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SPATIAL LABOR MARKETS AND TECHNOLOGY SPILLOVERS - ANALYSIS FROM THE US MIDWEST

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SPATIAL LABOR MARKETS AND TECHNOLOGY SPILLOVERS - ANALYSIS FROM THE US MIDWEST

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Abstract

The primary focus of this paper is the impact of knowledge creation and innovative activity on non-farm employment growth. Non-farm employment growth is modeled in a stylized model where new knowledge and local economic externalities are key factors driving technology growth. For our empirical application we assume that new knowledge and innovative activity are embodied in new patent filings within the county. To explicitly capture spillovers between counties we apply spatial econometric techniques. The econometric model, based on a 2-stage spatial econometric estimation procedure, is tested for all counties in US Midwestern States of Iowa, Minnesota, Missouri, Kansas, Nebraska, South Dakota and North Dakota. The results indicate the positive influence of knowledge creation and innovative activity, as captured by patents, on non-farm employment growth during the period 1969-2000. We also find strong evidence of local spatial employment growth spillovers contributing in a positive manner to explaining non-farm employment growth. The key results also hold when we consider sub-samples of the study period suggesting our model is quite robust to the time period of analysis.

Keywords: Patents, Employment Growth, Technology Spillovers, Spatial Spillovers

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Introduction

In the last half of the Twentieth Century, many small towns in the U.S. Midwest declined both in population and business activity and the majority of rural counties lost population. Declining transportation costs, growing agglomeration economies, changing structure of agriculture, and declining relative economic contribution of agriculture and other resources industries fueled a period of out-migration in many rural communities. However, some rural counties grew in terms of non-agricultural employment and gross county product without being in central locations or adjacent to metro areas. Identifying and understanding the factors explaining employment and output growth in these counties may provide useful information in developing rural growth incentives and promoting growth in other local areas and regions.

It has long been appreciated that technological change plays an important role in the economic growth process. Advancing technology is a necessary condition for economic growth but is not sufficient and requires the appropriate institutional framework and ideological adjustments to reap any potential benefits. There have been a number of research efforts devoted to the location of innovative activity (Sweeney, 1987; Hall and Markusen, 1985). Unfortunately, the role and mechanism of technological change and spillovers in economic growth is not well understood. While technological change is clearly an important component of economic growth (Schumpeter, 1934; Solow, 1970; Grossman and Helpman; 1994), there is a growing literature providing evidence that technology spillovers are important to the growth process (Jaffe, 1989; Jaffe, Trajtenberg, and Henderson, 1993; Anselin, Varga, and Acs, 1997; Anselin, Varga, and Acs, 2000). In both theoretical and empirical research technology spillovers are generally viewed as positive externalities, and it is in this way that production externalities were introduced into the pioneering growth model of Romer (1986)[3].

Conceptually, Romer's model is developed in a more aggregate, national framework that does not address the more micro fundamental of technological change and technology spillovers and the transmission of new knowledge in the local economic growth process. The mechanism through which new technology and technological externalities are transmitted may be quite important. If the new knowledge is transmitted through journal articles and scientific information available on the internet, then geographic location is not likely an important factor. However, if new

[3] This type of externality is alluded to in Shell (1966).

knowledge and other technological externalities are acquired via the local coffee shop, over dinner, or at a local business meeting, location fundamentals may play an important role in knowledge transmission. Such geographical considerations motivate the applied growth work of Glaeser et al. (1992), where the authors argue that intellectual breakthroughs must cross hallways and streets more readily than oceans and mountains. The possibility that such intellectual spillovers occur between firms is one justification for the high rental rates and long commutes incurred with employment in a large city. In a dynamic model where economic growth is driven by knowledge accumulation, Quah (2002) develops a spatial model where spatial knowledge spillovers play a role in the distribution of knowledge over space and time and finds economic growth need not be centered on a single, isolated point. Considering the importance of innovative externalities of a specific type, Jaffe (1989) finds that the location of university research has a significant effect on corporate patents, as well as indirectly on local innovation. Further, matching patent citations with patents cited, Jaffe, Trajtenberg, and Henderson (1993) find evidence of geographically localized knowledge spillovers.

In this paper we are specifically interested in the role of new knowledge and innovation in the rural growth process. In Glaeser et al. (1992) and Glaeser et al. (1995), the authors focus their analyses on growth of U.S. cities and the local ("within city") and national ("across cities") knowledge and innovation spillovers. Our questions are: Do knowledge and innovative spillovers occur between counties in rural areas as well as within cities? Do such spillovers partially compensate for not locating in a city? And how do such spillovers influence rural employment growth? We hypothesize that spatial proximity of knowledge creation and innovative activity spills over into adjacent counties, and that those spillovers coupled with own county knowledge creation and innovative activity are an important source of own county employment growth. Additionally, we hypothesize that employment growth in adjacent counties stimulates own county employment growth via a spatial employment externality, similar to the synergistic employment effects when cities grow (Glaeser, et al. 1992). By taking into consideration the spatial relationships of both innovative activities as well as in employment growth, we provide a more robust framework for explaining rural employment growth in the presence of knowledge creation and employment growth externalities.

In the following sections, we further explore the role of local knowledge creation and knowledge spillovers on economic growth in the context of employment growth. In the next section a simple conceptual framework is presented highlighting the role of knowledge creation and knowledge spillovers in an employment growth model. We then specify an econometric framework to capture in principle the role of direct knowledge effects and spillovers based on proximity to surrounding economic growth activity. Given the hypothesized correlation between underlying, unobservable economic growth forces and patent filing activity, we then estimate our employment growth equation using a two-step estimation process using data from 618 contiguous counties in the U.S. Midwest. We then present our results and discuss our findings on the roles of locally generated knowledge on local employment growth and knowledge creation and employment growth spillovers from neighboring counties. We conclude with a discussion of the more interesting highlights and implications of our results.

Analytical Framework

The modern economic growth literature is generally shifting away from the traditional neoclassical models to an increased focus on endogenous growth factors. Modern growth theories focus on the roles of ideas and technology embodied in human capital (Lucas 1988), physical capital (Romer 1986), social capital (Goldin and Katz 1999), and natural capital (Castle 1998). A number of studies have added cross-industry externalities and derived empirical estimates of total and sector employment growth in key industries for U.S. cities (Glaeser et al. 1992; Glaeser, Scheinkman, and Shleifer 1995). Unfortunately the primary focus of these theoretical and empirical works has been directed towards countries, and cities and as a result, rural economic growth issues have generally not been afforded the same level of attention. However these models, especially Glaeser et al. 1992, do provide a useful starting point for analysis.

The underlying theoretical model for this analysis follows Glaeser, et al. 1992 which described employment growth in city-industries in the U.S. The model adopted is that of a representative firm in region i=1,2,3,…,n that is assumed to take prices, wages (w_t), and technology (A_t), in their region as given and maximize a single input production function

$$A_{i,t} f\left(l_{i,t}\right) - w_{i,t} l_{i,t} \qquad (1)$$

Firms choose labor input, l_t, such that the marginal product of labor is equal to the wage rate. Taking this derivative again with respect to labor in t+1 we can express the ratio of these two derivatives at two points in time:

$$\frac{A_{i,t+1}}{A_{i,t}}\frac{f'(l_{i,t+1})}{f'(l_{i,t})}-\frac{w_{i,t+1}}{w_{i,t}}=0 \tag{2}$$

Assuming a Cobb-Douglas functional form for the production technology of $f(l)=l^{\alpha}$ where $\alpha\in(0,1)$, we can substitute into (2) and take logs to get an equation of labor growth shown in (3)

$$\ln\left(\frac{l_{i,t+1}}{l_{i,t}}\right)=\tau_1\ln\left(\frac{w_{i,t+1}}{w_{i,t}}\right)+\tau_2\ln\left(\frac{A_{i,t+1}}{A_{i,t}}\right) \tag{3}$$

$$\text{where } \tau_1=\frac{1}{\alpha-1}, \text{ and } \tau_2=\frac{1}{1-\alpha}$$

Glaeser, et al (1992) divides growth in technology into two parts - local (city) and national. Here also technology is divided into two components - local (county) and Midwest regional. We assign a Cobb-Douglas functional form to technology, $A=R^{\delta}A_c^{\gamma}$ where R is regional technology, and A_c is local technology. The parameters δ and γ represent the relative importance of their respective technologies. Thus, we can express the growth in employment as a function of the growth in wages, regional technology growth and local technology growth or

$$\ln\left(\frac{l_{i,t+1}}{l_{i,t}}\right)=\tau_1\ln\left(\frac{w_{i,t+1}}{w_{i,t}}\right)+\tilde{\tau}_2\ln\left(\frac{R_{t+1}}{R_t}\right)+\tilde{\tau}_3\ln\left(\frac{A_{c,i,t+1}}{A_{c,i,t}}\right) \tag{4}$$

$$\text{where } \tilde{\tau}_2=\frac{\delta}{1-\alpha}, \text{ and } \tilde{\tau}_3=\frac{\gamma}{1-\alpha}$$

Research by Entorf and Pohlmeier (1990) and Van Reenen (1997) find a positive relationship between innovation and employment levels using firm level data. Glaeser, et al (1992; 1995), using data from U.S. cities conducted empirical tests of various theories of economic growth. In Glaeser, et al (1992), they focus on the role of technological spillovers, and they assert knowledge spillovers in cities are particularly effective where there are ample opportunities for communication among people. They also find industry variety and local competition encourage industry growth while regional specialization has the opposite effect, implying knowledge spillovers may be more important between industries than within industries.

When considering a predominantly rural cross-section of Midwestern counties a number of interesting questions relating to the growth process arise. First, is urban employment growth significantly different from rural employment growth because rural areas lack knowledge spillovers and agglomeration externalities? Second, would the same factors that explain firm growth in cities explain the growth of firms in rural counties? Rural counties are typically at an earlier "stage of development" with respect to employment growth in non-farm sectors than in more mature city-industries. In fact, agglomeration diseconomies arising from past manufacturing activity in urban areas (i.e. congestion, higher land values, pollution, higher labor costs, etc.) are one reason rural manufacturing was able to experience such impressive employment growth through the 1970's, 1980's and 1990's (Haynes and Machunda 1987). Alternatively, entering at a later stage of development in a more service-oriented national (Echevarria 1997), or at least regional economy (Kuznets 1973), we might expect a different pattern of growth to emerge. In this paper we will explain county employment growth as a function of similar dynamic externalities and local spillovers as those described in Glaeser, et al (1992) as well as initial endowments. However, we focus particular attention on the role of new knowledge and innovation that occurs within the county and spills in from adjacent counties.

Econometric Model

The employment growth relationships estimated in this paper are based on a cross-section of Midwestern counties. Total employment growth between 1969 and 2000 is explained by resource endowments, as well as new technology and innovation created within the county. As a measure of new technology and innovation, total patent filings within each county for the years 1975-2000 is used as a proxy for new knowledge creation. In addition to the role of new technology and innovation in employment growth we are interested in a number of additional factors believed to play an important role in the economic growth process. Specifically these factors are classified in terms of county-specific human capital and knowledge externalities.

As economists we can appreciate the important role that technology plays in the growth process but at the same time understand the difficulties encountered when trying to measure it. Conceding that new technology and innovation is a somewhat unstructured variable and difficult to quantify, we believe new technology and innovation technological can best considered as a function of reasonable variables. The relations on the right hand side of (4) can be broken into components.

The growth in county specific technology, $A_{c,i}$, is of considerable interest here as the primary objective is to examine the impact of new technology and knowledge on employment growth. Local technology growth is assumed to be explained by the following relationship

$$\ln\left(\frac{A_{c,i,t+1}}{A_{c,i,t}}\right) = g\left(\sum_{j\in N_i}\ln\left(\frac{l_{i,j,t+1}}{l_{i,j,t}}\right), \sum_{k\in[t,t+1]} pat_{i,k}, emp_t, ss_{i,t}, cr_{i,t}\right) \tag{5}$$

where: $\sum_{j\in N_i}\ln\left(\frac{l_{i,j,t+1}}{l_{i,j,t}}\right)$ is the employment growth in "neighboring" counties as indicated by the counties in the neighborhood of county i, N_i.

pat_i - is the number of patents filed within the county;

emp_t - is initial employment;

dcv_i - is a demographic control variable; and

ct_i - is a concentration index of the intensity of employment industry domination.

Spatial externalities are believed to play a role in the new geographic economy (Fujita, Krugman, and Venables 1999) and should be modeled explicitly. Models of social interaction (Akerlof 1997) can be easily modified to accommodate interaction in physical space. The importance of explicit interaction with other economic agents stresses the need to consider the behavior of agents together rather than independently (Anselin, 2003). It is quite easy to postulate that more interaction is going to take place the nearer the proximity of agents. The term $\sum_{j\in N_i}\ln\left(\frac{l_{i,j,t+1}}{l_{i,j,t}}\right)$ embodies a type of spatial externality from neighboring counties as defined the neighborhood N_i for county i. The exact criteria used to define the neighborhood structure N_i for any given county is discussed in greater detail later in this section. There are reasons to believe greater interaction among economic agents will bring about greater exchange of ideas and thoughts. These ideas and thoughts are much more readily exchanged over short distances than great expanses of land or other geographic impasses. Thus it is hypothesized that if a county has the opportunity to benefit from spillovers from neighboring counties, these spillovers should have a positive effect on own county employment growth. That is, $g_1 > 0$ where the subscript refers to the partial with respect to the first argument i.e. $g_1 \equiv \frac{\partial g(.)}{\partial \sum_{j\in N_i}\ln\left(\frac{l_{i,j,t+1}}{l_{i,j,t}}\right)}$.

Patents are thought to provide us with a quantifiable embodiment of innovation and new knowledge created. Indeed patents have been used as a proxy for new knowledge and innovation fairly extensively in the literature (Jaffe 1989 and 1993; Hall, Jaffe, and Trajtenberg 2001; Anselin, Varga, and Acs 1997; Acs, Anselin, and Varga 2002). While it is true that some patented innovations are essentially worthless from an economic perspective while other valuable innovations are never patented, we nevertheless hypothesize that total new patent filings are expected to contribute positively to new knowledge and innovation and we expect $g_2 > 0$ a priori. Notice that total county patents are used here rather than say patents percapita. Total patents are used based on a general interpretation of knowledge as a non-rival, non-excludable public good. While it is true that the very nature of patenting implies a degree of excludability of the actual item, process, or idea, the knowledge embodied in the patented innovation is most likely both non-rival and non-excludable. Discoveries by leading firms, while increasing the firms own productivity, will also help to advance the technology frontier of competing firm's as well (Eeckhout and Jovanovic 2002). Hence, the total new contribution to the local stock, rather than a relative measure, of new innovation and knowledge is appropriate (i.e. patent counts vs. patents percapita).

The role of decreasing returns in aggregate local knowledge production prompts us to incorporate initial employment, emp_t, as an explanatory variable for local knowledge growth. The inclusion of this variable allows us to control for conditional or beta-convergence (Barro and Sala-I-Martin, 1991 and 1992). The basic argument for convergence in capital productivity in the neoclassical growth model comes from diminishing returns. In the current model a higher initial level of employment attainment may also be associated with a higher level of technological attainment and overall development. In the situation where conditional convergence does exist, we should expect $g_3 < 0$ since at higher levels of overall knowledge the incremental advancements to the local technology stock occur less frequently and at greater marginal cost. Local demographics and reliance on government supports will likely affect the local capacity for continued economic growth. The demographic control variable (dcv) is the sum of social security and medicare payments made within the county relative to total county income. While worker contributions to programs like social security can have impacts on both workforce supply and demand (Siebert, 1997), to our knowledge, no study has examined the effect of the effect of county income dependence on social security and medicare payments on local economic activity.

The final measure included in the specification of (5) is an industry concentration measure which addresses, at least indirectly, cross-industry externalities. This measure is computed as the squared share in employment summed for the largest four employment categories[4]. Higher values imply less industry diversity while lower values imply a greater degree of industry diversity. It is unclear exactly how we may expect local technology to be influenced by local diversity since the theory may be separated into the two competing areas. One school of thought believes diversity among industries promotes technology spillovers (Jacobs 1969; Bairoch 1988, Glaeser, et al. 1992). The idea is that technological spillovers are more important between rather than within sectors due to greater diversity of technologies and ideas. The competing belief suggests industry specialization is the best method to bring about technological development through exchange of ideas in the same area rather than a variety of sectors (Marshall 1890; Romer 1986; Arrow 1962; Porter 1990). A good example of the later is Silicon Valley during the high tech boom where imitation, spying, and high labor mobility tended to foster new innovation and advancement. Thus under the Jacobs-Bairoch school of thought it is expected $g_5 < 0$ and under the Marshall-Arrow-Romer-Porter hypothesis we should expect $g_5 > 0$ as higher concentrations reflect lower amounts of diversity.

Broader regional technology growth is much harder to capture in a cross-section analysis such as ours, but we do believe regional and location factors have an impact on the overall level of technology. Defining the state as our regional unit of observation we can control for state specific effects, which may include tax rates, institutional structure, and possibly, constituent attitudes. It has often been argued that one reason rural areas have not been able to realize as much economic growth as their urban counterparts is due to the distance to larger metro areas and lack of transportation infrastructure facilitating market access. Lack of a large population base and opportunity to interact with other individuals may restrict the exchange of new ideas between people and thus hinder the realization of growth spillovers. To examine whether rural areas are apparently disadvantaged in this respect, we include distance to a MSA and presence of an interstate in the county. The above relationships may be formalized in the following:

$$\ln\left(\frac{R_{t+1}}{R_t}\right) = f\left(s_{k=1},\ldots,s_{k=7}, dmsa, Id\right) \qquad (6)$$

[4] This computed in a manner similar to the Herfindalh-Hirschman index. Only the top four industries were used since data limitations prevented us from computing this index based on larger number of sectors.

where: s_k - are state effects for each of the k=1,2,…,7 States;

dmsa - is the distance to a metro area; and

Id - is an interstate dummy.

The signs for the state parameters cannot be assigned ex ante without more information on historical and current state policies and programs. Since distance to a metro area should hinder an individuals ability to interact with other people, a negative relationship is expected. Similarly, since the presence of an interstate should aid in market access, a positive relationship is expected.

Higher wages are usually associated with higher levels of worker productivity (Hellerstein, Neumark, and Troske, 1999) and it is likely for any given firm or industry worker productivity is going to be a function of the state of technology. Indeed if we were examining a specific firm or a specific industry, rather than a region, then we would want to consider more specifically the role of technology in wage growth. If the specific technology is factor augmenting, labor or capital, then we would expect an impact on the growth of wages. If so, we handle the embedded endogeneity between wages, technology and overall employment growth. Salter (1966) found a positive relationship between total factor productivity and labor growth by industry. However in our analysis we are interested in regional growth and are not specifically interested in the role of factor augmenting technical change (nor could we capture this if we wished). The class of technology we wish to capture in this paper is neither firm nor industry specific and is of a much broader class of technological advance contributing to the overall level of new ideas and knowledge created in a region.

The theory underlying employment growth in the current context does little to provide us with a clear indication on how to explain growth in wages. There is endogenous growth literature which does explain wage growth in terms of the ability to adopt new technologies in production as well as the indirect effects on increasing productivity (Lloyd-Ellis, 1999). However, such considerations are beyond the scope of existing data and we rely on the ability of initial wages to explain wage growth. The relationship for wage growth and these variables is represented by the function $h(.)$

$$\ln\left(\frac{w_{t+1}}{w_t}\right) = h(w_t) \tag{7}$$

Unfortunately, the theory does not allow us to sign the relationship in (7). On one hand we may assume a similar type of beta-convergence in wages to occur for wages as hypothesized with initial employment and local technological growth. Alternatively, higher wages may imply higher concentrations of human capital and productive potential which would attract more cutting edge employers and lead to greater income growth.

Assigning log-linear relationship to the functions $g(.), f(.)$ and $h(.)$ and applying this to relationships (5)-(7) and substituting into (4) will result in an estimable relationship. This specific empirical relationship takes the form

$$\begin{aligned} \ln\left(\frac{l_{i,t+1}}{l_{i,t}}\right) &= \beta_0 + \rho \sum\nolimits_{j \in N_i} \ln\left(\frac{l_{j,t+1}}{l_{j,t}}\right) + \beta_1 \ln \sum_{k \in [t,t+1]} pat_{i,k} + \beta_2 \ln ss_{i,t} + \beta_3 \ln cr_{i,t} \\ &+ \beta_4 \ln dmsa_{i,t} + \beta_5 \ln w_{i,t} + \beta_6 \ln emp_{i,t} + \beta_7 Id_{i,t} + \sum_{k=1}^{6} \beta_{7+k} s_k + \varepsilon \end{aligned} \tag{8}$$

where ε is a random error term distributed normally with constant variance, the parameters ρ, and β_0-β_{13} are to be estimated, and the other variables are defined as above. The spatial parameter rho, ρ, following conventional notation in the spatial econometric literature, is used to capture an explicit spatial relationship in the data. In the current model this relationship is a spatial growth externality. For completeness, based on our conceptual framework, the parameter terms τ_1, $\tilde{\tau}_2$, and $\tilde{\tau}_3$ are negative, positive, and positive respectfully in (4). Based on our specification of the empirical model the expected signs for the betas in (8) are; $\beta_1 > 0$; $\beta_2 < 0$; $\beta_4 < 0$; $\beta_5 > 0$; $\beta_6 < 0$; $\beta_7 > 0$; and β_3, β_8 - β_{13} are ambiguous. In matrix notation this equation can be described by

$$\begin{gathered} y = \rho W y + X\beta + \varepsilon \\ \varepsilon \sim N\left(0, \sigma^2\right) \end{gathered} \tag{9}$$

In equation (9) y is a nx1 vector of county (log) employment growth rates for our Midwestern cross-section of n counties. The spatial relationship is captured in the nxn spatial weights matrix W and is characterized by zeros along the main diagonal and has off diagonal elements representing the neighboring counties. The are a number of methods which can be used to specify the neighbors in the W matrix ranging from variations on a distance criteria (Anselin 1988; Anselin, Varga, and Acs 1997; Acs, Anselin, and Varga 2002) to some type of contiguity measure (Anselin 1988; Pace and LeSage 2003a and 2003b). Given that our cross-section of Midwestern counties occurs on a fairly regular lattice, we opt for creating the W matrix based on contiguity with the three closest counties[5]. The other explanatory variables and their associated parameter estimates are embodied in the nxk X matrix and the kx1 vector β respectively. The method used to derive estimates for (9) is based on a concentrated likelihood function and parameter estimates are computed based on the algorithm of Anselin (1988).

Aggregate county patent filings are used to capture new technology and innovation and it may be that patents themselves are a function of economics growth. That is, there are obvious reasons to believe there are underlying growth and technological forces not explicitly captured in the model that may result in patenting activity correlated with the error. The difficulty in quantifying technological growth is largely due to lack of data rather than model misspecification. To control for this potential problem a two-stage instrumental variable (IV) approach is used. As with any IV approach the task is to find instruments correlated with the independent variable, in this case patents, but not the error term. Although it is difficult to think of an instrument where patent filings, themselves indicators of a broader set of technological growth, are not correlated with unobservable underlying employment growth forces, the instruments used include: 1) percentage of the population with a college degree, 2) population, 3) per-capita personal income, and 4) a spatial lag for patent filings. The spatial lag for patents is computed in the same manner as for the standard employment growth equations. The relationship used to generate the patent IV is:

$$x = \rho_x Wx + X_x \beta_x + \varepsilon_x \qquad (10)$$
$$\varepsilon \sim N\left(0, \sigma_x^{\,2} I\right)$$

where x is a nx1 matrix of (log) total inventor patent filings per county[6], W is the same nxn standardized and symmetric spatial weights matrix used in (9), X_x is a nxk_x matrix of explanatory

[5] Here we use a Delaunay triangulation routine and pick out the three nearest counties based on the latitude and longitude coordinates for the county centroid. Delaunay triangulation computes a set of triangles such that no data points are contained in any triangle's circumcircle.

[6] We augmented the patent variable with a constant to ensure the spatial integrity of the sample. Another option would be to remove the observation from the sample, but such omission of in this case however results in an incomplete spatial structure. Removing an observation from a spatial dataset effectively

data, and β_x is a k_x x1 matrix of coefficients to be estimated. The error structure is assumed to adhere to the standard normality and homoskedastic conditions[7].

Since this is a two stage problem there is an issue of correcting the standard errors in the second stage. There are two approaches that may be taken here to correct for this. The first is to simply do nothing and consider the precision of our estimates with greater caution. The second, and more agreeable, approach is to correct our standard errors to control for the fact we are using predicted values in the second stage. In this case however, we much proceed with caution since while a method like standard bootstrapping may seem reasonable it is in fact not. Here we need to maintain the spatial structure of the model which would be destroyed by simple random sampling with replacement. It is the random sampling in regular bootstrapping which makes this method unworkable. However alternatives have been suggested to compute appropriate standard errors in a spatial two stage model (Anselin 1988; Kelejian and Prucha 1998 and 2002). To compute standard errors to determine the precision of our estimates we follow an augmented spatial bootstrap method. A description of this augmented spatial bootstrap method is found in the appendix.

Data

County growth in non-farm employment is considered over the period 1969-2000. Further, to capture the effect of business cycle and recession, the sample is split into two cross-sectional sub periods: 1969-1984 and 1985-2000. This splitting of the sample allows us to examine whether our model is robust over the time period chosen and if there are significant difference in the factors influencing non-farm employment growth over time. The sample is comprised of 618 counties in the U.S. Heartland states of Minnesota, Iowa, Missouri, Kansas, Nebraska, South Dakota, and North Dakota. Due low population density and absence of cities of significant size, most counties in the region are classified as rural (population less than 50,000). A spatial view of non-farm employment growth for our periods of study are shown in figures 1, 2, and 3. Based on these

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creates an "empty void". Thus, to adhere to the log-log specification, the spatial nature of the data can only be maintained by augmenting the data with a constant.

[7] It is reasonable to expect variability in patents to be larger for populous counties, thus heteroskedasticity may be an issue. In response, the classical assumption of homoskedasticity may need to be relaxed in favor of the following error structure $\varepsilon \sim N\left(0, \sigma^2 V\right)$ where V is a diagonal matrix whose elements need not be constant. In the estimations where homoskedasticity is not assumed a Heteroskedastic Bayesian Linear model is used based on a Markov Chain Monte Carlo or Gibbs sampling method (Geweke, 1993). However, estimation of the heteroskedastic model for the first stage of the 2-stage IV estimation did not appreciably affect results so further discussion based on this model has been suppressed.

geographic maps, employment growth appears to be occurring in clusters and does not appear random. While the pattern is not the same for all three of these maps, all appear to indicate spatial relationships.

A county measure of knowledge stock and technology embodied in physical capital does not exist at the county level. However, a common approach in the economics literature has been to use patents as a proxy for innovation and new knowledge. Positive results have been reported by Anselin, Varga, and Acs (1997), Acs, Anselin, and Varga (2002), Hall, Jaffe, and Trajtenberg (2001), and Jaffe (1999). To capture new knowledge creation within the county, a database of patents filed by residence of the lead inventor was developed for all counties in our sample. A list of utility patents filed in the United States for the years 1975 through 2000 was obtained from the United States Patent and Trademark Office. This dataset contained the mailing address for the lead inventor for each utility patent filed for this period. Using the lead inventor's mailing address and cross-matching with a list of cities by county from Census, a count of patents filed for each county and year was constructed[8]. For the period 1975-2000 counties filed an average of 125 patents with a median filing of 14. The county with the largest number of patents had a total of 12,065 patents. There were only a small number of counties with no lead inventor patent filings, 32, representing only about 5% of total counties. Given the predominantly rural composition of the Midwest this is really quite surprising.

Non-farm employment, population, and other county level data were obtained primarily from Bureau of Economic Analysis (BEA) data complied on the Regional Economic Information System (REIS) dataset. Additional data on educational attainment were from the census of population. Summary statistics are presented in table 1. We find that over the 1969-2000 period, county employment grew an average of 46%. The fastest growing county experienced employment growth of 207%, while the least successful county halved its non-farm employment. The average county employed almost 11,000 in 1969, the largest county employment was about 545,000, and the smallest county employment numbered only 105. County population averaged 26,000 with the largest county having 968,000 people and the smallest county having only 624 individuals. Wages are defined as total county earnings divided by total county employment, and as indicated by the low standard deviation, they exhibit little variation in our sample. The

[8] Similar to journal articles, patents often have more than one individual listed as the primary source of the work. Our analysis herein focuses on counts from only the lead author. However, further analysis by the authors suggests the general results would not greatly differ had all inventors rather that just the lead inventor for each patent been used.

measure of county non-farm employment concentration is the sum of the squared employment shares across the largest 4 sectors multiplied by 1,000 within the county using employment levels from 1969 or 1985, depending on the time frame of interest. The concentration measure has an average of 1,858 with a relatively low standard deviation. The human capital measure, percent of county population with a college degree, averaged about 6.5% in 1970. This measure ranged from about 30% to less than 0.5%, and displayed a high standard deviation. When evaluating the later cross-section of data, 1985-2000, comparable data are used to compute a set of starting values for 1985[9].

Results and Implications

Empirical estimation of the models presented in equations (9) and (10) are conducted in Matlab®. These equations may be estimated using OLS when ρ =0, that is, when no spatial interaction is assumed. In the presence of a spatially lagged dependant variable, simultaneity will result in OLS estimates which are both biased and inefficient. Maximum likelihood estimation can be used to derive efficient and unbiased estimates. The results from the estimation are presented in tables 2-5. The first three of these tables contain the results from the employment growth model estimation. For each time period of study the model is based on a cross-sectional data set of the 618 counties with non-farm employment growth as the dependant variable and our hypothesized set of explanatory variables on the right-hand side. For tables 2, 3, and 4, we include estimation results for i) OLS model specified with no spatial interaction, ii) a spatial model, and iii) a spatial model using a two-stage process. The equations used to fit the patent data in the two-stage estimation models are presented in table 5.

For the growth period 1969-2000, our results are presented in table 2. The first column of results, OLS estimates, do not control for any spatial relationships and 38% of the variability in employment growth is explained by this model. Using the OLS model, two tests are carried out to check for the presence of spatial autocorrelation in the error structure. Test statistics based on the likelihood ratio (LR) and Lagrange multiplier (LM) tests can be computed for the OLS specified model. Similarly, a spatial LM (LM-Sar) test statistic can be computed for the model estimated

[9] For 1985 there were three counties for which the calculation for the concentration index could not be computed directly due to missing data for either the third or fourth largest industry. Consequently where missing sector data was encountered a value of zero was used in the calculation of the index. Traditionally one would simply throw out the data point in question but this is not an option here since the use of spatial statistics requires the spatial lattice to be completely intact.

with a spatial lag (Anselin 1988). Values of 36.6 and 36.1 are computed for the LR and LM tests respectively, indicating a spatial relationship exists in model residuals, implying that the estimates may be inefficient[10]. Given the obvious difficulties interpreting the results of this model with any degree of confidence, we concentrate further discussion on the results of the two spatially specified models in the last two columns of table 2.

The spatial model in the second column of table 2 is given in equation (8). This model explains approximately 43% of the variability in non-farm employment growth for Midwestern counties over the years 1969-2000. The LM-Sar test statistic is 0.3 so we can conclude a spatial relationship does not exist in the model residuals at a high level of statistical confidence. Since the model is a ln-ln formulation, most of the parameter estimates can be interpreted directly as elasticities. The coefficient estimate for the patent parameter can be interpreted as a county with a 10% higher number of patents filed will have a 1.5% higher employment growth over the 1969-2000 period. Since patents are our indicator of new knowledge within the county it appears that new knowledge creation and knowledge spillovers within the county contribute in a significant manner to employment growth. This result is statistically significance at a 99% level of confidence. The spatial coefficient representing growth spillovers between counties, "rho", is estimated to be 0.34 and is statistically different from zero with at least a 99% level of confidence. This result does appear to add support for the presence of spatially induced spillovers. This parameter may also be interpreted directly as an elasticity. The spatial lag parameter can be interpreted as a 1% increase in the employment growth rate of surrounding counties (i.e. as defined by the spatial contiguity matrix W) will, *ceteris paribus*, result in a 0.34% increase in employment growth in the home county. To interpret this parameter in a more meaningful manner a county whose neighboring counties are growing are better positioned to enjoy growth spillovers and other externalities generated by surrounding counties than those counties which are isolated. Of course the negative of this also holds, if a county whose neighboring counties experience a recession or economic downturn, proximity can have the effect of suppressing home county economic activity. In the presence of this sort of depressed growth environment a type of "trap" may occur where it is difficult to stimulate home county employment growth in the absence of regional or area growth.

[10] The LR, LM, and LM Sar tests are distributed Chi-square with one degree of freedom. The critical value at the 99%, 95% and 90% levels are 6.63, 3.84, and 2.71 respectively.

We generally find the parameter estimates of consistent sign with our theoretical framework. The parameter for initial non-farm employment can be interpreted as a 10% increase in initial employment results in a 1.4% decrease in employment growth. This result is consistent with the hypothesis of beta-convergence. Initial wage was significantly different from zero with a 95% level of confidence and had a positive influence on non-farm employment growth. The parameters for market access as measured by distance to a MSA and presence of an interstate did not appear to have an appreciable effect on labor growth for this time period. Examining the state effects, Minnesota, Missouri, and South Dakota appear to have a more positive growth environment than the other states (including Iowa, which is the default state).

As discussed earlier there are strong reasons to believe our patent measure of innovation may be correlated with unobservable growth forces that will appear in our model residuals. The set of results where we instrument patents in a two stage process should result in a more reliable set of results from an efficiency perspective. The results from the two-stage estimation procedure are given in the 3rd column of table 2. In general the same conclusions hold, however the estimated coefficients themselves are more pronounced in a number of cases. For example, the patent parameter used to proxy knowledge and innovation within the county has an elasticity of 0.27, almost twice as large as 0.15 estimated in the standard spatial model. Using these estimates, the impact of innovative spillovers on employment growth is really quite large. In terms of cross industry externalities and spillovers we find support for the Marshall (1890)-Arrow (1962)-Romer (1986), aka MAR argument since a 1% increase in industry specialization in a county results in a 0.18% increase in employment growth. This result contradicts the Jacobs (1969) and Glaeser, et al. (1992) and tends to support Schumpeters (1942) original hypothesis that greater industry specialization promotes growth rather than industry diversity. The spatial spillover parameter was computed with a value of 0.32. In any case, within county, and between county externalities remain important factors regardless of the set of estimates used. The model estimates used to predict patents for the employment growth models are found in table 5 and indicate a spatial relationship with new patent fillings providing evidence of a spatial component to new technology and knowledge creation[11]. Our demographic control variable did not appear to have any appreciable affect on employment growth over this time frame for either of the spatial models in table 2.

[11] For a more complete explanation of similar empirical results see Monchuk and Miranowski 2004.

To examine more closely any time varying relationship that may exist, the growth period was further split into two periods: 1969-1984, and 1985-2000. The results from the spatial and two-stage spatial IV model are substantively the same, consequently we focus our attention on the two-stage spatial model. Examining the earlier of the two growth periods, 1969-1984, in table 3, the spatial IV model is able to explain 28% of the variability in employment growth. The spatial interaction parameter, rho, is found to have an elasticity of 0.27 which is comparable to the estimate in table 2. The coefficient for patent filings was estimated to have an elasticity of 0.16 and is statistically different from zero with at least a 99% level of confidence. Other things equal, a 10% increase in the number of patents filed in the home county leads to a 1.6 % increase in employment growth in the home county. It is interesting to note that the parameter estimate for patents in the two-stage model, 0.16, is more than three times the basic spatial model parameter of 0.05.

Once again, we find evidence of beta-convergence since the parameter estimate for initial employment is negative and significant since a 1% increase in initial employment would decrease employment growth by 0.14%. Wages had a positive and significant impact over the earlier sub-period 1969-1984. Higher wages over this period may have signaled a more skilled workforce, which attracted additional employment. We also found the presence of an interstate played a marginally significant role in explaining employment growth in this earlier sub-period. In the early period of study the Eisenhower interstate highway system throughout the Midwest was just being completed. It would be reasonable to expect the benefits of such transportation capital to have had an economic impact in the earlier period of study. It is also interesting to note that all states performed better than Iowa, as indicated by the state dummy coefficients.

Estimation of our employment growth model over the period 1985-2000 produced results that are similar in the spatial and patent parameters, but with minor differences in some other parameters. The two-stage model in the 3rd column of table 4 was able to explain about 38% of the variability in non-farm employment growth over the period. The LM Sar test statistic of 0.76 implies spatial autocorrelation in the residuals is likely not a problem with this model. We once again find spatial spillovers to have a significant impact on employment growth with an estimated coefficient for the spatial interaction term of 0.30, significantly different from zero at a high level of statistical confidence. Based on this coefficient, a 10% increase in non-farm employment growth in neighboring counties will result in roughly a 3% increase in employment growth in the home county. As a proxy of new knowledge and innovation, patent filings over 1985-2000 were found to have a positive and statistically significant relationship with employment growth with an estimated elasticity of 0.07. While it is difficult to directly compare the estimated coefficients of the patent parameter for the entire growth period and the two sub-growth periods, it is interesting to note how small this estimate is for either of the sub periods, 0.16 and 0.07 for 1969-84 and 1985-2000, respectively, as compared to 0.27 for the full growth period 1969-2000. This result points to the importance of the cumulative stock of new knowledge that is important to growth rather than advances in knowledge during shorter periods of time.

Initial employment is found to have a negative and significant influence on non-farm employment growth from 1985-2000 and provides further evidence of conditional convergence. The coefficient for the concentration index is 0.17 and is significantly different from zero at a 99% level of statistical confidence. This result further supports the hypothesis that spillovers occur more readily in specialized rather than diverse local economies and is consistent with MAR. This implication was not present in the earlier sub-sample suggesting a more specialized county economy structure has only been more beneficial in the more recent years. Interestingly, our demographic control variable is found to play a significant role in non-farm employment growth over 1985-2000, a result which was not present in the 1969-1984 regression model. Looking at the response to our demographic control variable, we find that an increase in the dependence on social security and medicare in the county at the mean from 0.13 to 0.14, an increase of 1 percentage point, will result in a 0.09% decrease in non-farm employment growth. From table 1 we can see that the range for this variable increased considerably between 1969 and 1985 and indicates retirement communities and counties (both planned and otherwise) may be less able to drive future growth from within. Neither distance to a MSA nor presence of an interstate was found to have a significant impact on non-farm employment growth. The lack of significance for these two parameters may imply that an improvement in communication and information networks may have taken an important role even before the information revolution of the 1990s. In table 4, the state dummies do illustrate significant differences in employment growth relative to Iowa (the excluded dummy). In general, Iowa has faired worse, in a statistical sense, than most of the other states. The states with better performance relative to Iowa were Missouri, Minnesota, and South Dakota driven in part by tourism and other state policies.

Conclusions and Extensions

The predominant motivation for this paper was to analyze the impact of new technology and new knowledge on non-farm employment growth in a cross section of Midwestern counties, most of which are primarily rural. In a recent column in Forbes commenting on where to find economic growth was written: "The most valuable natural resource in the 21st century is brains. … Watch where they go! Because where they go, robust economic activity will follow" (Karlgaard, 2003). This casual quote captures to a large degree much of the motivation to examine local impacts of new knowledge creation and technology spillovers on economic activity in rural areas. Using accumulated new patent filings as an indicator of new knowledge creation, we have found a strong relationship with non-farm employment growth. Based on these results we find that knowledge spillovers do exist. More specifically, we find that areas with a higher accumulation of new knowledge do experience greater employment growth. For the sub-growth periods, our results support the hypothesis that new knowledge contributes to positive employment growth but to a lesser degree than in the overall 1969-2000 period, suggesting our results are generally robust to the time period chosen. These results support the hypothesis that knowledge accumulation over time is more important to employment growth than the flow of knowledge. This finding is consistent with traditional views of the importance of accumulated knowledge to growth. In addition the knowledge and employment externalities, explicit spillover effects from neighboring counties captured by the spatial lag model, are significant and important, leading us to conclude modern communications and transportation technology, enhanced by the information-revolution are shrinking space and the comparative advantage of large urban areas.

Initial employment was found, in general, to have a negative and statistically significant impact on employment growth. This finding adds support to the conditional convergence theory – the greater the initial county employment, the slower will be its employment growth rate as higher levels of economic development are reached. On a positive note for current and future policy makers residing in rural regions and faced with selecting an economic development strategy, distance to a MSA was insignificant for the period 1985-2000 as was the impact of having an Interstate within the county. These results offer hope rural areas that can get the other factors right since conventional wisdom is that rural counties need to be located near large urban centers if they hope to grow. Rather, it is more important that knowledge creation and accumulation is occurring locally and in neighboring counties that will ultimately influence a county's future economic growth. The analysis for the 1985-2000 period also points to the importance of the demographic composition of the county population in providing continued economic improvements. A high portion of the population that is dependent on government programs like social security and medicare, such as many rural communities throughout the Midwest, may have reason for concern if long-term growth is a goal.

While it is difficult to discuss policy based on a limited amount of empirical analysis, a few seemingly important generalizations appear evident. The spatial models presented in this paper suggest there are considerable positive economic growth spillovers between counties. From a rural policy perspective, counties that hope to improve their economic outlook should exploit this spatial relationship. In part, this result may argue for regional, as opposed to local, growth strategies as well as cooperation and coordination among neighboring counties rather than direct competition for new business. If there is economic growth in neighboring counties, a county is able to benefit from this growth. However, if there is surrounding stagnation, and declining employment growth, it may be insurmountable to achieve local growth. In such a case a low-level equilibrium "trap" of sorts may occur in which it is impossible to realize local employment growth. It is evident from our analysis new technology and spatial interaction have local growth impacts even in a cross-section of predominantly rural counties in the US Midwest.

For rural areas to benefit from new knowledge and innovation and accompanying economic growth requires, in particular, a shift in conventional thinking because maintaining the rural status quo is not compatible with modern technology (Kuznets, 1973). Rural policy has generally focused on maintaining the status quo, while continuing to rely on a primary industries base and government entitlements. This reliance stifles new knowledge creation and innovation because the local economy is no longer reacting to market forces. The analysis here has demonstrated that new knowledge does play an important role in local economic activity and it is thus futile for rural constituents to try and improve their economic standings without adopting a policy, either implicit or explicit, to encourage the adoption and development of knowledge and innovation and to actively cooperate with neighboring counties to achieve non-farm employment growth.

References

Acs,Z.J., L.Anselin, and A.Varga "Patents and innovation counts as measures of regional production of new knowledge." *Research Policy* 31 (September 2002):1069-85.

Akerlof, G.A. "Social Distance and Social Decisions." *Econometrica* 65 (1997):1005-1027.

Anselin,L. *Spatial Econometrics: Methods and Models.* Boston, and London: Kluwer Academic Publishers Dordrecht, 1988.

Anselin, L. "Spatial Externalities" Forthcoming in *International Regional Science Review.* Online manuscript at: http://agec221.agecon.uiuc.edu/users/anselin/papers/intro_externalities.pdf (date retrieved: October 20, 2003).

Anselin,L., A.Varga, and Z.Acs "Geographical spillovers and university research: A spatial econometric perspective." *Growth and Change* 31 (2000):501-15.

----- "Local geographic spillovers between university research and high technology innovations." *Journal of Urban Economics* 42 (November 1997):422-48.

Arrow, Kenneth J. "The Economic Implications of Learning By Doing." *Review of Economic Studies* 29 (June 1962): 155-73.

Bairoch, P. *Cities and Economic Development: From the Dawn of History to the Present.* Chicago: University of Chicago Press, 1988.

Barro, Robert J., and Xavier Sala-I-Martin. "Convergence." *Journal of Political Economy 100* (April 1992): 223-51.

Barro, Robert J., and Xavier Sala-I-Martin. "Convergence Across States and Regions." *Brookings Papers on Economic Activity 1* (1991): 107-58.

Castle,E.N. "A conceptual framework for the study of rural places." *American Journal of Agricultural Economics* 80 (August 1998):621-31.

Echevarria, C. "Changes in Sectoral Composition Associated with Economic Growth." International Economic Review 38 (No. 2 May 1997): 431-452.

Eeckhout, J, and B. Jovanovic. "Knowledge Spillovers and Inequality." *American Economic Review 95* (December 2002): 1290-1307.

Efron, B., and R.J. Tibsirani. *An Introduction to the Bootstrap*. New York: Chapman and Hall, 1993.

Entorf, Horst, and Winifried Pohlmeier. "Employment, Innovation and Export Activity." In Microeconometrics: Surveys and Applications ed. J.P. Florens. London: Basil Blackwell, 1990.

Fujita, M., P. Krugman, and A. Venables *The Spatial Economy: Cites, Regions, and International Trade*. MIT Press, Cambridge MA., 1999.

Geweke,J. "Bayesian Treatment of the Independent Student t Linear Model." *Journal of Applied Econometrics* 8 (1993):19-40.

Glaeser,E.L. et al. "Growth in Cities." *Journal of Political Economy* 100 (December 1992):1126-52.

Glaeser,E.L., J.A.Scheinkman, and A.Shleifer "Economic-Growth in A Cross-Section of Cities." *Journal of Monetary Economics* 36 (August 1995):117-43.

Goldin,C. and L.F.Katz "Human capital and social capital: The rise of secondary schooling in America, 1910-1940." *Journal of Interdisciplinary History* 29 (1999):683-723.

Greene, W.H. *Econometric Analysis, 3rd Edition*. New Jersey: Prentice Hall, 1997.

Grossman, G,M., and E. Helpman "Endogenous Innovation in the Theory of Growth." *The Journal of Economic Perspectives* 8 (Winter 1994):23-44.

Hall, B, Jaffe, A., and Trajtenberg, M. "The NBER Patents Citations Data File: Lessons, Insights and Methodological Tools." WP 8498 National Bureau of Economic Research, 2001.

Hall, P., and A. Markusen. *Silicon Landscapes*. Boston: Allen and Unwin, 1985.

Hellerstein, Judith K., David Neumark, and Kenneth R. Troske. "Wages, Productivity, and Worker Characteristics: Evidence from Plant-Level Production Functions and Wage Equations." Journal of Labor Economics 17 No. 3 (Jul. 1999):409-446.

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

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

Jaffe,A.B., M. Trajtenberg, and R. Henderson. "Geographic Localization of Knowledge Spillovers as Evidenced by Patents." The *Quarterly Journal of Economics* 108 (Aug. 1993):577-598.

Karlgaard, Rich. "Digital Rules – Where to Get Rich." Forbes.com link:
http://www.forbes.com/forbes/2003/1006/039_print.html (date retrieved: October 6, 2003).

Kelejian,H.H. and I.R.Prucha "A Generalized Spatial Two-Stage Least Squares Procedure for Estimating a Spatial Autoregressive Model with Autoregressive Disturbances." *Journal of Real Estate, Finance, and Economics 17:1* (1998):99-121.

----- "2SLS and OLS in a spatial autoregressive model with equal spatial weights." *Regional Science and Urban Economics* 32 (November 2002):691-707.

Kuznets, Simon. "Modern Economic Growth: Findings and Reflections." *American Economic Review* 63 (June 1973):247-258.

Lloyd-Ellis, H. "Endogenous Technological Change and Wage Inequality." A*merican Economic Review 89* (1999): 47-77.

Lucas,R.E. "On the Mechanics of Economic-Development." *Journal of Monetary Economics* 22 (July 1988):3-42.

Marshall, Alfred. *Principles of Economics*. London: Macmillan, 1890.

Monchuk, D.C, and J. A. Miranowski “Innovative Behavior and Spatial Location – Using Patent Counts and Geographic Location to Estimate Innovative Spillins” Iowa State University Working Paper Series No. 2004.

Pace,R.K. and J.P.Lesage "Chebyshev Approximation of Log-determinants of Spatial Weight Matrices." *Computational Statistics and Data Analysis* (2003).a

----- "Likelihood Dominance and Spatial Inference." *Geographical Analysis Vol.35 No. 2* (April 2003): 133-147.b

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

Quah, D. “Spatial Agglomeration Dynamics” American Economic Review. Vol. 92 (2) (May 2002): 247-252.

Romer,P.M. "Increasing Returns and Long-Run Growth." *Journal of Political Economy* 94 (October 1986):1002-37.

Schumpeter, Joseph A. *Capitalism, Socialism, and Democracy*. New York: Harper, 1942.

Siebert, Horst. “Labor Market Rigidities: At the Root of Unemployment in Europe” Journal of Economic Perspectives. 11 No.2 (Summer 1997): 37-54.

Sweeney, P. *Innovation, Entrepreneurs and Regional Development*. New York: St. Martin Press, 1987.

Van Reenen, John. “Employment and Technological Innovation: Evidence from U.K. Manufacturing Firms.” Journal of Labor Economics 15 No.2 (Apr. 1997): 255-284.

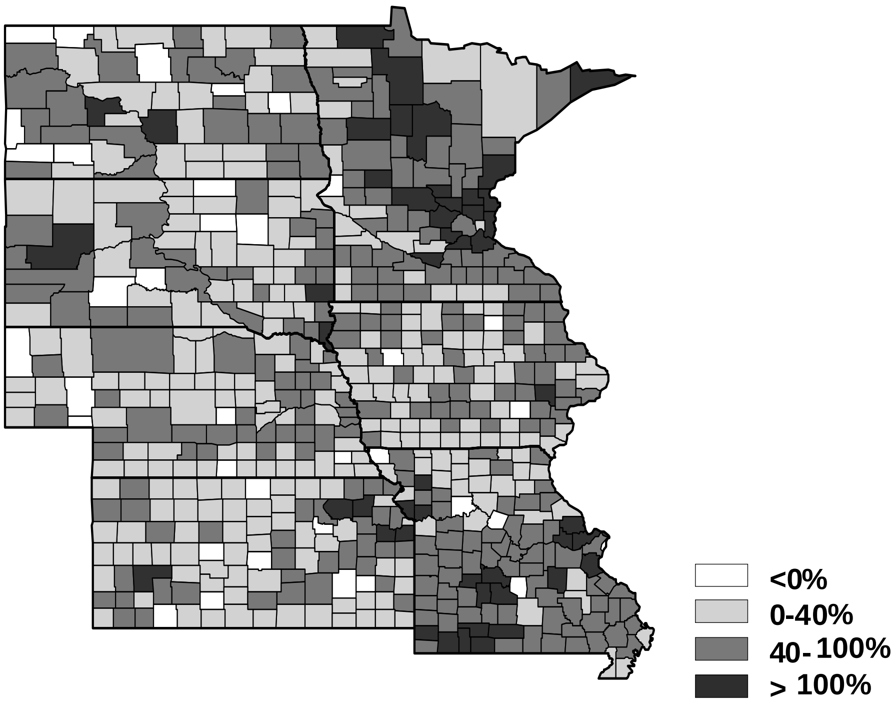

Figure 1. Spatial Distribution of Non-Farm Employment Growth 1969-2000

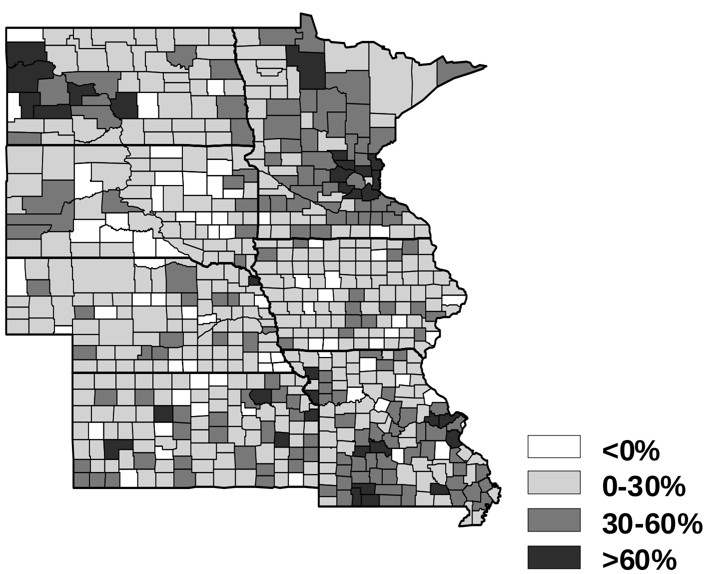

Figure 2. Spatial Distribution of Non-Farm Employment Growth 1969-1984

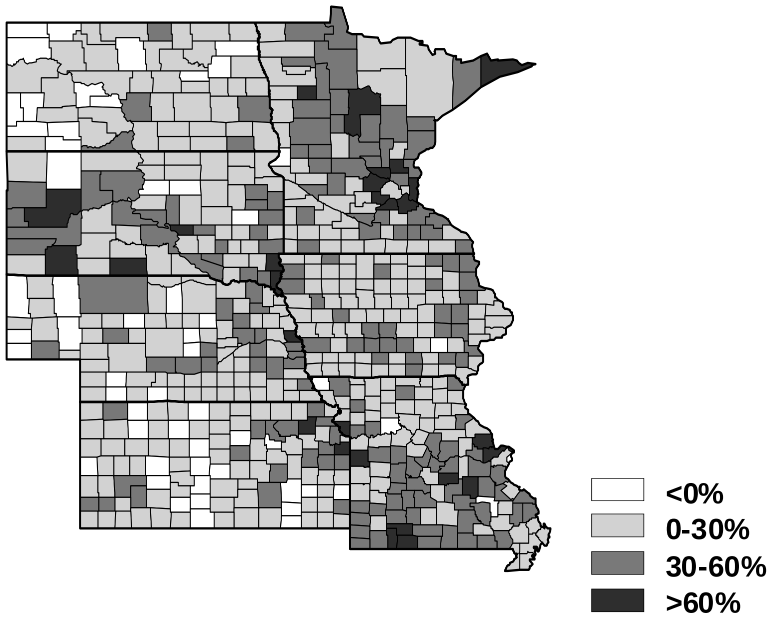

Figure 3. Spatial Distribution of Non-Farm Employment Growth 1985-2000

Table 1. Summary Statistics

Variable	Mean	Std. Dev.	Median	Minimum	Maximum	Count
Dependant Variable						
Employment Growth 1969-2000	0.4687	0.3664	0.4133	-0.5041	2.0744	
Employment Growth 1969-1985	0.2289	0.2258	0.2075	-0.5921	1.5380	
Employment Growth 1985-2000	0.2381	0.2002	0.2230	-0.3885	1.2124	
Independent Variables						
Total Patents Filed 1975-2000	125	666	14	0	12065	
Total Patents Filed 1975-1984	37	187	5	0	3206	
Total Patents Filed 1985-2000	89	483	9	0	8859	
Total Employment 1969	10876	40286	3431	105	544944	
Total Employment 1985	14521	52511	4362	86	794689	
Wage 1969	5.112	0.786	5.011	3.505	8.552	
Wage 1985	14.518	2.490	14.112	8.818	26.350	
Demographic Control Variable 1969	0.0711	0.0221	0.0687	0.0000	0.1632	
Demographic Control Variable 1985	0.1256	0.0345	0.1267	0.0296	0.2607	
Concentration Index 1969	1858	372	1783	1273	4521	
Concentration Index 1985	1055	447	976	230	5398	
Distance to a MSA	109	68	97	359	0.5	
Interstate						176
Instruments for Patent Equation						
Percent College Degree 1969	6.562	3.343	5.890	0.463	30.024	
Percent College Degree 1985	7.484	2.448	7.154	2.463	23.038	
Population 1969	26217	73742	11657	624	967826	
Population 1985	28158	75791	11919	478	985599	
Per capita income 1969	3.116	0.553	3.088	1.468	5.340	
Per capita income 1985	12.155	2.204	12.197	4.386	23.995	
State Counts						
Iowa						99
Kansas						105
Minnesota						87
Missouri						115
Nebraska						93
North Dakota						53
South Dakota						66

Table 2. Employment Growth - 1969-2000

Dependent Variable: ln (Non-farm Employment$_{2000}$/Non-farm Employment$_{1969}$)

Variable	OLS	Spatial Model	Spatial IV Model
Spatial Interaction			
Rho		0.339	0.326
		(6.636)***	(5.637)***
New Technology Created			
(ln) Total Patents - Sum 1975-2000	0.156	0.147	0.272
	(10.341)***	(10.203)***	(5.463)***
County Characteristics			
(ln) Wage 1969	0.312	0.284	0.353
	(2.524)**	(2.426)**	(2.889)***
(ln) Employment 1969	-0.160	-0.148	-0.267
	(-7.762)***	(-7.580)***	(-5.538)***
Demographic Control Variable 1969	-0.272	-0.319	0.489
	(-0.376)	(-0.465)	(0.592)
(ln) Concentration Index 1969	0.110	0.102	0.179
	(1.459)	(1.437)	(2.203)**
Market Access			
(ln) Distance to a MSA 1968	-0.048	-0.019	0.015
	(-2.738)***	(-1.115)	(0.677)
Presence of Interstate 1972	0.054	0.050	0.037
	(1.822)*	(1.788)*	(1.190)
State Effects			
Kansas	0.058	0.050	0.060
	(1.365)	(1.253)	(1.289)
Minnesota	0.244	0.135	0.063
	(5.377)***	(2.983)***	(1.112)
Missouri	0.327	0.243	0.265
	(7.600)***	(5.714)***	(5.351)***
Nebraska	0.045	0.045	0.069
	(1.017)	(1.076)	(1.414)
North Dakota	0.075	0.059	0.057
	(1.407)	(1.170)	(1.007)
South Dakota	0.179	0.160	0.220
	(3.525)***	(3.333)***	(3.781)***
Constant	0.086	-0.130	-0.408
	(0.135)	(-0.215)	(-0.632)

Table 2. (continued)

Diagnostics			
R-Square	0.381	0.432	0.368
R-Adj-Square	0.368	0.420	0.355
LR	36.693***		
LM	36.130***		
LM Sar		0.300	1.819

§ All values in parentheses are t-statistics reflecting for the test H_0: the given coefficient is equal to zero, ***= significant at the 1% level, **= significant at the 5% level, *= significant at the 10% level.

\# The patent variable used in this regression is based on predicted values obtained using elements of Table 5.

@ The standard errors were computed based on 1000 iterations of the augmented spatial bootstrap method described in the appendix.

Table 3. Employment Growth - 1969-1984

Dependent Variable: ln (Non-farm Employment$_{1984}$/Non-farm Employment$_{1969}$)

Variable	OLS	Spatial Model	Spatial IV Model
Spatial Interaction			
Rho		0.281	0.267
		(4.928)***	(4.745)***
New Technology Created			
(ln) Total Patents - Sum 1975-1984	0.051	0.049	0.163
	(4.973)***	(4.985)***	(4.427)***
County Characteristics			
(ln) Wage 1969	0.278	0.273	0.314
	(3.297)***	(3.367)***	(3.747)***
(ln) Employment 1969	-0.058	-0.055	-0.145
	(-4.501)***	(-4.453)***	(-4.851)***
Demographic Control Variable 1969	0.001	0.042	0.832
	(0.001)	(0.088)	(1.473)
(ln) Concentration Index 1969	-0.104	-0.100	-0.065
	(-2.035)**	(-2.043)**	(-1.156)
Market Access			
(ln) Distance to a MSA 1968	-0.019	-0.010	0.021
	(-1.619)	(-0.894)	(1.333)
Presence of Interstate 1972	0.055	0.052	0.041
	(2.700)***	(2.654)***	(1.927)*
State Effects			
Kansas	0.103	0.077	0.066
	(3.549)***	(2.734)***	(2.236)**
Minnesota	0.179	0.123	0.078
	(5.835)***	(3.954)***	(2.235)**
Missouri	0.184	0.141	0.154
	(6.256)***	(4.781)***	(4.879)***
Nebraska	0.068	0.058	0.074
	(2.251)**	(2.005)**	(2.451)**
North Dakota	0.167	0.129	0.140
	(4.626)***	(3.642)***	(3.620)***
South Dakota	0.026	0.034	0.065
	(0.762)	(1.028)	(1.804)*
Constant	0.904	0.785	0.790
	(2.091)**	(1.883)*	(1.706)*

Table 3. (continued)

Diagnostics			
R-Square	0.241	0.280	0.275
R-Adj-Square	0.225	0.264	0.259
LR	23.871***		
LM	26.074***		
LM Sar		0.014	3.064**

[§] All values in parentheses are t-statistics reflecting the test if the given coefficient is equal to zero, ***= significant at the 1% level, **= significant at the 5% level, *= significant at the 10% level.

[#] The patent variable used in this regression is based on predicted values obtained using elements of Table 5.

[@] The standard errors were computed based on 1000 iterations of the augmented spatial bootstrap method described in the appendix.

Table 4. Employment Growth - 2000-1984

Dependent Variable: ln (Non-farm Employment$_{2000}$/Non-farm Employment$_{1984}$)

Variable	OLS	Spatial Model	Spatial IV Model
Spatial Interaction			
Rho		0.295	0.295
		(5.495)***	(5.084)***
New Technology Created			
(ln) Total Patents - Sum 1985-2000	0.051	0.048	0.074
	(5.812)***	(5.723)***	(2.991)***
County Characteristics			
(ln) Wage 1984	-0.085	-0.076	-0.061
	(-1.385)	(-1.304)	(-1.020)
(ln) Employment 1984	-0.072	-0.066	-0.093
	(-5.342)***	(-5.107)***	(-3.472)***
Demographic Control Variable 1984	-0.986	-0.932	-0.892
	(-3.886)***	(-3.814)***	(-3.215)***
(ln) Concentration Index 1984	0.182	0.166	0.172
	(7.109)***	(6.757)***	(6.710)***
Market Access			
(ln) Distance to a MSA 1968	-0.037	-0.021	-0.015
	(-3.772)***	(-2.261)**	(-1.398)
Presence of Interstate 1972	-0.011	-0.010	-0.013
	(-0.656)	(-0.657)	(-0.761)
State Effects			
Kansas	-0.057	-0.036	-0.027
	(-2.453)**	(-1.557)	(-1.042)
Minnesota	0.098	0.062	0.052
	(4.047)***	(2.623)***	(2.018)**
Missouri	0.102	0.082	0.093
	(4.357)***	(3.626)***	(3.617)***
Nebraska	-0.048	-0.036	-0.031
	(-1.923)*	(-1.483)	(-1.168)
North Dakota	-0.062	-0.039	-0.039
	(-2.114)**	(-1.357)	(-1.295)
South Dakota	0.092	0.074	0.084
	(3.299)***	(2.774)***	(2.856)***
Constant	-0.038	-0.135	-0.096
	(-0.197)	(-0.730)	(-0.505)

Table 4. (continued)

Diagnostics			
R-Square	0.367	0.404	0.382
R-Adj-Square	0.353	0.391	0.368
LR	16.153***		
LM	15.435***		
LM Sar		2.425	0.756

§ All values in parentheses are t-statistics reflecting the test if the given coefficient is equal to zero, ***= significant at the 1% level, **= significant at the 5% level, *= significant at the 10% level.

The patent variable used in this regression is based on predicted values obtained using elements of Table 5.

@ The standard errors were computed based on 1000 iterations of the augmented spatial bootstrap method described in the appendix.

Table 5. IV Patent Equation

Dependent Variable: ln(Sum of first inventor patents)

N=618 **Variable**[&]	75-2000[§]	75-84	85-2000
Instruments			
Spatial Interaction - Rho	0.154	0.149	0.151
	(4.088)***	(3.476)***	(4.122)***
(ln) Per-capita income	1.024	1.052	0.756
	(4.883)***	(4.859)***	(3.870)***
(ln) Population	0.974	0.809	0.948
	(20.501)***	(16.639)***	(18.534)***
Percent with College degree	0.061	0.053	0.117
	(5.413)***	(4.594)***	(7.430)***
Other Variables			
County Characteristics			
(ln) Concentration Index	-0.405	-0.095	-0.147
	(-2.099)**	(-0.478)	(-1.345)
(ln) Distance to a MSA 1968	-0.148	-0.170	-0.107
	(-3.172)***	(-3.525)***	(-2.382)**
Presence of Interstate 1972	0.028	0.039	0.007
	(0.382)	(0.509)	(0.096)
Kansas	-0.056	0.091	-0.323
	(-0.503)	(0.794)	(-3.032)***
Minnesota	0.462	0.334	0.272
	(4.015)***	(2.831)***	(2.560)***
Missouri	-0.011	0.036	-0.206
	(-0.092)	(0.306)	(-1.996)**
Nebraska	0.007	0.032	-0.150
	(0.059)	(0.263)	(-1.344)
North Dakota	0.174	0.091	-0.043
	(1.257)	(0.639)	(-0.334)
South Dakota	-0.145	-0.000	-0.278
	(-1.063)	(-0.002)	(-2.164)**
Constant	-4.643	-6.147	-7.970
	(-2.823)***	(-3.631)***	(-9.516)***

Table 5 (cont'd)

Diagnostics			
R-Square	0.796	0.729	0.814
R-Adj-Square	0.792	0.724	0.811

[§] All values in parentheses are t-statistics reflecting the test if the given coefficient is equal to zero, ***= significant at the 1% level, **= significant at the 5% level, *= significant at the 10% level.
[&]Except where noted, the independent variables are for the earliest year for the respective patent range. For example, the period 1975-2000 uses population in 1969 and 1985-2000 uses population in 1985.

Appendix

Bootstrapping is a method used to obtain sampling properties of empirical estimators using the data itself rather than theoretical properties (Efron and Tibshirani, 1993;Greene, 1997). For example, consider a given data set $\mathbf{X}$ whose matrix of estimated coefficients are $\hat{\boldsymbol{\beta}}$. If we sample from this data set with replacement we can construct a total of R pseudo datasets, $\mathbf{X}_1,\mathbf{X}_2, \ldots, \mathbf{X}_R$, and for each of these data sets an estimate of the coefficients of interest can be obtained $\hat{\boldsymbol{\beta}}_1, \hat{\boldsymbol{\beta}}_2, \ldots, \hat{\boldsymbol{\beta}}_R$ for any given model. Using these estimates we can compute bootstrap estimates of both the coefficients and the dispersion.

The bootstrap estimate of the parameter estimates are

$$\hat{\boldsymbol{\beta}}_b = \frac{1}{R}\sum_{r=1}^{R}\hat{\boldsymbol{\beta}}_i \tag{11}$$

The bootstrap estimate of the variance-covariance is:

$$Var\left[\hat{\boldsymbol{\beta}}_b\right] = \left[\frac{1}{1-R}\right]\sum_{r=1}^{R}\left(\hat{\boldsymbol{\beta}}_r - \hat{\boldsymbol{\beta}}_b\right)\left(\hat{\boldsymbol{\beta}}_r - \hat{\boldsymbol{\beta}}_b\right)^{\prime} \tag{12}$$

Test statistics are then computed using the parameter estimates from the original data, $\hat{\boldsymbol{\beta}}$, and the variance-covariance structure above:

$$\mathbf{t} = \frac{\hat{\boldsymbol{\beta}}}{\left[\operatorname{diag} Var\left[\hat{\boldsymbol{\beta}}_b\right]\right]^{\frac{1}{2}}}$$

The estimate from the original data is used instead of the bootstrap estimate as the bootstrap estimate may introduce bias (Efron, 1982). In standard applications the sampling with replacement does not pose any problems, the same does not hold for spatial problems. The most notable difference between standard econometrics and spatial econometrics is the inherent spatial structure of the data. Consider the following two stage model with spatially lagged dependent variables:

$$\begin{aligned} \mathbf{x} &= \rho_x \mathbf{Wx} + \mathbf{X}_x \boldsymbol{\beta}_x + \boldsymbol{\varepsilon}_x \\ \mathbf{y} &= \rho_y \mathbf{Wy} + \mathbf{X}_y \boldsymbol{\beta}_y + \boldsymbol{\varepsilon}_y \end{aligned} \tag{13}$$

Where $\mathbf{X}_y = \left[\hat{\mathbf{x}}\ \tilde{\mathbf{X}}_y\right]$ and $\hat{\mathbf{x}}$ are the fitted values from the first stage and $\tilde{\mathbf{X}}_y$ are the usual other explanatory variables. Denoting $\mathbf{Z} = \left[\mathbf{y}\ \mathbf{X}_y\right]$ we can see that random sampling with replacement from **Z** to create additional data sets will damage the spatial structure of the data and does not take into consideration any possible error in predicting the first stage. That is, by randomly selecting from the matrix **Z** we are not taking into consideration the place in space of each of the data points. This is especially problematic given how important this neighboring relationship is for spatial problems. To obtain bootstrap style estimates of the parameter precision thus one needs to maintain the spatial integrity of the data. This can be done by using what we call an "augmented spatial bootstrap method". For the IV approach used in this paper to fitted patents are used in place of actual patents in the employment growth equations. Using the standard routine we can obtain estimates of the parameters of interest in the first equation of (13), $\hat{\rho}_x$ and $\hat{\boldsymbol{\beta}}_x$. Using these parameter estimates we can compute the resulting residual $\mathbf{u}_\mathbf{x}$:

$$\mathbf{u}_x = \mathbf{x} - \hat{\rho}_x \mathbf{W} \mathbf{x}_x - \mathbf{X}_x \hat{\boldsymbol{\beta}}_x \tag{14}$$

From (14) we can undertake sampling with replacement to obtain vectors of residuals $\mathbf{u}_{x,1}$, $\mathbf{u}_{x,2}$, …, $\mathbf{u}_{x,R}$. Using each vector of residuals one at a time, a vector of pseudo dependant variables can be computed in relation to each of these r = 1,2,…,R vectors of residuals:

$$\mathbf{x}_r = \left(\mathbf{I} - \hat{\rho}_x \mathbf{W}\right)^{-1} \left(\mathbf{X}_x \hat{\boldsymbol{\beta}}_x + \mathbf{u}_{x,r}\right) \tag{15}$$

The random assignment of the error term in (15) ensures the spatial structure of the data is maintained (Anselin, 1988). Using the newly created dependant variables from (15) we can estimate the following equation

$$\mathbf{x}_r = \hat{\rho}_{x,r} \mathbf{W} \mathbf{x}_r + \mathbf{X}_x \hat{\boldsymbol{\beta}}_{x,r} \tag{16}$$

Using the fitted values obtained from (16), $\hat{\mathbf{x}}_r$, these estimates are inserted into the dataset for the second stage regression $\hat{\mathbf{X}}_y = \left[\hat{\mathbf{x}}_r \ \tilde{\mathbf{X}}_y \right]$. With this dataset we can construct a new set of second stage residuals using the parameter estimates from the second equation in (13):

$$\mathbf{u}_y = \mathbf{y} - \hat{\rho}_y \mathbf{W}\mathbf{y} - \hat{\mathbf{X}}_y \hat{\boldsymbol{\beta}}_y \tag{17}$$

Drawing with replacement from (17) we can construct an error vector $\mathbf{u}_{y,r}$ and use these errors to construct a pseudo vector of dependant variables using

$$\mathbf{y}_r = \left(\mathbf{I} - \hat{\rho}_y \mathbf{W} \right)^{-1} \left(\hat{\mathbf{X}}_y \hat{\boldsymbol{\beta}}_y + \mathbf{u}_{y,r} \right) \tag{18}$$

Using the pseudo vector of dependant variables from (18) we can estimate the following equation and compute estimates of $\hat{\rho}_{y,r}$ and $\hat{\boldsymbol{\beta}}_{y,r}$

$$\mathbf{y}_r = \hat{\rho}_{y,r} \mathbf{W}\mathbf{y}_r + \hat{\mathbf{X}}_y \hat{\boldsymbol{\beta}}_{y,r} \tag{19}$$

We can follow this process a large number of times to obtain a vector of parameter estimates and then compute estimates of dispersion and the accompanying t-statistics in the usual fashion. Since each iteration requires the estimation of two spatial models, iterating a very large number of times can be somewhat computer intensive.