# 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 employment growth. A number of employment growth hypotheses are tested for counties in Iowa, Minnesota, Missouri, Kansas, Nebraska, South Dakota and North Dakota. We assume that new knowledge and innovative activity are embodied in patent filings for the years 1975-2000. Due to the spatial nature of the data, both spatially lagged dependant variables and spatial error models are employed. The results support the importance of knowledge creation and innovative activity as an important factor explaining employment growth in Heartland counties over the 1969-2000 period.

**Keywords**: patents, employment growth, spatial econometrics

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## Introduction

In the last half of the Twentieth Century, many small towns in the U.S. Heartland 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 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.

Unfortunately, the role and mechanism of technological change and spillovers in economic growth is not well understood. Simon Kuznets in 1962 suggested that an obstacle in understanding economic growth was the inability of scholars to empirically capture technological change. While technological change is an important component of economic growth, there is also considerable evidence that technology spillovers are important to the growth process (Anselin, Varga, and Acs 1997;Anselin, Varga, and Acs 2000;Jaffe 1989). Technology spillovers are 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 knowledge and other technological externalities are acquired via the local coffee shop, over dinner, or at a local business meeting, locational fundamentals may play an important role in knowledge transmission. Such geographical considerations motive the applied growth work of Gleaser, et al. (1992), where the authors argue that intellectual breakthroughs must cross hallways and streets more readily than oceans and mountains. The possibility

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

that such intellectual spillovers occur between firms is one justification for the high rental rates and long traffic commutes incurred in a large city. 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.

We are specifically interested in the role of new knowledge and innovation in the rural growth process. In Gleaser, et al, (1992) and Gleaser, 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 engine of county employment growth. Similarly, we hypothesize that employment growth in adjacent counties stimulates own county employment growth. By taking spatial autocorrelation into account in both knowledge creation and innovative activity 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.

The paper is arranged as follows: First, a conceptual framework is presented highlighting the role of technological change and technology spillovers in employment growth drawing on current macroeconomic thinking. Second using data from 618 counties in the U.S. Heartland states (Minnesota, Iowa, Missouri, Kansas, Nebraska, South Dakota, and North Dakota) and developing a new patents database for these counties to proxy the creation of new knowledge and innovative activity, we explain the creation of new knowledge and innovative activity and use the results to create an instrumental variable for the employment growth model. Third, employment growth during the 1969-2000 period is explained by predicted knowledge creation and innovative activity, knowledge and innovative spillovers, spillovers from employment growth in adjacent counties and a set of initial conditions. Fourth, based on the empirical results of the previous sections, policy implications are drawn and conclusions are presented.

**Analytical Framework**

The modern economic growth literature is shifting emphasis from the traditional neoclassical framework to a 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) natural capital (Castle 1998) and initial conditions, including infrastructure. A number of studies have added (Glaeser et al. 1992;Glaeser, Scheinkman, and Shleifer 1995) cross-industry externalities and derived empirical estimates of total and sector employment growth in key industries for U.S. cities. Obviously, economic growth is far more complex than captured by these stylized macro models. Further, these macro models have not attempted to provide specific consideration of rural economic growth, but these marco models, esp (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. A representative firm in region i=1,2,3,…,n is assumed to take prices, wages, $w_t$, and technology, $A_t$, in their region as given and maximize a single input production function

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

The 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 write the ratio of these two derivatives at two points in time:

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

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

$$\ln\left(\frac{l_{i,t+1}}{l_{i,t}}\right) = t_1 \ln\left(\frac{w_{i,t+1}}{w_{i,t}}\right) + t_2 \ln\left(\frac{A_{i,t+1}}{A_{i,t}}\right) \tag{3}$$

$$\text{where } t_1 = \frac{1}{a - 1}, \text{ and } t_2 = \frac{1}{1 - a}$$

Glaeser, et al (1992) divide growth in technology into two parts - local (city) and national. Here also technology is divided into two components - local (county) and Heartland regional. We write this relationship using a Cobb-Douglas functional form, $A = R^d A_c^g$ where R is regional technology, and $A_c$ is local technology. The parameters δ and γ represent the relative importance of such technology. Thus, we can express the growth in employment as a function of the growth in wages, regional technology growth and local technology growth or

$$\ln\left(\frac{l_{i,t+1}}{l_{i,t}}\right) = t_1 \ln\left(\frac{w_{i,t+1}}{w_{i,t}}\right) + \tilde{t}_2 \ln\left(\frac{R_{t+1}}{R_t}\right) + \tilde{t}_3 \ln\left(\frac{A_{c,i,t+1}}{A_{c,i,t}}\right) \tag{4}$$

$$\text{where } \tilde{t}_2 = \frac{d}{1 - a}, \text{ and } \tilde{t}_3 = \frac{g}{1 - a}$$

Glaeser, et al (1992; 1995), using data from U.S. cities provide 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. Their unit of observation is the top six two-digit industries in a city in 1956. They have 1,066 observations over 170 cities and the cities included in the sample are defined by the authors as rather mature. Glaeser, et al (1992) developed a number of hypotheses with respect to employment growth in city-industries and then proceeded to test these hypotheses using the **County Business Patterns** data for 1956 and 1987 produced by the Bureau of the Census.

A number of fascinating questions arise with respect to the Glaeser, et al (1992) analysis of rural economic growth. First, is urban employment growth significantly different from rural employment growth because of the lack of knowledge spillovers and agglomeration externalities? Second, would the same factors that explain firm growth in cities explain the growth of rural firms? Rural counties are typically at an earlier "stage of development" with respect to employment growth in sectors than in more mature city-industries, identified by Glaeser, et al (1992). Alternatively, entering at a later stage of development in a more service-oriented national, or at least regional economy, we might expect a different pattern of growth to emerge.

We model county employment growth as a function of similar dynamic externalities and local spillovers as well as initial endowments. However, explicit attention is given to the role of new knowledge and innovation within the county. The period 1969-2000 is examined as opposed to 1957-1987 growth. Unlike many of the cities in Glaeser, et al (1992) most of the Heartland counties witnessed population declines in the 1970's and 1980's and some witnessed employment growth rates that exceeded population growth rates in the 1990's. Obviously, these differences create difficulties in directly comparing the two studies, but the results do provide some useful insights into modern economic growth, especially in rural areas.

**Econometric Model**

The employment growth models estimated are based on a cross-section of Heartland counties. Total employment growth between 1969 and 2000 is explained by resource endowments and 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 to capture new knowledge created within the county. Resource endowments in terms of human capital, and knowledge externalities that are county-specific, a series of initial conditions including infrastructure and location-specific factors.

Returning to the earlier conceptual framework, 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 take on the following relationship

$$\ln\left(\frac{A_{c,i,t+1}}{A_{c,i,t}}\right) = g\left(pat_{t,t+1}, col_t, cr_t\right) \tag{5}$$

where: $pat_{t,t+1}$ - is the indicator of new knowledge (patents) over the study period;

$col_t$ - is an indicator of human capital; and

$ct_t$ - is a concentration index of the intensity of sectoral domination.

Consistent with the belief that new patents are a proxy for new knowledge and innovation (Jaffe 1989;Hall, Jaffe, and Trajtenberg 2001;Anselin, Varga, and Acs 1997), this measure is expected to contribute positively to knowledge and technology growth (Romer 1986;Lucas 1988), it is expected $g_1 > 0$. Here subscripts refer to the partial derivative with respect to the indicated argument, i,e $g_1 \equiv \frac{\partial g(.)}{\partial pat_{t,t+1}}$, this notation is used in the remained of the paper. To comply with the hypothesis human capital is a driver of technological change (Lucas 1988) the relationship $g_2 > 0$ is expected. Finally the sign of $g_3$ is ambiguous since there are conflicting theories on the sign of this parameter. One school of thought believes diversity among industries promotes technology spillovers (Jacobs 1969). The idea is technological spillovers are more important between rather than within sectors. The competing belief suggests industry specialization is the best method to bring about technological development through exploitation of market power (Schumpeter 1942;Romer 1986;Marshall 1890;Arrow 1962). Thus under the Jacobs school of thought it is expected $g_3 < 0$ and $g_3 > 0$ under the Marshall-Arrow-Romer hypothesis as higher concentrations reflect lower amounts of diversity.

Regional technology growth is defined in terms of State policies, programs, and possibly even State resident attitudes. In this grouping are also included distance to a metro area and presence of an interstate. These last two deal with the ability to interact with other economic agents and access to larger markets will increase the amount of technology spillover among agents (Glaeser et al. 1992). This relationship may be formalized by:

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

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 exante without more information on historical and current state policies and programs. These state level effects are thus left for the empirical analysis to determine. With respect to distance to a metro area a negative relationship is expected, and for the presence of an interstate, a positive relationship. The idea here basically suggesting the greater the opportunity and probability to interact with other individuals, the greater will be the spillover impacts.

Wage growth in the county can be explained to a certain degree by the underlying initial conditions within the county. Specifically, wage growth can be thought of as a function of initial wages, initial population, employment ratio, and initial employment. The relationship between wage growth and these variables is represented by the function $h(.)$

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

The expected sign of wage growth with respect to initial wage is negative since the higher is the initial wage, the lower will be wage growth other things equal implying $h_1 < 0$. Based on a scarcity argument, the higher is the original population, the slower should be the wage growth due to an abundance of potential labor, thus $h_2 < 0$. The sign for the employment ratio is expected to be positive since the higher is tighter is the market, the faster one would expect wages to grow implying $h_3 > 0$. Based on a similar argument, the more employment in a region, the tighter will be the market and the faster should be the wage growth. The expected sign for the last argument in (7) is positive, $h_4 > 0$.

It was proposed in the introductory comments geographic proximity has plays a relatively large role in describing how these innovative spillins affect inventor activity. The use of spatial econometric techniques has been quite prevalent in recent literature where the role of space is an important factor (Roe, Irwin, and Sharp 2002;Acs, Anselin, and Varga 2002). The spatial nature of our data set is captured via a spatial econometric framework. For this paper both a spatially lagged dependant variable and spatial error model (Lesage 1997;Anselin 1988) are estimated.

Typical Cobb-Douglas relationships are assumed for the functions $g(.), f(.)$ and $h(.)$. Assigning this functional form to (5)-(7) and substituting into (4) then taking logarithms to linearize the model will result in an estimable relationship. Under the spatially lagged dependant variable model a spatial parameter $r$ is used to capture an explicit spatial relationship in the data. This specific empirical relationship takes the form

$$\ln\left(\frac{l_{i,t+1}}{l_{i,t}}\right) = b_0 + r\sum_{j\in N_i}\ln\left(\frac{l_{j,t+1}}{l_{j,t}}\right) + b_1 \ln pat_{t,t+1} + b_2 \ln w_t + b_3 \ln e_t + b_4 er_t + b_5 cr_t + b_6 col_t \\ + b_7 dmsa_t + b_8 Id_t + \sum_{k=1}^{6} b_{8+k} s_k + e \tag{8}$$

where $N_i$ represents geographic or physically “close” neighbor counties for county i, and e is a random error term distributed normally with constant variance, the parameters ß$_0$-ß$_{14}$ are to be estimated, and the other variables are defined as before. For completeness, based on the conceptual framework given the parameter terms $t_1$, $\tilde{t}_2$, and $\tilde{t}_3$ are negative, positive, and positive respectfully in (4), the expected signs for the betas in (8) are

$b_1 > 0$;
$b_2 > 0$;
$b_3 < 0$;
$b_4 < 0$;
$b_5$ ambiguous;
$b_6 > 0$;
$b_7 < 0$;
$b_8 > 0$; and
$b_9$ through $b_{15}$ ambiguous.

The parameters $b_1, b_5$, and $b_6$ may be thought of as the local technology spillover parameters from the combination of equations (4) and (5). Likewise, regional spillovers are captured in terms

$b_7 - b_{14}$.Equation (8) is the spatially lagged dependant variable model where there is an explicit spatial relationship captured in the parameter $r$ . In matrix notation this equation can be described by

$$y = rWy + Xb + e \qquad (9)$$
$$e \sim N\left(0, s^2\right)$$

In the above y is the vector of county (log) employment growth rates related spatially to neighboring counties by the spatial interaction parameter, $r$ , to be estimated[4]. The explanatory variables and their associated parameter estimates are embodied in the matrix X and the vector β respectively. The matrix W is characterized by zeros along the main diagonal and has off diagonal elements representing the neighboring counties. The matrix W is created using a Delaunay triangulization[5] routine (Pace and Lesage 2003b;Pace and Lesage 2003a) that picks out the nearest three counties using latitude and longitude coordinates based on the center of the county then creates up to three additional relationships in the spatial weights matrix to ensure the matrix W is symmetric. This will imply that for any given county there may be up to a total of six counties making up the neighborhood structure. In addition to being symmetric, the spatial weight matrix W is also standardized to adhere to fairly strict requirement of the likelihood function often used for spatial statistical estimation.

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 is good reason to believe there are underlying technological and other growth forces that are not observable and cannot be captured in the data. To control for this potential problem an instrumental variable (IV) approach is used. In this two stage IV estimation the spatially lagged dependant variable model is used to obtain predicted patent

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[4] An alternative spatial model could take the following form where the spatial tendencies of the data are captured in the error structure

$$y = Xb + u$$
$$u = lWu + e$$
$$e \sim N\left(0, s^2 I\right)$$

In the above specification the spatial relationship in the error structure is captured in the “lambda” term to be estimated. However, in our estimation the results from estimating this model are suppressed as they were quite similar to the spatial lag model .

[5] Delaunay triangulation computes a set of triangles such that no data points are contained in any triangle's circumcircle.

values. In this framework the instruments used is the spatially lagged patent variable and percent of the county population with a college degree. 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. It is difficult to envision an instrument for this particular application where patent filings, themselves indicators of a broader set of technological growth, are not correlated with other underlying economic growth forces that are not correlated with the unobserved growth captured in the error for labor growth. The relationship used to generate the patent IV is:

$$pat_i = b_0 + r_x \sum_{j \in N_i} pat_j + b_1 er_i + b_2 dmsa_i + b_3 col_i + b_4 pop_i + b_5 ID_i + \sum_{k=1}^{6} b_{5+k} s_k + e \qquad (10)$$

or, in matrix notation[6];

$$x = r_x Wx + X_x b_x + e_x \qquad (11)$$
$$e \sim N\left(0, s_x^2 I\right)$$

where x is a nx1 matrix of (log) total inventor patent filings +1 per county, W is the same nxn standardized and symmetric spatial weights matrix used in (9), $X_x$ is a $nxk_x$ matrix of explanatory data, and $ß_x$ 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 the issue of correcting the standard errors in the second stage. Compounding the computation of standard errors in the fact that maximum-likelihood is used as an estimation tool to obtain predicted values for the patent variable. While bootstrapping may seem an obvious choice to compute standard errors, the failure to maintain the spatial structure in the predicted data sets renders this method unworkable. However alternatives have been suggested to compute

[6] As a side and also of economic interest in estimation of (11) is the interpretation of $?_x$. Noting some of the difficulties in interpreting the spatial interaction parameter when using aggregated data (Anselin 2002), this parameter estimate may be interpreted directly as an innovative spillin relationship.

[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 relaxed in favor of the following error structure

$$e \sim N\left(0, s^2 V\right)$$

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;Lesage 1999). However, estimation of the heteroskedastic model for the first stage of the2-stage IV estimation did not appreciably affect results so further discussion based on this model has been suppressed.

appropriate standard errors in a spatial two stage model (Anselin 1988;Kelejian and Prucha 1999;Kelejian and Prucha 2002). While the authors are indeed aware of this problem, the standard errors presented for the two stage models have not yet been corrected. So while we can make inferences from the estimated coefficients, we are not able to comment on the exact precision of these estimates.

Empirical estimation of the models presented in (9) and (11) are conducted in Matlab using various spatial econometric functions as part of an econometrics toolbox (Lesage 2003). These equations may be estimated using OLS when $r$ =0, that is, when no spatial interaction is assumed. However, in the presence of a spatially lagged dependant variable the simultaneity will result in OLS estimates which are both biased and inefficient. Maximum likelihood estimation can be used to derive efficient and unbiased estimates through an iterative process (Anselin 1988). The actual estimation of the relationships described in (9) and are made operational using sparse matrix algorithms (Lesage 2003). The following section describes the data used to estimate the above relationships.

**Data**

County growth in non-farm employment is considered over the period 1969-2000. The sample includes 618 counties in the U.S. Heartland states of Minnesota, Iowa, Missouri, Kansas, Nebraska, South Dakota, and North Dakota. Most counties in the region are classified as rural. The farm sector is declining as is the number of farms and the farm population. Over half of the farmer operators work off-farm, and if farm spouses are included, the probability that at least one spouse engages in off-farm work is close to 80 percent.

Information on technology embodied in capital and infrastructure 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 in a county, a database of patents filed by residence of the lead inventor was developed for all counties. 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-linking with a list of cities by county, a count of patents filed for each county and year was constructed. A list of the summary statistics on inventor patent filings is presented in Table

1 and supplementary tables 1.A and 1.B. A histogram depicting the frequency of patent filings in our sample is presented in figure 1. For the period 1975-2000 counties filed an average of 233 patents with a median filing of 18. The county with the largest number of patents had a total of 22,024 patents and there were also counties that had no patent filings during the period. A total of just over 138,000 patents were filed.

Employment, population, and other county level data were obtained from primarily Bureau of Economic Analysis (BEA) data complied on the Regional Economic Information System (REIS) dataset. Additional data on educational attainment were from the 1970 census. Summary statistics are presented in table 1 and supplementary tables 1.A through 1.O provide additional detail. Over the 1969-2000 period, employment grew an average of 32%. The fastest growing county experienced employment growth of 188%, while the slowest growing county actually had an employment decline of almost 50%. The average county employed just over 12,000 in 1969. The largest county employment was about 547,000 while the smallest county employment was only 291 individuals. 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 non-farm county earnings divided by total non-farm county employment, and as indicated by the low standard deviation, they exhibit little variation in our sample. The measure of county employment concentration is the sum of the squared employment shares across the largest 4 sectors within the county using 1969 employment levels, and the measure averages 1,858 with 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.

**Results and Implications**

The results from the primary regressions of interest are presented in table 2 A total of four sets of regression results are presented in this table. The first column presents results for an OLS specified model that does not account for the spatial structure of the data. The estimated OLS coefficients are used primarily for the purposes of comparison to the correctly specified spatial model. The Second column of table 2 presents results from the spatial model and is compared with the OLS counterpart. The third and fourth columns in table 2 are used to examine the results from the two-stage IV estimation. Table 3 summarizes the equation(s) used to obtain fitted patent values.

The results from the OLS estimation suggest just under 61% of the variability in employment growth is explained by this model. Examining the estimated coefficients we do find our proxy of new technology and innovation, total county patents filed, does have a positive and statistically significant impact on employment growth. However before drawing too heavily on these results we should first consider the reliability of these estimates. Two tests are carried out to check for the presence of spatial autocorrelation in the error structure in the OLS model and one test is carried out to test for spatial autocorrelation in the error in the spatial lag model. Test statistics based on the likelihood ratio (LR) and Lagrange multiplier (LM) tests can be computed for the OLS specified model and a spatial LM (LM Sar) test statistic can be computed for the model estimated with a spatial lag (Anselin 1988). Values of 38.9 and 38.7 are computed for the LR and LM tests respectively suggesting a spatial relationship does exist in the data[8]. Since the estimates from the OLS specified model are clearly not ereliable, attention is turned to the spatially specified models.

The spatial lag model in the second column of table 2 is essentially equation (8) above. This model is able to explain just over 63% of the variability in employment growth for Heartland counties over the years 1969-2000. The LM Sar test statistic was computed at 3.63 suggesting the spatial nature of the data has been handled with a greater level of satisfaction than in the OLS specified model. The model here is a log-log formulation so most of the parameters themselves can be interpreted directly as elasticities. The coefficient estimate for the patent parameter can be interpreted as a 10% increase in the number of patents filed within the county will be met with a 1.1% increase in employment growth. This result is found to be statistically greater than zero with at least a 99% level of confidence. If we interpret the patent parameter in the broader sense of an indicator of new technology, it does appear new technology and innovation does indeed have a considerable impact on employment growth. Human capital as captured by college graduates has a positive impact on employment growth. While the parameter estimate here is statistically significant, the estimated coefficient of only 0.026 implies that a 10% increase in the percentage of college graduates within a county will increase employment growth by just under 0.3%. The spatial lag coefficient, "rho", is estimated to be 0.29, a sizable estimate and is statistically different from zero with at least a 99% level of confidence. This parameter too may be interpreted directly as an elasticity. This estimated spatial lag parameter can be interprets as a 1% increase in the employment growth of surrounding counties as defined by the spatial contiguity matrix W will, *ceteris paribus*, result in a 0.3%

[8] 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.

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 likely 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 experiences a recession or an 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.

Some of the other parameters describing the county employment growth include initial employment and initial population. Initial employment was found to have a quite sizable negative impact on employment growth with an estimated elasticity -1.1. Initial county population, however, was found to have a sizable positive impact on employment growth with an estimated elasticity of just over 1. Both the initial employment and initial population parameter estimates were found to be statistically different from zero. The employment ratio, as defined by total count employment divided by total county population, did not have a significant influence on employment growth. The market access parameters for presence of an interstate and distance to a MSA do not appear to have an appreciable impact on employment growth in this model. Thus, when other factors such as education level, population, new technology, and spillover effects from other counties has been taken into consideration, access to larger urban centers is not nearly as important. This has implications for rural policy and suggests access to larger metro markets are most likely not quite as important as may have been thought.

The third and fourth columns of table 2 are used to examine the outcome of our IV estimation. The third column presents estimated coefficients to the spatial lag model identical to the model in the second column with the exception the college variable are omitted. The removal of the human capital parameter was due to estimation difficulties encountered when estimating the second stage. The college variable was thus removed from the employment growth equation under IV estimation. Predicted patents are likely quite highly correlated with percent with a college degree in 1970 and may be partly responsible for the estimation difficulties encountered. The equations used to instrument patents are found in table 3[9]. As a

[9] The two specifications make use of the same set of independent variables but differ in their estimation. In the first column the standard spatial model is estimated under the assumption of homoskedasticity. The second uses a Bayesian Linear model with a Gibbs sampler (Geweke 1993;Lesage 1999) to control for heteroskedasticity. The heteroskedastic model computes a more conservative spatial interaction relation "rho" but both estimates are significant statistically. For the rest of the variables in the model, the two sets of estimated coefficients are remarkably similar with only a sign discrepancy on the employment ratio

comparison between the spatial model without IV and the spatial model with IV in the third and fourth columns of table 2 respectively, the effect of new technology and innovation as captured by patenting is actually larger than implied by the non-IV estimations. In the third column of table 2 the estimated elasticity is 0.13 for the patent variable as opposed to 0.23 for the IV estimate. Interpreting the patent coefficient from the IV model, a 10% increase in the level of new technology and innovation will result in a 2.3% increase in employment growth. These parameters are found to be statistically different from zero with at least a 99% level of confidence. Thus a more ambitious estimate on the impact of new technology and innovation on employment growth is an elasticity of 0.23 with the bound end near 0.12. Aside from the impact of the IV estimation on the relative magnitude of the patent coefficient, the results are quite consistent throughout and the same general conclusions hold as in the earlier discussion.

The state dummies do illustrate significant differences in employment growth relative to Iowa (the excluded dummy). In general Iowa has fared worse than all of the other States, and in general, significantly worse in a statistical sense. The State with the best performance relative to Iowa was Missouri, no doubt driven in part by tourism. Tourism however is not likely to be the only factor in explaining these State differences as Nebraska also outperformed Iowa. The explanation of these State-level results most lies partly in the exploitation of natural amenities to leisure opportunities and State governmental policies in addition to citizens attitudes towards growth.

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parameter albeit both estimates are statistically insignificant. In estimation of the growth equation the estimates using the homoskedastic and heteroskedastic models were quite similar so only the second stage results using the homosekedastic model in the first column of table 3 are used.

**Conclusions and Extensions**

The predominant motivation of this paper was to analyze the role of new technology and new knowledge on employment growth. Using total new patents filed during the growth period as an indicator of new technology and knowledge we have found a strong relationship with employment growth. Empirical estimates to the size of the impact of new technology and innovation range from an elasticity of 0.12 in the basic spatial model to 0.23 in the IV model. These results do seem to suggest considerable innovation spillovers do occur at least in this sample of Heartland counties. In addition to the impact of new technology and innovation, explicit spillover effects from neighboring counties as captured by the spatial lag model do seem to exist and what is more, appear to be quite large. Measures of human capital as captured by a university degree tend to have positive and significant impacts on economic growth although of limited magnitude. Finally, state programs, policies, and growth climates do matter to a limited degree.

While it is difficult to make policy recommendations based on a limited amount of empirical analysis, a few seemingly important generalizations appear evident. The spatial econometric estimation has suggested there exists considerable positive spillovers between counties in terms of employment growth. From a rural policy perspective, counties that wish to improve their employment situation should pay closer attention to what is happening in neighboring counties. If there is positive growth, steps should be taken to benefit from this growth. If there is stagnation or decreased growth, then steps should be taken to distance their activities from those of the poorly performing counties. Initial employment was found in general have a negative and statistically significant impact on employment growth. This would seem to support part of the convergence theory – the county employment to begin with, the slower will be its growth rate. Interestingly though, population size generally has quite a strong impact, both in size and significance. A simple interpretation of this is that jobs tend to follow people and not vice-versa. This result is not encouraging for the smaller rural counties whose population base is already significantly diminished. As an upside from a rural policy point of view though, distance to a MSA did not have as strong an impact on employment growth as one may have expected. Presence of an interstate also did not appear to have overwhelming impacts. While generally positive, the estimated coefficients were not significant statistically when considered together in a completely specified model. These results are encouraging for more remote counties since the conventional wisdom suggesting counties need to be located near to large urban centers does not seem to hold.

This study has found a striking relationship between new innovation and technology on employment growth. This result is enhanced when we consider as well the economic spillovers from neighboring counties. This finding tends to support the widely held view purporting the importance of new technology and innovation on economic growth in addition to quantifying regional economic spillovers.

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**Table 1 - Summary Statistics**

| Variable | Mean | Std. Dev. | Median | Maximum | Minimum | Count |
|---|---|---|---|---|---|---|
| Total Patents Filed 1975-2000 | 223 | 1251 | 18 | 22024 | 0 | 138050 |
| Employment Growth 1969-2000 | 0.32 | 0.37 | 0.26 | 1.88 | -0.49 | |
| Total Employment 1969 | 12146 | 40320 | 4792.5 | 546573 | 291 | 7505934 |
| Wage 1969 | 5.27 | 0.88 | 5.26 | 8.85 | 3.15 | |
| Population 1969 | 26217 | 73742 | 11657 | 967826 | 624 | 16202000 |
| Total Wage Earnings | 76091 | 300098 | 23979 | 4194859 | 1210 | |
| Distance to a MSA | 109 | 68 | 97 | 359 | 0.5 | |
| Percent College Degree | 6.56 | 3.34 | 5.89 | 30.02 | 0.46 | |
| Employment Ratio 1969 | 0.43 | 0.08 | 0.43 | 1.46 | 0.19 | |
| Concentration Measure | 1858 | 372 | 1783 | 4521 | 1273 | |
| Land Value | 607 | 406 | 501 | 3722 | 67 | |
| Interstate | | | | | | 176 |
| Iowa | | | | | | 99 |
| Kansas | | | | | | 105 |
| Minnesota | | | | | | 87 |
| Missouri | | | | | | 115 |
| Nebraska | | | | | | 93 |
| North Dakota | | | | | | 53 |
| South Dakota | | | | | | 66 |

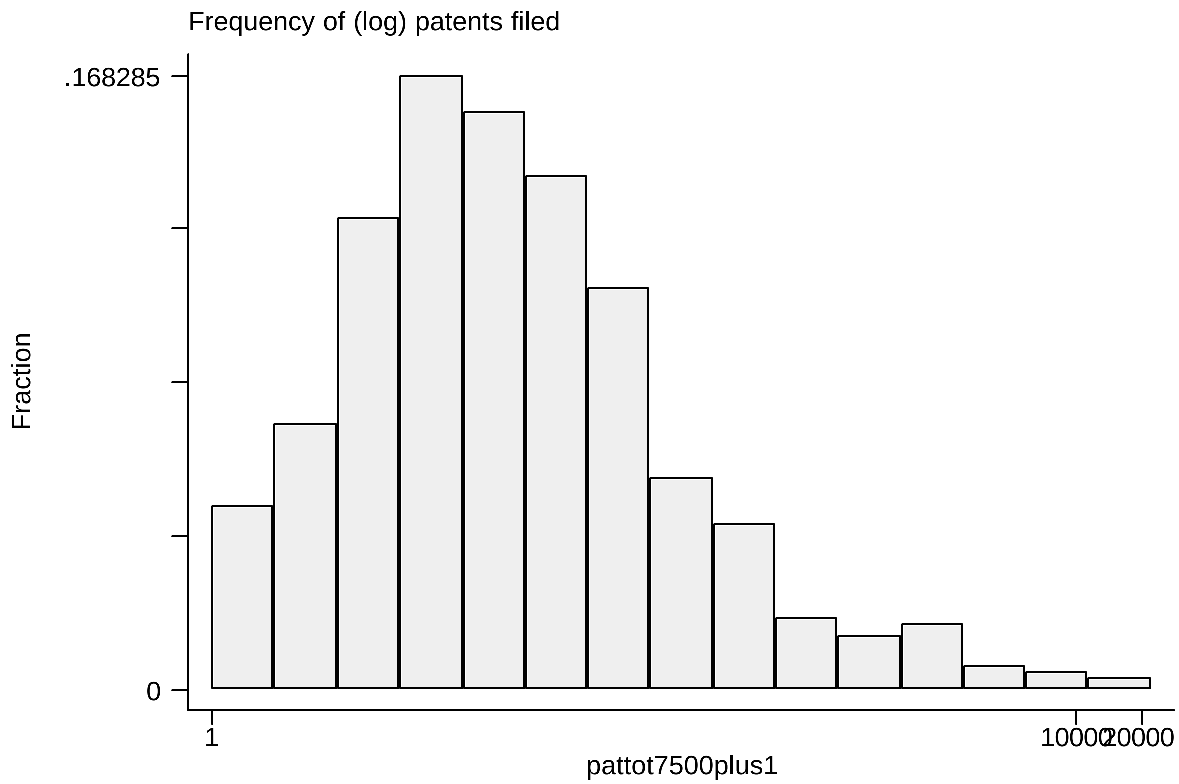


**Figure 1 – Distribution of total patent filings summed over the years 1975-2000 (log scale)**

Table 1.A - Top 10 patent count counties

| | County Name | Total Patents 1975-2000 |
|---|---|---|
| 1 | Hennepin, Minnesota | 22024 |
| 2 | Ramsey, Minnesota | 13582 |
| 3 | St. Louis, Missouri | 9193 |
| 4 | Washington, Minnesota | 9009 |
| 5 | St. Louis (Independent City), Missouri | 6061 |
| 6 | Dakota, Minnesota | 4484 |
| 7 | Olmsted, Minnesota | 4375 |
| 8 | Anoka, Minnesota | 3578 |
| 9 | Johnson, Kansas | 3050 |
| 10 | Linn, Iowa | 2952 |

Table 1.B - Top 10 counties - Patents per-capita

| | County Name | Patents per-capita 1975-2000 |
|---|---|---|
| 1 | Washington, Minnesota | 0.0722106 |
| 2 | Olmsted, Minnesota | 0.0444505 |
| 3 | Christian, Missouri | 0.0370428 |
| 4 | Cass, Missouri | 0.035667 |
| 5 | Platte, Missouri | 0.0343973 |
| 6 | Ramsey, Minnesota | 0.0286625 |
| 7 | Pottawatomie, Kansas | 0.0257191 |
| 8 | Carver, Minnesota | 0.0251691 |
| 9 | Story, Iowa | 0.0247806 |
| 10 | Lincoln, South Dakota | 0.0244575 |

Table 1.C - Top 10 Slowest growing counties 1969-2000

| | County Name | (log) Employment growth 1969-2000 |
|---|---|---|
| 1 | Pulaski, Missouri | -0.4864849 |
| 2 | St. Louis (Independent City), Missouri | -0.4217702 |
| 3 | Faulk, South Dakota | -0.4049667 |
| 4 | Slope, North Dakota | -0.3261695 |
| 5 | Geary, Kansas | -0.3221374 |
| 6 | Sioux, Nebraska | -0.3164315 |
| 7 | Jackson, South Dakota | -0.3069881 |
| 8 | Deuel, Nebraska | -0.3018977 |
| 9 | Atchison, Missouri | -0.2998965 |
| 10 | Jones, South Dakota | -0.2988554 |

Table 1.D - Top 10 fastest growing counties, 1969-2000

| | County Name | (log) Employment Growth 1969-2000 |
|---|---|---|
| 1 | Sherburne, Minnesota | 1.878901 |
| 2 | Taney, Missouri | 1.734735 |
| 3 | St. Charles, Missouri | 1.704297 |
| 4 | Dakota, Minnesota | 1.68472 |
| 5 | Johnson, Kansas | 1.628052 |
| 6 | Carver, Minnesota | 1.616457 |
| 7 | Christian, Missouri | 1.548296 |
| 8 | Washington, Minnesota | 1.540211 |
| 9 | Camden, Missouri | 1.527089 |
| 10 | Scott, Minnesota | 1.467159 |

Table 1.E - Top 10 Low wage counties, 1969

| | County Name | Wage 1969 |
|---|---|---|
| 1 | Linn, Kansas | 3.154735 |
| 2 | Caldwell, Missouri | 3.177059 |
| 3 | Blaine, Nebraska | 3.211845 |
| 4 | Bollinger, Missouri | 3.263574 |
| 5 | Benton, Missouri | 3.326124 |
| 6 | Daviess, Missouri | 3.435263 |
| 7 | Hickory, Missouri | 3.442497 |
| 8 | Mississippi, Missouri | 3.490566 |
| 9 | Ozark, Missouri | 3.50622 |
| 10 | Loup, Nebraska | 3.554124 |

Table 1.F - Top 10 High counties, 1969

| | County Name | Wage 1969 |
|---|---|---|
| 1 | Haskell, Kansas | 8.84787 |
| 2 | Platte, Missouri | 7.729761 |
| 3 | Ramsey, Minnesota | 7.724622 |
| 4 | Sarpy, Nebraska | 7.703568 |
| 5 | St. Louis (Independent City), Missouri | 7.677281 |
| 6 | Hennepin, Minnesota | 7.674838 |
| 7 | Clay, Missouri | 7.660892 |
| 8 | Lake, Minnesota | 7.445091 |
| 9 | Dakota, Minnesota | 7.428661 |
| 10 | St. Louis, Missouri | 7.29363 |

Table 1.F - 10 Least populous counties, 1969

| | County Name | Population 1969 |
|---|---|---|
| 1 | McPherson, Nebraska | 624 |
| 2 | Arthur, Nebraska | 639 |
| 3 | Blaine, Nebraska | 873 |
| 4 | Loup, Nebraska | 903 |
| 5 | Thomas, Nebraska | 905 |
| 6 | Logan, Nebraska | 986 |
| 7 | Hooker, Nebraska | 990 |
| 8 | Grant, Nebraska | 995 |
| 9 | Banner, Nebraska | 1035 |
| 10 | Wheeler, Nebraska | 1067 |

Table 1.G - 10 Most populous counties, 1969

| | County Name | Population 1969 |
|---|---|---|
| 1 | Hennepin, Minnesota | 967826 |
| 2 | St. Louis, Missouri | 898895 |
| 3 | Jackson, Missouri | 652604 |
| 4 | St. Louis (Independent City), Missouri | 643197 |
| 5 | Ramsey, Minnesota | 466374 |
| 6 | Douglas, Nebraska | 385472 |
| 7 | Sedgwick, Kansas | 350792 |
| 8 | Polk, Iowa | 285213 |
| 9 | St Louis, Minnesota | 224390 |
| 10 | Johnson, Kansas | 215221 |

Table 1.H - 10 counties closest to a MSA, 1969

| | County Name | Distance in Miles |
|---|---|---|
| 1 | Shawnee, Kansas | 0.4677248 |
| 2 | Greene, Missouri | 0.769835 |
| 3 | Sedgwick, Kansas | 0.8831688 |
| 4 | Olmsted, Minnesota | 0.9460275 |
| 5 | Black Hawk, Iowa | 0.9906488 |
| 6 | St. Louis (Independent City), Missouri | 1.039058 |
| 7 | Douglas, Nebraska | 1.674837 |
| 8 | Pennington, South Dakota | 1.760315 |
| 9 | Cass, North Dakota | 1.922723 |
| 10 | Lancaster, Nebraska | 1.938278 |

Table 1.I - 10 counties furthest from a MSA, 1969

| | County Name | Distance in Miles |
|---|---|---|
| 1 | Burke, North Dakota | 358.5234 |
| 2 | Renville, North Dakota | 348.5663 |
| 3 | Divide, North Dakota | 336.4468 |
| 4 | Mountrail, North Dakota | 322.0369 |
| 5 | Bottineau, North Dakota | 313.481 |
| 6 | Ward, North Dakota | 308.0268 |
| 7 | Williams, North Dakota | 300.6331 |
| 8 | McPherson, Nebraska | 276.0561 |
| 9 | Rolette, North Dakota | 274.806 |
| 10 | McHenry, North Dakota | 269.249 |

Table 1.J - 10 Least university educated counties, 1969

| | County Name | Percent over 25 with College degree 1970 |
|---|---|---|
| 1 | Wheeler, Nebraska | 0.4629999 |
| 2 | Logan, North Dakota | 1.156 |
| 3 | Kidder, North Dakota | 1.616 |
| 4 | Oliver, North Dakota | 1.7 |
| 5 | Ripley, Missouri | 1.724 |
| 6 | Douglas, South Dakota | 1.74 |
| 7 | Grant, North Dakota | 1.766 |
| 8 | Ozark, Missouri | 1.801 |
| 9 | Reynolds, Missouri | 1.831 |
| 10 | Stanley, South Dakota | 1.845 |

Table 1.K - 10 Highest university educated counties, 1969

| | County Name | Percent over 25 with College degree 1970 |
|---|---|---|
| 1 | Johnson, Iowa | 30.024 |
| 2 | Story, Iowa | 27.411 |
| 3 | Boone, Missouri | 26.455 |
| 4 | Riley, Kansas | 25.106 |
| 5 | Clay, South Dakota | 24.001 |
| 6 | Douglas, Kansas | 23.769 |
| 7 | Johnson, Kansas | 22.963 |
| 8 | Brookings, South Dakota | 18.031 |
| 9 | Olmsted, Minnesota | 17.32 |
| 10 | Lancaster, Nebraska | 16.859 |

Table 1.L - 10 lowest employment ratio counties, 1969

| | County Name | Employment ratio 1969 |
|---|---|---|
| 1 | Jefferson, Missouri | 0.1928086 |
| 2 | Sherburne, Minnesota | 0.2328437 |
| 3 | Carter, Missouri | 0.2342164 |
| 4 | Anoka, Minnesota | 0.2400355 |
| 5 | Washington, Minnesota | 0.2438089 |
| 6 | Shannon, South Dakota | 0.2535609 |
| 7 | Crawford, Missouri | 0.257587 |
| 8 | Ripley, Missouri | 0.260143 |
| 9 | Wayne, Missouri | 0.2625214 |
| 10 | Warren, Iowa | 0.2642833 |

Table 1.M - 10 Highest employment ratio counties, 1969

| | County Name | Employment ratio, 1969 |
|---|---|---|
| 1 | Geary, Kansas | 1.463307 |
| 2 | Pulaski, Missouri | 0.7673295 |
| 3 | St. Louis (Independent City), Missouri | 0.7112331 |
| 4 | Jones, South Dakota | 0.6821706 |
| 5 | Des Moines, Iowa | 0.6420732 |
| 6 | Greeley, Kansas | 0.631636 |
| 7 | Jackson, Missouri | 0.6097664 |
| 8 | Cole, Missouri | 0.6042479 |
| 9 | Comanche, Kansas | 0.6041056 |
| 10 | Hughes, South Dakota | 0.6033965 |

Table 1.N - 10 least specialized counties, 1969

| | County Name | Specialization Index 1969 |
|---|---|---|
| 1 | Dent, Missouri | 1272.66 |
| 2 | Gray, Kansas | 1285.369 |
| 3 | Coffey, Kansas | 1303.685 |
| 4 | Grant, Kansas | 1315.285 |
| 5 | Hanson, South Dakota | 1348.715 |
| 6 | Oliver, North Dakota | 1353.875 |
| 7 | Mercer, North Dakota | 1358.961 |
| 8 | Stevens, Kansas | 1369.65 |
| 9 | Cheyenne, Nebraska | 1373.286 |
| 10 | Keokuk, Iowa | 1391.902 |

Table 1. O - 10 Most specialized counties, 1969

| | County Name | Specialization Index 1969 |
|---|---|---|
| 1 | Itasca, Minnesota | 4521.347 |
| 2 | Sioux, North Dakota | 4351.274 |
| 3 | Buffalo, South Dakota | 4344.412 |
| 4 | Geary, Kansas | 4137.508 |
| 5 | Pulaski, Missouri | 4047.982 |
| 6 | Slope, North Dakota | 3928.669 |
| 7 | Shannon, South Dakota | 3746.953 |
| 8 | Lake, Minnesota | 3562.046 |
| 9 | Todd, South Dakota | 3457.915 |
| 10 | Union, South Dakota | 3453.861 |

**Table 2 - Employment Growth - Patent Measure of New Knowledge**

Dependent Variable: Log Employment Growth 1969-2000

| **Variable** | OLS§ | Spatial Lag Model | Spatial Lag Model | Spatial Lag - IV# Model |
|---|---|---|---|---|
| *Spatial Interaction* | | | | |
| Rho | | 0.289 | 0.256 | 0.235 |
| | | (5.750)*** | (5.443)*** | (4.679)*** |
| *New Technology Created* | | | | |
| Total Patents - Sum 1975-2000 | 0.122 | 0.114 | 0.133 | 0.232 |
| | (10.608)*** | (10.872)*** | (12.683)*** | (12.428)*** |
| *County Characteristics* | | | | |
| Wage 1969 | 0.042 | 0.021 | 0.083 | 0.114 |
| | (0.577) | (0.304) | (1.165) | (1.451) |
| Employment 1969 | -1.363 | -1.085 | -0.942 | -0.906 |
| | (-6.542)*** | (-7.302)*** | (-6.078)*** | (-4.089)*** |
| Population (log) | 1.300 | 1.028 | 0.896 | 0.734 |
| | (6.224)*** | (7.480)*** | (6.217)*** | (3.156)*** |
| employment ratio | 0.924 | 0.496 | 0.287 | 0.236 |
| | (2.060)** | (1.485) | (0.817) | (0.500) |
| Concentration Index 1969 | 0.043 | 0.040 | 0.088 | 0.038 |
| | (1.501) | (1.480) | (3.241)*** | (1.416) |
| Percent College Degree 1970 | 0.024 | 0.026 | | |
| | (6.412)*** | (7.256)*** | | |
| *Market Access* | | | | |
| log distance to a MSA 1970 | -0.010 | 0.013 | 0.015 | 0.034 |
| | (-0.688) | (0.902) | (1.046) | (1.993)** |
| Presence of Interstate 1970 | 0.015 | 0.015 | 0.031 | 0.013 |
| | (0.627) | (0.661) | (1.332) | (0.516) |
| *State Effects* | | | | |
| Kansas | 0.096 | 0.075 | 0.142 | 0.154 |
| | (2.633)** | (2.137)** | (4.063)*** | (4.056)*** |
| Minnesota | 0.117 | 0.042 | 0.047 | 0.028 |
| | (3.189)*** | (1.127) | (1.222) | (0.664) |
| Missouri | 0.233 | 0.171 | 0.178 | 0.241 |
| | (6.214)*** | (4.659)*** | (4.703)*** | (5.752)*** |
| Nebraska | 0.114 | 0.109 | 0.131 | 0.162 |
| | (3.149)*** | (3.176)*** | (3.673)*** | (4.124)*** |
| North Dakota | 0.035 | 0.039 | 0.030 | 0.054 |
| | (0.815) | (0.948) | (0.701) | (1.169) |
| South Dakota | 0.116 | 0.112 | 0.148 | 0.220 |
| | (2.811)*** | (2.861)*** | (3.655)*** | (4.898)*** |
| Constant | -1.426 | -1.159 | -1.166 | -0.292 |
| | (-3.482)*** | (-5.431)*** | (-5.049)*** | (-0.620) |

**Table 2 (cont'd)**

| | | | | |
|---|---|---|---|---|
| *Diagnostics* | | | | |
| R-Square | 0.607 | 0.635 | 0.602 | 0.533 |
| R-Adj-Square | 0.597 | 0.626 | 0.593 | 0.522 |
| LR | 38.900*** | | | |
| LM | 38.699*** | | | |
| LM Sar | | 3.363** | 6.332** | 6.441** |

[§]All values in parentheses are t-values, ***= 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 in the first column of Table 3.

**Table 3 - Patent Instrument Equations**

Dependent Variable: Total Patents Filed 1975-2000

| **Variable** | Spatial[§] Model | Spatial Heteroskedastic Model |
|---|---|---|
| *Spatial Interaction* | | |
| Rho | 0.205 | 0.179 |
| | (11.791)*** | (5.506)*** |
| *County Characteristics* | | |
| Population (log) | 1.065 | 1.092 |
| | (25.945)*** | (21.841)*** |
| employment ratio | -0.273 | 0.500 |
| | (-0.837) | (0.972) |
| Percent College Degree 1970 | 0.074 | 0.073 |
| | (6.849)*** | (6.993)*** |
| *Market Access* | | |
| log distance to a MSA 1970 | -0.144 | -0.113 |
| | (-3.162)*** | (-2.398)** |
| Presence of Interstate 1970 | 0.093 | 0.108 |
| | (1.148) | (1.381) |
| *State Effects* | | |
| Kansas | -0.140 | -0.164 |
| | (-1.145) | (-1.414) |
| Minnesota | 0.252 | 0.296 |
| | (2.070)** | (2.453)** |
| Missouri | -0.308 | -0.329 |
| | (-2.875)*** | (-3.095)*** |
| Nebraska | -0.102 | -0.171 |
| | (-0.810) | (-1.456) |
| North Dakota | 0.023 | 0.020 |
| | (0.153) | (0.139) |
| South Dakota | -0.387 | -0.403 |
| | (-2.720)*** | (-2.991)*** |
| Constant | -7.155 | -7.804 |
| | (-11.480)*** | (-12.772)*** |
| *Diagnostics* | | |
| R-Square | 0.790 | 0.788 |
| R-Adj-Square | 0.787 | |

[§]All values in parentheses are t-values, ***= significant at the 1% level, **= significant at the 5% level, *= significant at the 10% level.