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Keywords
patents, spatial econometrics, innovative spillins

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In this paper we examine the relation between geographic location and innovative behavior. Knowledge spillins, as opposed to knowledge spillovers, are modeled as an externality which exists between geographically close economic agents and enters the representative inventor production function explicitly from neighboring regions. To proxy new innovative behavior and new knowledge generated we use counts of patent filings per county. The proposed geographic spillin is tested for the US Midwestern States of Iowa, Minnesota, Missouri, Kansas, Nebraska, South Dakota and North Dakota using a newly constructed data set and implementing spatial statistical methods. The data set is comprised of primary inventor utility patent filings per county for the years 1975-2000. The results do indeed suggest spatial interaction does occur and innovative activity in surrounding counties is an important factor in explaining new innovative behavior. Further analysis also reveals lagged patenting behavior within the county also has a significant impact on patenting activity suggesting innovative externalities exist over both space and time.
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Introduction

The modern economy is more and more driven by new technology, ideas, and innovation and less and less by physical capital accumulation. This has represented a fundamental shift in the general understanding and conceptual model of the process of economic growth and wealth accumulation. In a recent article in Forbes online a columnist writes: "…scientists, engineers, *patents* and R&D grants--*the seed corn of wealth*"[3] (Karlgaard, 2003). If new technology and innovation, such as embodied in patents, truly are the seeds of wealth, we must strive to better understand the factors underlying innovative behavior and technological growth if we want to better understand economic growth. Given the paramount role of technology in explaining economic growth it is amazing we as economists have yet to examine every facet of its creation.

The location of innovative activity is clearly not random. From what we observe in practice it is clear some regions have a tendency to generate more ideas, knowledge, and new technology than other areas. If innovative activity truly was random we should expect people in the hinterlands of Nebraska to invent with the same propensity as researchers at the University of Minnesota in Minneapolis, such a proposition is obviously ludicrous. In close proximity to centers of innovative activity, such as universities, regularly are found research parks and companies that specialize in technology and related innovative behavior (Anselin, Varga, and Acs 1997). When there is increased research activity among economic agents, both within and between industries and fields, we can expect there will be positive externalities generated between firms as dissemination of new ideas and technologies is typically casual over short distances. Less obvious, but possibly no less important, are factors contributing to new idea creation through the informal interaction among bright and capable individuals whether they are interacting at work, sitting beside one another at a football game, or interacting indirectly through mutual friends, acquaintances, colleagues, or even adversaries. It is obvious we should expect novel ideas and innovative thought will much more readily cross hallways, dinner tables, and streets than expanses of land, mountains and forests (Glaeser et al. 1992). In this paper we believe proximity is likely to play an important role in this exchange of ideas, conscious or unintentional, between economic agents. In this paper we refer to this symbiotic relationship between economic agents interacting with one another as a spillin[4]. This relationship captures not only the

[3] Italics added.

[4] The term "spillin" was, according to our knowledge, first coined by Khanna, Huffman, and Sandler (1994) where the authors examined research spillins from neighboring States into the home State.

effect of the own inventors activity on surrounding economic agents, firms and individual inventors, traditionally referred to as a spillover (see McCunn and Huffman (2000); and Huffman and Evenson (1992)), but also the effect surrounding inventive behavior has on the home inventors themselves. In an effort to better understand the factors underlying technological growth and new knowledge creation the first question this paper addresses is if such a an innovative or technological spillin does exist locally, can we postulate a model and test for this hypothesized spillin empirically? The second follows that if we can empirically test for and identify a local innovative spillin, how large are these impacts and are the results meaningful?

The role and mechanism of technological growth and creation of new knowledge is not as well understood as would be desirable given the important of technology in an economic growth context. On this subject Simon Kuznets in 1962 suggested one of the largest obstacles in understanding economic growth was the inability of scholars to empirically capture technological change. While there is a general understanding that human capital and research expenditures play an important role in new knowledge and technology creation, there are additional factors which have been given little or no attention. One such relationship is the so called “innovative externality”. To understand and quantify the importance of these externalities one must address the underlying factors. The mechanism which allows the realization of these externalities may be quite important. In general endogenous growth and endogenous technical changes are modeled as positive externalities in the literature. It is in this way that production externalities enter the pioneering growth model of Romer (1986)[5]. If the mechanism is one of journal articles and scientific newsgroups on the internet then geographic location is unlikely to be a factor. However, if the externality is realized via the local coffee shop, over dinner, or at a meeting, then geographic location will play a much more important role than in the former. Such geographic considerations motive the work of Gleaser, et al. (1992) where the authors argue intellectual breakthroughs must cross hallways and streets more readily than oceans and mountains. The possibility for such intellectual spillins between firms to occur is one justification of the high rental rates and long traffic commutes incurred in situating in a large city. In an attempt to quantify the importance of innovative externalities of a specific type Jaffe (1989) looks at geographic spillovers and finds university research has a significant effect on corporate patents, as well as indirectly on local innovation.

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

In this paper we examine more closely the link between innovative behavior and innovative spillins in a spatial framework. The conceptual framework is based on a county aggregated production function where technology is an input in addition to usual labor and non-labor inputs. The technology production function used here has roots in the knowledge production function of Grilliches (1979). Following the general discussion, a simple model is presented to highlight the role geographic closeness plays in the innovation process. In this model patents are used to capture new knowledge produced (other studies using patents in this manner include Jaffe 1989 and 1993; Hall, Jaffe, and Trajtenberg 2001; Anselin, Varga, and Acs 1997; and Acs, Anselin, and Varga (2002)). Aditionally, there has been some work devoted to the location of innovative activity (Sweeney, 1987; Hall and Markusen, 1985). The mechanism of the spillin postulated in this study is underscored by the role of physical interaction and physical closeness between economic agents. The proposed relationship is tested empirically using a patent-inventor filing dataset for the US Midwest over the years 1975-2000 using spatial econometric techniques which incorporates the notion of spillovers between "neighboring" inventors.

A Conceptual Model with Innovative Spillins

In the model that follows, representative inventors are assumed to solve a profit maximization problem by choosing the level of firm specific technology through patenting behavior. Inventors utilize their time and cognitive ability to create an economically useful new technology. In this model an innovative spillin occurs as a result of geographic proximity to other innovative activity. In the framework to follow a representative inventor can be thought to be representative of the inventive activity within a certain geographical area like a county, state, or county.

The representative inventor's revenue is based on the quality of the innovations they produce, and on the price they are able to capture for their innovation. The revenue function for a representative inventor may be represented as

$$P\left(I_i\right) * I_i \tag{1}$$

where I(.) is an index of the quality of innovative discoveries. The quality of new discoveries is assumed to occur along some positive continuum where larger values represent higher quality. For example, a new highly efficient fuel cell made up of many smaller complex ideas and innovations would appear near the top of the continuum whereas a new type of oscillating sprinkler drawing on a small number of relatively simple ideas would appear considerably lower on the same continuum. An innovation of a given quality will be able to receive a return of P, which is also a function of the quality of the invention. This reflects the notion of monopoly power the inventor is able to exert over their own invention. This may occur through a legal mandate, such as a patent, or secrecy through a trade secret. The index of innovative quality is captured by the function g(.)

$$I_i = g\left(d_i, \tilde{D}_i, h_i; E_i\right) \quad (2)$$

The representative inventor in region i own contribution to discoveries in their respective region is d_i and the "innovative spillin" from other inventors $\tilde{D}_i$. Endowed human capital (h_i) or inert inventive ability and other environmental impacts (E_i) capturing local economic conditions are also included. It is assumed quality of innovation is increasing in the first three arguments, $g_1, g_2, g_3 > 0$, where g_l is the first partial derivative with respect to the l^{th} argument for l=1,2,3. The sign with respect to local environmental conditions is indeterminate, i.e. sign of g_4 is indeterminate, without additional specific information to the components of the vector E. The innovative spillin is premised on the idea that "nearer" inventive activity is more beneficial than "further" inventive activity. Returning to our example of the fuel cell created in region r, the local contributions to the new innovation would be embodied in d_r whereas the spillin from other neighboring or geographically close regions is captured in $\tilde{D}_r$. Essentially the closer an inventor is to other inventive behavior, the greater will be the spillin effect. If we consider the idea of geographic spillin neighborhoods then as one moves further away the spillin effect decreases. There are a total of N of these neighborhoods, than in its extended form is related to all other inventive behavior. That is, there is a complete network and each regions inventive activity affects all other regions according to some type of distance decay criteria. The spillin can be formalized in the following manner:

$$\tilde{D}_i = \phi_1 \sum_{j \in n_1} d_{j,1} + \phi_2 \sum_{j \in n_2} d_{j,2} + \phi_3 \sum_{j \in n_3} d_{j,3} + \ldots + \phi_N \sum_{j \in n_N} d_{j,n} = \sum_{n=1}^{N} \phi_n \sum_{j} d_{j,n} \quad (3)$$

The strength of the different neighborhood spillins are constrained by the ϕ_j's which are assumed to be contained in the interval $\phi_j \in (1,0] \;\; \forall j$ and the closer in the neighboring innovator the larger is the potential for spillin i.e. $\phi_1 \geq \phi_2 \geq \phi_3 \geq ...\phi_N \geq 0$. It is quite possible for reasonable applications that beyond some critical distance the parameter $\phi_j = 0$. If we assume the neighboring innovative activity interacts with the inventors own discoveries in a positive manner then these two complement one another so $g_{12} > 0$.

Patents have often been used to proxy new innovative ideas and discoveries of new knowledge (Hall et al. 2001, and Acs, Anselin, and Varga (2002)). Following this here too are assumed discoveries are a function patents. The relationship linking patented ideas with discoveries is via the function f(.). This function could be thought of as embodying risk and uncertainty associated with turning patentable ideas into useful discoveries and the fact that many patented ideas are not economically useful.

$$d_i = f\left(x_i\right) \tag{4}$$

The function f(.) satisfies the properties $f^{/} > 0, f^{//} < 0$ where the primes represent the first and second derivatives respectively. For the other discoveries

$$\tilde{D}_i = \sum_{n=1}^{N} \phi_n \sum_j f\left(x_{j,n}\right) = k\left(\sum_{\forall j \neq i} x_{j,n}\right) = k\left(\tilde{X}_i\right) \tag{5}$$

where $\tilde{X}_i = \sum_{n=1}^{N} \phi_n \sum_j x_{j,n}$ and h(.) satisfies the properties $k^{/} > 0, k^{//} < 0$. Using (2)-(5) the profit maximization problem facing the representative inventor is written as:

$$\prod = P\left(g\left(f\left(x_i\right), k\left(\tilde{X}_i\right), h_i; E_i\right)\right) * g\left(f\left(x_i\right), k\left(\tilde{X}_i\right), h_i; E_i\right) - P_x x_i \tag{6}$$

The inventors choice variable is x_i and faces an opportunity cost to inventing of P_x. Due to the ability to influence the price of the innovated good embodied in P(.) the inventor may be able to earn positive economic rents. The resulting first order condition for an interior solution from (6) can be solved to yield

$$x_i^* = x_i\left(P_x, \tilde{X}_i, h_i, E_i\right) \tag{7}$$

For estimation purposes (7) is the equation of primary interest since. Essentially this equation relates patenting activity of the representative inventor to the activity of surrounding inventors in addition to human capital and the usual input and output prices. This equation is in effect a reaction function which takes the actions of the other firms as given[6]. However, in our representative agent framework it is unlikely any one agent will perceive its actions affecting others in surrounding counties. This lack of information between agents suggests the relationship $\frac{dx_i^*}{d\tilde{X}_i}$ is a true externality since inventors themselves do not realize how their actions affect other inventors and how surrounding inventors affect their behavior. From a practical point of view this is a reasonable assumption since it is unlikely an individual inventor understands or knows how their actions affect those of surrounding inventors. The relationship described here embodies the innovative spillin described by neighboring inventors and innovators and will in general have a positive impact given the functional forms chosen.

Econometric Model and Spatial Estimation Considerations

The innovative spillin embodied in function (7) is essentially a geographically mediated innovative or knowledge externality. Since we are dealing explicitly with locations in space the use of spatial statistical methods is an obvious choice to estimate any hypothesized innovative spillin. Unfortunately spatial econometric techniques have been almost non-existent in main-stream econometric texts so economists in the past have generally little exposure to both the application, estimation, and interpretation of spatial statistical results. For example, Amemiya (1985), Chow (1983), Greene (2002), Intrilligator (1979), Maddalla (1977), and Pindyck and Rubinfeld (1981) make no mention of spatial issues whatsoever. An exception to this is the text by Anselin (1988) which is devoted entirely to spatial econometric issues and estimation. Recently there has been an explosion in the literature relating to applied spatial econometrics to answer a variety of different

[6]The above equation will be the primary focus of the empirical work since in such a representative model it is unlikely any one agent within the (county) will perceive their actions effects either within or between counties even if collectively these actions have effects. However, for completeness it may be useful to go a step further to impose a non-competitive equilibrium condition. Defining $X_i = x_i + \tilde{X}_i$, and invoking a Nash equilibrium condition will require $\tilde{X}_i = \tilde{X}_j \quad \forall j \neq i$. That is, in equilibrium all inventors would choose the same aggregate amount of patenting activity. This requires no collusion, only optimization by firms but also requires a full information assumption which is relaxed in the current model.

economic questions. In particular, in a recent article by Acs, Anselin, and Varga (2002) the authors examine the impacts of private and university research on creation of new knowledge where new knowledge is defined as either innovation or patent counts. However, their analysis is based on 125 MSA regions in 1982 so the spatial structure in their models is best described by clusters rather than a continuous spatial lattice. In addition the authors do not examine other factors such as human capital which may be an important factor in new knowledge creation.

The concept of new knowledge or innovative behavior, while obviously an important component of economic growth, is difficult to quantify and derive empirical estimates. In the literature patents have been used as indicators of innovation and new ideas (Anselin, Varga, and Acs 1997;Acs, Anselin, and Varga 2002;Hall, Jaffe, and Trajtenberg 2001;Jaffe 1989). However, it must be noted many patented innovations are not economically useful themselves and some useful innovations are not patented. In academia a similar parallel can be drawn on the usefulness of actual journal publications as indicators of useful new knowledge (Griliches (1979), and Pakes and Griliches (1980)). Nevertheless in this study we use utility patent counts aggregated at the county level for intervals over the years 1975-2000 as an indicator of new innovative behavior. The definition given by the US Patent and Trademark Office (USPTO) for the definition of a utility patent states:

> "(a utility patent) may be granted to anyone who invents or discovers any new, useful, and non-obvious process, machine, article of manufacture, or composition of matter, or any new and useful improvement thereof."

This definition clearly identifies utility patents as reasonable indicators of new innovative activity and an implied embodiment of new knowledge.

The explanatory variable of primary interest is the amount of innovative activity and new knowledge generated in surrounding counties, i.e. the quantity of patents filed, which is drawn from a neighborhood around the home county. Additional explanatory variables include indicators of human capital. Endowed human capital within the county is indicated by the percentage of individuals with a college degree. Per capita income is also included here as an indicator of economic viability within the county and may be interpreted as an additional indicator of human capital. In addition to these the local environment vector is comprised of number of important county characteristics to control for other location specific factors such as distance from a MSA, presence of an interstate within the county. State characteristics, as reflected by a vector of State dummies, are used to control for differing government policies, tax incentives and/or disincentives, programs, and even citizen attitudes related to new knowledge and innovation. The addition of population as an explanatory variable is an obvious choice as we should expect, *ceteris paribus*, more populous counties to report a greater number of patents. In terms of the cost of inventing, P_x, there is unfortunately no county level data that we are aware of to indicate how expensive is inventing within the county. However, since we have already controlled for human capital and per-capita income, it is not unreasonable to assume the term P_x is relatively constant across counties and will captured in our regression analysis via the constant term. A Cobb-Douglas functional form is proposed for empirical estimation of the relationship described in (7) and takes on the following form:

$$h_i = a\left(\sum_{j\in N_i} h_j\right)^{\rho} c^{\beta_1}\left(pci_i\right)^{\beta_2}\left(pop_i\right)^{\beta_2}\left(dm_i\right)^{\beta_3} e^{\beta_5(Id)+\sum_{k=6}^{11}\beta_k s_{i,k-5}+\varepsilon} \tag{8}$$

where the above parameters are defined by:

h_i – the total number of inventor patent filings +1 per county for the time period[7];

c_i - the average percent of the education with a college education per county in period;

pci_i – the average county per capita income for the given period;

dm_i - the distance from the center of the county to a MSA in 1970;

Id_i - an interstate dummy =1 if the county had an interstate in 1970;

s_i - a dummy variable to capture State level effects, Iowa is the default State;

ε - a random error not correlated with the other regressors; and

parameters $\rho, a,$ and β_1 through β_{11} are to be estimated by the regression.

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[7] The dependant variable here is defined as the log of the sum of county patents over the period of interest, T, plus one i.e. $\ln\left(\sum_{i=1}^{T} pat_i + 1\right)$ rather than the log of average patents filed over the period plus one i.e. $\ln\left(\frac{\sum_{i=1}^{T} pat_i}{T} + 1\right)$. Note that augmenting the dependant variable with "+1" is required since a small number of counties did not report any patent filings. Due to the extreme variability and potential for heteroskedasticity and the need to maintain a complete spatial structure the use of logarithms necessitates augmenting the dependant variable in this manner. The chosen method augmenting the sum of patents rather than the average is chosen as addition of the "+1" will have a smaller relative impact. The need to both take logs and also maintain the spatial integrity of the data set does not allow us to simply "throw out" counties which did not report any patents.

The expression in (8) is made econometrically tractable by taking logs which allows the parameter estimates themselves to be interpreted directly as elasticities:

$$\begin{aligned} \ln h_i = \beta_0 + \rho \ln\left(\sum_{j \in N_i} h_j\right) + \beta_1 \ln c_i + \beta_2 \ln pci_i + \beta_3 \ln p_i + \beta_4 d_i \\ + \beta_5 Id_i + \sum_{k=6}^{11} \beta_k s_{i,5-k} + \varepsilon \end{aligned} \tag{9}$$

where $\beta_0 = \ln a$ and the other variables are defined as previously. For each cross section of data studied we use period averages to smooth over any bumps or yearly irregularities that may exist in the data with the exception of the dependant variable. For example, for the period 1975 to 2000, the sum of patents is the dependant variable, averages are used for college graduates, per capita income, and population, and the remaining variables remain constant over time. For purposes of estimation the functional form in (9) is described with the following matrix notation:

$$\begin{aligned} h = \rho W h + X\beta + \varepsilon \\ \varepsilon \sim N\left(o, \sigma^2 I_n\right) \end{aligned} \tag{10}$$

where h is a nx1 matrix described by inventor patent filings, W is a nxn standardized spatial weights matrix, X is a nxk matrix of explanatory described in (8), and β and ρ are a kx1 matrix and a scalar, respectively, are the parameters to be estimated. The spatial neighborhood structure is embodied in the spatial weights matrix W. The matrix W is a standardized and symmetric spatial weights matrix that relates counties based on their geographic location. Here a Delaunay triangulization routine is implemented to determine the neighborhood structure embodied in W (see Pace and LeSage (2003) a) and b) for examples using the Delaunay routine). There are no restrictions imposed on any of the parameters except ρ which is required to be contained in the interval $\rho \in \left(\frac{1}{\lambda_{\min}}, \frac{1}{\lambda_{\max}}\right)$ where $\lambda_{\min}$ and $\lambda_{\max}$ are the minimum and maximum eigen values for the spatial weights matrix W respectively (Sun et al., 1999).

As a modification to the relationship described in (9) we can include a lag variable. This lag in patent filings would capture the effect previous inventive activity has had in the current periods inventive activity. This new relationship accounting for both a spatial and time lag relationship is written as:

$$\begin{aligned}\ln h_i = \beta_0 + \rho \ln\left(\sum_{j\in N_i}\frac{1}{\eta_j}h_j\right) + \alpha \ln h_{i,-t} + \beta_1 \ln c_i + \beta_2 \ln pci_i + \beta_3 \ln p_i + \beta_4 d_i \\ +\beta_5 Id_i + \sum_{k=6}^{11}\beta_k s_{i,5-k} + \varepsilon\end{aligned} \tag{11}$$

where $h_{i,-t}$ is the number of patents filed in the previous time period within the county and α is the parameter to be estimated quantifying this relationship. All other variables and parameters are the same as they appear in (9). Equation (11) will allow us to examine not only the effect of neighboring inventive activity but also the effect the recent stock of local patents has on future patenting behavior. Thus we are able to capture an inventive spillin of types over both space and time.

The above relationships may be estimated using OLS when ρ=0, that is, when a spatial relationship is absent. However, in the presence of a spatially lagged dependant variable in (10), simultaneity of will cause OLS estimates to be both biased and inefficient. We thus opt for maximum likelihood estimation which can be used to derive efficient and unbiased estimates. To simplify the estimation procedure we use a concentrated log-likelihood function and follow the algorithm of Anselin (1988) to derive maximum likelihood estimates[8]. Additionally, we can test for the presence of a spatial relationship in our model residuals using a Lagrange Multiplier, Likelihood ratio, and a modified Lagrange Multiplier test (Anselin, 1988). The next section describes in detail our dataset and is followed by presentation of the results.

Data

Using data from the USPTO and census listings of town names for each county, a dataset of patents per county was created. A list of all utility patents filed in the United States for the years 1975-2000 was obtained from the USPTO for the US Midwestern states of Minnesota, Iowa, Kansas, Missouri, Nebraska, South Dakota, and North Dakota. This Midwestern sample represents a unique set of observations as people have not flocked in general to the Midwest unlike regions in California and

[8] The estimation was performed in Matlab using sparse matrix algorithms written by Lesage (1999).

Colorado. Thus do to the nature of this Midwestern sample we are able to control to a large extent the endogenous location decisions of agents. Further, this region has not been a hotbed of innovative activity and the endogenous nature of inventor location has also been controlled. The dataset from the USPTO contained the following information on each utility patent filed: i) a patent number the year, ii) the inventors name, iii) the inventors mailing address, and iv) rank of the inventor[9]. While the year the patent was filed was not contained in the dataset, supplemental information from the USPTO was used to assign a year based on the patent number. Using the inventors mailing address and cross-referencing this with a list of cities by county from we were able to determine how many patents were filed for each county per year using two different criteria: 1) patent counts based on first inventors only and, 2) patent counts based on the combination of first and co-inventors. A case may be made for using each one of these as indicators of new innovative activity. Using only first inventors we are essentially capturing the driving force behind each patent filed and give each patent equal weight. Using the combination of both first inventor and co-inventors, we account for all new innovation contributing to the new innovation. However, we do create a double-counting problem since patents listing more than one inventor will be given greater weight.

For the data description to follow we highlight primarily the 1975-2000 period with a complete listing of summary statistics for all periods given in Table 1. For the years 1975 through 2000 there were a total of 77,502 patents filed within our area of study based only on the number of primary inventor patent filings. There were a number of counties that did not have any patents filed within the county and the county with the highest patent count filed during this period reported a total of 12,065 patents. The mean patent filing is 125 with a relatively high standard deviation of 666 patents[10]. Figure 1 maps the spatial distribution of patent filings summed over the years 1975-2000. What we see is there is a large amount of activity near and around large cities like Minneapolis-St.Paul, St.Louis, Kansas City, and Des Moines. There appears to be quite a clear spatial relationship with clusters in these areas. Using all inventors, inventors names appeared on patents a total of 138,050 times with 22,024 occurring in one county alone. Using total inventors we find an average inventor-patent count of 223 with a standard deviation of 1,251. A map of the total inventor patent count is given in figure 2. This figure has basically the same pattern as in figure 1 with the scaling being the predominant difference between the two.

[9] Similar to journal articles, patents commonly have multiple inventors associated with the patent with the first inventor as the primary and others as co-inventors.

[10] The median patent filing is 14 so it is clear there is potential for heteroskedasticity which necessitates the need to take logarithms.

The average percentage of the population with a college degree is 8.1% with a standard deviation of 2.8%. While there is considerably less variation as compared to patent filings, the range is actually quite wide with a minimum of 3.1% and the most highly educated county averaged just over 25% of its residents having a college degree. Mean per capita income average $13.3 thousand with a relatively small standard deviation of $2.1 thousand. The county with the smallest per capita income was found to have an average income $6.2 thousand which is about a quarter of the county with the highest per capita income of $23.5 thousand. Since our data sample is based on a select group of Midwestern states, many of which are rural and a number which are home to some very large cities, we should expect a large range of population. The average county had a population of just under 29 thousand residents with a standard deviation of almost 78 thousand. The smallest county had a population averaging only 486 while the largest county averaged over 1 million people.

For each county we are also interested in whether or not the counties had an interstate and how far were the counties away from a metro area. For this analysis we hold both of these variables constant based on presence of an interstate within the county in 1972 and distance from a MSA in 1968. We find that the average distance from the center of the county to a large metro area was 109 miles with a standard deviation of 68 miles. The largest distance between any one county and a metro area was just over 358 miles. For counties which essentially contain MSA's themselves the distance is negligible. In addition, 176 or roughly 16% of the counties in our sample had an interstate within the county.

Results

In this section we present the results from our regression analysis of equations (9) and (11). Equation (11) is estimated for the periods 1980-84, 1985-1989, 1990-94, and 1995-2000 since these are the blocks for which an appropriate lag in patenting activity is available. Equation (9) is estimated along side the periods coinciding with periods previously mentioned in addition to the years 1975-79, and the entire sample period 1975-2000. The results of these estimations are in tables 2-7. When appropriate we also conduct tests to determine if the spatial structure of the data has been handled in a satisfactory manner.

The set of results for the broader 1975-2000 time period are shown in table 2. In this table two groupings of results are given with the first a set of results for first inventor patents only and a second set of results where all inventor patent filings, primary plus all secondary inventors, are the dependant variable. In each of these the spatial model is presented along side an OLS specification which omits the spatial interaction parameter. We compute likelihood ratio (LR) and Lagrange multiplier (LM) test statistics to check for a spatial relationship in the data. The LR and LM test statistics are 16.0 and 17.6 respectively, both of which imply rejection of the hypothesis: no spatial relationship exists in the residuals[11]. In light of this fact we will not dwell upon these OLS results as this model specification does not adequately capture the spatial relationship inherent in the data. A spatial LM test a test statistic of 2.9 suggesting we cannot with a high level of statistical confidence reject the null hypothesis: no spatial relationship exists in the model residuals.

The spatial model with based on the sum of first inventor patent filings over the period 1975-2000 is able to explain about 82.5% of the variation in patent filings and the spatial model where all inventor patent filings are used explains almost 83% of the variability in patent filings. Both of these indicate a relatively good fit for our patent model given the cross-sectional data. Using first inventor patent filings the estimated coefficient for spatial interaction is 0.13 and is significantly different from zero with at least a 99% level of confidence. Since this is a log-log formulation this coefficient can be interpreted directly as an elasticity. That is, a 10% increase in the first inventor patents filed by inventors in neighboring counties will *ceteris paribus* result in a 1.3% increase in the number of patents filed in the home county. This finding would suggest innovative spillins do occur between counties. The fourth column of table 2 reports an estimate for rho of 0.165 and is significantly different from zero with a high probability suggesting a 10% increase in the number of total inventors, not just primary inventors, in neighboring counties as defined by the spatial weights matrix W will be met with a 1.65% increase in the number of inventor patent filings in the home county. This spillin estimate is similar in magnitude to that computed using only first inventors i.e. 0.165 vs. 0.13.

In our earlier discussion of the model we identify a number of other variables believed to play and important role in new innovative activity, i.e. patents, and we discuss these here. Human capital as

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[11] Both the LR and LM tests are distributed Chi-Square with one degree of freedom. The critical value for the Chi-square distribution is 6.35 at the 99% level of confidence so both test easily reject the hypothesis of no spatial interaction.

embodied in college graduates and represented as the (average) percentage of the population with a college degree is computed to be 0.83 for first inventor and 0.86 for total patents summed over the period 1975-2000, both of these estimates are statistically different from zero. This result gives further support human capital plays an important role in generating new technology. Another indicator of human capital, per capita personal income, averaged over this period also had a positive and statistically significant impact on patent filings. The estimation results suggest a 1% increase in per capita income results in a 1.08% increase in the number of patents filed in the home county and this result is statistically different from zero with at least a 99% level of probability. The same variable for total patents is very similar in magnitude with a computed elasticity of 1.18 and is also statistically different from zero with a high level of confidence. If we are to correctly interpret both percent of the population with a college degree and average per capita county income as indicators of human capital then we have established another clear convincing link between innovative behavior and new knowledge creation.

As expected population plays an important role in explaining new patents within the county. The elasticity computed for the sum of first inventors only suggests a 1% increase in the population will result in a 0.92% increase in the number of patents filed within the county and for total inventors the comparable elasticity is 0.97. Once again both of these results are statistically different from zero. The parameters for market access included distance to a MSA and presence of an interstate. The spatial models for both first and total patent inventor filings resulted in an estimated elasticity of -0.1 and was marginally significant with at least a 95% probability the coefficient is different from zero. A 10% increase in the distance from a metro area is met with a 1% decline in the level of patenting under either first or all inventor patent counts. This parameter is of the expected sign since it was expected distance would impede the ability of economic agents to interact. It was found presence of an interstate did not have an appreciable effect on patent filings.

Returning to figures 1 and 2 with the mapping of patent filings for our Midwestern selection of States, we can see Iowa and Minnesota appear to perform relatively better than the other States in terms of patenting behavior. This observation is evident when examining the State dummies in table 2. With Iowa as the default State, Minnesota performs better and the rest of the States generally perform poorer than Iowa. These results may be an indication of the State attitudes and programs designed to encourage new innovation. The variable estimates and level of significance are generally quite similar when using either the first or total inventor patent filings as was the case in the above discussion.

Thus when discussing further results in the remainder of the paper we consider only the first inventor patent filings as the results do not appear to differ a great deal with those estimates obtained using the total inventor patent counts.

While it is useful to examine the period 1975-2000 as a whole, it is also important to examine sub sections in greater detail as there may be some time sensitive relationships that are missed by examining a larger time period. We thus further consider the five year increments from 1975-79, 1980-84, 1985-89, 1990-94, and a six year bloc from 1995-2000. Also, by using sub sections we are also able to include a lagged patent variable for the most recent four of these sub-periods. The analysis for the years 1975-1979 are presented in table 3, the spatial model is able to explain about 70% of the variability in first inventor patent filings and the spatial LM indicates the spatial structure of the data has been handled in a satisfactory manner in this model. The innovative spillin elasticity is computed at 0.156, a value similar to that computed for the period 1975-2000, and is significantly different from zero with a high level of statistical confidence. Human capital as captured by percent of the population with a college degree is again found to have a positive and significant impact with an estimated coefficient of 0.71. Our other indicator of human capital, per capita income, is also found to be positive and significantly different from zero with an estimated elasticity of 0.91 once again suggesting human capital was an important factor in innovative activity during the earlier stages of our sample period. Population was once again found to be highly significantly different from zero with an estimated elasticity of 0.67. The market access parameters indicate distance to a metro area is important with an estimated elasticity of -0.18 and is significantly different from zero. The interstate variable is once again not found to be significant. Examining the State dummies it is interesting to note that only Minnesota performed better relative to Iowa and all other States were statistically insignificant.

The remaining four periods of study, 1980-84, 1985-89, 1990-1994, and 1995-2000 allows us to add an additional variable, namely lagged patents, as described by the relationship in equation (11). In this specification we are able to examine not only the spillin across counties, but the relationship with innovative activity overtime in the home county as well. The results for these four periods are presented in tables 4-7. In each table three sets of results are presented: 1) OLS, 2) spatial, and 3) spatial with a lag. In all four periods of study we find evidence of a spatial relationship in the data as indicated by the LM and LR test statistics so we consider only the spatial and spatial-time lag models which are contained in the last two columns of each table.

First we consider the results of these four sub-periods of study under the same parameters as tables 2 and 3, the following paragraph is devoted to interpreting results which include patent lag parameter. The results from the spatial model estimation for these last four sub-periods are quite similar in terms of the general interpretation and significance of the broader period 1975-2000 but with some key differences. Consistent with our conceptual model the importance of innovative spillins do appear to exist between counties over time as the spatial interaction terms were of similar both in terms of statistical significance and magnitude. Other parameters like education, and population continued to have a positive and significant impact on patenting activity. A departure from general results enters when we examine per capita income plays continued to play a significant role for the periods 1980-85 and 1985-89, but is only marginally significant for the period 1990-94 and is not found to be significant for the period 1995-2000. This may be an indicator of the per capita income variable decreasing over time as an indicator of human capital within the county. Distance continues to play an important role in explaining patenting activity where greater distances from a metro area imply less patenting activity. State impacts as captured in the State dummies are mixed but generally imply Minnesota performs better than Iowa while States like Kansas and South Dakota tend not to perform quite as well in comparison to Iowa.

In each of the spatial specifications with time lagged patents the model parameter estimates are given in the third column and we find this specification was able to explain 81% or more of the variability in first inventor patent filings. The r-squares for these models are quite similar to those in table 2 where more time varying impacts are implicitly captured due to the longer time period. Considering the last column now for each of tables 4 through 7, the spatial interaction term is found to range from 0.06 to 0.12 with the coefficient either marginally or strongly different from zero in a statistical sense. The patent time lag parameter is much larger than the spatial spillin parameter by comparison. The estimated coefficients, which can also be directly interpreted as an elasticity, exhibit a very tight range from a low of 0.580 in 1985-89 to a high of 0.598 for the period 1990-94. All of these time lag coefficients were found to be statistically different from zero with a high degree of statistical confidence. For the period 1980-84 this lag variable implies that an increase of 10% in patents filed for the previous years 1975-79 resulted in a 0.597% increase in the number of patents filed. Also of interest is these coefficients relationship to one. As seen by the very low standard errors all these coefficients are also statistically different from 1 so there is not a one-to-one relationship between how many patents are filed this period and how many patents will be filed next period. To make a casual interpretation of this parameter may be to interpret new innovation, as measured by patents, as concave function of patents filed in the previous period possibly implying decreasing returns over time. Although the other coefficients are not as large in the simple spatial model, education and population do retain a significant role in explaining patent filings in all of these periods. The tremendous explanatory power of lagged patents no doubt had a dwarfing impact on the other parameters within the model.

Discussion and Conclusions

In this paper we used spatial econometric methods to test for the presence of a geographic innovative spillin. We do indeed find the hypothesized innovative spillin does have a positive and significant effect on new knowledge creation giving us a further understanding of the important factors underlying technological growth. In models where a time lag was not used in the estimation, the innovative spillin effect was found to have an elasticity ranging from 0.13 to 0.20 depending on the time period used. When a five-year patent lag was introduced into the model we found the spillin ranged from 0.06 to 0.12. In either of these model specifications however, it is apparent an innovative spillin of the type hypothesized in this paper is supported by the data given the generally high level of statistical confidence in the parameter estimates. While at first glance these effects may seem small, especially when compared to the relatively large effect from lagged patents, this is not necessarily the case. In reality it is likely the actual spillin is larger than what was estimated here. The empirical model was set up to estimate the innovative spillin from geographically close counties and in doing so is not able to pick up activity occurring within the county itself. The structure of the spatial weights matrix, W, used here does not allow us to pick up the interaction between individuals themselves, only the interactions that cross county lines so we should expect actual values to be larger. In any case given the macro nature of the data, from the point of view of an individual inventor, our estimates do provide a lower bound and future research with more concise data may be able to improve upon the reliability of our estimates.

While the primary objective of this paper was to test for the presence and the magnitude of the so called innovative spillin, we do gain some useful insights into some of the other variables that also play a role in generating patents. Most notable of these is the importance of human capital. The results are really quite convincing that areas with higher concentrations of individuals with a high level of education will also experience a larger level of patenting behavior. The is a results that adds to the already quite well developed literature suggesting human capital plays an important role in the creation of new ideas, knowledge, and technology. Further, if we interpret per capita income as an indicator of human capital, then new technology created as indicated by new patents also responds in a positive manner to this variable. Other variables found to have a generally significant effect on patenting activity include population and distance to a metro area, both of these tend to speak for themselves. It should however be noted that with respect to population, while it will obviously play an important role, the relationship is generally not one-to-one suggesting further it is not simply stock of people that generates new ideas that in turn generate new growth. Rather, stock of knowledge as embodied by both lagged patents, and concentration of educated individuals, play a much more important role.

Given the broad scope of our indicator used in this paper as an indicator of new knowledge, i.e. patents, it would be misleading to interpret these results as only applied to patents. Noting that while patents are good indicators of new technology created they are not indicators of economic value (Griliches, 1979; Pakes and Griliches, 1980; Hall et al., 2001). The proper interpretation for these conclusions needs to be applied to a much broader interpretation of innovative thought and ideas that includes informal technology creation, possibly for either actual inventions or processes, that are not or cannot be patented but still have significant economic value. While we concede the use of patents as a proxy for new technology is a limited indicator for technology as applied to our economic models in general, however, given that more precise indicators of new knowledge are not readily available; the current analysis lists cautious evidence to the existence of knowledge externalities over space. An opportunity for future research is to identify and create better indicators and provide more precise estimates of the magnitude of knowledge externalities between economic agents at various levels of aggregation.

In this paper we formulated a model to describe how technological and innovative spillins may affect local innovative activity. It has long been believed that technological spillins as defined by this paper do exist. Working within the confines of the available data we test for the presence and estimate the relative size of these so called innovative spillin effects. The model specification appears to be robust to both the specific choice of explanatory variables and the years chosen. Even taking into consideration the limitations of using patents to proxy innovative behavior, these results are still quite impressive. While we have indicated some of the limitations of our analysis, in particular drawing micro conclusions from aggregate county data, it does seem apparent an innovative spillin does exist.

Refinements to the data and methods may improve the accuracy of the estimates but the general conclusions will most likely remain unchanged.

References

Acs, Zoltan J, Anselin, Luc, and Varga, Atilla "Patents and Innovation Counts as Measures of Regional Production of New Knowledge." *Research Policy* 31 (2002):1069-1085.

Amemiya, T. *Advanced Econometrics.* Cambridge, MA: Harvard University Press, 1985.

Anselin, L. *Estimation Methods for Spatial Autoregressive Structures*, (New York: Regional Science Dissertation and Monograph Series 8), 1980.

Anselin,L., A.Varga, and Z.Acs "Local geographic spillovers between university research and high technology innovations." *Journal of Urban Economics* 42(November 1997):422-48.

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

Boots, B. "Comments on the Use of Eigenvalues to Measure Structural Properties of Geographic Networks." *Environment and Planning* 14 (1982):1063-1072.

Boots, B. "Evaluating Principal Eigenvalues as Measures of Network Structure." *Geographical Analysis* 16 (1984):270-75.

Boots, B. "Size Effects in the Spatial Patterning of Nonprincipal Eigenvectors of Planar Networks." *Geographical Analysis* 17 (1985) 74-81.

Boots, B., and K. Tinkler, "The Interpretation of Non-Principal Eigenfunctions of Urban Structure." *Modeling and Simulation* 14 (1983):715-19.

Chow, G. Econometrics, New York: McGraw-Hill, 1983.

Garison, W., and D. Marble, "Factor-Analytic Study of the Connectivity of a Transportation Network." *Papers: Regional Science Association* 12 (1964) 231-38.

Glaeser, Edwardl., Heidi D. Kallal, Jose A. Scheinkman, and Andrei Scleifer. "Growth in Cities." *Journal of Political Economy* 100 (December 1992):1126-1152.

Gould, P. "On the Geographic Interpretation of Eigenvalues." *Transactions, Institute of British Geographers* 42 (1967):53-92.

Greene W.H. *Econometric Analysis, 5rd ed.* Upper Saddle River, N.J: Prentice Hall, 2002.

Griffith, D. "Measurement of the Arrangement Property of a System of Areal Units Generated by Partitioning a Planar Surface." In *Recent Developments in Spatial Data Analysis*, edidted by G. Bahrenberg, M. Fischer, and P. Nijkamp (1984):191-99.

Grilliches, Zvi. "Issues in Assessing the Contribution of Research and Development to Productivity Growth." *Bell Journal of Economics* 10 (Spring 1979):92-116.

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.

Huffman,W.E. and R.E.Evenson "Contributions of Public and Private Science and Technology to United-States Agricultural Productivity." *American Journal of Agricultural Economics* 74 (August 1992): 751-6.

Intrilligator, M. *Econometric Models, Techniques and Applications.* Englewood Cliffs: Prentice-Hall, 1978.

Jaffe, Adam B. “Real Effects of Adademic Research.” *The American Economic Review* 79 (December 1989):957-970.

Karlgaard, Rich. “Digital Rules – Where to Get Rich.” Forbes.com October 6, 2003. link: http://www.forbes.com/forbes/2003/1006/039_print.html (date retrieved: October 20, 2003).

Khanna,J., W.E.Huffman, and T.Sandler. "Agricultural-Research Expenditures in the United-States – A public Goods Perspective." *Review of Economics and Statistics* 76 (May 1994):267-77.

Knight, Frank H. “Diminishing Returns from Investment,” *Journal of Political Economy* 52 (March 1944):26-47.

Lesage, James P. “The Theory and Practice of Spatial Econometrics” Online Manuscript www.spatial-econometrics.com Department of Economics, University of Toledo (date retrieved: October 20, 2003).

Maddala, G.S. *Econometrics*, New York: McGraw-Hill, 1977.

McCunn,A. and W.E.Huffman. "Convergence in US productivity growth for agriculture: Implications of interstate research spillovers for funding agricultural research." *American Journal of Agricultural Economics* 82 (May 2000):370-88.

Pace, R. Kelley and James P. LeSage. “Likelihood Dominance and Spatial Inference.” *Geographical Analysis* 35 (April 2003):133-147.a

Pace, R. Kelley and James P. LeSage. “Chebyshev Approximation of Log-determinants of Spatial Weight Matrices.” Forthcoming in *Computational Statistics and Data Analysis* (2003)

Pace, R.K., and R. Barry. “Quick Computation of Spatial Autoregressive Estimators.” *Geological Analysis* 29 (Number 1997):232-247.

Pakes, A., and Griliches, Z. “Patents and R$D at the firm level: A first report.” *Economics Letters* 5 (1980):377-381.

Pindyck, R. and D. Rubinfeld. *Econometric Models and Econometric Forecasts*. New York: McGraw-Hill, 1981.

Roe,B., E.G.Irwin, and J.S.Sharp. "Pigs in Space: Modeling the Spatial Structure of Hog Production in Traditional and Non-traditional Production Regions." *American Journal of Agricultural Economics* 84 (May 2002):259-78.

Romer, Paul. “Increasing returns and Long-Run Growth.” *The Journal of Political Economy* 94 (October 1986):1002-1037.

Shell, Karl. “Toward a Theory of Inventive Activity and Capital Accumulation.” *American Economic Review* 56 (March 1966):62-68.

Sun, D., R.K. Tsutakawa, P.L. Speckman. “Posterior Distribution of Hierarchical Models Using CAR(1) Distributions.” *Biometrika* 86 (1999): 341-350.

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

Tinkler, K. “The Physical Interpretation of Eigenvalues of Dichotomous Matrices.” *Transactions, Institute of British Geographers* 55 (1972):17-46.

Tobler, W. “Cellular Geography.” In *Philosophy and Geography*, edited by S. Gale and G. Olsson. Dordrecht: Reidel, (1979): 379-86.

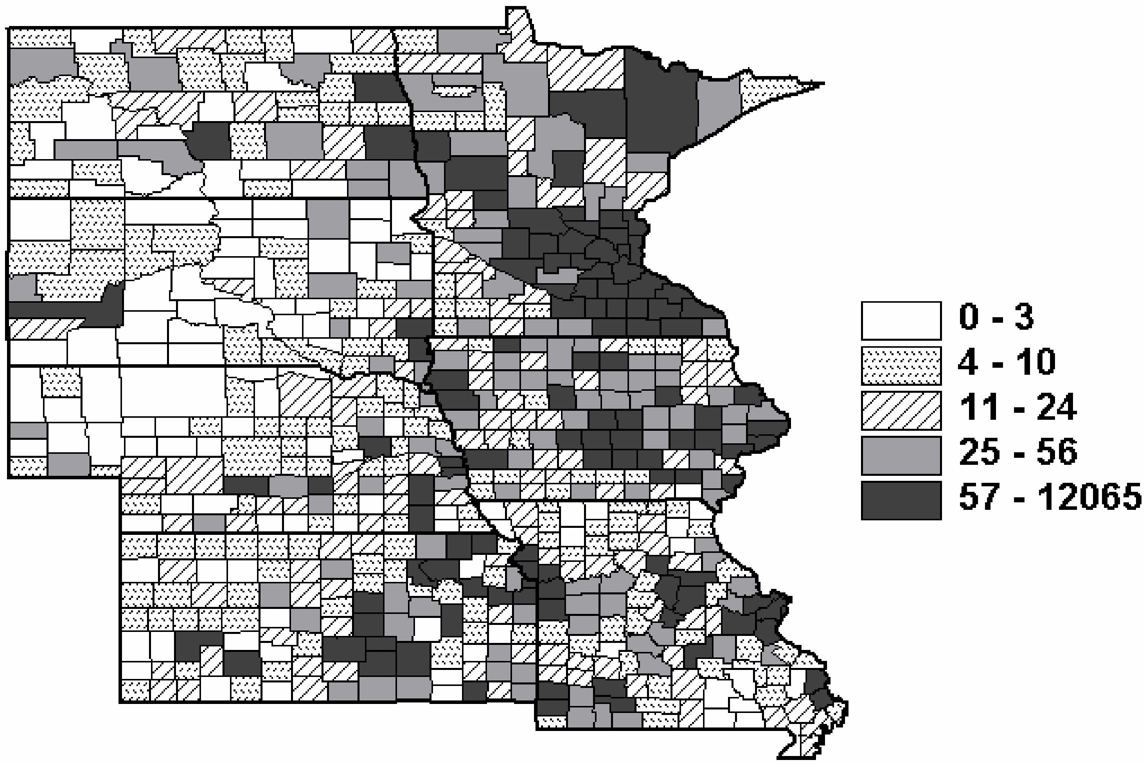

Figure 1: Sum of First Inventor County Patent Filings, 1975-2000

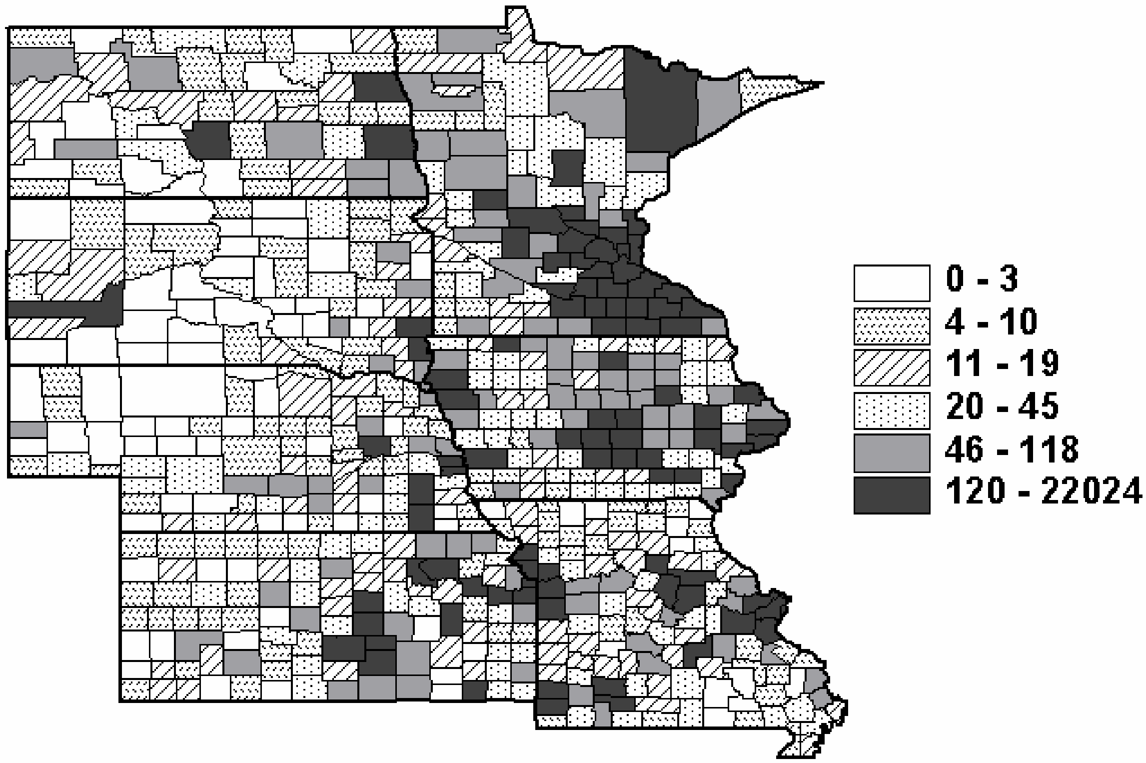

Figure 2: Sum of Total Inventor County Patent Filings, 1975-2000

Table 1. Summary Statistics

Variable	Mean	Std. Dev.	Min	Max	Count
Sum of First Inventor Patents					
1975-2000	125	666	0	12065	77502
1975-79	19	97	0	1654	11790
1980-84	18	91	0	1552	10845
1985-89	20	111	0	2121	12640
1990-94	26	141	0	2554	15875
1995-2000	43	233	0	4184	26352
Sum of All inventor Patents					
1975-2000	223	1251	0	22024	138050
1975-79	27	142	0	2408	16976
1980-84	26	136	0	2320	15938
1985-89	32	184	0	3514	20038
1990-94	46	271	0	4752	28701
1995-2000	91	533	0	9030	56397
Mean Percent with a College Degree					
1975-2000	8.07	2.76	3.11	25.22	
1975-79	6.55	2.37	2.46	22.36	
1980-84	7.02	2.29	2.59	21.49	
1985-89	7.95	2.63	2.19	24.59	
1990-94	9.00	2.92	2.07	27.38	
1995-2000	10.16	3.22	2.38	29.87	
Mean Per-Capita Income					
1975-2000	13.28	2.16	6.17	23.46	
1975-79	6.56	1.01	3.01	10.46	
1980-84	9.86	1.67	4.03	16.80	
1985-89	13.20	2.23	5.19	23.04	
1990-94	16.58	2.91	7.96	36.50	
1995-2000	20.64	3.70	5.68	37.87	
Mean Population					
1975-2000	28762	77657	486	1012285	
1975-79	27405	73464	578	967993	
1980-84	28269	76861	463	1006842	
1985-89	28269	76861	463	1006842	
1990-94	29177	79886	458	1051443	
1995-2000	30606	83288	439	1095946	

Table 1 (cont'd)

Variable	Mean	Std. Dev.	Min	Max	Count
Other County Characteristics					
Distance to a MSA	109	68	0.47	358.5	
Presence of an Interstate	.16				176
Iowa					99
Kansas					105
Minnesota					87
Missouri					115
Nebraska					93
North Dakota					53
South Dakota					66

Table 2. 1975-2000 First and Total Inventor Patent Filings per County

	(log) Sum First Inventor Patent Filings (+1)		(log) Sum Total Inventor Patent Filings (+1)	
	OLS	Spatial	OLS	Spatial
Independent Variables				
Spatial Interaction				
rho		0.1345		0.1650
		(3.7927)***		(4.7068)***
Education Attainment				
Percent with 4 years college	0.7564	0.8303	0.7564	0.8597
	(5.8206)***	(6.4742)***	(5.3776)***	(6.2404)***
County Characteristics				
(log) per capita income	1.2285	1.0817	1.3724	1.1779
	(5.4847)***	(4.8849)***	(5.6604)***	(4.9496)***
(log) population	0.9547	0.9163	1.0244	0.9724
	(22.6343)***	(21.5792)***	(22.4380)***	(21.2971)***
Market Access				
log distance to a MSA	-0.1475	-0.1010	-0.1637	-0.0995
	(-3.4553)***	(-2.3134)**	(-3.5432)***	(-2.1234)**
presence of interstate	0.0098	-0.0121	0.0436	0.0161
	(0.1387)	(-0.1751)	(0.5718)	(0.2174)
State Effects				
Kansas	-0.3015	-0.2478	-0.3741	-0.2975
	(-2.8839)***	(-2.4016)**	(-3.3051)***	(-2.6791)***
Minnesota	0.2515	0.1907	0.2585	0.1782
	(2.4118)**	(1.8516)*	(2.2900)**	(1.6124)
Missouri	-0.2345	-0.1764	-0.2838	-0.2038
	(-2.2186)**	(-1.6887)*	(-2.4802)**	(-1.8142)*
Nebraska	-0.3163	-0.2024	-0.4262	-0.2648
	(-2.9596)***	(-1.8574)*	(-3.6845)***	(-2.2489)**
North Dakota	-0.0973	-0.0087	-0.1221	-0.0060
	(-0.7642)	(-0.0687)	(-0.8860)	(-0.0438)
South Dakota	-0.5271	-0.3735	-0.6266	-0.4175
	(-4.4006)***	(-3.0221)***	(-4.8321)***	(-3.1354)***
Constant	-10.0104	-10.0515	-10.6571	-10.7332
	(-15.3982)***	(-15.8181)***	(-15.1444)***	(-15.7248)***
Diagnostics				
R-Square	0.8205	0.8254	0.8210	0.8285
R-Adj-Square	0.8173	0.8222	0.8178	0.8253
LR	16.0066***		24.4018***	
LM	17.5674***		27.6017***	
Spatial LM		2.8927*		3.9917**

Note: All values in parentheses are t-values, ***= significant at the 1% level, **= significant at the 5% level, *= significant at the 10% level.

Table 3. 1975-79 First Inventor Patent Filings per County

	(log) Sum First Inventor Patent Filings (+1)	
	OLS	Spatial
Independent Variables		
Spatial Interaction		
rho		0.1561
		(3.5217)***
Education Attainment		
Percent with 4 years college	0.6643	0.7149
	(5.1333)***	(5.6080)***
County Characteristics		
(log) per capita income	1.0386	0.9065
	(4.2122)***	(3.7179)***
(log) population	0.7001	0.6662
	(15.1018)***	(14.4195)***
Market Access		
log distance to a MSA	-0.2292	-0.1867
	(-5.0661)***	(-4.0038)***
presence of interstate	0.0426	0.0212
	(0.5671)	(0.2886)
State Effects		
Kansas	0.0791	0.0838
	(0.6993)	(0.7567)
Minnesota	0.2679	0.2210
	(2.3644)**	(1.9793)**
Missouri	0.0396	0.0806
	(0.3363)	(0.6963)
Nebraska	0.0327	0.1109
	(0.2839)	(0.9678)
North Dakota	-0.0326	0.0616
	(-0.2415)	(0.4592)
South Dakota	0.0279	0.1190
	(0.2130)	(0.9108)
Constant	-7.3755	-7.3374
	(-11.3766)***	(-11.5673)***
Diagnostics		
R-Square	0.6940	0.7014
R-Adj-Square	0.6885	0.6960
LR	11.1262***	
LM	11.6987***	
Spatial LM		0.9972

Note: All values in parentheses are t-values, ***= significant at the 1% level, **= significant at the 5% level, *= significant at the 10% level.

Table 4. 1980-84 First Inventor Patent Filings per County

	(log) Sum First Inventor Patent Filings (+1)		
	OLS	Spatial	Spatial - time lag
Independent Variables			
Spatial Interaction			
rho		0.1781	0.0673
		(4.0728)***	(1.8172)*
Time Lag			
Previous 5-year county sum of patents			0.5966
			(18.7754)***
Education Attainment			
Percent with 4 years college	0.7153	0.7751	0.2613
	(5.1095)***	(5.6587)***	(2.3123)**
County Characteristics			
(log) per capita income	0.9441	0.7914	0.3122
	(4.0822)***	(3.4891)***	(1.6933)*
(log) population	0.6657	0.6326	0.2465
	(15.1574)***	(14.5038)***	(6.0432)***
Market Access			
log distance to a MSA	-0.2225	-0.1714	-0.0702
	(-5.0197)***	(-3.7699)***	(-1.9137)**
presence of interstate	0.0481	0.0279	0.0227
	(0.6526)	(0.3883)	(0.3933)
State Effects			
Kansas	-0.1399	-0.0955	-0.1122
	(-1.2804)	(-0.8936)	(-1.3083)
Minnesota	0.2900	0.2280	0.1469
	(2.6476)***	(2.1162)**	(1.6969)*
Missouri	0.0666	0.0972	0.0964
	(0.6018)	(0.8989)	(1.1100)
Nebraska	-0.1608	-0.0570	-0.0781
	(-1.4303)	(-0.5067)	(-0.8610)
North Dakota	-0.0759	0.0141	0.0189
	(-0.5700)	(0.1074)	(0.1790)
South Dakota	-0.0932	0.0159	-0.0436
	(-0.7237)	(0.1236)	(-0.4209)
Constant	-7.4351	-7.3894	-2.8205
	(-11.5407)***	(-11.7711)***	(-5.0380)***
Diagnostics			
R-Square	0.7017	0.7113	0.8143
R-Adj-Square	0.6963	0.7061	0.8106
LR	20.4001***		
LM	23.0835***		
Spatial LM		3.5284*	2.0772

Note: All values in parentheses are t-values, ***= significant at the 1% level, **= significant at the 5% level, *= significant at the 10% level.

Table 5. 1985-89 First Inventor Patent Filings per County

	(log) Sum First Inventor Patent Filings (+1)		
	OLS	Spatial	Spatial - time lag
Independent Variables			
Spatial Interaction			
rho		0.1732	0.0969
		(4.1667)***	(2.8196)***
Time Lag			
Previous 5-year county sum of patents			0.5796
			(19.0158)***
Education Attainment			
Percent with 4 years college	0.9833	1.0394	0.5410
	(7.2577)***	(7.8370)***	(4.9767)***
County Characteristics			
(log) per capita income	0.6774	0.5444	0.2367
	(3.1178)***	(2.5427)**	(1.3781)
(log) population	0.6959	0.6587	0.2896
	(16.8994)***	(16.0589)***	(7.6304)***
Market Access			
log distance to a MSA	-0.1985	-0.1475	-0.0520
	(-4.6545)***	(-3.3747)***	(-1.4896)
presence of interstate	0.0352	0.0145	-0.0058
	(0.4994)	(0.2113)	(-0.1053)
State Effects			
Kansas	-0.2589	-0.2051	-0.1388
	(-2.4844)**	(-2.0036)**	(-1.7020)*
Minnesota	0.3719	0.2876	0.1969
	(3.5597)***	(2.7751)***	(2.3842)**
Missouri	-0.0276	0.0175	0.0151
	(-0.2625)	(0.1707)	(0.1843)
Nebraska	-0.1446	-0.0560	0.0257
	(-1.3459)	(-0.5223)	(0.3003)
North Dakota	0.1281	0.1649	0.1978
	(0.9836)	(1.2962)	(1.9537)**
South Dakota	-0.1942	-0.0804	-0.0197
	(-1.5832)	(-0.6578)	(-0.2020)
Constant	-7.8820	-7.8040	-3.6754
	(-12.0907)***	(-12.2913)***	(-6.6873)***
Diagnostics			
R-Square	0.7411	0.7497	0.8416
R-Adj-Square	0.7364	0.7451	0.8385
LR	15.3472***		
LM	16.6983***		
Spatial LM		1.4808	0.0595

Note: All values in parentheses are t-values, ***= significant at the 1% level, **= significant at the 5% level, *= significant at the 10% level.

Table 6. 1990-94 First Inventor Patent Filings per County

	(log) Sum First Inventor Patent Filings (+1)		
	OLS	Spatial	Spatial - time lag
Independent Variables			
Spatial Interaction			
rho		0.1508	0.0618
		(3.6876)***	(1.7869)*
Time Lag			
Previous 5-year county sum of patents			0.5982
			(17.9832)***
Education Attainment			
Percent with 4 years college	1.1539	1.2024	0.4556
	(7.0619)***	(7.5086)***	(3.3391)***
County Characteristics			
(log) per capita income	0.4616	0.3645	0.1054
	(2.1207)**	(1.7056)*	(0.6043)
(log) population	0.7709	0.7360	0.3429
	(18.8647)***	(17.9667)***	(8.5899)***
Market Access			
log distance to a MSA	-0.1431	-0.1027	-0.0198
	(-3.2787)***	(-2.2964)**	(-0.5421)
presence of interstate	0.0658	0.0415	0.0375
	(0.9165)	(0.5905)	(0.6569)
State Effects			
Kansas	-0.2588	-0.1989	-0.0793
	(-2.4534)**	(-1.9119)*	(-0.9345)
Minnesota	0.2776	0.2138	0.0561
	(2.6111)***	(2.0271)**	(0.6502)
Missouri	-0.1222	-0.0725	-0.0464
	(-1.1547)	(-0.6972)	(-0.5488)
Nebraska	-0.1113	-0.0229	0.0240
	(-1.0191)	(-0.2099)	(0.2710)
North Dakota	0.1002	0.1501	0.0728
	(0.7633)	(1.1666)	(0.6956)
South Dakota	-0.3284	-0.2071	-0.1071
	(-2.7027)***	(-1.6871)*	(-1.0674)
Constant	-8.3437	-8.2759	-3.6379
	(-12.6563)***	(-12.8473)***	(-6.2261)***
Diagnostics			
R-Square	0.7515	0.7581	0.8404
R-Adj-Square	0.7470	0.7537	0.8372
LR	15.1946***		
LM	16.9142***		
Spatial LM		2.0698	0.0015

Note: All values in parentheses are t-values, ***= significant at the 1% level, **= significant at the 5% level, *= significant at the 10% level.

Table 7. 1995-2000 First Inventor Patent Filings per County

	(log) Sum First Inventor Patent Filings (+1)		
	OLS	Spatial	Spatial - time lag
Independent Variables			
Spatial Interaction			
rho		0.1986	0.1197
		(5.1265)***	(3.6077)***
Time Lag			
Previous 5-year county sum of patents			0.5822
			(16.8854)***
Education Attainment			
Percent with 4 years college	1.0881	1.1264	0.4327
	(7.8463)***	(8.4011)***	(3.6489)***
County Characteristics			
(log) per capita income	0.3418	0.2340	0.2493
	(1.6843)*	(1.1909)	(1.5265)
(log) population	0.8142	0.7699	0.3364
	(19.2726)***	(18.3744)***	(7.7615)***
Market Access			
log distance to a MSA	-0.1868	-0.1192	-0.0746
	(-4.0875)***	(-2.5603)**	(-1.9448)*
presence of interstate	0.0213	-0.0062	-0.0254
	(0.2838)	(-0.0855)	(-0.4224)
State Effects			
Kansas	-0.3470	-0.2518	-0.1415
	(-3.1695)***	(-2.3503)***	(-1.5826)
Minnesota	0.2227	0.1270	0.0410
	(2.0090)**	(1.1718)	(0.4553)
Missouri	-0.2302	-0.1608	-0.0848
	(-2.0685)**	(-1.4845)	(-0.9399)
Nebraska	-0.2922	-0.1561	-0.1354
	(-2.5579)**	(-1.3703)	(-1.4289)
North Dakota	-0.1070	-0.0011	-0.0840
	(-0.7799)	(-0.0082)	(-0.7543)
South Dakota	-0.4290	-0.2457	-0.1002
	(-3.4027)***	(-1.9423)*	(-0.9463)
Constant	-8.3390	-8.4017	-3.7789
	(-12.6612)***	(-13.2006)***	(-6.3561)***
Diagnostics			
R-Square	0.7729	0.7841	0.8512
R-Adj-Square	0.7687	0.7802	0.8482
LR	42.6285***		
LM	48.9950***		
Spatial LM		13.2569***	1.9551

Note: All values in parentheses are t-values, ***= significant at the 1% level, **= significant at the 5% level, *= significant at the 10% level.