in nearby firms (Koo, 2005). Earlier research on RIS supported this view and showed that the innovative activity of firms was based on localized resources such as a specialized labor market, supplier systems, local learning processes, supporting agencies or organizations, and the size of the local economy (Asheim *et al.*, 2003; Cooke *et al.*, 2000). Innovating firms have strong incentives to cluster together to take advantage of the various positive agglomeration economies provided by geographic spillovers (Koo, 2005).

Role of Agglomeration Effects on Innovative Activity

Henderson (1986) showed that agglomeration could affect the productivity levels of local firms through external economies and thereby boost the economic performance of a region, suggesting that such agglomeration effects arose from the diversity of deep local labor markets and information. Malecki (1991) also found that agglomerative economies took the form of two related effects such as localization economies and urbanization economies.

Localization economies occur largely from concentrations of labor and knowledge spillovers, particularly related to high-tech industries (Black, 2004). Rosenthal and Strange (2001) found that firms could benefit from reduced innovation costs generated by lower labor costs if the search for and acquisition of skilled labor is easier due to the proximity of a relevant labor pool, suggesting why many industries requiring certain types of skilled workers are clustered geographically. This labor pooling effect can be especially beneficial to high-tech industries requiring highly skilled and trained workers (Glaeser, 2000). Therefore, the innovative activity in a region may be greater with the presence of a relatively high-tech labor pool (Black, 2004).

Urbanization economies exist because of positive externalities primarily related to the size of a geographic area (large populations and employments), indicating the importance of the size of the local economy (Black, 2004; Jacobs, 1960). The size of a local economy can provide agglomerative economies through greater access to networks among workers, firms and institutions located in the area. Black (2004) also argued that the opportunity for increased communication and interaction among these agents could enhance the innovation process and the ability to perform innovative activity in the area.

Geographical Spillovers of Innovative Activity

Several papers asserted that knowledge spillovers had clear spatial boundaries because the communication between firms and workers depended on their geographical proximity (Feldman and Audretsch, 1999). Baptista (2000) provided empirical evidence that innovations diffused faster within clusters. Lawson and Lorenz (1999) also gave an increased role for the importance of local institutions in encouraging spillovers. It was maintained that relational proximity played a prominent role along with geographical spillovers.

A significant research effort was devoted to finding evidence of regional spillovers. Jaffe *et al.* (1993) found evidence for both the existence of knowledge spillovers and their boundedness in space. They concluded that citations (1972 through 1980) to patents were more likely to come from the same region as the patents to which the citations were made, indicating a spatial phenomenon. It is indicated in several recent studies that companies were attracted to the close proximity of external knowledge inputs such as universities (Audretsch and Stephan, 1996; Zucker et al., 1998). Thus, both theory and empirical findings pointed in the direction that geographical spillovers was critical for the spread of innovations (Feldman, 1994).

A popular approach to empirically model the local characteristics of RIS as well as to test for their influence on regional innovative activities is the knowledge production function framework initiated by Griliches (1979, 1984). This framework has been widely applied in empirical studies of regional innovation in the US (Jaffe, 1989; Anselin et al., 1997, 2000), in Italy (Capello, 2002), in Austria (Fischer and Varga, 2003) and in Germany (Fritsch, 2001). The literature emphasized the importance of interaction between actors, and proximity among innovators is regarded as a core characteristic of RIS (Asheim and Isaksen, 1997).

Regional scientists and economists also have used many different research methodologies in their attempts to assess the existence and magnitude of urban spillovers to rural areas. Much of this literature used the Carlino-Mills modeling frameworks. Henry *et al.* (1999) used a Carlino-Mills model to explain population and employment changes in rural areas based on urban area growth. The model developed by Henry *et al.* (1997, 1999) was extended to the traditional Carlino-Mills model by the addition of a spatial weight matrix as proposed by Boanet (1994). They concluded that rural areas were sensitive to the performance of nearby urban areas, indicating that the spillovers were stronger in rural areas near urban areas with rapid population growth. They also found that employment and population growth in rural areas was significantly impacted by growth in the nearby urban areas.

2.2.5 The Role of RIS in Regional Economic Growth

In the past decades there has been increasing recognition that innovations contributed substantially to local economic growth. According to the new growth theory (*i.e.* the endogenous growth theory), innovation spillovers are an engine of economic growth (Romer, 1986, 1990; Lucas, 1993). The positive relationship between innovation systems and economic growth has been investigated since the works of Schumpeter (1947). Given their purported importance as the sources of regional economic growth, innovation spillovers received considerable treatment in the economic literatures in both empirical and theoretical studies (Griliches, 1984).

Empirical support for the role of innovative activity 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 *et al.*, 2005). Schunk *et al.* (2005) used county-level utility patents and university research and development expenditures as measures of local innovative capacity. Their findings indicated that roughly two-thirds of the variation in county-level per capita income across the U.S. could be explained by variations in these measures of innovation and innovative capacity. They also found that counties with higher levels of patents and university research and development had faster rates of growth (Schunk *et al.*, 2005).

Although the literature on the role of innovative activity on regional economic growth is extensive (Enright, 2001; Porter, 1996; Barkley and Henry, 1997), there is limited evidence on the role of RIS in non-metro or rural areas (Barkley *et al*., 2006; Barkley *et al*., 1999). These studies indicated that nonmetropolitan innovative clusters contributed to higher wages and an increase in business start-ups, but employment was more volatile with industry concentrations. Barkley *et al*. (1996) found that rapid metropolitan growth would stimulate economic activity in hinterlands nearest the metro cores but little spillover of growth was evident in the more peripheral rural areas of the functional economic areas.

Barkley *et al*. (2006) also found a strong correlation between local indicators of RIS and measures of economic growth 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, and only 21 of the metropolitan areas were classified as RIS based on relatively high levels for the selected measures of innovation. Their findings indicated that nonmetro counties near a metro regional innovation system experienced more rapid population and employment growth; however, nonmetro growth rates varied among the three types of metro RIS. In addition, proximity to a metro regional innovation system had a stronger impact on nonmetro population change than on nonmetro employment (Barkley *et al*., 2006).

2.3 Overview of Innovative Activity in the South[4]

Since data on innovations generally are not available at the local level, patents in metropolitan and county areas often are used as a measure of innovative activity. This measure has its disadvantages, since some innovations are not patented and patents differ in their economic impacts. Nonetheless, patents remain a useful measure of the generation of ideas (Barkley *et al*., 2006; Acs *et al*., 2000). Acs *et al*. (2002) used the KPF approach to test whether patent data was a reliable proxy measure of innovative output as opposed to innovation count data (as represented by SBA innovation counts). Preliminary analysis indicated that patent data and innovation count data had a positive correlation coefficient of 0.79. They concluded that patents were a reliable measure of innovative activity. However, Acs *et al*. (2002) suggested that patent data over emphasized the effects of localized interactions. Alternatively, the influences of university R&D were under represented in the model that used patent data.

2.3.1 Innovative Activity in the Southern Counties

The innovative activity in Southern counties, as measured by utility patents 1990-99, varied across the 1342 counties.[5] The average county had 88.89 patents from 1990 to 1999 for an average of 8.94 patents per 10,000 residents (patent intensity). One-hundred and eighteen counties (8.79%) reported no patents for the 10 year period (Figure 2.2). Another 680 counties (50.67%) averaged less than one patent per year for the time period. Thus over

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[4] The revised version of this section was published in the author's article "Innovative Activity in Rural Areas: The Role of Local and Regional Characteristics" (Barkley, Henry, and Lee, 2006).

[5] The data set for employment and population is from the CD-ROM versions of the 1988, 1994, and 2000 County and City Data Books, produced by U.S. Census Bureau. The time span is 11 years, 1990-2000. Because county patents data in 2000 are not available, the time span for patents in this study is 10 years, 1990-1999.

one-half (50.67%) of the Southern counties had fewer than 10 patents over the 10 year period. Alternatively, a relatively small number of counties were very active in innovation. Twenty five counties averaged more than 100 patents per year from 1990 to 1999. These 25 counties accounted for 57,648 patents or 48.33% of the all patenting activity among the 1342 Southern counties (Figure 2.3).

Figure 2.2 Total Patents of Southern Counties, 1990-99

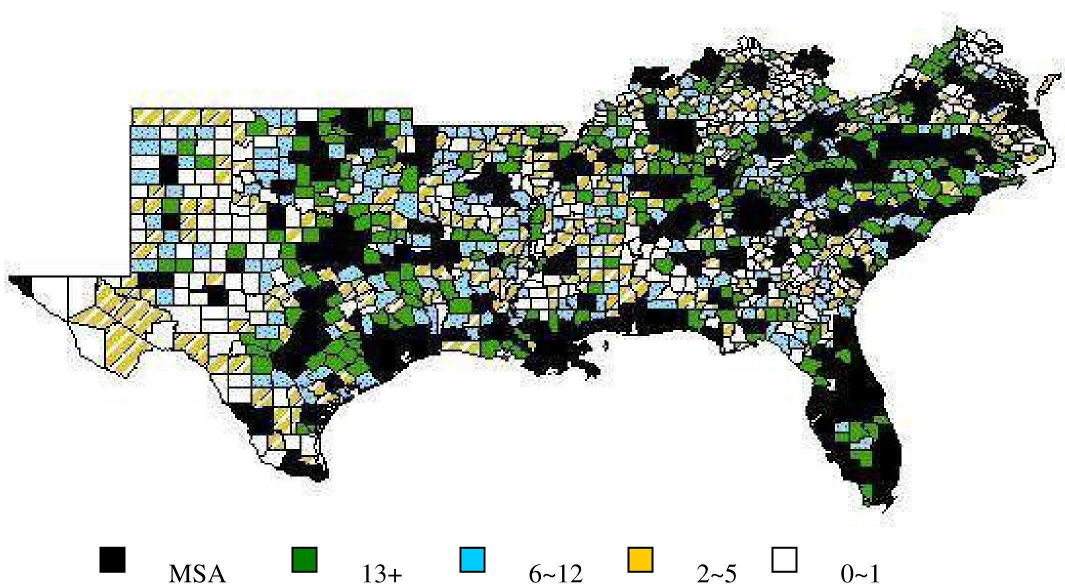
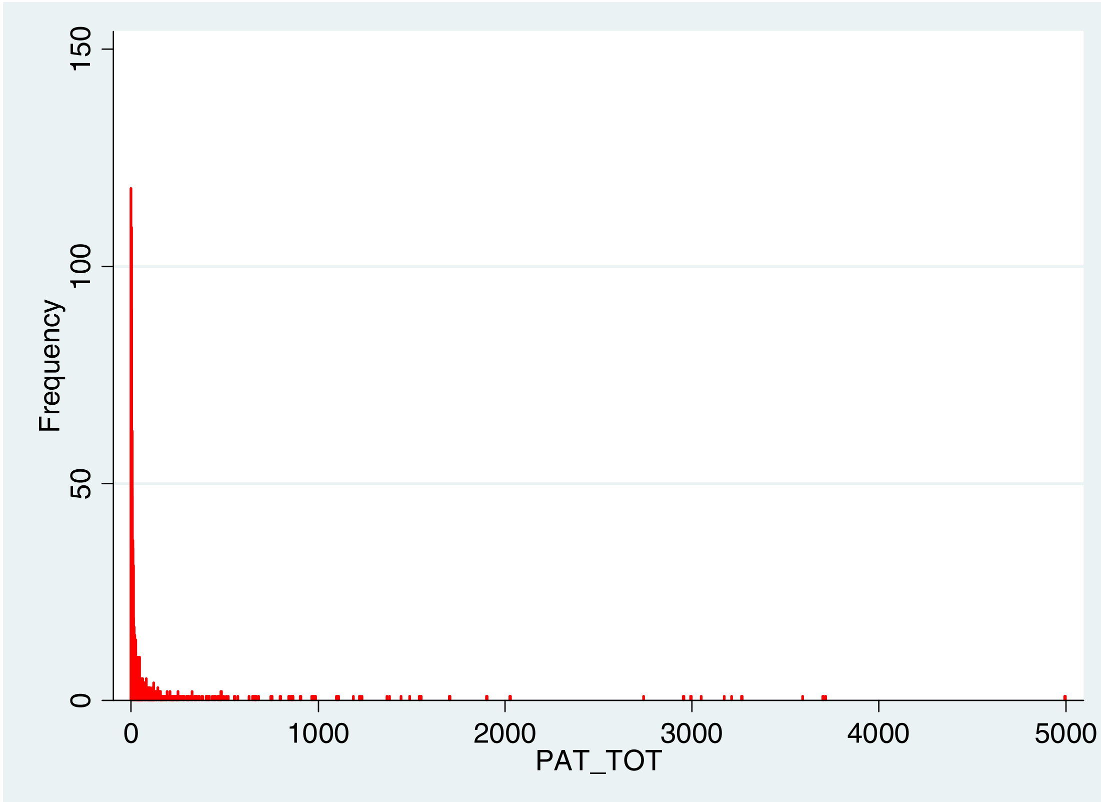


Figure 2.3 Histogram for Patent Totals (PAT_TOT) of 1342 Counties, 1990-1999



2.3.2 Innovative Activity in Metro and Nonmetro Counties

Metropolitan areas had significantly more patenting activity than nonmetro counties (Table 2.1 and 2.2). 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 (LMA) with a metro core versus the 374 nonmetro counties in LMA consisting entirely of nonmetro counties.

Table 2.1 Descriptive Statistics for Patent Totals, 1990-1999 by County Type

County Type	Number of Counties	Mean	Standard Deviation	Min.	Max.
Southern Counties	1342	88.89	357.51	0	4993
Metropolitan	377	287.39	654.34	0	4993
Nonmetropolitan	965	13.10	32.60	0	554
Nonmetro Subgroups					
Metro LMA	591	13.15	31.37	0	480
Nonmetro LMA	374	13.03	34.49	0	554

Source: USPTO, 1999

Table 2.2 Descriptive Statistics for Patent Totals per 10,000 Population, 1990-1999.

County Type	Number of Counties	Mean	Standard Deviation	Min.	Max.
Southern Counties	1342	8.94	20.99	0	384.32
Metropolitan	377	18.73	33.73	0	384.32
Nonmetropolitan	965	5.11	10.17	0	163.25
Nonmetro Subgroups					
Metro LMA	591	5.11	10.59	0	163.25
Nonmetro LMA	374	5.10	9.49	0	114.61

Source: USPTO, 1999

The patent activity in Southern nonmetropolitan counties varied significantly across the 965 counties (1990 nonmetro designation). Six-hundred and forty nine counties (67%) averaged less than one patent per year during the 10 year period (Figure 2.4). In other words, over two-thirds of the Southern nonmetropolitan counties have fewer than 10 patents over the time period. Alternatively, a relatively small number of nonmetro counties were very active in innovation. Seventeen nonmetro counties averaged more than 10 patents per year from 1990 to 1999. These 17 counties account for 3,255 patents or 25.7% of the all patenting activity among the 965 Southern nonmetro counties (Table 2.3). Barkley *et al.* (2006) explain that 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).

Figure 2.4 Distribution of Annual Average Patenting Activity, 965 Southern Nonmetro Counties, 1990-1999.

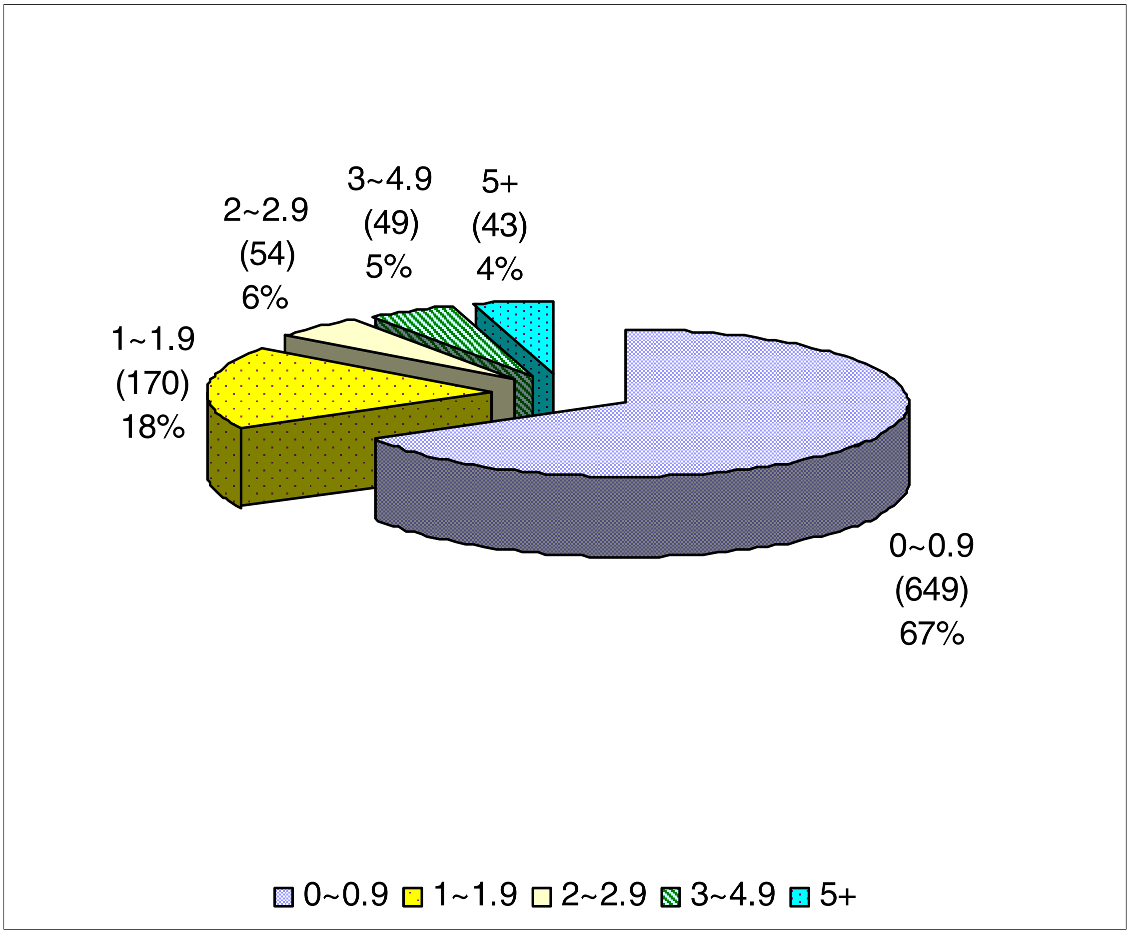


Table 2.3 Southern Counties That Averaged More Than 10 Patents Per Year, 1990-1999.

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
Total	17 Counties	3,255

2.3.3 Identification of Innovation Clusters in the South

Previous research indicated that innovative activity was positively associated with the availability of localization and urbanization economies (Gordon and McCann, 2005; Anderson *et al.*, 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 (Barkley *et al.*, 2006). Of particular interest to this study is the identification of innovation clusters in the South and the role of nonmetro areas in these clusters.

Anselin (1995) suggested the use of local indicators of spatial association (LISA) for the analysis of intra-regional linkages. Anselin's local Moran statistic (I_i) was selected as the local indicator of spatial association. The local Moran for each county *i* is defined as

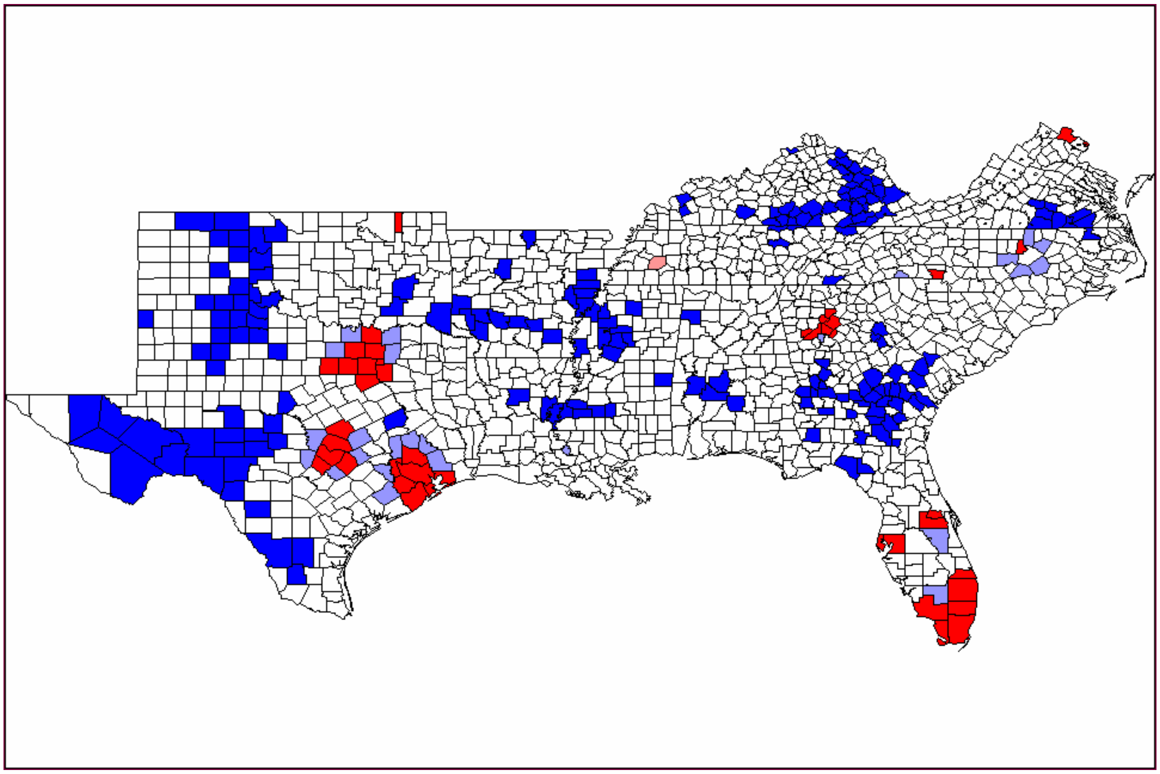
$$I_i \;=\; z_i\left[\sum_j w_{ij}\, z_j\right] \tag{2.1}$$

where I_i is local Moran for county *i*; the attribute value z_i is the standardized value (mean=0, s.d.=1) of patent counts or patents per 10,000 population for county *i*; z_j is the standardized value of patent counts or patents per 10,000 population for county *j*; and the spatial proximity measure w_{ij} is in row-standardized form ($w_{ij} = 1/n$, where *n* is the number of nonzero elements in row *i* of the contiguity matrix $\boldsymbol{W}$). The selected spatial weights matrix ($\boldsymbol{W}$) is a contiguity matrix where $w_{ij}=0$ if counties *i* and *j* are not contiguous and $1/n$ if the counties share a boundary (*n* = number of counties contiguous to county *i*). The county attributes are total patents 1990-1999 and total patents per 10,000 people, 1990-1999.

A large positive value for Moran's I_i indicates that the county is surrounded by counties with similar values, either high or low. A large negative value for I_i indicates that the county is surrounded by counties with dissimilar values. The local Moran enables researchers to identify four types of spatial association: high z_j associated with a high z_i, high z_j associated with a low z_i, low z_j associated with a low z_i, and low z_j associated with a high z_i. Thus, insights into both positive and negative associations are available. The local Moran value for each county gives an indication of the extent of significant spatial clustering of similar values around that county. The local Moran area statistics decompose the global Moran's *I* into the contribution for each location. These local statistics are used to identify regions that differ significantly from those expected under the null hypothesis, which is there is no association between the value observed at a location and the values observed at nearby sites.

Figure 2.5 provides the LISA results for total patents, using ArcGIS and Anselin's Lab toolbox (GeoDa). The result is a special choropleth map showing those locations with a significant local Moran statistic classified by type of spatial correlation: bright red for the high surrounded by high, bright blue for low surrounded by low, light blue for low surrounded by high, and light red for high surrounded by low. The high-high and low-low counties suggest clustering of similar values, whereas the high-low and low-high counties indicate spatial outliers. Forty-six counties are included in clusters of high patenting activity, which include 43 metro counties and 3 non-metro counties (Table 2.4). The high-high cluster counties for total patenting activity are founded in Texas (Houston, Austin and Dallas), Atlanta area, South Florida, Raleigh-Durham area, Northern Virginia and Washington County OK (home of Conoco-Phillips Petroleum). Also evident in Figure 2.5 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.

Figure 2.5 LISA Cluster Map for Total Patents of Southern Counties, 1990-99



High-High Low-Low Low-High High-Low

Table 2.4 High-High Cluster Counties for Total Patents (PAT_TOT), 1990-1999

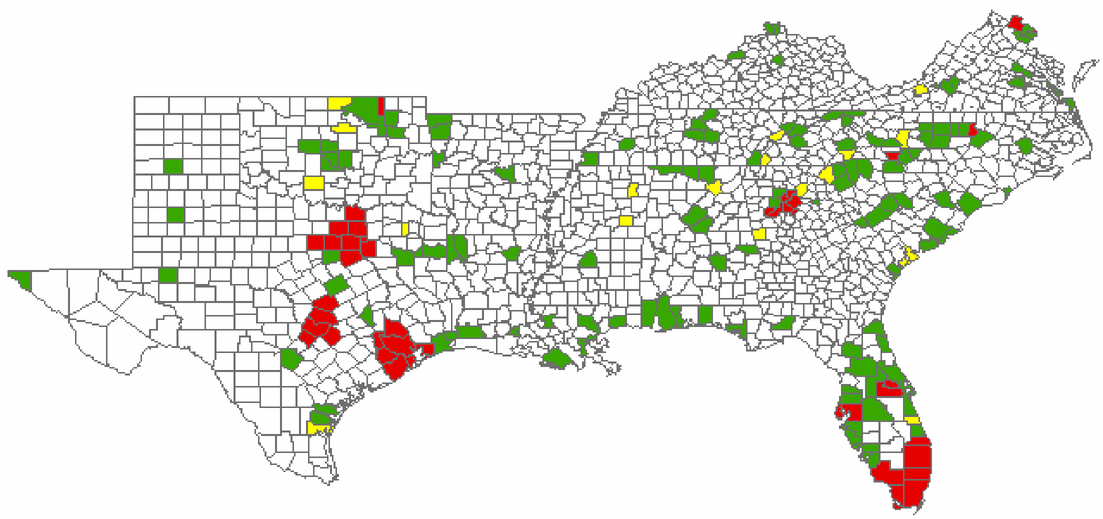
NAME	STATE	PAT_TOT	NAME	STATE	PAT_TOT
Chambers	Texas	89	Washington*	Oklahoma	554
Douglas	Georgia	96	Seminole	Florida	632
Bell	Texas	96	Kaufman	Texas	668
Monroe*	Florida	113	Durham	North Carolina	797
Lake	Florida	129	Hillsborough	Florida	844
Forsyth	Georgia	129	Rockwall	Texas	984
Indian River*	Florida	145	Brazoria	Texas	1106
Ellis	Texas	147	Fulton	Georgia	1383
Rockdale	Georgia	152	Gwinnett	Georgia	1541
Hays	Texas	152	De Kalb	Georgia	1550
Cherokee	Georgia	156	Pinellas	Florida	1702
Bastrop	Texas	163	Tarrant	Texas	1902
Falls Church	Virginia	171	Dade	Florida	2027
Fairfax City	Virginia	199	Dallas	Texas	2740
Grayson	Texas	204	Denton	Texas	2992
Loudoun	Virginia	208	Broward	Florida	3050
Waller	Texas	214	Collin	Texas	3173
Pasco	Florida	217	Montgomery	Texas	3212
Arlington	Virginia	274	Palm Beach	Florida	3266
Collier	Florida	298	Fort Bend	Texas	3592
Martin	Florida	326	Travis	Texas	3700
Galveston	Texas	461	Williamson	Texas	3715
Alexandria	Virginia	520	Harris	Texas	4993

* Non-metro counties

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 2.5 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 (Barkley *et al.*, 2006). To identify the "fringe" and "hot spot" counties, I add all counties with 89 or more patents from 1990 to 1999 because 89 is the fewest number of patents for a county included in a high-high cluster.

One-hundred and fifty additional counties are identified using the modified selection criteria, 18 nonmetro and 132 metro counties (Figure 2.6). 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" that are defined as 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 (Barkley *et al.*, 2006).

Figure 2.6 LISA Cluster Map including 89 Total Patents or More Counties, 1990-99



High-High County

Non-metro County with 89 or more

Metro County with 89 or more

Figure 2.7 provides the LISA results for patent intensity as measured by total patents 1990-99 per 10,000 population. The 43 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 intensity is high in these nonmetro Southwest counties (13 nonmetro counties) more because of sparse population than high patent output (Table 2.5).

The fringe and "hot spot" counties missed by the LISA are identified by including all counties with more than 8.586 patents per 10,000 population, which is the minimum patent intensity among the 43 counties in the high-high clusters. Two-hundred and ninety one counties met the selected criteria for fringe and hot spots, including 116 nonmetro and 175 metro (Figure 2.8). Most metropolitan areas in the South are represented as hot spots based on the relatively low cut-off of 8.586 patents from 1990 to 1999 per 10,000 residents. In addition, many of the identified nonmetro counties are fringe counties of the identified metropolitan areas. In sum, it appears that the LISA for total patents is more discriminating than that for patent intensity (Barkley *et al.*, 2006).

Figure 2.7 LISA Cluster Map for Patent Intensity of Southern Counties, 1990-99

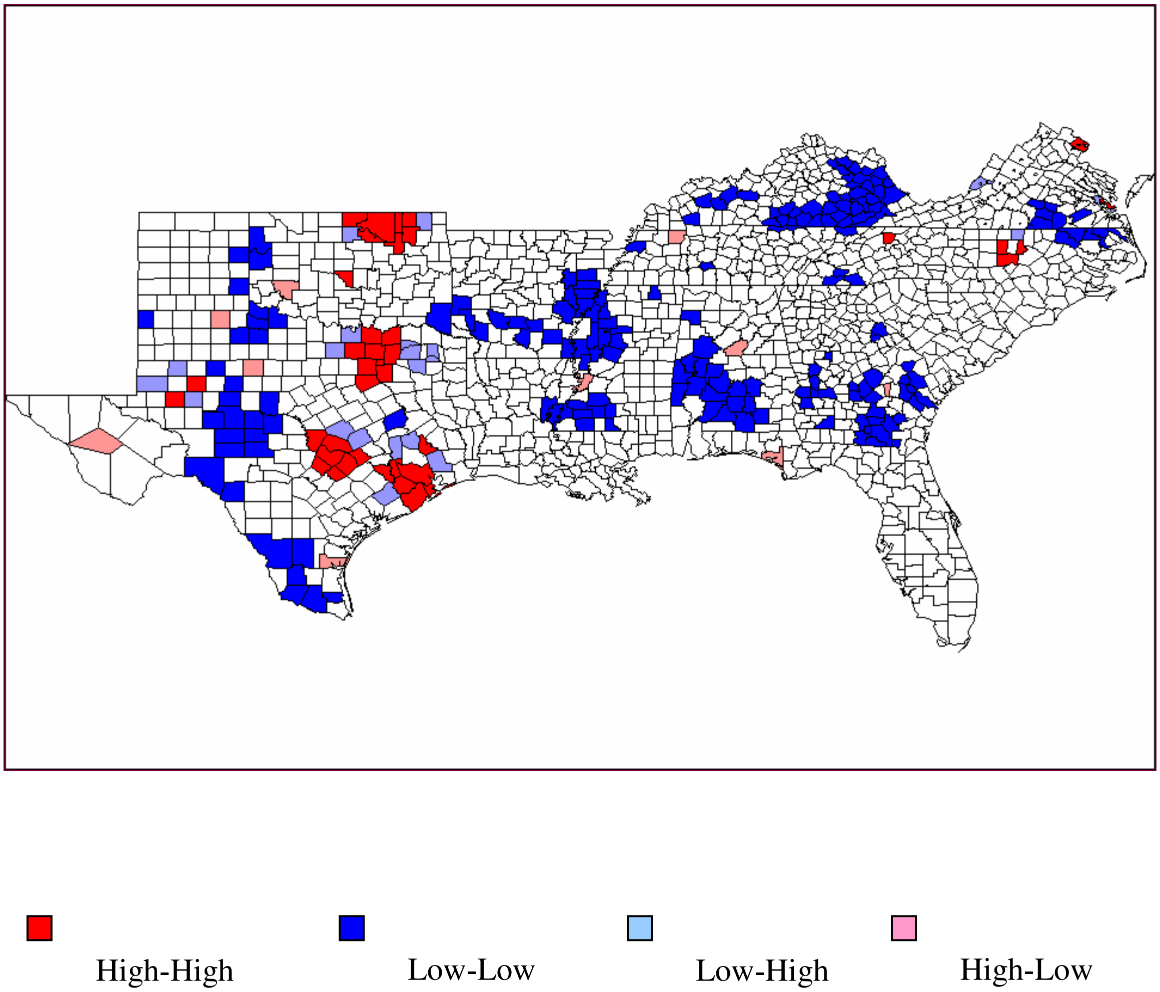
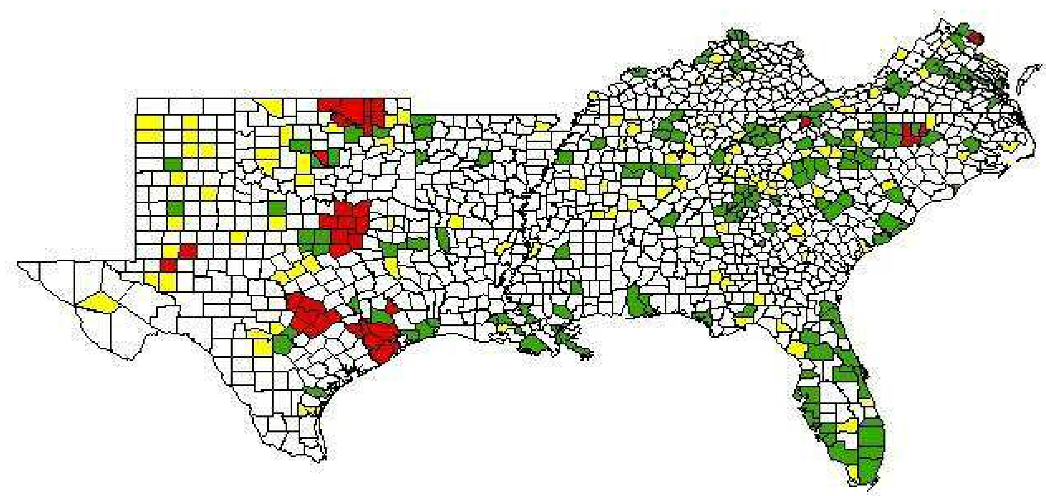


Table 2.5 High-High Cluster Counties for Total Patents per 10,000 Population (Patent Intensity), 1990-1999

NAME	STATE_NAME	PAT_INT	NAME	STATE_NAME	PAT_INT
Lee*	Texas	8.58637	Grayson	Texas	21.46894
Tulsa	Oklahoma	9.53628	Kay*	Oklahoma	28.67774
Fannin*	Texas	10.06725	Bedford City	Virginia	29.63939
Hunt	Texas	10.10211	Grady*	Oklahoma	34.07922
Washington	Tennessee	10.18253	Bastrop	Texas	42.5999
Radford*	Virginia	10.66499	Durham	North Carolina	43.83095
Howard*	Texas	10.84028	Nowata*	Oklahoma	44.19446
Caldwell	Texas	11.74598	Poquoson City	Virginia	46.34257
Midland	Texas	12.38146	York	Virginia	48.55971
Alamance	North Carolina	12.38299	Brazoria	Texas	57.69221
Pawnee*	Oklahoma	14.68429	Travis	Texas	64.19075
Mayes*	Oklahoma	14.70474	Rogers	Oklahoma	75.4033
Dallas	Texas	14.78835	Waller	Texas	91.49209
Arlington	Virginia	16.02939	Denton	Texas	109.3867
Austin*	Texas	16.08768	Washington*	Oklahoma	114.6096
Tarrant	Texas	16.25498	Collin	Texas	120.173
Burnet*	Texas	17.2155	Kaufman	Texas	127.9203
Fairfax	Virginia	17.64022	Fort Bend	Texas	159.3463
Harris	Texas	17.71699	Osage	Oklahoma	217.0729
Chatham	North Carolina	20.89837	Williamson	Texas	266.2109
Galveston	Texas	21.20525	Rockwall	Texas	384.315
San Jacinto*	Texas	21.35839			

* Non-metro counties

Figure 2.8 LISA Cluster Map including 8.586 Patent Intensity or More Counties, 1990-99



High-High County

Non-metro County with 8.586 or more

Metro County with 8.586 or more

2.4 Summary

In recent years, the concept of RIS has evolved into a widely used analytical framework providing the foundation for regional economic development policy making. Yet, the approaches using this framework remain ambiguous on key issues such as the extent of region and the role played by institutions or the institutional context in the emergence and sustenance of RIS at the local level.

This chapter reviewed the theoretical relationship between innovative activity and regional economic growth from RIS. These research studies provided a better understanding of the local characteristics of RIS, suggesting a road map for the next stages of data analysis. The findings from the review suggest that RIS are characterized by innovation sources (entrepreneurial firms and large firms as private R&D providers, and government agencies and universities as research institutes), knowledge spillovers (industry specialization, industry diversity, and local competitiveness), and regional spillovers (agglomeration economies and geographic spillovers). In the next chapter, a KPF is employed to examine the effects of sources of innovation and knowledge and regional spillovers on innovative activity at the nonmetro and rural area level. The remainder of this study also will address the question of metropolitan to non-metropolitan spillovers of innovative activities.

CHAPTER 3

INNOVATIVE ACTIVITY IN THE SOUTH[6]

3.1 Introduction

Although the popularity of the concept of RIS is increasing, the basic argument is how to apply the systems to particular regions or localities where the innovation system is visible. A potential shortcoming of the RIS strategy is that 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 patent activity would not necessarily be detrimental to the economic development prospects of areas with little 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 (Barkley *et al.*, 2006). 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 nonmetropolitan 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 (Barkley *et al.*, 2006).

The purpose of this chapter is to identify the local characteristics of RIS associated with innovative activity in nonmetro and rural counties in South. Innovative activity will be measured by utility patent counts for the ten-year period 1990 through 1999.

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[6] An earlier version of this chapter was published in the author's article "Innovative Activity in Rural Areas: The Role of Local and Regional Characteristics" (Barkley, Henry, and Lee, 2006).

This chapter is organized as follows. First, the following section describes the variables and the construction of the models for data analysis. Next, I conduct data analysis of patenting activity of nonmetro and rural county areas in the South. This discussion presents the variables and data employed and the hypotheses to be tested. Knowledge production functions are estimated for the 591 nonmetropolitan counties and the 647 nonmetro and rural counties in labor market areas (LMA) with a metropolitan core. The principal goal of these estimations is to determine the local characteristics of RIS and the influence of metro innovative activity on non-metro county innovative activities in the metro area's LMA. In the final section, a summary of the findings is provided.

3.2 Model and Data

3.2.1 The Knowledge Production Function

To empirically estimate the existence of local characteristics of RIS in the South, past research (Black, 2004; Acs et al. 1994; Anselin et al. 1997, 2000; Audretsch and Feldman 1996; Feldman 1994; Jaffe 1986, 1989) used the "knowledge production function" (KPF). Griliches (1979) first used the production function approach to model the production of knowledge outputs as a function of knowledge inputs in an effort to estimate the returns to R&D. His KPF included a measure of external knowledge available to firms in order to explicitly capture the spillover of knowledge between firms and industries. The model of KPF (Griliches, 1979) can be represented as:

$$IA = \alpha HK^{\beta} RD^{\gamma} \varepsilon \tag{3.1}$$

where IA is the degree of innovative activity; RD is industrial R&D expenditures; HK is human capital inputs; α, β and γ are estimated parameters; and ε is the error term.

The units of observation for estimating the model of the KPF can be at county, industry, or firm level.

Studies identifying the extent of knowledge spillovers are based on the model of the KPF applied at a spatial unit of observation. Jaffe (1989) modified the traditional approach to estimate a model specified for both spatial and product dimensions as:

$$IA = \alpha IRD^{\beta_1} UR^{\beta_2} (UR \cdot GC)^{\beta_3} \varepsilon \qquad (3.2)$$

where IRD represents private industry expenditures on R&D; UR is university research expenditures; GC measures the geographic coincidence of university and industry research activity within the state; and α, β_1, β_2 and β_3 are estimated parameters.

The unit of observation for Jaffe's estimation was at the state and industry level. Jaffe (1989) provided empirical evidence that β_1, β_2 and β_3 were all greater than zero, supporting the existence of knowledge spillovers from university research laboratories as well as from industry R&D laboratories.

Following Griliches (1979) and others (Jaffe *et al.*, 1993; Fritsch, 2002; and Acs, 2002), the concept of a KPF was used to identify the contributing factors to a county's innovative activity. The analysis of this study follows Feldman (1994) in employing a KPF to model the relationship between innovative activity and local characteristics of RIS such as sources of innovation, knowledge spillovers, and regional spillovers at the local level. This general relationship is provided in Equation (3.3):

$$IA_r = IS_r^{\alpha} KS_r^{\beta} RS_r^{\delta} \qquad (3.3)$$

where IA stands for innovative activity (in this research, the total number of patents from 1990 to 1999); IS stands for innovation sources (such as small and large firms, university and government); KS represents knowledge spillovers (as related to industry specialization, competitiveness, and diversity); RS represents regional spillovers (as reflected by patents in nearby counties, regional amenities, the size of local economy, high-tech employment, distances between a county and a metropolitan, and metro innovative activities); α, β, and δ are parameter coefficients; and *r* represents the nonmetro or rural county area.

Decomposing Equation (3.3) into specific sources of innovation, knowledge spillovers, and regional components yields the general-form function represented in the following equation:

$$P_r = f(PR_r, UR_r, SF_r, LF_r, S\_MFG_r, D_r, C_r, C_r^2, (W \cdot P)_r, AMTY_r, EMP_r, HTECH_r, DIST_r, MET_r) \quad (3.4)$$

where *P* is total patents in the regional area *r* 1990-1999; *PR* is the proxy for private R&D; *UR* is the proxy for university R&D; *SF* is the proxy for small firms; *LF* is the proxy for large firms; *S_MFG* is the location quotient of manufacturing industry; *D* is the measure of industry diversity; *C* is the measure of regional competitiveness; *(W·P)* is the spatially lagged dependent variable; *AMTY* is the proxy variable for natural amenity; *EMP* is the total employment; *HTECH* is the percent of total employment in high-technology manufacturing; *DIST*[7] is miles from the largest city in a county to core city in LMA's MSA; and MET represents one of four alternative measure of innovative activity in the core MSA of the county's LMA.

Table 3.1 defines the variables used in the empirical estimation. In the following section, I will discuss the variables in more details. Data on patents, the dependent variable, are count data, and three estimation procedures for count data analysis will be introduced.

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[7] I measured the distance data using "City Distance Tool" from the website: http://www.geobytes.com/CityDistanceTool.htm.

Table 3.1 Variable Descriptions and Data Sources

Variable	Hypothesis	Description
% Tech Occup., ***PR***	Positive	Percent of employment in technical professions – computer science; engineering; natural, physical and social sciences (BLS, 1990)
College Enrol, ***UR***	Positive	Number of individuals in county enrolled in college (Census, 1990)
Small Est. per capita, ***SF***	Positive	County establishments with fewer than 20 employees per capita
Large Est. per capita, ***LF***	Positive	County establishments with more than 500 employees per capita
Mfg LQ, ***S_MFG***	Uncertain	LQ in manufacturing, Eq (3.10), 1990 (BEA)
Competitiveness, ***C***	Uncertain	The ratio of local to national establishments per worker, Eq. (3.11), 1990 (CBP).
Diversity, ***D***	Positive	Inverse of Krugman Index, Eq. (3.13), one-digit SIC, 1990 (BEA)
Amenities, ***AMTY***	Positive	McGranahan Index of natural amenities (ERS, USDA, 1999)
Total Emp, ***EMP***	Positive	Total county employment, 1990 (BEA)
% High-Tech. , ***HTECH***	Positive	Percent of total county employment in high-technology manufacturing, 1992 (Census of Manufacturers)
W • Patents, ***W·P***	Positive	Spatially lagged dependent variable, W = contiguity matrix
Distance, ***DIST***	Negative	Miles from largest city in county to core city in LMA's MSA
MSA Patents, ***MET_T***	Positive	MSA patent totals, 1990-1999 (USTPO)
MSA Patent Den., ***MET_D***	Positive	MSA patents per 10,000 population, 1990-1999 (USTPO)
%MSA Tech. , ***MET_PR***	Positive	MSA technical employment as percent of total employment (BLS, 1990)
MSA Uni R&D, ***MET_UR***	Positive	MSA University expenditures for research and development per capita, 1990-1999 (NSF)

3.2.2 Count Data Models

Count data describe events that take nonnegative integer values for each observation. Count data usually have a non-negligible probability of zero, which makes the use of log-linear relationships problematic. One possibility for dealing with the impossibility of taking a logarithm of zero is to eliminate all groups of data that include observations of zero, but this requires that the number of these groups is small compared to the whole sample. Another possibility is to add a small value to all zero observations, and to add a dummy variable to implicitly allow a value different from one so that the logarithms can be taken.

However, none of these devices are satisfactory because an ordinary least square (OLS) analysis does not constrain the expected number of events to be nonnegative, and thus the analysis will suffer from a sample selection bias (King, 1988). King (1988) reviewed several of the possibilities for dealing with problems where observations were equal to zero, and concluded that OLS estimates of count data were inefficient with inconsistent standard errors, and that logged OLS estimates on event count data had the same problems and were also biased and inconsistent (King, 1988). Various authors have shown that the analysis of count data is improved by the use of discrete distributions, such as the Poisson and the negative binomial distribution (Hausman *et al.*, 1984; Cameron and Trivedi, 1998; King, 1989).

Poisson Regression Models

The Poisson distribution has been widely used to avoid the approximation of count data using a continuous distribution. The primary equation of the model is (Greene, 2003):

$$P(Y_i = y_i \mid \lambda_i) = \frac{e^{-\lambda_i} \cdot \lambda_i^{y_i}}{y_i!}, \ \lambda_i > 0 \text{ and } y_i = 0, 1, 2, \ldots \qquad (3.5)$$

where Y_i denotes the number of occurrences of a certain event for an individual *i* within a given interval of time; and any realization y_i is observed only at the end of each interval.

The first two moments of the Poisson distribution are equal, and are given by $E[Y_i] = VAR[Y_i] = \lambda_i$. If the data are fairly homogenous, this functional form does not cause difficulties, but if some observations are large outliers that cannot be excluded, then λ_i becomes very large and the loglikelihood of this observation becomes extremely small. The assumed equality of the conditional mean and variance functions is the major shortcoming of the Poisson Regression Model (PRM). Many alternatives have been suggested (Hausman *et al.*, 1984; Cameron and Trivedi, 1998; and Winkelmann, 2003). The most common is the Negative Binomial Regression Model (NBRM) which arises from a natural formulation of cross-section heterogeneity, and is discussed below.

Negative Binomial Regression Models

Greenwood and Yule (1920) were credited for first deriving and applying the negative binomial distribution in the literature, even though some special forms of this distribution were already discussed by Pascal (1679). The suitability of the NBRM is verified by a test to determine whether overdispersion exists. The NBRM addresses the failure of the PRM by adding a parameter, α, that reflects unobserved heterogeneity among observations. Cameron and Trivedi (1998) offered several different tests for overdispersion. A simple regression based procedure was used for testing the hypothesis. The null hypothesis is that $Var(y_i)=E(y_i)$; the alternative hypothesis that $Var(y_i) = E(y_i)+\alpha g(E(y_i))$.

Following Cameron and Trivedi (1998), the negative binomial equation takes the form:

$$\Pr(y \mid x) = \frac{\Gamma\left(y+\alpha^{-1}\right)}{y!(\alpha^{-1})}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\lambda}\right)^{\alpha^{-1}}\left(\frac{\lambda}{\alpha^{-1}+\lambda}\right)^{y}, \; y_i=0,1,2,\ldots, \text{ and } \alpha \geq 0, \tag{3.6}$$

where Γ() is the gamma function; and $E(y_i/xi)=\lambda_i=\exp(x_i`\beta)$.

The negative binomial distribution relaxes the Poisson condition that the mean equals the variance so that the variance is given by

$$\nu_i = V(y_i \mid x_i) = \nu(\lambda_i, \alpha) = \lambda_i + \alpha\lambda_i^2. \tag{3.7}$$

In the case of overdispersion, as is evident in this analysis, the mean (λ) is less than the variance (υ). Thus, the larger the value of α, the greater the overdispersion. The PRM corresponds to α =0. The likelihood ratio test (LRT) is a test of the overdispersion parameter α (in the case of STATA, lnα). When the overdispersion parameter is zero, the negative binomial distribution is equivalent to a Poisson distribution (Long and Freese, 2006). In this study, the estimates of α are significantly greater than zero, indicating the NBRM is better suited than the PRM for the county patent data (Appendix 2 and 4).

3.2.3 Zero-inflated Negative Binomial Regression Models

The NBRM improves upon the underprediction of zeros in the PRM by increasing in the conditional variance without changing the conditional mean. The hurdle model addresses the underprediction of zeros by using two equations, a binary model to predict zeros and a zero-truncated model for the remaining counts because the zero outcome of the data generating process is qualitatively different from the positive ones (Greene, 2003). Mullahy (1986) argued that this fact constituted a shortcoming of the NBRM and suggested a hurdle model as an alternative. Greene (1994) analyzed an extension of the hurdle model in which the zero outcomes could arise from one of two regimes. In one regime, the outcome is always zero. In the other, the usual NBRM is at work, which can produce the zero outcomes or some others.

Zero-inflated count models, introduced by Lambert (1992), change the mean structure to allow zeros to be generated by two distinct processes, compared with one process generating zeros in the hurdle model. The zero-inflated model assumes that there are two latent (*i.e.* unobserved) groups. An individual in the Always-Zero group (Group A) has an outcome of zero with a probability of one, whereas an individual in the Not-Always-Zero group (Group B) might have a zero count, but there is nonzero probability that it has a positive count (Winkelmann, 2003).

Winkelmann (2003, p. 148) suggested that the ZINBM combines a binary variable c_i with a standard count variable y_i* (with support over the nonnegative integers) such that the observed count y_i is given by

$$y_i = \begin{cases} 0 \ if \ c_i = 1 \\ y_i^* \ if \ c_i = 0 \end{cases} \tag{3.8}$$

If the probability that c_i=1 is denoted by ω_i, the probability function of y_i can be written compactly as

$$f(y_i) = \omega_i d_i + (1-\omega_i) g(y_i), \ \ y_i = 0,1,2,... \tag{3.9}$$

where d_i=1-min{y_i, 1} and g(y_i) is the negative binomial probability function.

Winkelmann (2003, p. 149) found that the difference between the zero-inflated model and the hurdle model is that in the latter, there is a single type of zeros whereas in the former one obtains two types of zeros: zero outcomes can either arise from Group A (c_i=1) or from Group B (c_i=0 and y_i*=0).

When interpreting ZINBM using STATA, there are two equations. The first equation is labeled the Logit Equation (the unlikelihood of patenting) that contains for the factor change the odds of being in the Always Zero group compared with the Not Always Zero group. These can be interpreted just as the coefficients for a binary logit model. The second equation is labeled the Count Equation (the rate of patenting or the number of patents) and it contains the coefficients for the factor change in the expected count for those in the Not Always Zero group. This group comprises those counties that have patents. The coefficients can be interpreted in the same way as coefficients from the NBRM. When the same explanatory variables are included in both equations, the signs of the corresponding coefficients from the logit equation (the probability of no patents) are often in the opposite direction of those from the count equation (Long and Freese, 2006). This makes substantive sense because the logit equation is predicting membership in the group that always has zero patents (Group A), so a positive coefficient indicates lower probability of having a patent. The count process predicts number of patents so that a negative coefficient would indicate lower number of patents (Long and Freese, 2006, p.400).

3.2.4 The Dependent Variables

In this study, innovative activity, measured as the total utility patents issued from the U.S. Patent and Trademark Office (USPTO) 1990-99, is the dependent variable in the models. Barkley et al. (2006) identified RIS using a cluster analysis of 20 indicators of innovative and entrepreneurial activity. Their measures of the innovative activity in a region generally focused on innovative inputs (such as expenditures for R&D or employment in scientific and technical occupations), an intermediate output (such as patents), or innovative capacity (such as employment in high technology and information technology industries, technical occupations, or venture capital funding for new enterprises). Among these alternatives, since data on innovations are not generally available at the local level, total patents in a county were selected as the measure of RIS.

This measure, however, has its disadvantages since some innovations are not patented and patents differ enormously in their economic impact. Another problem is that patenting activity is concentrated in manufacturing because new ideas in trade and service industries are less likely to be patented. Many authors are credited to the home address of the lead scientist on the patent, and this location can not be the same county where the research and development occurred (Barkley *et al*., 2006; Acs *et al*., 2000). Nonetheless, patents remain a useful measure of the generation of ideas. Although Acs *et al*.(2000) recognized the shortcomings of patent data, they found a reasonably high (0.79) correlation between patent numbers and SBA innovation counts at the metropolitan level, and patent and innovation counts were associated in a similar manner to explanatory variables included in their regional KPF.

3.2.5 The Explanatory Variables of Sources of Innovation

The proxy variable selected for industry R&D (PR) is percent of county employment in scientific and technical occupations in 1990 because measures of private R&D expenditures by county are not available. Scientific and technical professions are defined as computer science; engineering except civil; and natural, physical, and social sciences. The proxy variable for potential university R&D (UR) is the number of individuals in the county enrolled in college. Measures of university R&D expenditures are available, but only for the larger universities. Total R&D expenditures at universities and colleges are available from the National Science Foundation for only 15 nonmetro counties among the 591 counties (Table

3.2). Thus, this research substituted number of college students[8] as the measure for potential university R&D. Positive coefficients for private and university R&D are hypothesized. However, the proxy variable for university R&D is correlated with county size as measured by total population in 1990 (0.66), indicating that college enrollment may be reflected agglomeration economies.

Table 3.2 Total Expenditures for Nonmetro University R&D Expenditure, 1990-1999

County Name, State	R&D expenditure *	County Name, State	R&D expenditure *	County Name, State	R&D expenditure *
Montgomery, VA	1460249	Franklin, KY	21679	Brewster, TX	2962
Macon, AL	123066	Pasquotank, NC	6783	Marshall, MS	2741
Lincoln, LA	52774	Tangipahoa, LA	4771	Jackson, NC	2177
Kleberg, TX	42866	Dallas, AL	4679	Wood, TX	1302
Orangeburg, SC	39426	Watauga, NC	3602	Radford city, VA	454

* Dollars in thousands
Source: National Science Foundation/SRS, Survey of Research and Development Expenditures at University and Colleges, Fiscal Year 1997 and 1999.

The proxy variable for small firms (SF) is county establishments with fewer than 20 employees per capita in 1990. The proxy measure of large firms (LF) is county establishments with greater than 500 employees per capita in 1990. Research on innovative activity in states and metropolitan areas indicates a positive association between area patent numbers and proportion of small and large firms in the area (Gordon and McCann, 2005).

[8] The coefficient of correlation between county population (1990) and the number of individuals in county enrolled in college (1990) is 0.659.

3.2.6 The Explanatory Variables for Knowledge Spillovers

It is important how measures of specialization in manufacturing, local competitiveness, and industry diversity are defined because the estimation results may be sensitive to different variable measures. The measures employed in this study are discussed below.

Specialization

Specialization of manufacturing industry in region *r* is measured by the location quotient (LQ) which is defined as:

$$S\_MFG_r = \frac{EMP_{i,r} / EMP_r}{EMP_{i,US} / EMP_{US}} \tag{3.10}$$

where EMP_{ir} is manufacturing employment in county *r*; EMP_r is total employment in county *r*; $EMP_{i,us}$ is U.S. employment in manufacturing industry; and EMP_{us} is total U.S. employment. Thus, The S_MFG is the ratio of the share of local manufacturing industry employment to the share of national manufacturing industry employment. If a value is greater than one, it means that manufacturing industry employment is more concentrated in county *r* compared to the national level. The MAR and Porter theories of external economies suggested that industry specialization will stimulate innovative activities in that region. The hypothesized coefficient on the variable representing specialization in manufacturing industry (S_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.

Competitiveness

Following Glaeser et al. (1992), the degree of local competitiveness in region *r* is measured by the ratio of local to national establishments per worker:

$$C_r = \frac{EST_r \,/\, EMP_r}{EST_{US} \,/\, EMP_{US}} \tag{3.11}$$

where EST_r and EST_{us} are establishments in county *r* and in the U.S., respectively; and EMP_r and EMP_{us} are employment in county *r* and in the U.S, respectively.

Thus, more establishments per worker mean more competitiveness (Koo, 2005). Values of C greater than one indicate that there are more firms in county *r* relative to its employment compared to that of the nation.

The competitiveness variable (C) assesses whether local regional competitiveness is higher or lower than national competitiveness. According to MAR, intensive local competitiveness impeded economic growth and innovative activities. In case of intensive competitiveness, MAR assumed that enterprises limited their amount of innovative activities because too much new knowledge spilled over to competitors. According to Jacobs and Porter, however, intensive local competitiveness benefited innovative activities because enterprises were forced to innovate.Therefore, the effects of local competitiveness within industries on innovation are ambiguous. However, a U-shaped relationship between competitiveness and patents (Glaeser U-shaped competitiveness) is consistent with innovation occurring primarily in the largest and smallest establishments (Glaeser *et al.*, 1992).

Specialization and competitiveness are different concepts in that specialization deals with the clustering of workers, while competitiveness deals with the clustering of businesses in this study. Since the number of workers and the number of establishment may be positively correlated, the variables specialization and competitiveness may also be correlated. In this dataset, the correlation between specialization and competitiveness is -0.2639. This value is low enough to assume that the model outcomes do not suffer from multicollinearity.

Diversity

Following Krugman (1991a), the diversity of region *r* is defined as:

$$SPE_r = \sum_{i=1}^{7} \left| \frac{EMP_{i,r}}{EMP_r} - \frac{EMP_{i,US}}{EMP_{US}} \right| \tag{3.12}$$

$$D_r = \frac{1}{SPE_r} \tag{3.13}$$

where $EMP_{i,r}$ and EMP_r are industry *i* employment in county *r* and total employment in county *r*, respectively; and $EMP_{i,us}$ and EMP_{us} are U.S. employment in industry *i* and total U.S. employment, respectively.

To explore the possible effects of local industrial diversification, I construct the sum of the absolute value of county employment share, in 1990, accounted for by seven one-digit SIC industries.[9] In Equation (3.12), the summation increase if a region is more specialized than the nation. Alternatively, if the industrial mix follows the national average (industry diversity), the summation will be close to zero, and also the value of D will increase (in Equation (3.13). However, the diversity index takes into account the industry diversity of the entire regional economy, so a local economy can have a few specialized industries as well as industry diversity (Koo, 2005).

[9] The industries are construction; manufacturing; transportation, communications, and public utilities; wholesale trade; retail trade; services; and FIRE (finance, insurance, and real estate).

Research on innovative activity in states and metropolitan areas indicated a positive association between area patent numbers and diversity of the local economy (Anderson, Quigley, and Wilhelmsson, 2005). The industry diversity of the county economy (D) is represented by the inverse of the Krugman Index, and a positive association is anticipated between regional diversity and county patents.

3.2.7 The Explanatory Variables of Regional Spillovers

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 indicated a positive association between area patent numbers and (a) employment in high-tech industries (Riddel and Schwer, 2003); (b) size and density of the local economy (Anderson, Quigley, and Wilhelmsson, 2005); (c) the availability of local amenities (Deller et al., 2001); 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 statistical areas (MSA) and patent counts in non-metro counties in the labor market areas (LMA) of the MSA.

Total county employment in 1990 (EMP) is the proxy variable for the size of the county economy. EMP is hypothesized to be positively associated with patenting activity. HTECH is the percentage of county employment in high-technology manufacturing industries[10], and the coefficient on HTECH is hypothesized to be positive.

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

A common way of modeling spillovers between regions is using spatial econometric models. This often involves the use of a spatial weights matrix (W) that allows for explicit modeling of the spatial dependence structure. Typically, the weight matrix consists of positive elements for 'neighboring' locations, and zero elements for other of regions (Anselin, 2003). A positive estimated coefficient on the spatially lagged dependent variable (W ·P) indicates a positive association between patent total in a county and patent activity in surrounding counties.

Some patenting activity in rural 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.

Finally, *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 (MET_T); total patents per 10,000 residents (MET_D); total academic R&D expenditures 1990-1999 (MET_UR); and percentage of employment in scientific and technical occupations in 1990 (MET_PR). A positive coefficient for *MET* supports the hypothesis of a spillover of innovative activity from metro to rural areas.

A list of the variables and data sources is provided in Table 3.1. All explanatory variables except metro patents and metro university R&D expenditures used 1990 values to control for possible endogeneity issues. All the models were estimated with STATA 9.2 for count data analysis.

3.3 Innovative Activity in Non-metropolitan Areas

3.3.1 The Data

The Study Area

Labor Market Areas (LMA), as defined by the Economic Research Service of the USDA (1990), are areas within which individuals live and work (based on the commuting data). The LMA and its component counties were identified for the 117 MSA/CMSA's for the 13 Southern states. Each LMA is differentiated into metro counties and nonmetro counties. The LMA used in this paper were developed by Tolbert and Sizer (1996) to identify the multi-county metro and nonmetro geographic areas that captured economically dependent counties based on commuting data. Among the Southern rural counties, 591 non-metropolitan counties were assigned to LMA with a metro core while 349 counties were members of rural LMA. Of particular interest to this study is the association between innovative activity in metropolitan areas (MSA) and patent counts in nonmetro counties in the LMA of the MSA. The following model was estimated for the 591 Southern non-metropolitan counties in LMA with a metro core area.

The Dependent Variable

Innovative activity, measured as the total utility patents in a county 1990-1999, is the dependent variable in the models. To gain some information about the total patents in county 1990-1999, it is informative to look at a histogram of the observed data in Figure 3.1. Many counties have very few total patents during 1990-1999, and very often not even a single patent. The distribution seems to have a long tail. Apart from the long tail the data could be Poisson distributed, but as the histograms reveal overdispersion, an adjusted

Poisson distribution or a negative binomial distribution will describe the data better. The descriptive statistics of the dependent variable are provided in Table 3.3.

Figure 3.1 Histogram for Total Patents (pat_t) of 591 Non-metro counties, 1990-99

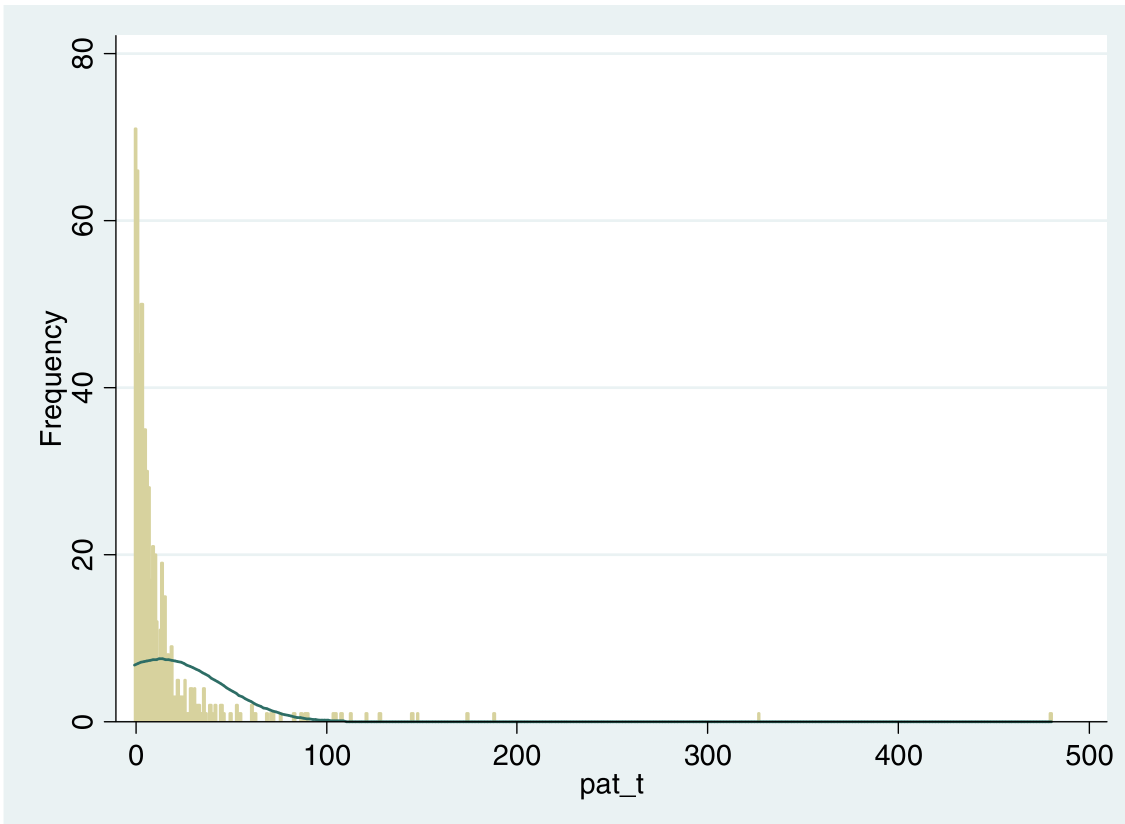


Table 3.3 Summary Statistics for Variables, 591 Non-metropolitan Counties

Variables	Mean	SD	Min.	Max.
Total Patents, 1990-99, ***P***	13.1489	31.36955	0	480
% Tech Occupation, ***PR***	4.263848	1.396378	0	17.40226
College Enrol. 1990, ***UR***	942.3316	1452.083	0	23197
Small Est. per capita, ***SF***	.0175041	.0055288	.0056221	.0429402
Large Est. per capita, ***LF***	.0000298	.0000483	0	.0003712
LQ of MFG, ***S_MFG***	1.23095	.9052159	0	4.354384
Indust. Diversity, ***D***	3.26096	1.291843	1.04626	11.86529
Competitiveness , ***C***	.9974521	.222759	.0951137	2.155624
Competitiveness squared, $\boldsymbol{C^2}$	1.044448	.4561264	.0090466	4.646717
Amenity Rank, ***AMTY***	3.705584	.6898435	2	6
Total Employment, 1990, ***EMP***	9458.675	8974.4	95	57681
% High Tech Emp, ***HTECH***	1.312094	2.555225	0	23.17731
W. PAT, ***W·P***	.005676	.6657916	-.419161	7.37502
Distance (miles), ***DIST***	52.08122	39.58603	1	381
MSA PAT, ***MET_T***	1053.844	2386.88	14	13688
MSA PAT DEN, ***MET_D***	13.02176	12.04527	.9646847	91.71298
MSA UNIV R & D per capita, ***MET_UR***	1081.982	2909.791	0	28203.04
%MSA Tech Emp., ***MET_PR***	4.957243	.6648119	3.404496	7.201031

3.3.2 The Count Data Analysis

The single parameter is equal to the expected value of the Poisson distribution in the PRM, and the independent variables are introduced into the model by expressing as a deterministic function of these variables. In order to guarantee a positive expected value, the functional form estimated by STATA is $\lambda_i = \exp(x_i \beta)$, where β is the parameter vector; and **x** is the vector of independent variables.

$$\lambda = \exp\begin{pmatrix} \alpha + \beta_0 PR + \beta_1 UR + \beta_2 SF + \beta_3 LF + \beta_4 S\_MFG + \beta_5 D + \beta_6 C + \beta_7 C^2 + \\ \beta_8 (W \cdot P) + \beta_9 DIST + \beta_{10} AMTY + \beta_{11} EMP + \beta_{12} HTECH + \gamma MET \end{pmatrix} \tag{3.14}$$

where PR, UR, SF, LF, S_MFG, D, C, WP, DIST, AMTY, EMP, and HTECH are as defined earlier (Table 3.1); β_0, β_1, β_2, β_3, β_4, β_5, β_6, β_7, β_8, β_9, β_{10}, β_{11} and β_{12} are estimated parameters; MET represents one of four alternative measures of innovative activity in the core MSA of the county's LMA; and γ is the estimated parameter for MET.

Innovative activity in the metro area (*MET*) is measured by total patents 1990-1999; patents per 10,000 residents; total academic R&D expenditures 1990-1999; or percentage of employment in scientific and technical occupations[11] in 1990. A positive coefficient for MET supports the hypothesis of a spillover of innovative activity from metro to nonmetro areas.

All the results for PRM and NBRM are provided in the appendices (Appendix 1 through Appendix 4). Five models are estimated to determine the role of non-metro 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 non-metro county's LMA. The associations between non-metro county characteristics and county

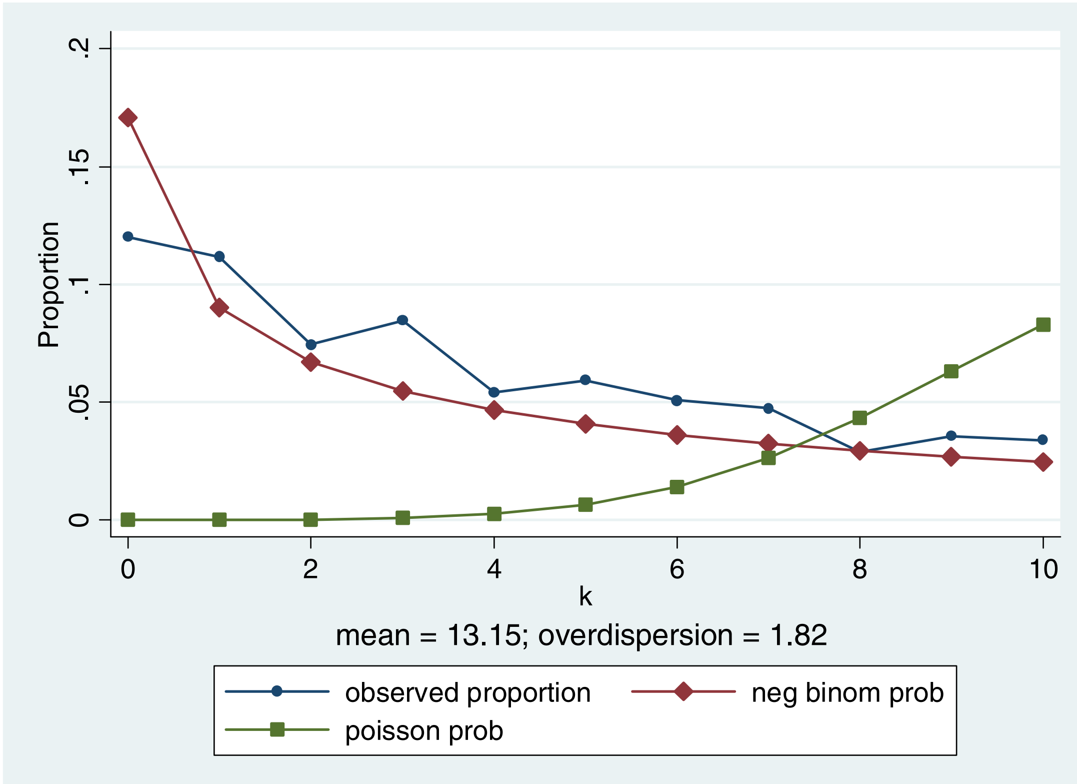
[11] For the metropolitan areas, total patents 1990-1999 is a proxy for innovation outputs while total academic R&D expenditures measures university innovation inputs and total employment in scientific and technical occupations is a proxy for industry R&D inputs.

patent totals are similar to those found in earlier studies using state-level and metro-level data.

Although we have good results in PRM, the use of the Poisson model is only appropriate if the data have null dispersion, that is, if the mean of the dependent variable is equal to its variance. The likelihood ratio test (LRT) at the bottom of Appendices 2 and 4 is a test of the overdispersion parameter α. When the overdispersion parameter is zero, the negative binomial distribution is equivalent to a Poisson distribution. In this case, α is significantly different from zero and thus reinforces the assumption that the Poisson distribution is not appropriate. I also checked to see how well the variable, total patents (1990-99), fits both the Poisson and negative binomial distributions using graphs (Figure 3.2). The plots compare the PRM and NBRM, and the NBRM seems to fit theses data better than the PRM.

Table 3.4 and 3.5 show the empirical results from the final step of the zero inflated negative binomial models (ZINBM). The ZINBM using STATA provided two equations. The first equation is labeled Logit Equation (the unlikelihood of patenting) which contains the coefficients for the factor change in the odds of being in the Always Zero group compared with the Not Always Zero group. The second equation is the Count Equation (the rate of patenting) that contains the coefficients for the factor change in the expected count for those in the Not Always Zero group. A Vuong test was used to compare the NBRM and ZINBM. The significant, positive value of Vuong test statistics supports the ZINBM over NBRM (Table 3.5). Overall, these tests provide evidence the ZINBM fits the data best. The following section will discuss the results of the ZINBM for the patent activity in nonmetro county areas.

Figure 3.2 Comparison of the Poisson and Negative Binomial Models.



3.3.3 The Unlikelihood of Patenting: Logit Equations

Table 3.4 presents the estimated results from the first-step, logit equations of the ZINBM. The equation contains coefficients for the factor change in the odds of being in the Always Zero group compared with the Not Always Zero group. These can be interpreted similarly to the coefficients for a binary logit model.

Table 3.4 Logit Equation for the Unlikelihood of Patenting, 591 Nonmetro Counties[a]

Independent Variables	Model 1 No MSA Term	Model 2 MSA PAT Total	Model 3 MSA PAT Density	Model 4 MSA UNIV R & D	Model 5 MSA S & Tech
%Tech Occ., *PR*	-.4247665 (-0.60)[b]	-.2039754 (-0.36)	-.5063406 (-0.84)	.4669769 (0.93)	-.1654851 (-0.23)
Coll. Enrol., *UR*	-.0355308 (-1.41)	-.0305247 (-1.45)	-.0374867* (-1.90)	-.0753321** (-1.99)	-.0887346** (-2.22)
Small Est. *SF*	38.29621 (0.23)	84.85271 (0.52)	28.20712 (0.17)	-54.31193 (-0.31)	-36.07048 (-0.20)
Large Est. *LF*	-199327.5 (-0.00)	-277296.9 (-0.00)	-221511.4 (-0.00)	2219.243 (0.00)	-12303.42 (-0.00)
Mfg. LQ, *S_MFG*	-2.034927 (-1.28)	-1.87566 (-1.49)	-2.078064 (-1.41)	-1.953603 (-1.19)	-2.074104 (-1.11)
Diversity, *D*	-.6459022 (-0.74)	-.8195975 (-0.93)	-.7706326 (-0.85)	-.5855629 (-0.63)	-.9141287 (-0.82)
Comp, *C*	-25.29788 (-1.64)	-30.34673** (-2.35)	-27.95367* (-1.88)	-15.19805 (-0.88)	-14.25612 (-0.73)
Comp², C^2	14.1924* (1.78)	15.69648** (2.40)	15.88556** (2.03)	8.926593 (1.07)	8.849306 (0.91)
Amenities, *AMTY*	-.4721216 (-0.59)	-.3203033 (-0.47)	-.722906 (-0.81)	-.1833251 (-0.22)	.3719719 (0.37)
Total Emp., *EMP*	-.0008729 (-1.43)	-.0010718** (-2.12)	-.0009221* (-1.75)	-0.22 (-0.46)	-.000346 (-0.55)
% High Tech, *HTECH*	-3.69598 (-1.50)	-3.508667 (-1.47)	-3.744786 (-1.62)	-2.196791 (-1.01)	-3.500787 (-1.49)
W. PAT, *W·P*	-1.807701 (-0.50)	-5.490153** (-2.04)	-1.692683 (-0.45)	-1.608916 (-0.42)	-.493001 (-0.15)
Distance, *DIST*	-.0189788* (-1.82)	-.0174601* (-1.75)	-.0157345 (-1.33)	-.0182625 (-1.62)	-.0264661* (-1.80)
MSA PAT, *MET_T*		.0008399** (2.31)			
MSA PAT D., *MET_D*			-.1083704 (-0.76)		
MSA U. R & D, *MET_UR*				.0009136** (2.31)	
MSA Tech. *MET_PR*					-1.696109 (-1.34)
Intercept	20.28992** (2.00)	20.38708** (2.40)	23.64063** (2.17)	14.50878 (1.50)	24.37518* (1.81)
Loglikelihood	-1799.892	-1797.36	-1797.561	-1797.901	-1798.044

[a] Non zero observations = 520; and zero observations = 71.
[b] z-values for the coefficients are provided in parentheses.
*, P-Value <0.1; **, P-Value <0.05; and *** P-Value<0.01

Sources of Innovation

The number of individuals in the county enrolled in college, the proxy variable for university R&D (UR), is negatively and significantly related to the unlikelihood of patenting in nonmetro areas. Thus, areas where firms can appropriate knowledge from the academic community into their innovation process are more likely to see some patent activity than areas where firms do not have access to nearby research universities, indicating that proximity to a university is an important component in the decision to innovate. However, other coefficients of the innovation sources variables are not significant.

The finding for university R&D is consistent with previous evidence of innovation research. Anselin et al. (1997, 2000) and Feldman (1994) found that academic R&D had a significant effect on the number of innovations. This finding is also supported by evidence on the role of geographic proximity between patents and patent citations. Jaffe *et al.* (1993), for example, found that citations to other patents are significantly more likely to refer to patents from university research.

Knowledge Spillovers

The specialization of employment in manufacturing (S_MFG) has no significant impact on the unlikelihood of patenting within nonmetro county areas. However, the unlikelihood of patenting is weakly related to Glaeser's U-shaped competitiveness measure (C, C^2). 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, indicating the role of local monopoly or the importance of large sized establishments. Regional diversity (D) has no significant impact on the unlikelihood of patenting at the nonmetro county level.

Regional Spillovers

The coefficient of percent of high tech employment (HTECH) and amenity rank (AMTY) are negative but not significant at the 10% level. A negative impact of the size of local economy (EMP) on the unlikelihood of patenting is found, indicating the probability of having a patent is influenced by the size of local economy.

Of principal interest to this study is the role of spillovers on nonmetro county patent activity. The coefficient of the spatially lagged dependent variable (W ·P) are negative, indicating a positive association between the probability of having a patent and patent activity in surrounding counties. However, an unexpected positive and significant relationship exists between the unlikelihood of county patenting and metro innovative activity and capacity. Distance from the metropolitan core (DIST) is negatively related to no patenting activity in nonmetro county areas, indicating that an increase in the distance between metropolitan city and nonmetro county city leads to a significant increase in the probability of the nonmetro county area having patent activity. This suggests the proximity of metro characteristics play an inverse role in the unlikelihood of patenting among firms at the nonmetro county area level. The unlikelihood of patenting is significantly associated with metro innovative activities (MET_T and MET_UR), indicating that there are "backwash" effects.

3.3.4 The Rate of Patenting: Count Equations

The previous section provided evidence that the local characteristics of RIS played a role in whether or not at least one patent was issued within a nonmetro county area. The second stage of the estimation process determines whether these variables also influence the frequency of patent activity. Table 3.5 shows the empirical results from the negative binomial equations in ZINBM. It is clear from the results that there is a strong positive impact of innovation sources, knowledge spillover, and regional spillovers on patent activity.

What stands out in Table 3.4 is the overall stronger contribution of the local characteristics of RIS to the number of patents compared to the unlikelihood of county patenting. Many of the independent variables are significant, and when they are, it is at a higher level. These results indicate that innovation sources, knowledge spillovers, and regional spillovers have a stronger association with the rate of patenting (innovative activity) than indicated in the logit estimations (the unlikelihood of patenting).

Sources of Innovation

The significance of the percent of employment in scientific and technical professional occupations, the proxy variable for private R&D (PR), increases between the logit and count equations. The significant, positive effect of industrial R&D activity appears at traditional levels of significance when analysis shifts to the number of patents (the rate of county patenting). This suggests private R&D is vital to the rate of county patenting. Considerable prior evidence indicated that firms appropriate knowledge generated by local universities, and that this knowledge is a key determinant of county innovative activity. Compared to the other components of the local characteristics of RIS, the frequency of county patents does not depend strongly on the number of individuals in the county enrolled in college (UR), suggesting that proximity to university R&D is not strongly related to the rate of patenting in nonmetro areas.

The significance of research universities, though, is weaker in the count equations compared to the logit equations at a nonmetro county level. Research universities play a greater role in determining the unlikelihood of innovative activity than the rate of patenting.

For county patent activity, these results suggest that proximity to universities matters more in terms of providing access to knowledge than in the volume of knowledge provided, thereby allowing innovative activity to take place in areas where it otherwise would not. This coincides with the argument that local universities provide knowledge through mechanisms besides research, such as the education of the local workforce.

The variables representing small firms (SF) and large firms (LF) also are positively associated with the rate of patenting activity, suggesting a significant role for small and large firms on the number of patents in nonmetro county areas.

Knowledge Spillovers

The concentration of employment in manufacturing (S_MFG) is not significant, implying that the positive spillovers associated with proximity to similar firms matter less in determining the frequency of innovation than merely the presence of innovative activity. A relatively large manufacturing sector is not significantly related to patenting activity. However, non-metro total patents are positively associated with the industry diversity (D) of the local economy. The results indicate that less geographical specialization rather than more local specialization, promotes innovation and growth, because most important knowledge transfers are from outside industries (Jacobs' hypothesis).

The competitiveness of the local industry structure (C) is weakly correlated with innovative activity in the nonmetro counties with an inverse U-shaped form. 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 inverse U-shaped relationship indicates that the rates of patenting are highest for counties with large sized establishments or local monopoly.

Regional Spillovers

The size of the local economy (EMP) is a more decisive factor of the rate of patenting (the number of county patents) than the unlikelihood of patenting, indicating that non-metro total patents are positively associated with the size of the local economy (urbanization economies). No significant relationship is found between high-technology employment (HTECH) in non-metro counties and the number of patents. Acs (2002) found that a base of high-tech firms in a nonmetro area appeared to offer little advantage in terms of increased patenting activity. This is consistent with earlier findings by Barkley *et al.* (1988) that nonmetro high-tech firms differed little from firms in traditional nonmetro manufacturing industries.

The spatially lagged dependent variable (W • P) 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. The availability of local amenities (AMTY) and proximity to metro areas (DIST) areas are 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 (Barkley, *et al.*, 2006).

MSA patent totals (MET_T) and MSA patents per 10,000 persons (MET_D) are positively associated with nonmetro patent activity at the traditionally significant levels. One of the metro inputs for the innovation process, metro university R&D (MET_UR), is negatively related to nonmetro patent counts but not at high levels of statistical significance.

The other input measure, the proxy variable of metro private R&D (MET_PR), is positively associated with county innovative activity, but not statistically significant.

The absence of a strong correlation between MSA innovation measures and patent counts in nearby non-metro counties is not unexpected. Recent research founds evidence of technology spillovers within metropolitan areas (Fischer and Varga, 2003; Lim, 2004; and Acs, 2002); however, this research also noted that these spillovers dissipated with distance. Fischer and Varga (2003) concluded that knowledge spillovers followed a distinct distance decay pattern. These findings were similar to the research of Shapira (2004) who noted that Georgia's innovation and technology development initiatives had little "trickle down" impact outside the Atlanta metropolitan region. The findings for Southern non-metropolitan counties appear to indicate that these counties are too distant from the metro innovation centers to benefit greatly from available spillovers.

Table 3.5 Count Equation for the Number of Patents, in 591 Nonmetro Counties[a]

Independent Variables	Model 1 No MSA Term	Model 2 MSA PAT Total	Model 3 MSA PAT Density	Model 4 MSA UNIV R & D	Model 5 MSA S & Tech
%Tech Occ., *PR*	.1465425*** (3.82)[b]	.144043*** (3.76)	.1393616*** (3.66)	.1556613*** (4.06)	.1482322*** (3.88)
Coll. Enrol., *UR*	.0000411 (1.40)	.0000447 (1.52)	.0000432 (1.46)	.0000395 (1.35)	.0000399 (1.36)
Small Est. *SF*	36.64243*** (2.98)	37.7247*** (3.08)	36.18055*** (2.96)	36.33426*** (2.98)	36.84798*** (3.01)
Large Est. *LF*	3495.108*** (3.46)	3498.06*** (3.48)	3533.334*** (3.52)	3540.635*** (3.52)	3448.718*** (3.41)
Mfg. LQ, *S_MFG*	-.0616448 (-1.01)	-.0625702 (-1.03)	-.0581255 (-0.96)	-.0644573 (-1.06)	-.0476173 (-0.77)
Diversity, *D*	.1971231*** (4.88)	.1921723*** (4.78)	.1971608*** (4.90)	.1947132*** (4.82)	.1986315*** (4.91)
Comp, *C*	1.194586 (1.21)	1.220218 (1.24)	1.307574 (1.33)	1.299124 (1.32)	1.238354 (1.26)
Comp^2, C^2	-.9974994** (-2.20)	-1.008185** (-2.23)	-1.028623** (-2.29)	-1.056319** (-2.35)	-1.019614** (-2.27)
Amenities, *AMTY*	.2823737*** (4.60)	.2751303*** (4.49)	.272293*** (4.43)	.2803957*** (4.57)	.2830506*** (4.60)
Total Emp., *EMP*	.0000713*** (10.61)	.0000705*** (10.57)	.0000704*** (10.52)	.0000715*** (10.67)	.0000722*** (10.66)
% High Tech, *HTECH*	-.0641657 (-1.07)	-.0666373 (-1.12)	-.0608697 (-1.02)	-.0620373 (-1.03)	-.0615716 (-1.02)
W. PAT, *W·P*	.1514184** (2.45)	.1417427** (2.33)	.1353633** (2.22)	.1517955** (2.45)	.1538216** (2.48)
Distance, *DIST*	-.0022466** (-2.32)	-.0023654** (-2.46)	-.0023623** (-2.44)	-.002313** (-2.39)	-.0021511** (-2.22)
MSA PAT, *MET_T*		.0000279* (1.72)			
MSA PAT D., *MET_D*			.0064539* (1.95)		
MSA U. R & D, *MET_UR*				-5.25e-06 (-0.37)	
MSA Tech. *MET_PR*					.0536324 (0.92)
Intercept	-1.634681*** (-2.70)	-1.63276*** (-2.70)	-1.721383*** (-2.86)	-1.687076*** (-2.80)	-1.972343*** (-2.96)
Lnα	-.3881751*** (-5.42)	-.4000764*** (-5.58)	-.3948457*** (-5.53)	-.3889654*** (-5.46)	-.383633*** (-5.39)
Vuong test [p-value]	3.63 [0.0001]	3.61 [0.0002]	3.54 [0.0002]	3.59 [0.0002]	3.80 [0.0001]

[a] Non zero observations = 520; and zero observations = 71.
[b] z-values for the coefficients are provided in parentheses.
*, P-Value <0.1; **, P-Value <0.05; and *** P-Value<0.01

3.4 Innovative Activity in Rural Areas

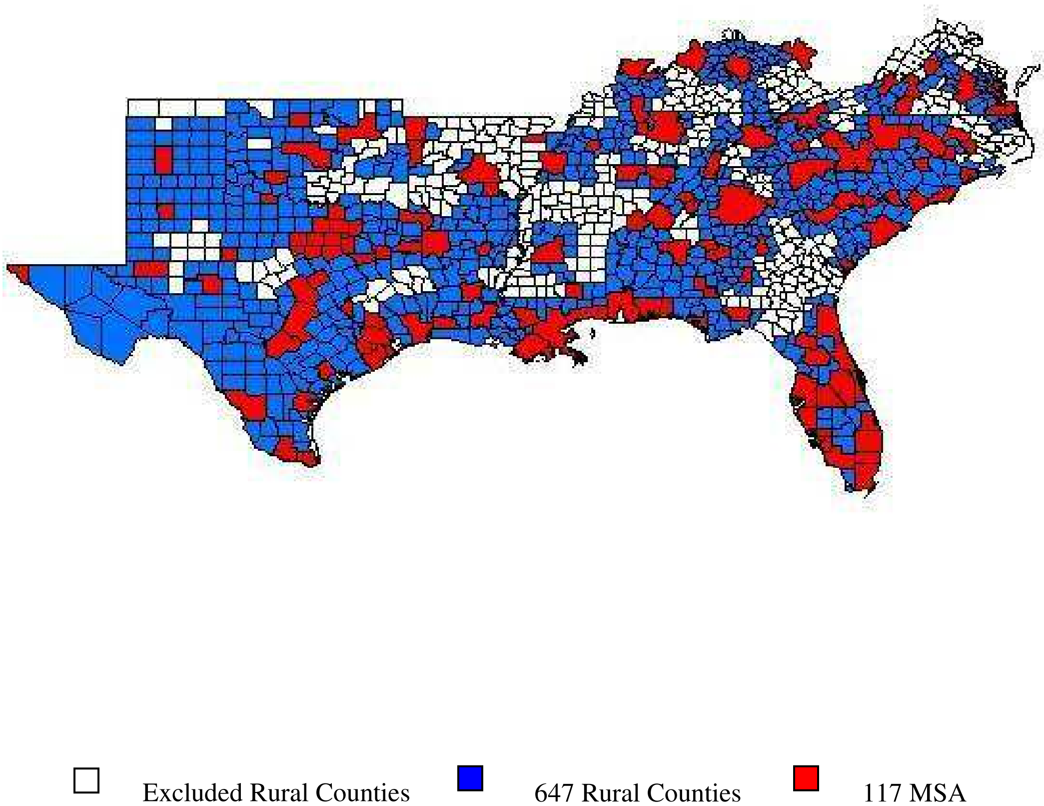
3.4.1 The Data

The Study Area

One interpretation to the findings provided in section 3.3 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). In Figure 3.3, 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.

Of particular interest to this study is the association between innovative activity in MSA and patent counts in the nonmetro and rural counties in the LMA of the MSA. The following model was estimated for the 647 Southern rural counties in LMA with a metro core area (Figure 3.3).

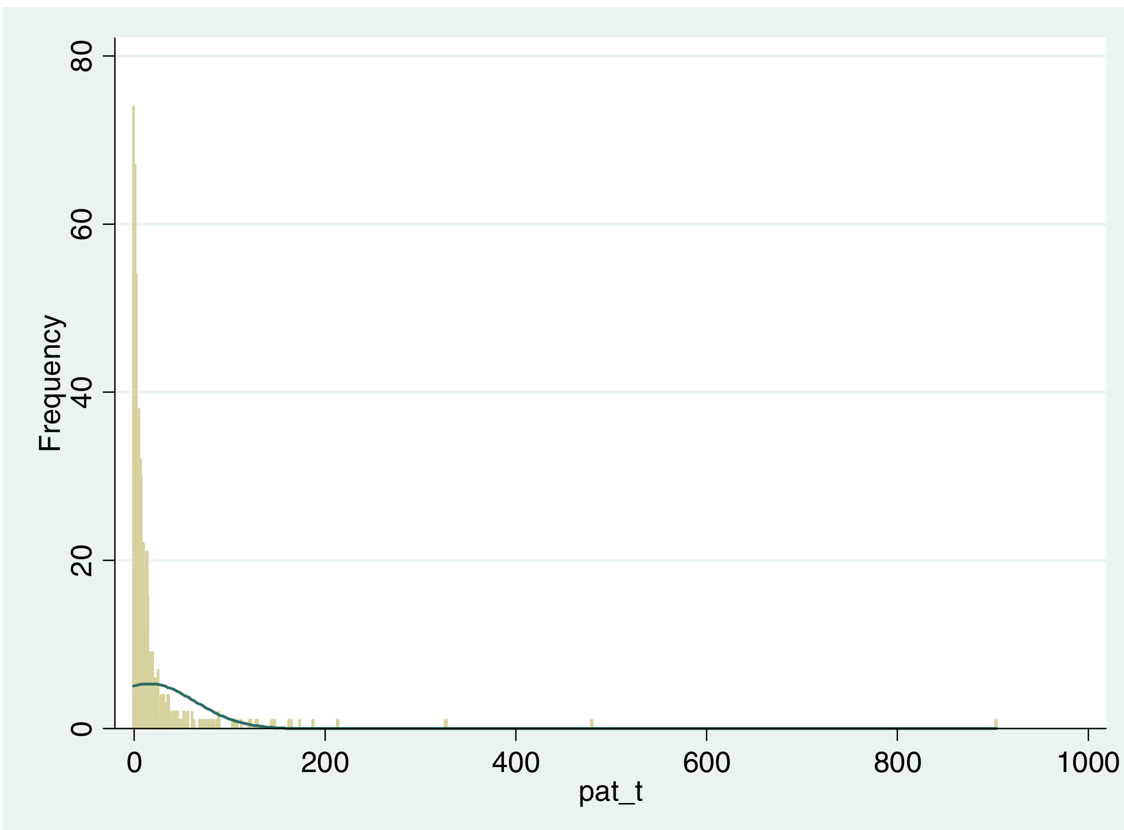
Figure 3.3 The Map of Study Area, 647 Rural Counties and 117 MSAs



The Dependent Variable

In this chapter, innovation, measured as the total patents in county 1990-1999, was the dependent variable in the models. To gain some information about the total patents in 647 counties in 1990-1999, it is informative to look at a histogram of the observed data in Figure 3.4. Many rural counties have very few total patents during 1990-1999, and very often not even a single patent. The distribution seems to have a long tail. Thus, the ZINBM are used for the data analysis (resulting from overdispersion test and Vuong test in Table 3.9).

Figure 3.4 Histogram for Total Patents



The Explanatory Variables

The selected explanatory variables are the same as those used for the previous estimations for 591 nonmetro counties. A list of the summary statistics for independent variables is provided in Table 3.6. All explanatory variables except metro patents and metro university R&D expenditures used 1990 values to control for possible endogeneity issues.

Table 3.6 Summary Statistics for Variables, 647 Rural Counties

Variables	Mean	SD	Min.	Max.
Total Patents, 1990-99	16.00773	48.2375	0	904
% Tech Occupation, ***PR***	4.494523	1.748212	0	17.40226
College Enrol. 1990, ***UR***	953.8192	1412.423	0	23197
Small Est. per capita, ***SF***	.0171661	.0055104	.0056221	.0429402
Large Est. per capita, ***LF***	.0000285	.0000469	0	.0003712
LQ of MFG, ***S_MFG***	1.225023	.89368	0	4.354384
Indust. Diversity, ***D***	3.280918	1.306286	1.04626	11.86529
Competitiveness , ***C***	.9989444	.2245908	.0951137	2.155624
Competitiveness squared, $\boldsymbol{C^2}$	1.048253	.4677014	.0090466	4.646717
Amenity Rank, ***AMTY***	3.698609	.6794515	2	6
Total Employment, 1990, ***EMP***	9400.184	8884.167	95	58803
% High Tech Emp, ***HTECH***	1.318546	2.604619	0	23.17731
W. PAT, ***W·P***	-.0036592	.6546974	-.331852	9.411605
Distance (miles), ***DIST***	49.89954	38.6412	1	381
MSA PAT, ***MET_T***	1096.652	2449.257	14	13364
MSA PAT DEN, ***MET_D***	13.54642	12.76103	.9646847	94.03884
MSA UNIV R & D per capita, ***MET_UR***	1179.787	3125.045	0	28203.04
%MSA Tech Emp., ***MET_PR***	4.942929	.6861581	3.378928	7.201031

3.4.2 The Unlikelihood of Patenting: Logit Equations

The dependent variable in the knowledge production functions, rural county patents 1990-1999, is count data with an overdispersion of observations of zero or near zero. Five models were estimated to determine the role of rural 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 rural county's LMA. Table 3.7 shows the empirical results for the logit equation (the unlikelihood of county patenting) of the zero inflated negative binomial model described in section 3.2 for rural county areas.

Sources of Innovation

Among the variables representing sources of innovation, the number of individuals in the county enrolled in college, the proxy variable for university R&D (UR), is negatively but not significantly related to the unlikelihood of a rural area receiving total patents except in model 5 (Table 3.7). None of the remaining measures of sources of innovation (PR, SF, and LF) are significantly related to the unlikelihood of patenting.

Knowledge Spillovers

The specialization in manufacturing (S_MFG) and industry diversity (D) are not significant. The unlikelihood of county patenting is positively related to Graeser U-shaped competitiveness, indicating the importance of large sized establishments or local monopoly in the probability of having a patent. 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.

Regional Spillovers

The unlikelihood of patenting is negatively related to the percent of high technology employment (HTECH), indicating a positive role for high tech employment on the probability of receiving a patent. The coefficients of amenity rank (AMTY) were negative but not significant at the 10% level. The negative impact of the size of local economy (EMP) on the unlikelihood of patenting was found, indicating the probability of having a patent was related to the size of local economy (urbanization economies).

Of principal interest to this study is the role of spillovers in rural county patent activity. The coefficient of the spatially lagged variable (W ·P) was not significant. An unexpected positive or significant relationship existed for metro innovative activity and capacity. Distance from metropolitan (DIST) was negatively related to the unlikelihood of patenting in rural county areas, indicating that proximity to metro innovative activity was not related to the probability of having a patent in a rural area. There was a significant, positive impact of metropolitan university R&D (MET_UR) on the unlikelihood of patenting, suggesting that the proximity to metro innovation had little impact on the probability of patenting among firms at the rural county level (sometimes with "backwash" effects). Thus one of possible explanation for the unexpected coefficient of DIST is due to the "backwash" effects from the metro innovative activities.

Table 3.7 Logit Equation for the Unlikelihood of Patenting, 647 Nonmetro Counties[a]

Independent Variables	Model 1 No MSA Term	Model 2 MSA PAT Total	Model 3 MSA PAT Density	Model 4 MSA UNIV R & D	Model 5 MSA S & Tech
%Tech Occ., *PR*	.2668697 (1.11)[b]	.2655259 (1.06)	.2710321 (1.14)	.1891753 (0.83)	-.1327267 (-0.19)
Coll. Enrol., *UR*	-.004791 (-0.82)	-.0043432 (-0.72)	-.0050058 (-0.85)	-.0057123 (-0.95)	-.0911886** (-2.20)
Small Est. *SF*	114.3135 (1.27)	130.9052 (1.38)	121.6789 (1.31)	128.3717 (1.36)	-41.59584 (-0.23)
Large Est. *LF*	3878.994 (0.34)	804.7219 (0.05)	5006.652 (0.45)	7876.563 (0.76)	-19612.57 (-0.00)
Mfg. LQ, *S_MFG*	-1.086215 (-1.50)	-1.117151 (-1.44)	-1.098413 (-1.55)	-1.012491 (-1.43)	-2.166938 (-1.14)
Diversity, *D*	-.0606097 (-0.12)	-.0811522 (-0.15)	-.0614642 (-0.12)	-.0557212 (-0.10)	-.9178669 (-0.81)
Comp, *C*	-12.31396* (-1.90)	-12.89799* (-1.89)	-12.11546* (-1.85)	-12.33637* (-1.80)	-13.6651 (-0.65)
Comp^2, C^2	4.374228 (1.59)	4.628088 (1.60)	4.309972 (1.54)	4.640129 (1.56)	8.421657 (0.80)
Amenities, *AMTY*	-.4326725 (-0.82)	-.3993298 (-0.74)	-.4913975 (-0.92)	-.3499835 (-0.65)	.4162143 (0.41)
Total Emp., *EMP*	-.0012657** (-2.09)	-.0014049** (-2.25)	-.0013425** (-2.16)	-.0014078** (-2.30)	-.0003193 (-0.48)
% High Tech, *HTECH*	-2.732221 (-1.53)	-2.771548 (-1.54)	-2.687683 (-1.58)	-3.281859* (-1.65)	-3.516331 (-1.46)
W. PAT, $W{\cdot}P$	-1.290955 (-0.92)	-2.188269 (-0.79)	-1.611374 (-0.87)	-1.136636 (-0.77)	-.4082088 (-0.10)
Distance, *DIST*	-.0159077* (-1.84)	-.0174257* (-1.77)	-.016504* (-1.92)	-.015528* (-1.71)	-.0264658* (-1.77)
MSA PAT, *MET_T*		.0001572 (0.93)			
MSA PAT D., *MET_D*			.0205432 (0.65)		
MSA U. R & D, *MET_UR*				.0002145** (2.05)	
MSA Tech. *MET_PR*					-1.785851 (-1.38)
Intercept	9.924377** (2.35)	9.885168** (2.23)	9.811829** (2.28)	9.68453** (2.15)	24.61819* (1.78)
Loglikelihood	-2072.102	-2062.898	-2066.278	-2069.956	-2071.218

[a] Non zero observations = 573; and zero observations = 74.

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

*, P-Value <0.1; **, P-Value <0.05; and *** P-Value<0.01

3.4.3 The Rate of Patenting: Count Equations

Table 3.8 shows the estimated effects of the local characteristics of RIS on the number of patents (the rate of patenting) within a rural area. It is clear from the results that knowledge spillovers, regional spillovers, and sources of innovation on patent activity had a strong positive association with the rate of patenting.

Sources of Innovation

Noticeable differences exist between the impacts of the local characteristics of RIS on the number of patents in rural areas compared to the unlikelihood of patenting across rural areas. The positive and significant coefficient for private R&D play appears in the negative binomial estimations, but not in the first-stage logit estimations. An increased presence of overall private R&D activity has significant effect on the number of patents (the rate of patenting) in all five models.

University spillovers (UR) are more important in determining the number of patents than the unlikelihood of patenting in a rural area. An increase in university R&D expenditures leads to a significant increase in the number of patents issued within a rural area. There are also strong effects of small firms (SF) and large firms per capita (LF), suggesting that the rate of patent activity benefits from both small and large firms. All of the four variables (UR, PR, SF, and LF) for the sources of innovation are positively associated with the rate of county patenting activity.

Table 3.8 Count Equation for the Number of Patents, in 647 Nonmetro Counties[a]

Independent Variables	Model 1 No MSA Term	Model 2 MSA PAT Total	Model 3 MSA PAT Density	Model 4 MSA UNIV R & D	Model 5 MSA S & Tech
%Tech Occ., *PR*	.2927817*** (9.92)[b]	.2847479*** (9.98)	.2810757*** (9.65)	.2940469*** (9.97)	.2902912*** (9.88)
Coll. Enrol., *UR*	.0000753* (1.79)	.0000602 (1.58)	.0000722* (1.76)	.0000749* (1.78)	.0000789* (1.79)
Small Est. *SF*	44.87106*** (3.50)	45.45471*** (3.58)	44.7978*** (3.53)	45.18657*** (3.52)	47.91868*** (3.70)
Large Est. *LF*	3437.458*** (3.26)	3764.579*** (3.57)	3687.25*** (3.52)	3449.693*** (3.27)	3253.759*** (3.08)
Mfg. LQ, *S_MFG*	-.1292988** (-2.04)	-.1442152** (-2.30)	-.136173** (-2.17)	-.130278** (-2.05)	-.0937554 (-1.46)
Diversity, *D*	.1753627*** (4.28)	.1514632*** (3.75)	.1681002*** (4.16)	.1734485*** (4.23)	.1805133*** (4.35)
Comp, *C*	.9191045 (0.90)	1.291688 (1.28)	1.191698 (1.19)	.9045193 (0.89)	1.16138 (1.15)
Comp^2, C^2	-1.276219*** (-2.86)	-1.375354*** (-3.13)	-1.353645*** (-3.10)	-1.268001*** (-2.84)	-1.356251*** (-3.07)
Amenities, *AMTY*	.3078132*** (4.73)	.2769958*** (4.30)	.2803781*** (4.31)	.3049261*** (4.69)	.3068363*** (4.65)
Total Emp., *EMP*	.0000642*** (8.60)	.0000657*** (9.11)	.0000633*** (8.65)	.0000641*** (8.59)	.0000657*** (8.49)
% High Tech, *HTECH*	-.0026869 (-0.04)	-.0064781 (-0.09)	.0050023 (0.07)	-.0048564 (-0.07)	.0004369 (0.01)
W. PAT, $W{\cdot}P$	.2485394*** (3.40)	.2288489*** (3.29)	.2258115*** (3.19)	.2520361*** (3.43)	.261504*** (3.45)
Distance, *DIST*	-.0031201*** (-3.08)	-.0033409*** (-3.39)	-.0033178*** (-3.30)	-.003208*** (-3.16)	-.002925*** (-2.86)
MSA PAT, *MET_T*		.0000607*** (3.93)			
MSA PAT D., *MET_D*			.0101468*** (3.19)		
MSA U. R & D, *MET_UR*				-.0000131 (-0.95)	
MSA Tech. *MET_PR*					.0642411 (1.09)
Intercept	-1.601673** (-2.52)	-1.712419*** (-2.73)	-1.741576*** (-2.78)	-1.567072** (-2.46)	-2.217727*** (-3.20)
Lnα	-.235313*** (-3.63)	-.2653404*** (-4.05)	-.2536599*** (-3.90)	-.2384627*** (-3.67)	-.1869373*** (-2.95)
Vuong test [p-value]	3.51 [0.0002]	3.51 [0.0002]	3.46 [0.0003]	3.59 [0.0002]	3.75 [0.0001]

[a] Non zero observations = 573; and zero observations = 74.

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

*, P-Value <0.1; **, P-Value <0.05; and *** P-Value<0.01

Knowledge Spillovers

Rural county total patents are negatively associated with the specialization in manufacturing (S_MFG). This finding is consistent with the hypothesis that "manufacturing towns" are unattractive places for innovative activity (Acs et al., 2002). However, rural patent totals are positively associated with industry diversity (D) of the local economy. These results indicate that less specialization promotes innovation and growth because most important knowledge transfers are from outside industries (Jacobs' hypothesis).

The competitiveness of the local industry structure is statistically correlated with innovative activity in the non-metro counties with an inverse U-shaped form, indicating the role of local market power. 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.

Regional Spillovers

The availability of local amenities (*AMTY*) and proximity to metro areas (*DIST*) areas are positively associated with the number of rural patents. An increase in amenity quality in rural areas contributes to an increase in the number of patents issued within a rural area. This finding may indicate that the more innovative firms in rural 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 rural counties but work in metro areas (Barkley, *et al*., 2006).

Rural patent totals are positively associated with the size of the local economy (EMP) indicating that as the rural employment grows, the number of patents significantly increases. The strong positive effect of the size of a rural area is consistent with a similar effect found by Jaffe (1989) and Feldman (1994) at the state level. No significant relationship is found between high-technology employment (HTECH) in rural counties and number of local patents.

The spatially lagged dependent variable (W • P) 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. MSA patent totals (MET_T) and MSA patents per 10,000 persons (MET_D) were positively associated with rural patent activity at the 10% significant level, indicating "spread" effects. One of the metro inputs for the innovation process, MSA_UR, is negatively related to rural patent counts but not at a high level of statistical significance. The other input measure, MSA_PR, is positively associated with county innovative activity, but not statistically significant.

3.4.4 Comparison to the Nonmetro and Rural Innovative Activity

In this chapter the knowledge production functions expressed in Equation (3.4) were re-estimated for the 591 nonmetro counties plus the 56 rural counties in the Southern MSA. The MSA characteristics in each LMA were re-calculated to reflect the exclusion of the rural counties from the MSA. The regression results for the 647 counties are presented in Table 3.7 and Table 3.8. The findings are similar to those for the nonmetro county data analysis in Table 3.4 and Table 3.5 with a couple of notable exceptions.

First, proximity to research universities has a significant effect on the unlikelihood of patent activity in nonmetro county area. Alternatively, university R&D had a significant effect on the number of patents in the "rural" sample. The significant effect of university research spillovers is important for policy makers concerned with nonmetro innovative activity in the early stage of innovation process. Second, all of variables representing innovation sources (PR, UR, SF, LF) in the rural county areas are more significantly associated with the number of patents (in the rate of patenting models) than in nonmetro county areas. Third, the negative effect of the specialization in manufacturing (S_MFG) in rural county areas was stronger on the number of patents than that of S_MFG in nonmetro county areas. The negative coefficient on the percent of high technology employment (HTECH) was significant in the unlikelihood of patenting in the rural county areas, while it was not significant for the nonmetro county sample.

The unlikelihood of patenting in nonmetro counties was more positively related to MSA patent totals (MET_T) and MSA university R&D (MET_UR), indicating "backwash" effects. 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 (McCann and Simonen, 2005).

The number of patents (the rate of patenting) in nonmetro plus metro rural counties were more strongly related to MSA patent total (MET_T) and MSA patent intensity (MET_D). 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 MSA also is consistent with earlier findings of a limited spatial dimension to innovation spillovers (Barkley *et al.*, 2006). MSA fringe counties appear to "benefit" from patent activity in the urban MSA counties. In sum, innovation spillovers from patents are evident but spatially limited.

3.5 Summary of Findings

This chapter has presented empirical estimates of the impacts of the local characteristics of RIS on innovative activity in nonmetro and rural counties. Using utility patents as the measure of innovative activity, this impact was examined at two levels: (1) on the unlikelihood of patenting in rural areas and (2) on the level of innovative activity.

First, the evidence indicates that the negative impacts of university spillovers (UR) and economy size (EMP) is strong on the unlikelihood of patenting in the first stage of the zero inflated negative binomial models. Alternatively, the probability of having a patent in rural or nonmetro county areas is positively related to university spillovers and the size of local economy. However, the unlikelihood of patenting was positively related to the metro patent activities, indicating "backwash" effects.

Second, this chapter also provided evidence that local characteristics of RIS effected the level of innovative activity in rural areas (the rate of patenting). The empirical findings indicated that innovation sources, knowledge spillovers, and regional spillovers lead to greater patent activity. This supports previous research with similar findings at both the state and metropolitan area levels for patents and innovation counts. Innovative activity is most evident where the county has sources of innovation (private R&D, university R&D, small firms, and large firms), knowledge spillovers (industry diversity, no specialization of manufacturing industry), and regional spillovers (high technology employment, spatial proximity, quality of amenities, the size of local economy).

However, evidence of metropolitan innovation spillovers to rural county areas is relatively limited. The findings indicated that patent activity in metro areas had a small but statistically significant association with the number of patent totals for nearby rural economies. This research did not find any relationship between university research and development expenditures in the metro core and patenting activity in the remaining rural counties of the LMA. 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 non-metropolitan areas. The following chapter examines the impact of the rural innovative activity and the local characteristics of RIS on the economic growth of nonmetro and rural counties (647 counties).

CHAPTER 4

THE ROLE OF RIS IN RURAL GROWTH

4.1 Introduction

This chapter investigates the relationship between the characteristics of rural RIS and economic growth rates (population, earnings, employment, and income growth) in 647 rural counties of the South from 1990 to 2000 period. The main goal of this chapter is to investigate the role of RIS in the regional economic growth at the rural level in the South. Of special interest is the role of local innovative activity in rural economic growth. Specifically, is the regional economic growth in rural counties associated with the RIS in the county and the innovative activity in the metro core, and if so, what characteristics of rural counties contribute to increased economic growth?

This chapter is organized as follows. First, the research describes the variables and data employed, the hypotheses to be tested, and the construction of the models. Next, rural economic growth models such as the Glaeser OLS model and the Carlino-Mills model are estimated for the 647 rural and nonmetro counties in LMA with a metropolitan core. The principal goal of these estimations is to determine the influence of the characteristics of rural RIS and metro innovative activity on population, earnings, employment, and income changes in the 647 counties in the Southern LMA. The findings indicate that the local characteristics of RIS in rural areas had a statistically significant association with rural growth. However, the innovative activities in metro areas had a negative association with rural economic growth, suggesting "backwash" effects.

4.2 Model and Data

4.2.1 The Study Area

The study area is the 591 nonmetro counties in Southern LMA with metro cores. In addition, according to Isserman's criteria (rural, mixed rural, mixed urban, and urban), 56 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. The following models were estimated for the 647 Southern counties in LMA with a metro core area (nonmetro plus rural counties in MSA).

4.2.2 The Dependent Variables

This study hypothesizes that rural counties near metro areas with significant innovative activity have more rapid economic growth than rural areas proximate to metro areas with less innovative activity. Previous research (Barkley *et al.*, 1994) suggested, however, that the spillover of economic activity from the metro core to nearby rural counties was a function of characteristics of both the MSA and surrounding rural counties. This study builds on the empirical framework of Glaeser and Saiz (2003) to determine the effects of local characteristics of RIS in rural economics growth. Four models are estimated for Southern rural counties according to the following specifications:

$$\ln\left(\frac{POP_{r,2000}}{POP_{r,1990}}\right) = \alpha_0 + \alpha_1 \ln\left(\frac{POP_{m,2000}}{POP_{m,1990}}\right) + \sum \alpha_{2i} MSA\_CHR_r + \sum \alpha_{3i} MSA\_RIS_r + \sum \alpha_{4i} CHR_r + \sum \alpha_{5i} RIS_r + \varepsilon_1 \quad (4.1)$$

$$\ln\left(\frac{EPR_{r,2000}}{EPR_{r,1990}}\right) = \gamma_0 + \gamma_1 \ln\left(\frac{EPR_{m,2000}}{EPR_{m,1990}}\right) + \sum \gamma_{2i} MSA\_CHR_r + \sum \gamma_{3i} MSA\_RIS_r + \sum \gamma_{4i} CHR_r + \sum \gamma_{5i} RIS_r + \varepsilon_2 \quad (4.2)$$

$$\ln\left(\frac{EMP_{r,2000}}{EMP_{r,1990}}\right) = \beta_0 + \beta_1 \ln\left(\frac{EMP_{m,2000}}{EMP_{m,1990}}\right) + \sum \beta_{2i} MSA\_CHR_r + \sum \beta_{3i} MSA\_RIS_r + \sum \beta_{4i} CHR_r + \sum \beta_{5i} RIS_r + \varepsilon_3 \quad (4.3)$$

$$\ln\left(\frac{PI_{r,2000}}{PI_{r,1990}}\right) = \delta_0 + \delta_1 \ln\left(\frac{PI_{m,2000}}{PI_{m,1990}}\right) + \sum \delta_{2i} MSA\_CHR_r + \sum \delta_{3i} MSA\_RIS_r + \sum \delta_{4i} CHR_r + \sum \delta_{5i} RIS_r + \varepsilon_4 \quad (4.4)$$

where:
POP=Population; *EPR*=Net earnings by place of residence; *EMP*=Employment;
PI=Personal Income; *2000*=Year 2000; *1990*=Year 1990; *r*= Rural couny;
MSA_CHR_r=Characteristics of MSA in county r's LMA;
MSA_RIS_r= MSA total patents 1990-99; CHR_r=Rural characteristics of county r;
RIS_r=Rural characteristics of RIS of county r, 1990; *m*= metropolitan;
α, β, γ and δ are the parameter coefficients; and ln stands for log transformation.

In this chapter, four variables are selected as the dependent variables in the models: the growth rate of population, the growth rate of net earnings by place of residence[12], the growth rate of employment, the growth rate of personal income[13]. All variables are expressed in log form. To gain some information about the dependent variables in the 647 counties, it is useful to look at a histograms of the observed data in Figure 4.1 through Figure 4.4. Table 4.1 and Table 4.2 provide the definition and descriptive summary statistics for the four dependent variables.

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[12] BEA note that "Net earnings by place of residence is earnings by place of work-the sum of wage and salary disbursements, supplements to wages and salaries, and proprietors' income-less contributions for government social insurance, plus an adjustments to convert earnings by place of work to a place of residence basis." (BEA, www.bea.gov, 2006)

[13] BEA noted that "Personal Income (PI) is the income that is received by all persons from all persons from all sources. It is calculated as the sum of wage and salary disbursements, supplements to wages and salaries, properties' income with inventory valuation and capital consumption adjustments, rental income of persons with capital consumption adjustment, personal dividend income, personal interest income, and personal current transfer receipts, less contributions for government social insurance." (BEA, www.bea.gov, 2006).

Figure 4.1 Histogram for the Growth of Population (POP)

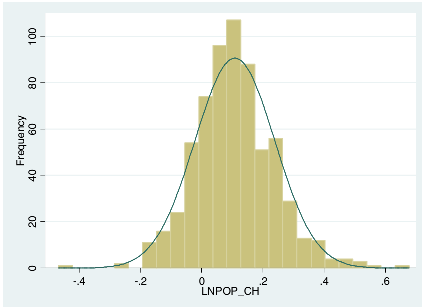

Figure 4.2 Histogram for the Growth of Earnings by Place of Residence (EPR)

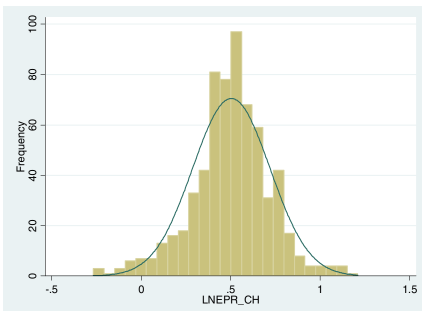

Figure 4.3 Histogram for the Growth of Employment (EMP)

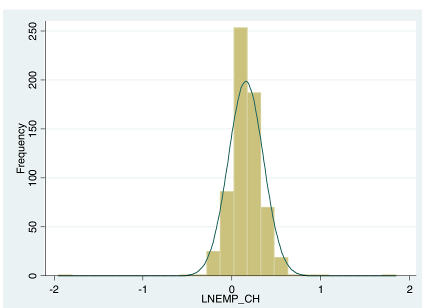

Figure 4.4 Histogram for the Growth of Personal Income (PI)

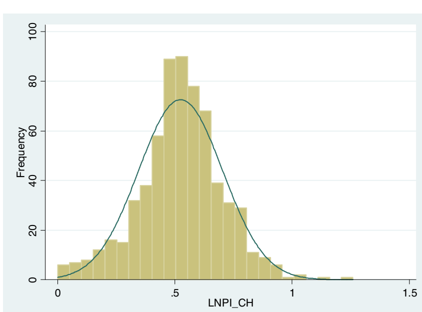

Table 4.1 Variable Descriptions and Data Sources

Variables	Description
% Tech Occup., ***PR***	Percent of employment in technical professions – computer science; engineering; natural, physical and social sciences (BLS, 1990)
% Coll. Enrol. 90, ***UR***	Percent of individuals in county enrolled in college, 1990 (Census)
Small Est. per capita, ***SF***	County establishments with fewer than 20 employees per capita
Mfg LQ, ***S_MFG***	LQ in manufacturing, Eq (3.10), 1990 (BEA)
Competitiveness, ***C***	The ratio of local to national establishments per worker, Eq. (3.11), 1990 (CBP).
Diversity, ***D***	Inverse of Krugman Index, Eq. (3.13), one-digit SIC, 1990 (BEA)
Amenities, ***AMTY***	McGranahan Index of natural amenities (ERS, USDA, 1999)
% High-Tech. , ***HTECH***	Percent of total county employment in high-technology manufacturing, 1992 (Census of Manufacturers)
Emp Density 90, ***EMPD***	(County employment, 1990)/(County area, 1990), Census
Distance, ***DIST***	Miles from largest city in county to core city in LMA's MSA
PAT per 10000 Pop, ***PATD***	Total patents per 10,000 population, 1990-1999 (USTPO)
MSA Patent Den., ***M_PAT***	MSA patents per 10,000 population, 1990-1999 (USTPO)
W • Growth, ***W·Y***	Spatially lagged dependent variable, W = contiguity matrix
Med. House Val90, ***HVAL***	Median value of housing, 1990 (Census)
% Non-white 90, ***NWHITE***	Percent of county population nonwhite, 1990 (Census)
Pop Density 90, ***POPD***	(County population, 1990)/(County area, 1990), Census
Pop 90, ***POP90***	County population, 1990 (Census)
Total Emp 90, ***EMP90***	Total county employment, 1990 (BEA)
Earnings 90, ***EPR90***	County net earnings by place of residence, thousands of dollars, 1990 (BEA)
Personal Incom90, ***PI90***	County personal income, thousands of dollars, 1990 (BEA)
MSA Pop Den.90, **ln*M_POPD***	(MSA population, 1990)/(MSA area, 1990), Census
MSA Emp D.90, ***M_EMPD***	(MSA employment, 2000)/(MSA area, 1990), BEA and Census
MSA Gr. Pop, ***M_GPOP***	(MSA population, 2000)/(MSA population, 1990), Census
MSA Gr. Earn., ***M_GEPR***	(MSA earnings per worker by place of residence, 2000)/ (MSA earnings per worker by place of residence, 1990), BEA
MSA Gr. Emp, ***M_GEMP***	(MSA employment, 2000)/(MSA employment, 1990), BEA
MSA Gr.PI., ***M_GPI***	(MSA personal income, 2000)/ (MSA personal income, 1990), BEA

4.2.3 The Explanatory Variables of Metro Characteristics

The previous four regression models (Equation (4.1) through (4.4)) are used to determine factors related to rural county growth rates in population, net earnings by place of residence, employment, and personal income. The model specifications use the MSA values for the dependent variables, such as the 1990 to 2000 MSA population growth rate, to investigate the relationship between urban growth and rural growth. This is consistent with the conclusions by Partridge et al. (2005) that urban growth drives the regional economy and creates significant positive impacts on nearby rural areas. Thus, growth rates in rural counties are hypothesized to be driven by changes in population, net earnings by place of residence, employment and earnings in the LMA's core metro areas.

Three other MSA-level variables are included to estimate the influence of metropolitan area characteristics (MSA_CHR) on the growth rates of rural counties in the metro area's LMA. First, the 1990 to 1999 patent counts per 10,000 residents (patent intensity) were used as the proxy variable for innovative activity in metro areas. A positive coefficient on the MSA innovative activity variable (lnM_PAT) is hypothesized if proximity to MSA innovative activity is associated with more rapid growth rates in rural counties.

Second, MSA population density (lnM_POPD) will be positively related to rural growth rates if urban population density reflects congestion and higher social costs in the urban area. Alternatively, metro population density will be negatively related to rural growth rates if population density reflects the availability of urbanization economies in the metro area and these urbanization economies contribute to a "backwash" effect on nearby rural counties (Barkley *et al.*, 2006). Thus, the sign on the density coefficient is indeterminant, a priori.

Third, the metropolitan characteristic hypothesized to influence the urban-to-rural spillover of growth is MSA employment density (lnM_EMPD) in the metro area. MSA employment density is hypothesized to be negatively related to rural employment and income growth if employment density reflected agglomeration economies in the metro areas, and thus "pulled" economic activity into the LMA's core city. Alternatively, high employment density may reflect congestion costs and thus encourage the spillover of jobs to rural counties in the LMA (Barkley *et al.*, 2006). Thus, the effect of metro employment density is mixed.

4.2.4 The Explanatory Variables of RIS and Rural Characteristics

Characteristics of RIS

The simple descriptive statistics for all variables are provided in Table 4.2. The hypotheses regarding local innovative activity, innovation sources, knowledge spillovers and regional spillovers are the same as those provided in Chapter 3. The 1990 to 1999 patent counts per 10,000 residents (lnPATD)[14] is used as the proxy variable for rural innovative activity. The literature on the role of innovative activity in nonmetro or rural areas indicates a significant positive effect of rural innovative activity on the economic growth (Acs and Varga, 2004; Porter, 1996).

[14] For log-transformation, I set all zero observations in county total patents equal to 0.5.

Table 4.2 Descriptive Statistics for Variables in 647 Rural Counties

Variables	Mean	S.D.	Min	Max
Log-Growth Rate of Population	.1083496	.1307066	-.468137	.678199
Log-Growth Rate of EPOR	.5039228	.2166498	-.266722	1.212025
Log-Growth Rate of Employment	.1590089	.1975022	-1.94974	1.846991
Log-Growth Rate of PI	.5243009	.1791372	.000042	1.259838
% Technical Occup.90, ln*PR*	1.440018	.3523472	-1	2.82581
% Coll. Enrol. 90, ln*UR*	1.255387	.4311866	-1.069134	3.888923
Small Est. per cap. 90, ln*SF*	-4.115439	.3221685	-5.181057	-3.147948
Mfg. LQ 90, ln*S_MFG*	1.014461	.4429398	0	2.086716
Competitiveness, *lnC*	-.0301072	.2579144	-2.352679	.76808
Diversity 90, ln*D*	1.11981	.3638358	.045222	2.473617
Amenities 90, *AMTY*	3.698609	.6794515	2	6
% High Tech Emp, ln*HTECH*	-2.036933	.9874523	-5.03851	2.639511
Emp Density 90, ln*EMPD*	2.451452	1.088464	-1.958017	7.768068
Distance, ln*DIST*	3.734595	.592247	-.693147	5.942799
PAT per 10000 Pop, ln*PATD*	.9611426	1.409291	-3.912023	5.38022
MSA Patents90-99, ln*M_PAT*	5.668658	1.59809	2.639057	9.50032
Med. House Val90, ln*HVAL*	10.63764	.2750759	9.615739	11.92636
% Non-white 90, ln*NWHITE*	2.572763	1.257618	-2.780621	4.456533
Pop 90, ln*POP90*	9.648438	.8743722	4.672829	11.93232
Emp 90, ln*EMP90*	8.778104	.897548	4.553877	10.98195
Earnings 90, ln*EPR90*	11.75646	.9288631	7.007601	14.02716
Personal Incom90, ln*PI90*	12.23737	.8906188	7.886081	14.77927
Pop Density 90, ln*POPD*	3.430136	1.13888	-2.307206	7.38911
MSA Gr. Pop, ln*M_GPOP*	.1299873	.0860902	-.040479	.395237
MSA Pop Den.90, ln*M_POPD*	5.30838	.6290271	3.671236	6.904737
MSA Gr. Earn., ln*M_GEPR*	.5422453	.142214	.223389	1.091419
MSA Emp D.90, ln*M_EMPD*	4.751464	.6833522	2.774389	6.27786
MSA Gr. Emp, ln*M_GEMP*	.2066269	.093838	-.00425	.506645
MSA Gr.PI., ln*M_GPI*	.5501758	.1162953	.3210681	.9938933

The proxy variable selected for industry R&D (lnPR) is percent of county employment in scientific and technical occupations because measures of private R&D expenditures by county are not available. The proxy variable for potential university R&D (lnUR) is the percent of individuals in the county enrolled in college. The positive coefficients of private and university R&D are hypothesized. The proxy variable for small firms (lnSF) is the county establishments with fewer than 20 employees per capita in 1990. However, since the proxy variable of large firms in Chapter 3 had many zero value, I cannot use the log transformation. Research on innovative activity in states and metropolitan areas indicated a positive association between economic growth rates numbers and proportion of small firms in rural areas (Gordon and McCann, 2005).

The MAR and Porter theories of external economies suggested that industry specialization will stimulate growth of the sector in that region. However, the hypothesized coefficient on the variable representing specialization in manufacturing (lnS_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. According to MAR, intensive local competitiveness (lnC) in a sector impeded economic growth in that sector. In the case of intensive competitiveness, MAR assumed that enterprises limited their innovative activities because too much new knowledge spilled over to competitors. According to Jacobs and Porter, intensive local competitiveness benefited economic growth because enterprises were forced to innovate. Thus, the impact of regional competitiveness is mixed.

In Equation (3.12), when a region is more specialized than the nation, the summation increases. On the other hand, when the industrial mix follows the national average (i.e., if the region is diversified), the summation decreases. Unlike the specialization index that focuses only one industry, the diversity index takes into account the industry mix of the entire regional economy. Therefore, contrary to popular belief, specialization and diversity are not necessarily mutually exclusive concepts. A regional economy can have a few specialized industries and at the same time be diverse. The industrial diversity of the county economy (lnD) is represented by the inverse of the Krugman Index (Equation 3.13), and a positive association is anticipated between industry diversity and county economic growth rates.

County and regional characteristics found in earlier research to be associated with regional economic growth rates are the structure of the local economy, characteristics of the local labor market, and economic growth rates in nearby communities (spillovers). A common way of modeling spillovers between regions is using spatial econometric models. A positive estimated coefficient on the spatially lagged dependent variable indicates a positive association between economic growth rates in a county and growth rates in surrounding counties. The distance variable (lnDIST) reflects proximity to urbanization economies in the LMA's metro area. A negative relationship between distance and county growth rates is hypothesized.

Deller et al. (2001) extended the Carlino-Mills model to explore the nature of amenity attributes on rural development. Their main hypothesis was that regional economic growth rates are conditional upon regional amenity factors. Their findings indicated that workers in low amenity regions were compensated by higher wages than workers that live in areas with high levels of amenities. This study hypothesizes that rural growth rates are positively related to the perceived local quality of life as reflected in the McGranahan (1999) index for natural amenities (AMTY). The percentage of county employment in high-technology manufacturing industries (lnHTECH)[15] is also hypothesized to be positively related to county growth rates (Riddel and Schwer, 2003).

Regional Characteristics

Local school quality or the local educational environment is represented by the instrument Median Value of Housing (lnHVAL), 1990. An increase in local housing value is associated with an increase in available funding for schools and a higher demand by residents for student performance (Barkely, Henry, and Nair, 2006). This research anticipate a positive relationship between county population and earnings growth rates and median housing value if local school quality is an important determinant of residential location choice. Local quality of life measures also may be positively related to county employment growth. I hypothesize that employers are concerned to areas with a high quality of life because labor is less expensive in or more easily attracted to such locations (Roback, 1982).

Racial diversity is measured as the percentage of the county population that is non-white (lnNWHITE), and a negative relationship is hypothesized between racial diversity and growth rates. The county population density variable (lnPOPD) is the proxy for the availability of urbanization economies in the rural county, and a positive coefficient is hypothesized for the variable. Employment density (lnEMPD) is the proxy for county urbanization economies and it is hypothesized to be positively related to county employment and earnings growth.

Table 4.1 provides the detailed variable definitions and data sources. The characteristics are selected based on the findings of previous research regarding rural county characteristics associated with economic growth (Deller, et al., 2001); metro and rural county

[15] For log-transformation, I set all zero observations in county high technology employments equal to 0.5.

characteristics related to urban-to-rural spillover effects (Henry et al., 1997); and county attributes associated with the geographic spread of innovative activity (Acs, 2002). All MSA and rural county characteristics variables are expressed as shares of area totals. Base year (1990) values of the explanatory variables are used to control for possible endogeneity issues except for the innovative activity variables. The models are estimated for the 647 Southern nonmetro and rural counties in LMA with metropolitan core cities. All variables were expressed in log form except for the quality of life indices (natural amenity ranks). As such, the estimated coefficients are elasticities. All the models were estimated with STATA 9.2.

4.3 The Data Analysis with the OLS Models

4.3.1 The OLS Model for Population Growth

The OLS model for the growth rate in nonmetro and rural county population, 1990-2000, is as follows:

$$\begin{aligned} \ln GPOP = {} & \alpha_0 + \alpha_1 W \cdot \ln GPOP + \alpha_2 \ln HVAL + \alpha_3 AMTY + \alpha_4 \ln NWHITE + \alpha_5 \ln DIST + \\ & \alpha_6 \ln EMP90 + \alpha_7 \ln POPD + \alpha_8 \ln PR + \alpha_9 \ln UR + \alpha_{10} \ln SF + \alpha_{11} \ln S\_MFG + \alpha_{12} \ln D + \\ & \alpha_{13} \ln C + \alpha_{14} \ln HTECH + \alpha_{15} \ln PATD + \alpha_{16} \ln M\_PAT + \alpha_{17} \ln M\_POPD + \alpha_{18} \ln M\_GPOP + \varepsilon_1 \end{aligned} \tag{4.5}$$

where ln stands for log transformation; $a_0, a_1, a_2, a_3, a_4, a_5, a_6, a_7, a_8, a_9, a_{10}, a_{11}, a_{12}, a_{13}, a_{14}, a_{15}, a_{16}, a_{17}$ and a_{18} are estimated parameters; and the ε_1 is the error term.

Metro Characteristics

The findings of the OLS regression analysis for the population change are presented in Table 4.3. Several patterns are evident from the estimated equations. As hypothesized, the growth rate of rural county population is significantly related to metro characteristics (metropolitan population density and the growth rate of metro population). Rural county population growth rate (lnGPOP) is higher if the nearest metro area has experienced relatively rapid population growth. These results indicate that MSA growth provides positive spillovers or "spread" effects to rural counties in the MSA's labor market area. Evidence of population spread effects is also consistent with earlier research of nonmetro county growth (Bakley *et al.*, 2006; Henry *et al.*, 1997). However, the estimated coefficients for the metro patenting activity variable (lnM_PAT) do not support the hypothesis that innovative activity in a metropolitan area provides benefits to proximate rural areas. The negative coefficients indicate the possibility of a "backwash" effect from metro innovative activity.

RIS and Regional Characteristics

The percent of employment of in scientific and technical occupations (lnPR) is also positively associated with the growth rate of population. The industry diversity (lnD) is positively related to the growth rate of county population. The results indicate that less geographical specialization rather than more local specialization, promotes local population growth because many important knowledge transfers are from outside industries (Jacobs' hypothesis). However, the negative, significant coefficients of the proxy variables for small firms (lnSF) and the size of local economy (lnEMP90) are not consistent with hypothesized relationships. The population growth rate is not significantly related to the rural patent activity (lnPATD). The remaining RIS characteristic variables (regional competitiveness, distance, manufacturing specialization, percent of high-technology employment) are also not significant.

As hypothesized, the rural county population growth rate (lnGPOP) is significantly related to local quality of life as reflected in local amenities (AMTY) and school quality (lnHVAL). The spatially lagged dependent variable (W •lnGPOP) indicates a positive association between the population growth rate in a county and the rates in surrounding counties. That is, counties with low growth rates tend to cluster, and counties with high growth rates tend to locate near similar counties. The proxy variable for racial diversity (lnNWHITE) is negatively related to the growth rate of rural county population. The county population density variable (lnPOPD) is positively associated with the population growth rate in rural areas, indicating the availability of urbanization economies in the rural county. Thus all of coefficients of rural characteristics are significant, suggesting the importance of the rural characteristics on the growth rate of rural population.

4.3.2 The OLS Models for Earnings Growth

The OLS model for growth rates in rural net earnings by place of residence, 1990-2000, is as follows:

$$\begin{aligned} \ln GEPR = {} & \gamma_0 + \gamma_1 W \cdot \ln GEPR + \gamma_2 \ln HVAL + \gamma_3 AMTY + \gamma_4 \ln NWHITE + \gamma_5 \ln DIST + \\ & \gamma_6 \ln EPR90 + \gamma_7 \ln POPD + \gamma_8 \ln PR + \gamma_9 \ln UR + \gamma_{10} \ln SF + \gamma_{11} \ln S\_MFG + \gamma_{12} \ln C + \\ & \gamma_{13} \ln D + \gamma_{14} \ln HTECH + \gamma_{15} \ln PATD + \gamma_{16} \ln M\_PAT + \gamma_{17} \ln M\_POPD + \gamma_{18} \ln M\_GEPR + \varepsilon_2 \end{aligned} \tag{4.6}$$

where $\gamma_0, \gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5, \gamma_6, \gamma_7, \gamma_8, \gamma_9, \gamma_{10}, \gamma_{11}, \gamma_{12}, \gamma_{13}, \gamma_{14}, \gamma_{15}, \gamma_{16}, \gamma_{17}$ and γ_{18} are estimated parameters; and the ε_2 is the error term.

Metro Characteristics

The findings of the OLS regression analysis are presented in Table 4.3. The net earnings growth rate (lnGEPR) in a rural county is significantly related to metro characteristics (metro population density and the net earning growth in metro area). The rural county earnings growth rate is higher if the nearest metro areas experienced relatively high population density, indicating MSA spillovers or "spread" effects to rural counties in the MSA's labor market area. However, the estimated coefficients for the metro patenting activity variable (lnM_PAT) do not support the hypothesis that innovative activity in a metropolitan area provides benefits to proximate rural areas. "Backwash" effects are indicated by the negative coefficients.

RIS and Regional Characteristics

The earnings growth is negatively related to the relative number of small firm establishments (lnSF), indicating a negative effect of rural small firms on the growth rate of rural earnings by place of residence. As hypothesized, rural industry diversity (lnD) and regional competitiveness (lnC) are positively related to the growth rate of net earnings by place of residence. The rural earnings growth rate is positively associated with local quality of life as reflected in amenities (AMTY). The percent of high technology employment (lnHTECH) is positively related to the earnings growth. The coefficient of the rural patent activity variable (lnPATD) is positive and significant, indicating the role of rural innovative activity on the earnings growth. The coefficients of the remaining variables related to RIS characteristics (the proxy variables for private R&D and university R&D, manufacturing industry specialization, distance) are not significant at the traditional level.

The regression results for the growth rate of earnings by place of residence indicate that the earnings growth rate is highest among rural counties with relatively low base year earnings (lnEPR90). The growth rate of net earnings is related to good school quality as reflected in 1990 median housing values (lnHVAL) and relatively available urbanization economies as indicated by county population density (lnPOPD). The spatially lagged dependent variable (W •lnGEPR) indicates a positive association between the earnings growth rates in a county and the earnings growth rates in surrounding counties. The proxy variable for racial diversity (NWHITE) is negatively related to the growth rate of rural county earnings.

Table 4.3 OLS Results for Growth Rates in Population and Earnings

	Population Change, ln*GPOP*		Change in Net Earnings by Residence, ln*GERP*	
Variables	Coefficient	t-value	Coefficient	t-value
% Technical Occup.90, ln*PR*	.0436451***	2.94	-.0079148	-0.31
% Coll. Enrol. 90, ln*UR*	-.0145164	-1.60	.0056903	0.38
Small Est. per cap. 90, ln*SF*	-.0520776***	-2.90	-.2013186***	-6.94
Mfg. LQ 90, ln*S_MFG*	-.0079146	-0.72	.0205268	1.10
Diversity 90, ln*D*	.0256193**	2.11	.0777676***	3.80
Competitiveness, *lnC*	-.0132735	-0.56	.0719159*	1.83
Amenities 90, *AMTY*	.0150319***	2.62	.0165044*	1.75
% High Tech Emp, ln*HTECH*	-.00092	-0.24	.0172344***	2.65
Emp 90, ln*EMP90*	-.0187389***	-2.73		
W ·ln*GPOP*	.0575632***	10.10		
W ·ln*GEPR*			.0894588***	8.73
Distance, ln*DIST*	-.0042194	-0.62	-.0148421	-1.29
PAT per 10000 Pop, ln*PATD*	.0024308	0.87	.0087127*	1.85
Med. House Val90, ln*HVAL*	.121572***	6.20	.2479338***	7.58
% Non-white 90, ln*NWHITE*	-.0112753***	-3.94	-.0148285***	-3.10
Earnings 90, ln*EPR90*			-.068857***	-5.94
Pop Density 90, ln*POPD*	.0217319***	3.16	.039271***	3.43
MSA Patents90-99, ln*M_PAT*	-.0156814***	-3.85	-.0297283***	-4.49
MSA Pop Den, ln*M_POPD*	.024235***	2.69	.0284755*	1.96
MSA Gr. Pop, ln*M_GPOP*	.3171697***	5.86		
MSA Gr. EPR, ln*M_GEPR*			.4099697***	7.60
Intercept	-1.470225***	-6.12	-2.531497***	-6.44
R^2 (Adjusted)	0.5859		0.5741	
Obs. Number	647		647	

*, P-Value <0.1; **, P-Value <0.05; and *** P-Value<0.01

4.3.3 The OLS Models for the Employment Growth

The OLS models for growth rates in rural employment, 1990-2000, are as follows:

$$\begin{aligned}\ln GEMP = {} & \beta_0 + \beta_1 W \cdot \ln GEMP + \beta_2 \ln PR + \beta_3 \ln UR + \beta_4 \ln SF + \beta_5 \ln S\_MFG + \\ & \beta_6 \ln D + \beta_7 \ln C + \beta_8 \ln DIST + \beta_9 AMTY + \beta_{10} \ln EMPD + \beta_{11} \ln EMP90 + \beta_{12} \ln HTECH + \\ & \beta_{13} \ln PATD + \beta_{14} \ln M\_PAT + \beta_{15} \ln M\_EMPD + \beta_{16} \ln M\_GEMP + \varepsilon_3\end{aligned} \tag{4.7}$$

where β_0, β_1, β_2, β_3, β_4 ,β_5 ,β_6 , β_7, β_8 ,β_9, β_{10}, $\beta_{11,}$ β_{12} β_{13}, β_{14}, β_{15} and β_{16} are estimated parameters; and the ε_3 is the error term.

Metro Characteristics

The findings of the OLS regression for employment growth rates (lnGEMP)are presented in Table 4.4. Rural county employment growth rates are significantly related to metro characteristics (metro employment density and the growth rate of metro employment). Rural county employment growth rates are higher if the nearest metro areas have experienced relatively rapid employment growth. These results indicate that MSA growth provided "spread" effects to rural counties in the MSA's labor market area. However, the estimated coefficients for the metro patenting activity variable (lnM_PAT) do not support the hypothesis that innovative activity in a metropolitan area provides benefits to proximate rural areas.

RIS and Regional Characteristics

The growth rate of rural employment is positively and significantly related to the rural patent activity (lnPATD). Thus, evidence of higher employment growth from rural innovative activity is found in Southern rural counties. The percentage of the county's labor force in science and technology professions (lnPR) is positively and significantly related to the employment growth. However, the proxy variable for university R&D (lnUR) is not significant. County employment growth rates are negatively related to the number of small firm establishments per capita (lnSF), indicating inconsistence with the hypothesis. The coefficients of the specialization in manufacturing (lnS_MFG) and rural industry diversity (lnD) are not significant. A relatively large manufacturing sector is not significantly related to the employment growth rate. However, the growth rate in local employment is positively related to the rural competitiveness measure (lnC) with statistically high significance, which is consistent with Porter's hypothesis.

The regression results for the growth rate of rural employment indicate that the employment growth rate is highest among rural counties with relatively low base year employment (lnEMP90). The availability of local amenities (AMTY) is positively associated with the rural employment growth rate, indicating that employment growth in rural areas is concentrated in counties with higher amenities. The county employment growth rate is also positively related to county employment in high tech industries (lnHTECH). The spatially lagged dependent variable (W •lnGEMP) indicates a positive association between the employment growth rate in a county and the employment growth rates in surrounding counties. The coefficients of remaining variables related rural characteristics (rural employment density, distance) are not significant at the traditional level.

4.3.4 The OLS Models for the Income Growth

The OLS model for growth rates in county personal income, 1990-2000, is as follows:

$$\begin{aligned}\ln GPI = {} & \delta_0 + \delta_1 W \cdot \ln GPI + \delta_2 \ln PR + \delta_3 \ln UR + \delta_4 \ln SF + \delta_5 \ln S\_MFG + \\ & \delta_6 \ln D + \delta_7 \ln C + \delta_8 \ln DIST + \delta_9 AMTY + \delta_{10} \ln EMPD + \delta_{11} \ln PI90 + \delta_{12} \ln HTECH + \\ & \delta_{13} \ln PATD + \delta_{14} \ln M\_PAT + \delta_{15} \ln M\_EMPD + \delta_{16} \ln M\_GPI + \varepsilon_4\end{aligned} \tag{4.8}$$

where δ_0, δ_1, δ_2, δ_3, δ_4, δ_5, δ_6, δ_7, δ_8, δ_9, δ_{10}, $\delta_{11,}$ δ_{12} δ_{13}, δ_{14} , δ_{15} and δ_{16} are estimated parameters; and the ε_4 is the error term.

Metro Characteristics

The findings of the OLS regression for the growth rate of county personal income are presented in Table 4.4. The growth rate in personal income (lnGPI) is significantly related to metro characteristics (metro employment density and the growth of personal income), indicating that the rural county growth rate is higher if the nearest metro areas have experienced relatively rapid income growth. These results indicate that MSA growth provides positive spillovers or "spread" effects to rural counties in the MSA's labor market area. However, the estimated coefficients for the metro patent activity variable (lnM_PAT) do not support the hypothesis that innovative activity in a metropolitan area provides benefits to proximate rural areas. "Backwash" effects are indicated by the negative and significant coefficient on the metro patents variable. The findings for Southern non-metropolitan and rural counties appear to indicate that these counties do not benefit from spillovers of metro innovative activity.

RIS and Regional Characteristics

In Table 4.4, the rural income growth rate is positively and significantly related to the rural patent activity (lnPATD), evidence of higher income growth from rural innovative activity in Southern rural counties. The percentage of the labor force in science and technology professions (lnPR) is positively related to the county income growth. However, the income growth rate is negatively related to the relative number of small firm establishments in the county (lnSF). Rural county income growth rates are positively associated with the rural industry diversity (lnD). Rural county income growth rates are also positively related to employment density (lnEMPD) and employment in high tech industries (lnHTECH). The availability of local amenities (*AMTY*) is positively associated with rural income growth rates. The significant, positive coefficient of the spatially lagged dependent variable (W •lnGPI) indicates a positive association between the income growth rates in a rural county and the growth rates in surrounding counties. However, there are no significant coefficients on the RIS proxy variables for university R&D (lnUR), specialization in manufacturing (lnS_MFG), rural competitiveness (lnC), and distance from rural county to metro core (lnDIST).

Table 4.4 OLS Results for Growth Rates in Employment and Income

	Employment Change, ln*GEMP*		Change in Personal Income, ln*GPI*	
Variables	Coefficient	t-value	Coefficient	t-value
% Technical Occup.90, ln*PR*	.0646193**	2.42	.0504161**	2.57
% Coll. Enrol. 90, ln*UR*	.0244438	1.46	.0044094	0.36
Small Est. per cap. 90, ln*SF*	-.2024283***	-6.41	-.1551538***	-6.62
Mfg. LQ 90, ln*S_MFG*	.0072946	0.36	.0136806	0.91
Diversity 90, ln*D*	.0197812	0.88	.0409774**	2.52
Competitiveness, *lnC*	.3181089***	7.41	.0481975	1.53
Amenities 90, *AMTY*	.0260143**	2.57	.0377142***	5.06
% High Tech Emp, ln*HTECH*	.0170997**	2.37	.0142367***	2.71
Emp 90, ln*EMP90*	-.0309808**	-2.39		
Emp Density, ln*EMPD*	.0145126	1.20	.0299436***	3.23
Distance, ln*DIST*	.0080252	0.63	-.0128001	-1.38
PAT per 10000 Pop, ln*PATD*	.0144659***	2.78	.0095743**	2.52
W ·ln*GEMP*	.0348542***	3.85		
W ·ln*GPI*			.1083284***	13.61
Personal Income 90, ln*PI90*			-.0365176***	-3.69
MSA Patents90-99, ln*M_PAT*	-.0082477	-1.11	-.0199321***	-3.52
MSA Emp Den, ln*M_EMPD*	.0400625**	2.46	.0401122***	3.41
MSA Gr. Emp, ln*M_GEMP*	.3386405***	4.29		
MSA Gr. PI, ln*M_GPI*			.283649***	5.37
Intercept	-.8992832***	-4.75	-.1794476	-1.20
R^2 (Adjusted)	0.3619		0.5901	
Obs. Number	647		647	

*, P-Value <0.1; **, P-Value <0.05; and *** P-Value<0.01

4.4 The Data Analysis with the Carlino-Mills Models

4.4.1 The Model

Model Specification

Many researchers have suggested that both firms' and households' location decisions are dependent upon each other. This extends itself to the argument of the direction of causality regarding whether "people follow jobs" or "jobs follow people" (Steinnes and Fischer, 1974). Carlino and Mills (1987) used a simultaneous equation systems model for population and employment change to address this problem. Since, several studies have used variations of this model to address various issues relating to population and employment growth in counties and metro areas. The Carlino and Mills model (CM model) defines the equilibrium population and employment in linear functional form as:

$$POP^* = f(EMP^* / \Omega^{POP}), \tag{4.9}$$

$$EMP^* = g(POP^* / \Omega^{EMP}) \tag{4.10}$$

where POP* and EMP* are population and employment of the county at equilibrium, respectively; and Ω^{POP} and Ω^{EMP} are the set of independent indicators to explain population and employment at initial level. The following equations are used to identify the direction of causality issue (Greene, 2003):

$$POP^* = b_0 + b_1 EMP^* + \sum d_{1i} \Omega_i^{POP} \tag{4.11}$$

$$EMP^* = c_0 + c_1 POP^* + \sum d_{2i} \Omega_i^{EMP} \tag{4.12}$$

where, *b*, *c* and *d* are the parameter coefficients. Under the assumption that population and employment are independent, the variables would return to their equilibrium values after an adjustment period. The basic assumption of the above model is that both households and firms adjust toward equilibrium levels of population and employment. Carlino and Mills (1987) assumed a lagged adjustment toward equilibrium population and employment as:

$$POP = POP_{-p} + \nu_{POP}(POP^* - POP_{-p}), \tag{4.13}$$

$$EMP = EMP_{-p} + \nu_{EMP}(EMP^* - EMP_{-p}). \tag{4.14}$$

where the subscript *-p* refers to the indicated variable lagged *p* period, and υ_{POP} and υ_{EMP} are the speed of adjustments coefficients, with $0 \leq \upsilon_{POP}, \upsilon_{EMP} \leq 1$. By rearranging terms, the equations are expressed:

$$\Delta POP = POP - POP_{-p} = \nu_{POP}(POP^* - POP_{-p}), \tag{4.15}$$

$$\Delta EMP = EMP - EMP_{-p} = \nu_{EMP}(EMP^* - EMP_{-p}) \tag{4.16}$$

where $\Delta P_t, \Delta E_t, \Delta I_t$ are the change in population and employment between 1990 and 2000; and POP_{-p} and EMP_{-p} are the initial condition, the 1990 levels. Substituting (4.11) and (4.12) into (4.15) and (4.16) gives:

$$\Delta POP = \nu_{POP} b_0 + \frac{b_1 \nu_{POP}}{\nu_{EMP}} \Delta EMP - \nu_{POP} POP_{-p} + b_1 \nu_{POP} EMP_{-p} + \sum \nu_{POP} d_{1i} \Omega_i^{POP} \tag{4.17}$$

$$\Delta EMP = \nu_{EMP} c_0 + \frac{c_1 \nu_{EMP}}{\nu_{POP}} \Delta POP - \nu_{EMP} EMP_{-p} + c_1 \nu_{EMP} POP_{-p} + \sum \nu_{EMP} d_{2i} \Omega_i^{EMP} \tag{4.18}$$

Furthermore, the model can be expressed:

$$\Delta POP = a_{POP0} + a_{POP1} \Delta EMP + a_{POP2} POP_{-p} + a_{POP3} EMP_{-p} + \sum e_{1i} \Omega_i^{POP} + \varepsilon_1 \tag{4.19}$$

$$\Delta EMP = a_{EMP0} + a_{EMP1} \Delta POP + a_{EMP2} POP_{-p} + a_{EMP3} EMP_{-p} + \sum e_{2i} \Omega_i^{EMP} + \varepsilon_2 \tag{4.20}$$

where a_0, a_1, a_2, a_3, e_{1i} and e_{2i} are the estimated parameters; ε_1 and ε_2 are the random error terms. The above equations (4.19) and (4.20) are modeled to give short term equilibrium instead of long-term equilibrium so that it would be easier to determine the effects of RIS's on rural economic growth rates. The Carlino-Mills framework in growth model form would be:

$$POP^* = A(EMP^*)^{b_1}\,\Omega_{POP}^{d_1}\,, \tag{4.21}$$

$$EMP^* = B(POP^*)^{c_1}\,\Omega_{EMP}^{d_2} \tag{4.22}$$

And the equilibrium condition would be,

$$\frac{POP}{POP_{-p}} = \left(\frac{POP^*}{POP_{-p}}\right)^{v_{POP}}\,, \tag{4.23}$$

$$\frac{EMP}{EMP_{-p}} = \left(\frac{EMP^*}{EMP_{-p}}\right)^{v_{EMP}}\,. \tag{4.24}$$

Substituting (4.19) and (4.20) into (4.21) and (4.22), and using a log transformation will give,

$$\Delta \ln POP = a_{POP0} + b_1 \Delta \ln EMP + a_{POP1} \ln POP_{-p} + a_{POP2} \ln EMP_{-p} + \sum e_{1i} \ln \Omega_i^{POP} + \varepsilon_1\,, \tag{4.25}$$

$$\Delta \ln EMP = a_{EMP0} + c_1 \Delta \ln POP + a_{EMP1} \ln POP_{-p} + a_{EMP2} \ln EMP_{-p} + \sum e_{2i} \ln \Omega_i^{EMP} + \varepsilon_2\,. \tag{4.26}$$

Specifically, the estimated CM models are

$$\begin{aligned} \ln GPOP = {} & \alpha_0 + \alpha_1 \ln GEMP + \alpha_2 \ln POP90 + \alpha_3 \ln EMP90 + \alpha_4 W \cdot \ln GPOP + \alpha_5 \ln PR + \\ & \alpha_6 \ln UR + \alpha_7 \ln SF + \alpha_8 \ln C + \alpha_9 \ln D + \alpha_{10} \ln DIST + \alpha_{11} AMTY + \alpha_{12} \ln HVAL + \\ & \alpha_{13} \ln NWHITE + \alpha_{14} \ln POPD + \alpha_{15} \ln HTECH + \alpha_{16} \ln PATD + \alpha_{17} \ln M\_PAT + \\ & \alpha_{18} \ln M\_GPOP + \alpha_{19} \ln M\_POPD + \varepsilon_1 \end{aligned}\,, \tag{4.29}$$

$$\begin{aligned} \ln GEMP = {} & \beta_0 + \beta_1 \ln GPOP + \beta_2 \ln POP90 + \beta_3 \ln EMP90 + \beta_4 W \cdot \ln GEMP + \beta_5 \ln PR + \\ & \beta_6 \ln UR + \beta_7 \ln SF + \beta_8 \ln S\_MFG + \beta_9 \ln D + \beta_{10} \ln C + \beta_{11} \ln DIST + \beta_{12} AMTY + \\ & \beta_{13} \ln EMPD + \beta_{14} \ln HTECH + \beta_{15} \ln PATD + \beta_{16} \ln M\_PAT + \beta_{17} \ln M\_EMPD + \\ & \beta_{18} \ln M\_POPD + \beta_{19} \ln M\_GEMP + \varepsilon_2 \end{aligned} \tag{4.30}$$

where lnGPOP is the growth rate of county population; lnGEMP is the growth rate of county employment; all dependent variables are the same as earlier defined (Table 4.1); and ε_1, ε_2 are error terms.

The variables names and descriptive statistics are provided in Tables 4.1 and 4.2. The main purpose of these models is to investigate the role of RIS characteristics on regional economic development. Specifically, the models can test whether a rural county's innovative activities promote regional economic growth. The model can be used to test whether neighboring areas' innovation has an impact on regional economic growth. To distinguish the impacts of spatial knowledge spillovers on regional economic growth between metropolitan and rural counties, all the above models are estimated by including metro variables.

The Three Stage Least Square (3SLS) Estimation

The three stage least square (3SLS) method is preferred to two stage least squares (2SLS) method because there are several instruments common to both equations, and the 3SLS method will correct for the correlation occurring across equations (Greene, 2003). Thus, the above growth rate system of equations (Equation (4.29) and (4.30)) is estimated using the 3SLS method. The dependent variables are first estimated using their sets of instrument variables. In the second stage, the estimated value from the first stage are used to run an OLS regression to derive the parameters, and the third stage takes into account the correlations among the error estimates between the equations to improve the regression estimates (Greene, 2003).

The growth rate systems of equations are used in this analysis, as it makes it easier to interpret the estimated coefficients. The equations are estimated for the nonmetro plus rural counties (647 counties) in the metro LMA for the 13 Southern states, for the time period of 1990-2000. The regression results are shown in Table 4.5. These empirical results provide evidence of the relationship between rural RIS characteristics and the growth rates in employment and population. Estimations were made using STATA 9.2.

4.4.2 The Data Analysis for Population Growth

Estimates for the coefficients for beginning period employment and population give an estimate of the speed of adjustment to equilibrium levels as shown in the CM model. The positive coefficients of initial population (lnPOP90) suggest that the population growth rate is dynamically stable for rural counties, and the opposite in the initial employment (lnEMP90). However, neither of the coefficients is significant.

Metro Characteristics

The findings of the 3SLS regression results are presented in Table 4.5. The growth rate in county population (lnGPOP) is significantly related to the growth rate in metro population. Rural county growth rates are higher if the nearest metro areas experienced relatively rapid population growth. These results indicate that MSA growth provided positive spillovers or "spread" effects to rural counties in the MSA's LMA. However, the population growth rates were negatively and significantly related to metro innovative activities (lnM_MAT), suggesting the "backwash" effects.

RIS and Regional Characteristics

Table 4.5 provides the results for the county population growth rate model. The growth rates in county population are negatively related to the percent of individuals in county enrolled in college (lnUR) and percent of high technology employment (lnHTECH), indicating inconsistencies with the hypothesis. The growth rates in county population are also negatively related to the measure of local competitiveness (lnC), suggesting MAR's hypothesis. The availability of local amenities (AMTY) and proximity to metro areas (lnDIST) areas are associated with the growth rate of county population. These findings indicate that more rapid population growth in counties with higher amenities and access to metro areas. The coefficients of remaining variables related to RIS characteristics (the proxy variable for private R&D, specialization for manufacturing industry, industry diversity, small firm establishments per capita, rural patent activity) are not significant at the traditional level.

The spatially lagged dependent variable (W •lnGPOP) indicates a positive association between the population growth rate in a county and the rates in surrounding counties. That is, counties with low growth rates tend to cluster and counties with high growth rates tend to locate near similar counties. The growth rate of county population (lnGPOP) is positively and significantly associated with the county employment growth (lnGEMP), indicating that county employment growth rates would increase county population growth rates.

The rural county population growth rate is significantly related school quality (lnHVAL). The proxy variable for racial diversity (NWHITE) is negatively related to the growth rate of rural county population. A household's decision to locate in a county appears to be influenced by its social and demographic characteristics, indicating that areas with a high percentage of non-whites have slower growth rates of population.

Table 4.5 3SLS Results for Growth Rates in Population and Employment

	Population Change, ln*GPOP*		Employment Change, ln*GEMP*	
Variables	Coefficient	z-val	Coefficient	z-val
ln*GPOP*			.8781805***	8.86
ln*GEMP*	.5273619***	3.02		
Pop 90, ln*POP90*	.0455707	0.48	.1193623	0.89
Emp 90, ln*EMP90*	-.0370359	-0.39	-.1307933	-0.99
% Technical Occup.90, ln*PR*	.0224713	1.46	-.0101941	-0.40
% Coll. Enrol. 90, ln*UR*	-.0239276**	-2.33	.0402229***	2.64
Small Est. per cap. 90, ln*SF*	.0939664	1.24	-.0519266	-0.40
Mfg. LQ 90, ln*S_MFG*	.0106932	1.00	-.0045653	-0.24
Diversity 90, ln*D*	.0116881	0.91	.0048781	0.24
Competitiveness, *lnC*	-.2100847***	-2.73	.2113424	1.61
Amenities 90, *AMTY*	.0107798*	1.91	-.0117745	-1.17
Emp Density 90, ln*EMPD*			-.0111714	-1.27
% High Tech Emp, ln*HTECH*	-.0085092*	-1.95	.0138673**	2.12
Distance, ln*DIST*	-.0180948**	-2.32	.0248672**	2.11
PAT per 10000 Pop, ln*PATD*	-.0045133	-1.28	.0108105**	2.27
Med. House Val90, ln*HVAL*	.0828248***	3.06		
% Non-white 90, ln*NWHITE*	-.007583**	-2.54		
W ·ln*GPOP*	.0305419***	2.73		
W ·ln*GEMP*			.005741	0.93
MSA Patents90-99, ln*M_PAT*	-.0086517**	-2.01	-.0001713	-0.02
MSA Gr. Pop, ln*M_POPD*	.0320219	0.87	-.0325377	-0.51
MSA Emp D.90, ln*M_EMPD*			.0314581	0.49
MSA Gr. Pop, ln*M_GPOP*	.1621873***	3.15		
MSA Gr. Emp, ln*M_GEMP*			.0392406	0.53
Intercept	-.6589561*	-1.85	-.1714742	-0.42
R^2	0.4776		0.4743	
chi2	936.88		541.91	
Obs. Number	647		647	

*, P-Value <0.1; **, P-Value <0.05; and *** P-Value<0.01

4.4.3 The Data Analysis for Employment Growth

Table 4.5 provides the estimated results for the growth rate of county employment. The coefficient for change in population growth rate is positive and significant, suggesting that population growth rates are significantly related to employment growth rates. The coefficient of employment growth rate in the population growth equation is 0.527, whereas the coefficient of population growth rate in the employment growth equation is 0.878. These findings support the view that "jobs follow people."

Metro Characteristics

The metropolitan characteristics hypothesized to influence the urban-to-rural spillover of employment growth are MSA employment density (M_EMPD), MSA employment growth rates (M_GEMP), and innovative activity in the metro area (M_PAT). However, rural county employment growth rates were not significantly related to the three metro characteristics. The absence of a strong correlation between metro patent activity and the rural employment growth rates is not an unexpected results. Barkley et al. (2006) found that Southern nonmetropolitan and rural counties were too distant from the metro innovation centers to benefit greatly from available spillovers of metro innovative activity.

RIS and Regional Characteristics

The growth rates in county employment are positively related to the percent of individuals in county enrolled in college (lnUR) and high technology employment (lnHTECH), while the growth rates in county population are negatively associated with lnUR and lnHTECH. These findings suggest that university R&D and high technology employment affect county growth through county employment growth. The coefficient on the measure of distance between largest local city and the metro core city (lnDIST) is positive, which is inconsistent with the hypothesis. One possible explanation is from the research of Renkow (2003). Renkow stated that population deconcentration was increasing as workers were traveling greater distance to work. Renkow (2003) also pointed out that during 1990-2000, average commuting times in southern states increased by 11 percent. The county employment growth rates are positively and significantly related to the rural patent activity (lnPATD). Thus, evidence of higher employment growth from rural innovative activity is found in the Southern counties. However, no correlation between MSA innovation measures and rural employment growth rates was evident. All other remaining variables are not statistically significant.

4.5 Summary of Findings

The estimation results of all OLS models indicated a spillover of economic growth from metro areas to rural counties in the LMA (Table 4.3 and 4.4). In all equations the growth rates of population, employment, income, and earnings in the metro area were positively related to the economic growth rates in the nearby rural counties, suggesting "spread" effects. Thus, rural areas will benefit from proximity to the economic growth in nearby metro areas. Contrary to the hypothesis, the coefficients of metro innovative activity in all the OLS equations were negative and significant, indicating "backwash" effects. However, all of the coefficients of the rural patent activity (lnPATD) are positive in all of OLS equations, suggesting significant effects of rural patent activity on county economic growth rates.

All the significant, positive coefficients of spatially lagged dependent variables indicates a positive association between the economic growth rates in a rural county and the growth rates in surrounding counties. Quality of life variables in rural county were positively associated with all the economic growth rates in the OLS models. In all the economic growth equations, county growth rates were related to local RIS characteristics such as source of innovation (industry R&D), knowledge spillovers (regional competitiveness, industry diversity) and regional spillovers (local natural amenities, high technology employment).

The findings from the extended Carlino-Mills models indicate a more focused role of RIS characteristics on population and employment growth rates than that in OLS models. The CM models support a role for rural innovative activity in employment growth but not population growth. Other results from the CM models are similar to those of the OLS models.

CHAPTER 5

CONCLUSION

The goal of this study was to expand our understanding of the relationship between regional economic growth and the local characteristics of RIS. The research identified the existence and importance of sources of innovation, knowledge spillovers, and regional spillovers as the principal characteristics of RIS in the South. It also examined the effects of the local characteristics of RIS on rural economic growth and explored whether the characteristics had a differential effect on rural economic growth rates. In addition, this study attempted to identify the characteristics of rural areas that benefited most from the spillovers of innovative and economic activities from the metro areas in LMA.

<u>Nonmetro Innovative Activity</u>. A knowledge production function approach was used to estimate the determinants of innovative activity in rural counties. The empirical model was based on a zero inflated negative binomial model to capture the role of the local characteristics of RIS on the existence and volume of innovative activity at the county level. First, the empirical findings from the unlikelihood of patenting equation were that the probability of having a patent in rural areas was positively associated with the presence of research universities (university R&D), high technology employment, and the size of local economy. However, the unlikelihood of patenting was not related to the metro innovative activities.

Second, this research also provided evidence that local characteristics of RIS affected the relative level of patenting activity in rural areas. The findings from the rate of patenting equations were that the determinants of number of total utility patents included access to sources of innovation (private R&D, university R&D, small firms, large firms); knowledge spillovers (industry diversity, no specialization of manufacturing); and regional spillovers (spatial proximity to innovative activity, quality of amenities, size of local economy). However, the findings of this research indicated only a limited association between innovative activity in the urban core of the LMA and patent levels in the nonmetro and rural counties in the MSA's labor market area.

Nonmetro Economic Activity. Analysis using OLS models found that rural areas near a metro RIS had less rapid growth in economic activity (as measured by growth rates in population, earnings by place of residence, employment, and personal income) than rural areas not near a metro RIS. These findings indicate a possible "backwash" effects from innovative activity in metro areas. In the OLS equations for rural economic growth, the growth rates of population, employment, personal income, and net earnings by place of residence in the nonmetro area were positively related to the economic growth rates in the nearby metro areas, suggesting "spread" effects. Thus, rural areas benefited from proximity to the economic growth in nearby metro areas. Quality of life variables in a rural county were positively associated with all the economic growth rates in the OLS models. In all the economic growth equations, the local measures of innovation (industry R&D, regional competitiveness, industry diversity) and regional spillovers (local natural amenities, high technology employment) were positively and significantly related to nonmetro economic growth rates. Finally, the research confirmed the role of county patent activity on rural economic growth.

The results from the simultaneous equation model (Carlino-Mills model) indicated that the rural patenting activity had positive spillovers with regards to increase in employment growth rates in rural areas. No spillovers from the metro RIS to rural areas were found for population and employment growth rate. Furthermore, the metro patenting activity indicated the presence of "backwash" effect on rural population growth rates. In sum, the findings for Southern rural counties indicated that innovative activities in rural county areas played a role on the rural economic growth, while metro innovative activities provided "backwash" effects.

Policy Implications. Two main policy implications are suggested from this research. The first is related to the determinants of RIS, and the second is associated with economic development. The research presented in this study supports prior evidence that sources of innovation, knowledge spillovers, and regional spillovers contributed to rural RIS. This research also provided evidence on the positive contributions of rural patenting activity to economic growth. Given this evidence, policymakers may well consider strengthening local R&D efforts as a potential road for stimulating innovation and economic development in their areas.

The empirical results of this research also have important implications related to economic development policies. First, local economic development policies should not ignore the innovative activity in local researchers. Policymakers should be directed to stimulating the interaction between local researchers and institutions or firms in the local economy because incentives to attract innovative firms may fall short unless sufficient regional spillovers and knowledge spillovers take place (Black, 2004). Black (2004, p.100) suggested that incentives to stimulate local innovation should include R&D tax credits, corporate tax reductions, targeted funding for education and training for the quality of local labor force, and government programs to aid small and new firms in the innovation process, such as business incubators.

Second, the differential effects of the local characteristics of RIS means that policymakers should also consider the types of research fund and investment for local innovative activities in their areas. For most nonmetro counties in the South, the RIS in metro areas will be benign at best or detrimental if significant "backwash" effects exist. Thus, the implication from these findings is that regional policymakers should be careful of investments in metro RIS if the goal is to develop the nearby rural areas. Barkley et al. (2006, p. 301) suggested that "the economic future is less promising for rural areas near MSAs that have limited innovative and entrepreneurial activity. For these LMAs, a twin approach will need to be pursued that addresses the competitiveness needs of the metro core as well as prepares the rural counties to take advantages of any spillovers from the core."

In summary, increased R&D expenditures at universities and government research centers in rural 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 increases in innovative activity are to ultimately lead to significant new economic activity (Barkley et al., 2006). Moreover, insights into the spatial spillovers effects on innovative activity suggest that regional economic policymakers consider the specific geographies of knowledge spillovers, specifically how the RIS might promote regional economic growth.

Further Study. Although this research does not answer all questions about the relationship between the local characteristics of RIS and rural economic growth, it is a step towards formulating strategies for further research in several directions. First is to link patenting activity of local firms to industrial classifications at the county level because the linking of patent data to additional firm-level data bases could provide further insight on the firms performing innovative activities. Second, although this research provides evidence of the effects of the local characteristics of RIS on innovative activity over a ten-year period, it does not show up whether this effect has changed over time. A useful extension of this study would explore this time dimension by exploiting the time series analysis of the patent data, including Granger causality (Black, 2004). Due to data constrains, this study was based on a cross-sectional analysis. Using panel data analysis, future research also may answer the question of what is the long-run effect of geographically-proximate knowledge spillovers on RIS, including fixed effects, random effects, and between effects.

APPENDICES

Appendix 1 Poisson Estimation Results for Total Patents in 591 Nonmetro Counties[a]

Independent Variables	Model 1 No MSA Term	Model 2 MSA PAT Total	Model 3 MSA PAT Density	Model 4 UNIV R & D	Model 5 MSA S & Tech
%Tech Occ., *PR*	.2052733** (2.45)[b]	.2035754** (2.35)	.2027351** (2.37)	.2076578** (2.46)	.2127619** (2.30)
Coll. Enrol., *UR*	.0000702*** (5.11)	.0000705*** (4.94)	.0000698*** (5.15)	.0000695*** (5.03)	.0000709*** (5.34)
Small Est. *SF*	38.25265 (1.35)	38.10541 (1.33)	37.89404 (1.31)	38.35028 (1.35)	38.73543 (1.34)
Large Est. *LF*	632.3688 (0.22)	615.9704 (0.22)	583.0711 (0.20)	606.6892 (0.21)	602.8758 (0.21)
Mfg. LQ, *S_MFG*	.103113 (0.66)	.1029466 (0.66)	.101125 (0.64)	.1017409 (0.65)	.0911425 (0.65)
Diversity, *D*	.1665094*** (3.23)	.1661472*** (3.17)	.1665609*** (3.23)	.164828*** (3.22)	.1667857*** (3.24)
Comp, *C*	.6587308 (0.37)	.6568063 (0.37)	.7193794 (0.40)	.6185414 (0.35)	.529454 (0.31)
Comp², C^2	-.7523861 (-1.04)	-.746959 (-1.03)	-.7768098 (-1.08)	-.7406301 (-1.05)	-.7003289 (-1.06)
Amenities, *AMTY*	.3901233*** (5.41)	.3894112*** (5.37)	.3816626*** (4.95)	.3870808*** (5.40)	.3960203*** (5.34)
Total Emp., *EMP*	.0000504*** (8.88)	.0000502*** (8.82)	.0000504*** (8.93)	.0000501*** (8.79)	.0000503*** (8.92)
% High Tech, *HTECH*	.0208474 (1.07)	.0210402 (1.07)	.0206263 (1.07)	.02199 (1.15)	.0204726 (1.04)
W. PAT, *W·P*	.1366442*** (3.72)	.136193*** (3.69)	.1334463*** (3.56)	.1369679*** (3.71)	.1396706*** (3.66)
Distance, *DIST*	-.0061064** (-2.16)	-.0062453** (-2.32)	-.0061325** (-2.18)	-.0061705** (-2.16)	-.0057708** (-2.49)
MSA PAT, *MET*		4.03e-06 (0.20)			
MSA PAT D., *MET_D*			.0031416 (0.62)		
MSA U. R & D, *MET_UR*				-.000014 (-0.95)	
MSA Tech. *MET_PR*					-.0879325 (-0.58)
Intercept	-1.70086 (-1.46)	-1.687229 (-1.43)	-1.725173 (-1.50)	-1.645644 (-1.47)	-1.256586 (-1.49)
Loglikelihood	-4167.0774	-4166.7279	-4161.3422	-4163.0681	-4153.961
Goodness-of-fit(P-value)	6367.987 (0.0000)	6367.288 (0.0000)	6356.516 (0.0000)	6359.968 (0.0000)	6341.754 (0.0000)
Pseudo R²	0.5336	0.5337	0.5343	0.5341	0.5351

[a] The analysis followed the Woolridge (1991) poisson estimation procedure with robust standard errors with robust standard errors. Estimations were made using STATA 9.2 (www.state.com)
[b] z-values for the coefficients are provided in parentheses.
*, P-Value <0.1; **, P-Value <0.05; and *** P-Value<0.01

Appendix 2 NB Estimation Results for Total Patents in 591 Nonmetro Counties

Independent Variables	Model 1 No MSA Term	Model 2 MSA PAT Total	Model 3 MSA PAT Density	Model 4 UNIV R & D	Model 5 MSA S & Tech
%Tech Occ., *PR*	.1575121*** (4.04)[a]	.1498068*** (3.83)	.1485367*** (3.82)	.158016*** (4.05)	.156231*** (4.01)
Coll. Enrol., *UR*	.0000367 (1.19)	.0000402 (1.29)	.0000396 (1.27)	.0000364 (1.18)	.0000356 (1.15)
Small Est. *SF*	24.82802** (2.05)	25.37751** (2.09)	24.81072** (2.06)	24.74024** (2.04)	25.90068** (2.13)
Large Est. *LF*	3774.916*** (3.66)	3750.187*** (3.64)	3810.159*** (3.72)	3769.899*** (3.66)	3664.046*** (3.55)
Mfg. LQ, *S_MFG*	-.0081085 (-0.13)	-.0068681 (-0.11)	-.0050169 (-0.08)	-.008806 (-0.14)	.0081036 (0.13)
Diversity, *D*	.2229911*** (5.30)	.2185934*** (5.21)	.2226767*** (5.33)	.2225461*** (5.28)	.2238782*** (5.32)
Comp, *C*	2.054969** (2.19)	2.05402** (2.18)	2.171018** (2.32)	2.042826** (2.17)	1.991021** (2.11)
Comp^2, C^2	-1.331475*** (-3.07)	-1.316781*** (-3.03)	-1.363498*** (-3.16)	-1.32625*** (-3.05)	-1.301019*** (-2.99)
Amenities, *AMTY*	.2839034*** (4.53)	.2748049*** (4.38)	.2712786*** (4.32)	.283287*** (4.52)	.2813704*** (4.48)
Total Emp., *EMP*	.0000735*** (9.43)	.0000733*** (9.42)	.0000724*** (9.36)	.0000734*** (9.42)	.0000747*** (9.49)
% High Tech, *HTECH*	.0109024 (0.58)	.0084853 (0.45)	.0093417 (0.50)	.0113578 (0.60)	.009414 (0.50)
W. PAT, *W·P*	.1613228** (2.47)	.1524478** (2.36)	.1397526** (2.18)	.1621593** (2.47)	.1645235** (2.51)
Distance, *DIST*	-.0020695** (-2.13)	-.0021847** (-2.26)	-.0022374** (-2.30)	-.0020974** (-2.15)	-.0019289** (-1.98)
MSA PAT, *MET*		.0000272 (1.62)			
MSA PAT D., *MET_D*			.0084383** (2.43)		
MSA U. R & D, *MET_UR*				-4.04e-06 (-0.28)	
MSA Tech. *MET_PR*					.0784753 (1.30)
Intercept	-2.254568*** (-3.88)	-2.221686*** (-3.83)	-2.35221*** (-4.07)	-2.237887*** (-3.83)	-2.652264*** (-4.05)
Loglikelihood	-1829.9616	-1828.5651	-1826.754	-1829.9233	-1829.1102
Overdispersion Test, LRT H_0:Alpha=0	4674.23 Prob>=chibar2 = 0.000	4676.33 Prob>=chibar2 = 0.000	4669.18 Prob>=chibar2 = 0.000	4666.29 Prob>=chibar2 = 0.000	4649.70 Prob>=chibar2 = 0.000
Pseudo R^2	0.1179	0.1186	0.1194	0.1179	0.1183

[a] z-values for the coefficients are provided in parentheses.
*, P-Value <0.1; **, P-Value <0.05; and *** P-Value<0.01

Appendix 3 Poisson Estimation Results for Total Patents in 647 Rural Counties[a]

Independent Variables	Model 1 No MSA Term	Model 2 MSA PAT Total	Model 3 MSA PAT Density	Model 4 UNIV R & D	Model 5 MSA S & Tech
%Tech Occ., *PR*	.2619218*** (5.96)[b]	.2560329*** (6.00)	.2617342*** (6.31)	.2617806*** (5.92)	.2632358*** (6.06)
Coll. Enrol., *UR*	.0000561*** (4.25)	.0000603*** (4.60)	.0000552*** (4.25)	.0000557*** (4.22)	.000054*** (3.64)
Small Est. *SF*	25.33365 (0.80)	25.97971 (0.84)	24.72462 (0.78)	25.0353 (0.79)	25.39136 (0.80)
Large Est. *LF*	2512.528 (0.72)	2537.145 (0.72)	2584.132 (0.72)	2477.59 (0.71)	2601.442 (0.72)
Mfg. LQ, *S_MFG*	-.1036022 (-0.47)	-.1179231 (-0.53)	-.121321 (-0.54)	-.1050474 (-0.47)	-.09536 (-0.46)
Diversity, *D*	.1316785*** (2.65)	.1058163* (1.94)	.1274419** (2.50)	.1296564*** (2.62)	.1309367** (2.58)
Comp, *C*	1.83085 (0.96)	1.764651 (0.94)	2.002644 (1.01)	1.74722 (0.94)	2.075899 (0.97)
Comp², C^2	-1.67994* (-1.91)	-1.576147* (-1.83)	-1.758583* (-1.91)	-1.633641* (-1.92)	-1.81637* (-1.77)
Amenities, *AMTY*	.5012442*** (5.54)	.4855103*** (5.48)	.4736933*** (5.08)	.4932596*** (5.55)	.5030365*** (5.37)
Total Emp., *EMP*	.0000512*** (7.36)	.0000498*** (7.49)	.0000514*** (7.62)	.0000509*** (7.33)	.0000517*** (7.00)
% High Tech, *HTECH*	-.0047895 (-0.20)	-.0017202 (-0.07)	-.0037604 (-0.16)	-.0030314 (-0.13)	-.0047266 (-0.20)
W. PAT, *W·P*	.2344747*** (3.79)	.2343879*** (3.66)	.2249872*** (3.62)	.234912*** (3.81)	.2307898*** (3.90)
Distance, *DIST*	-.0131906** (-2.08)	-.0166198** (-2.31)	-.0131361** (-2.02)	-.0132998** (-2.09)	-.013769** (-2.01)
MSA PAT, *MET*		.0000704** (2.48)			
MSA PAT D., *MET_D*			.0099656** (2.55)		
MSA U. R & D, *MET_UR*				-.000015 (-1.15)	
MSA Tech. *MET_PR*					.0917774 (0.56)
Intercept	-1.574754* (-1.65)	-1.393017 (-1.41)	-1.679648* (-1.73)	-1.468316 (-1.60)	-2.138242* (-1.86)
Loglikelihood	-6666.616	-6478.7027	-6550.3816	-6657.9842	-6647.3941
Goodness-of-fit(P-value)	11123.61 (0.0000)	10747.79 (0.0000)	10891.15 (0.0000)	11106.35 (0.0000)	11085.17 (0.0000)
Pseudo R²	0.5093	0.5231	0.5178	0.5099	0.5107

[a] The analysis followed the Woolridge (1991) poisson estimation procedure with robust standard errors with robust standard errors. Estimations were made using STATA 9.2 (www.state.com)

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

*, P-Value <0.1; **, P-Value <0.05; and *** P-Value<0.01

Appendix 4 NB Estimation Results for Total Patents in 647 Rural Counties

Independent Variables	Model 1 No MSA Term	Model 2 MSA PAT Total	Model 3 MSA PAT Density	Model 4 UNIV R & D	Model 5 MSA S & Tech
%Tech Occ., *PR*	.2943809*** (9.74)[a]	.2845593*** (9.75)	.2803702*** (9.44)	.2953167*** (9.76)	.2953035*** (9.84)
Coll. Enrol., *UR*	.0000846* (1.81)	.0000634 (1.53)	.0000796* (1.76)	.000084* (1.80)	.000081* (1.75)
Small Est. *SF*	36.25799*** (2.85)	36.4164*** (2.90)	36.50258*** (2.90)	35.99547*** (2.83)	37.88599*** (2.97)
Large Est. *LF*	3578.1*** (3.34)	3915.496*** (3.66)	3833.882*** (3.60)	3562.148*** (3.32)	3515.782*** (3.27)
Mfg. LQ, *S_MFG*	-.0509027 (-0.80)	-.0702862 (-1.12)	-.062818 (-1.00)	-.0513421 (-0.81)	-.0368578 (-0.57)
Diversity, *D*	.2087193*** (4.87)	.1817807*** (4.31)	.1983292*** (4.70)	.2073357*** (4.83)	.2057956*** (4.81)
Comp, *C*	2.012885** (2.09)	2.301266** (2.42)	2.245442** (2.37)	1.993873** (2.07)	1.975572** (2.06)
Comp^2, C^2	-1.647812*** (-3.86)	-1.708199*** (-4.05)	-1.704309*** (-4.07)	-1.636966*** (-3.82)	-1.628143*** (-3.82)
Amenities, *AMTY*	.3001164*** (4.48)	.2663484*** (4.02)	.2706352*** (4.04)	.2982011*** (4.46)	.2942531*** (4.38)
Total Emp., *EMP*	.0000689*** (7.93)	.0000715*** (8.51)	.0000682*** (8.04)	.0000688*** (7.91)	.0000702*** (8.04)
% High Tech, *HTECH*	-.0018634 (-0.10)	-.0055136 (-0.31)	-.0033676 (-0.19)	-.0010271 (-0.06)	-.003027 (-0.17)
W. PAT, $W \cdot P$	.2729373*** (3.44)	.2508378*** (3.34)	.2454085*** (3.22)	.2777058*** (3.48)	.2749184*** (3.46)
Distance, *DIST*	-.0028225*** (-2.76)	-.0030407*** (-3.05)	-.0030715*** (-3.03)	-.0028955*** (-2.83)	-.0027047*** (-2.65)
MSA PAT, *MET*		.0000633*** (3.92)			
MSA PAT D., *MET_D*			.0116873*** (3.46)		
MSA U. R & D, *MET_UR*				-.0000125 (-0.88)	
MSA Tech. *MET_PR*					.0842587 (1.40)
Intercept	-2.4726*** (-4.11)	-2.501435*** (-4.24)	-2.579738*** (-4.34)	-2.43405*** (-4.03)	-2.904145*** (-4.31)
Loglikelihood	-2101.4855	-2092.5998	-2094.6711	-2101.1128	-2100.4991
Overdispersion Test, LRT H_0:Alpha=0	9130.26 Prob>=chibar2 = 0.000	8772.21 Prob>=chibar2 = 0.000	8911.42 Prob>=chibar2 = 0.000	9113.74 Prob>=chibar2 = 0.000	9093.79 Prob>=chibar2 = 0.000
Pseudo R^2	0.1104	0.1141	0.1133	0.1105	0.1108

[a] z-values for the coefficients are provided in parentheses.
*, P-Value <0.1; **, P-Value <0.05; and *** P-Value<0.01

REFERENCES

Acs, Z. J. 2002. Innovation and the Growth of Cities. Northampton, MA: Edward Elgar.

Acs, Z. J., L. Anslein, and A. Varga. 2002. "Patents and Innovation Counts as Measures of Regional Production of New Knowledge." Policy Research 31: 1069-1085.

Acs, Z. J., D. Audretsch, and M. Feldman. 1994. "R&D Spillovers and Recipient Firm Size." The Review of Economics and Statistics 100(2): 336-40.

Anderson, R., J. M. Quigley, and M. Wilhelmsson. 2005. "Agglomeration and the Spatial Distribution of Creativity." Papers in Regional Science 84(3):446-464.

Anderson, R., J. M. Quigley, and M. Wilhelmsson. 2004. "University Decentralization as Regional Policy: the Swedish Experiment." Journal of Economic Geography 4:371-388.

Andersson, M., and C. Karlsson. 2002, "Regional Innovation Systems in Small and Medium-Sized Region.A critical Review and Assessment." Working paper 2002-2, Jönköping International Business School.

Anselin, L. 1995. "Local indicators of spatial association – LISA." Geographical Analysis 27(2): 93–115.

Anselin. L. 2003. GeoDa 0.9 User's Guide. Spatial Analysis Laboratory, Department of Agricultural and Consumer Economics and CSISS, University of Illinois, Urbana, IL.

Anselin, L., A. Varga, and Z. Acs. 1997. "Local geographic spillovers between university research and high technology innovations." Journal of Urban Economics 42:422-448

Anselin, L., A. Varga, and Z. Acs. 2000. "Geographic and sectoral characteristics of academic knowledge externalities." Papers in Regional Science 79(4):435-443.

Arrow, K.J. 1962. "The economic implications of learning by doing." Review of Economic Studies 29:155-173.

Asheim, B., A. Isaksen. 2002. "Regional innovation systems: The integration of local 'sticky' and global 'ubiquitous' knowledge." Journal of Technology Transfer, 27: 77-86.

Asheim, B., A. Isaksen. 1997. "Location, Agglomeration and Innovation: Towards Regional Innovation Systems in Norway?" European Planning Studies 5 (3): 299-330.

Asheim, B., A. Isaksen, C. Nauwelaers, F. Tötdling. 2003. Regional innovation policy for small medium enterprises, Cheltenham, UK and Lyme, US : Edward Elgar

Audretsch, D. and M.P. Feldman. 2003. "Knowledge Spillovers and the Geography of Innovation" in J. Vernon Henderson and Jacque Thisse, ed. Handbook of Urban and Regional Economics, Volume 4. Amsterdam: North Holland Publishing.

Audretsch, D.B., and M.P. Feldman. 1996. "R&D spillovers and the geography of innovation and production." American Economic Review 86:630-640.

Audretsch, D.B., and P.E. Stephan. "Company-Scientist Locational Links: The Case of Biotechnology." American Economic Review 86(3): 641-652.

Baptista, R. 2000. "Do innovations diffuse faster within geographical clusters?" International Journal of Industrial Organization 18(3): 515-535

Barkley, D. L. and M. S. Henry. 1997. "Rural Industrial Development: To Cluster or Not to Cluster." Review of Agricultural Economics 19: 2-22.

Barkley, D. L., M. S. Henry, and S. Bao. 1996. "Identifying 'Spread' versus 'Backwash' Effects in Regional Economic Areas: A Density Functions Approach." Land Economics 72(3): 336-357.

Barkley, D. L., R. Dahlgren, and S. M. Smith. 1988. "High-Technology Manufacturing in Rural Areas: Gold or Just Glitter." American Journal of Agricultural Economics 70(3):560-71.

Barkley, D. L., M. S. Henry, and Y. Kim. 1999. "Industry Agglomerations and Employment Change in Non-metropolitan Areas." Review of Urban and Regional Development Studies 11: 168-186.

Barkley, D. L., M. S. Henry, and D. Lee. 2006. "Innovative Activity in Rural Areas: The Role of Local and Regional Characteristics." Paper presented at the 2006 Annual Meetings of the Canadian Agricultural Economics Society, Montreal, May.

Barkley, D. L., M. S. Henry, and S. Nair. 2006. "Regional Innovation Systems: Implications for Nonmetropoltian Areas and Workers in the South." Growth and Change 37(2): 278-306.

Baumol, W.J. 2004. "Four Sources of Innovation and Stimulation of Growth in the Dutch Economy." De Economist 152(3):321–351.

Black, G. 2004. The Geography of Small firm Innovation. Norwell, MA: Kluwer Academic Publishers.

Boanet, M.G. 1994. "An Empirical Model of Intrametropolitan and Population and Employment Growth." Papers in Regional Science 74: 1-20.

Carlino, G.A. and E.S. Mills. 1987. "The Determinants of County Growth." Journal of Regional Science 73: 135-153.

Cameron, A.C. and P. Trivedi. 1998. Regression Analysis of Count Data. Vol. 30 of Econometric Society Monograph. New York: Cambridge University Press.

Capello, R. 2002. "Spatial and Sectoral Characteristics of Relational Capital in Innovation Activity." European Planning Studies 10(2):177-200.

CHI Research, Inc. 2003. "Small Serial Innovators: The Small Firm Contribution to Technical Change." Haddon Heights, NJ: U.S. Small Business Administration (SBA) Office of Advocacy.

CHI Research, Inc. 2004. "Small Firms and Technology: Acquisitions, Inventor Movement, and Technology Transfer." Haddon Heights, NJ: U.S. Small Business Administration (SBA) Office of Advocacy.

Cooke, P. 2001. "Regional innovation systems, clusters, and the knowledge economy." Industrial and Corporate Change 10 (4): 945-974.

Cooke, P. 1992. "Regional innovation systems: competitive regulation in the new Europe." GeoForum, 23: 365-382.

Cooke, P., P. Boekholt and F. Tödtling. 2000. The Governance of Innovation in Europe: Regional Perspectives on Global Competitiveness. London: Pinter.

Cooke, P., M.G. Uranga, and G. Etxebarria. 1998. "Regional Systems of Innovation: an Evolutionary Perspective." Environment and Planning A 30: 1563-1584.

Cooke, P., and Morgan K. 1998. The Associational Economy: Firms, Regions and Innovation. Oxford: Oxford University Press.

Chesire, P. C. and E. Malecki. 2004. "Growth, Development, and Innovation: A Look Backward and Forward." Papers in Regional Science 83:249-67.

Deller, S.C., T-H Tsai, D.W. Marcouiller, and D.B.K. English. 2001. "The Role of Amenities and Quality of Life in Rural Economic Growth." American Journal of Agricultural Economics 83(2): 352-365.

Doloreux D. and S. Parto. 2004. "Regional Innovation Systems: A Critical Synthesis." Discussion Paper Series. United Nations University, Institute for New Technologies, #2004-17.

Enright, M.J. 2001. "Regional Clusters: What We Know and What We Should Know." Paper prepared for the Kiel Institute International Workshop on Innovation Clusters and Interregional Competition, November 12-13: 2-15.

Fischer, M.M. and A. Varga. 2003. "Spatial knowledge spillovers and university research: Evidence from Austria." Annals of Regional Science, 37(2):303-323.

Feldman, M. P. 1994. The Geography of Innovation. Dordtecht, The Netherlands: Kluwer Academic Publishers.

Feldman, M. P. 2001. "The Entrepreneurial Event Revisited: An Examination of New Firm Formation in the Regional Context." Industrial and Corporate Change 10: 861-891.

Feldman, M. P., and D. B. Audretsch. 1998. "Innovation in Cities: Science-based Diversity, Specialization, and Localized Competition." European Economic Review 43: 409-429.

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

Freeman, Christopher. 1987. Technology Policy and Economic Performance. London: Pinter.

Fritsch, M. 2001. "Co-operation in Regional Innovation Systems." Regional Studies 35(4):297-307.

Fritsch, M. 2002. "Measuring the Quality of Regional Innovation Systems: A Knowledge Production Function Approach." International Regional Science Review 25(1):86-101.

Fujita M, Ogawa H (1982) Multiple equilibrium and structural transition of non-monocentric urban configurations. Regional Science and Urban Economics 12:161-196.

Glaeser, E. 2000. "The New Economics of Urban and Regional Grwoth." In The Oxford Handbook of Economic Geography, eds. Gordon Clark, Maryann Feldman, and Meric Gertler, 83-98. Oxford: Oxford University Press.

Glaeser, E. L. and A. Saiz. 2003. "The Rise of the Skilled City." NBER Working Paper 10191, National Bureau of Economic Research, Cambridge, MA, December.

Glaeser, E.L., H.D. Kallal, J.A. Scheinkman, A. Shleifer. 1992. "Growth in cities." Journal of Political Economy 100:1126-1152.

Green, W.H. 1994. "Accounting for Excess Zeros and Sample Selection in Poisson and Negative Binomial Regression Models." Working Paper No. EC-94-10, Department of Economics, Stern School of Business, New York University.

Green, W.H. 2003. Econometric Analysis. 5th ed. Upper Saddle River, NJ: Prentice Hall.

Greenwood, M. and G.U. Yule. 1920. "An Enquiry into the Nature of Frequency Distributions of Multiple Happenings, with Particular Reference to the Occurrence of Multiple Attacks of Disease or Repeated Accidents." Journal of the Royal Statistical Society, Series A, 83:255-279.

Griliches Z. 1979. "Issues in Assessing the Contribution of R&D to Productivity Growth." Bell Journal of Economics 10:92-116.

Griliches, Z. (ed.) 1984. R&D, Patents and Productivity. Chicago: University of Chicago Press.

Gordon, I. R. and P. McCann. 2005. "Innovation, Agglomeration, and Regional Development." Journal of Economic Geography 5:523-543.

Hausman, J., B. Hall, B., and Z. Griliches. 1984. "Econometric Models for Count Data with an Application to the Patents-R&D Relationship." Econometrica 52:909-938.

Henderson V (1986) Efficiency of resource usage and city size. Journal of Urban Economics 19:47-70.

Henderson, V., A. Kuncoro, and M. Turner. 1995. "Industrial development in cities." Journal of Political Economy 103:1067-1090.

Henry, M.S., D.L. Barkley, and S. Bao. 1997. "The Hinterlands Stake in Metropolitan Growth: Evidence from Selected Southern Regions." Journal of Regional Science 37(3): 479-501.

Henry, M.S., B. Schmitt, K. Kristensen, D.L. Barkley, and S. Bao. 1999. "Extending Carlino-Mills Models to Examine Urban Size and Growth Impacts on Proximate Rural Area." Growth and Change 30: 526-548.

Henry, M.S., B. Schmitt, K. Kristensen, D.L. Barkley, and S. Bao. 1999. "Extending Carlino-Mills Models to Examine Urban Size and Growth Impacts on Proximate Rural Area." Growth and Change 30: 526-548.

Isserman, A. M. 2005. "In the National Interest: Defining Rural and Urban Correctly in Research and Public Policy." International Regional Science Review 28(4):465-499.

Jacobs, J. 1969. The Economy of Cities. New York: Vintage.

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

Jaffe, A. B. 1989. "Real Effects of Academic Research." American Economic Review 79(5):957-70.

Jaffe, A. B., M. Trajtenberg, and R. Henderson. 1993. "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations." Quarterly Journal of Economics, 577-598.

King, Gary. 1988. "Statistical Models for Political Science Event Counts: Bias in Conventional Procedures and Evidence for the Exponential Poisson Regression Model." American Journal of Political Science 32:838-863.

King, Gary. 1989. "Variance Specification in Event Count Models: From Restrictive Assumptions to a Generalized Estimator." American Journal of Political Science 33:762-784.

Koo, J. 2005. "Agglomeration and spillovers in a simultaneous framework." Annals of Regional Science, 39(1): 35-47.

Krugman, P. 1991a. Geography and Trade, Gaston Eyskens lecture series. Cambridge, Mass.: MIT Press.

Krugman, P. 1991b. "Increasing returns and economic geography." Journal of Political Economy 99:183-199.

Lambert, D. 1992. "Zero-Inflated Poisson Regression, with an Application to Defects in Manufacturing." Technometrics 34: 1-14.

Lawson, E., and C. Lorenz. 1999. "Collective Learning, Tacit Knowledge and Regional Innovative Capacity." Regional Studies 33(4): 305-317

Lim, U. 2004. "Knowledge Spillovers, Agglomeration Economies, and the Geography of Innovative Activity: A Spatial Econometric Analysis." The Review of Regional Studies 34(1):11-36.

Long, J.S. and J. Freese. 2006. Regression Models for Categorical Dependent Variables Using Stata. College Station, TX: Stata Press.

Lucas, R.E. 1993. "Making a miracle." Econometrica 61:251-272.

Malecki, E.J. 1994. "Entrepreneurship in regional and local development." International Regional Science Review 16:119-153.

Malecki, E.J. 1991. Technology and Economic Development: the Dynamics of Loca, Regional, and National Change. Essex, UK: Longman Scientific & Technicl.

Markusen, A., K. Chapple, G. Schrock, D. Yamamoto, and P. Yu. 2001. "High-Tech and I-Tech: How Metros Rank." The Humbert Humphrey's Institute of Public Affairs, University of Minnesota Minneapolis, August.

Markusen, Ann, Peter Hall, and Amy Glasmeier. 1986. High tech America: The what, how, where, and why of the sunrise industries. Boston, MA: Allen & Unwin.

Marshall, A. 1890. Principles of Economics. London: Macmillan.

McCann, P. and J. Simonen. 2005. "Innovation, Knowledge Spillovers, and Local Labor Markets." Papers in Regional Science 84(3):465-486.

McGranahan, D. 1999. National Amenities Drive Population Change, Agri. Econ. Report 781, Economic Research Service, USDA, Washington, D.C., September.

Mullahy, J. 1986. "Specification and Testing of Some Modified Count Data Models." Journal of Econometrics 33: 341-365.

National Science Board. 2000. Science and Engineering Indicators—2000. Arlington, VA: U.S. National Science Foundation

National Science Foundation, Division of Science Resources Studies. 1999. Academic Research and Development Expenditures: Fiscal Year 1997. Arlington, VA.

National Science Foundation, Division of Science Resources Studies. 2001. Academic Research and Development Expenditures: Fiscal Year 1999. Arlington, VA.

Nelson, R. (ed.) 1993. National Innovation Systems. New York: Oxford University Press.

Niosi, J. 2000. "Regional systems of innovation: Market pull and government push." A presentation to the Annual Meeting of the Canadian Research Network on Regional Innovation Systems. Montreal, May.

Orlando, M. J. and M. Verba. 2005. "Do Only Big Cities Innovate? Technological Maturity and the Location of Innovation." Economic Review, Federal Reserve Bank of Kansas City, Second Quarter: 31-57.

Partridge, M., R.D. Bollman, M.R. Olfer, A. Alasia. 2005. "Riding the Wave of Urban Growth in the Countryside: Spread, Backwash, or Stagnation." Presented paper, North American Meetings of Regional Science Association International, Las Vegas, NV, November.

Pascal, Blaise. 1679. "Varia Opera Mathematica D.Petri de Fermat." Tolossae.

Porter, M. E. 1990. The Competitive Advantage of Nations. London: Macmillan.

Porter, M. E. 1998. "Clusters and Competition: New Agendas for Companies, Governments, and Institutions." On Competition. Boston: Harvard Business School Publications, 7:199-271.

Porter, M.E. 1996. "Competitive Advantage, Agglomeration Economies, and Regional Policy." International Regional Science Review 19:85-90.

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

Renkow, M. 2003. "Employment Growth, Worker Mobility, and Rural Economic Development." American Journal of Agricultural Economics 85(2): 503-513

Riddel, M. and R. K. Schwer. 2003. "Regional Innovative Capacity with Endogenous Employment: Empirical Evidence from the U.S." The Review of Regional Studies 33(1):73-84.

Roback, J. 1982. "Wages, Rents, and the Quality of Life." Journal of Political Economy 90: 1257-1278.

Romer, P. 1990. "Endogenous Technological Change." Journal of Political Economy 98:71-102.

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

Rosenthal, Stuart S. and William C. Strange, "The Determinants of Agglomeration," Journal of Urban Economics 50(2), 2001, 191-229.

Saxenian, AnnaLee. 1996. Regional advantage: Culture and competition in Silicon Valley and Route 128. Cambridge, MA: Harvard University Press.

Shapira, P. 2004. "Innovation Challenges and Strategies in Catch-Up Regions: Development Growth and Disparities in Georgia, USA." In Rethinking Regional Innovation and Change: Path Dependency or Regional Breakthrough, G. Fuchs and P. Shapira (eds), Norwell, MA: Kluwer Academic Publishers.

Schumpeter, J. A. 1947. Capitalism, Socialism and Democracy, 2nd ed., New York: Harper and Brothers.

Schunk, D., D. Woodward, F. Hefner. 2005. "Innovative Capacity as a Determinant of U.S. County Per Capita Income." Presented paper, Regional Science Association International North American Conference, November 10-12, Las Vegas, NV.

Steinnes, D. and W. Fischer. 1974. "An Econometric Model of Intra-urban Location." Journal of Regional Science 14: 65-80.

Storper, M. 1997. The Regional World. New York: The Guilford Press.

Tolbert, C.M. and M. Sizer 1996. U.S. Commuting Zones and Labor Market Areas: A 1990 Update. Staff Paper No. AGES 9614, USDA-ERS, Washington, DC.

U.S. Patent and Trademark Office (USPTO). 2000. United States Patent Grants by State, County, and Metropolitan Area (Utility Patents 1990-1999). Report of Technology and Forecast Assessment, April.

U.S. Small Business Administration, 1995. The State of Small Business: A Report of the President,1994. Washington, D.C.: U.S. Government Printing Office.

Van Stel, A. J. and H.R. Nieuwenhuijsen. 2004. "Knowledge Spillovers and Economic Growth: An Analysis Using Data of Dutch Regions in the Period 1987-1995." Regional Studies 38 (4): 393-407.

Varga, A. 2000. "Local Academic Knowledge Transfers and the Concentration of Economic Activity." Journal of Regional Science 40(2).

Wiig, H. 1999. An empirical study of the innovation system in Finnmark. Oslo: STEP report.

Wiig, H. and M. Wood. 1995 "What comprises a regional innovation system? An empirical study." STEP Report series 199501, The STEP Group, Studies in technology, innovation and economic policy.

Winkelmann, R. 2003. Econometric Analysis of Count Data. 4th Ed. Berlin, Germany: Springer Verlag

Wolfe, D. 2003. Clusters Old and New: The Transition to a Knowledge Economy in Canada's Regions. Kingston: Queen's School of Policy Studies

Woodward, D., O. Figueiredo, and P. Guimaraes. 2006. "Beyond the Silicon Valley: University R&D and high-technology location." Journal of Urban Economics 60(1): 15-32.

Woolridge, J. M. 1991. "On the Application of Robust, Regression-Based Diagnostics to Models of Conditional Means and Conditional Variances." Journal of Econometrics 47:5-46.

Zucker, L. G. and M. R. Darby. 2006. "Movement of Star Scientists and Engineers and High-Tech Firm Entry." Working Paper 12172, National Bureau of Economic Research, www.nber.org/papers/W12172.

Zucker, L.G., M.R. Darby, and J. Armstrong. 1998. "Geographically Localized Knowledge: Spillovers or Markets?" Economic Inquiry 36: 65-86.