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An Application of Spatial Poisson Models to Manufacturing Investment Location Analysis

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The influence product markets, agglomeration, labor, infrastructure, and government fiscal attributes had on manufacturing investment flows in Indiana between 2000 and 2004 were estimated using Poisson regression, geographically weighted regression, and a spatial general linear model. Counties with access to urbanization economies, product markets, available labor, a high-quality workforce, and transport infrastructure were more likely to attract manufacturing investment. These effects were magnified to some extent when inter-county spatial effects were modeled. The distributional assumptions of the spatial models are different, but both methods are useful for understanding the spatial context of the factors influencing manufacturing investment flows.

Key Words: geographically weighted regression, location determinants, location theory, manufacturing site selection, Poisson spatial generalized linear model

JEL Classifications: R1, R3

The Indiana economy had a net loss of more than 100,000 manufacturing jobs between 2000 and 2004, or roughly 16% of the state's manufacturing employment (Bureau of Labor Statistics). By early 2004, the U.S. economy had shown signs of recovery, but employment had not. The rate and distribution of employment growth as the economy recovers is a critical issue for state and local policy. Globalization, however, has seen low-tech manufacturers seek low-wage workers from offshore sites, while other U.S. manufacturing investment has sought locations that offer access to skilled labor, business services, markets, and information technology.

Business restructuring and recession influenced Indiana's economy during the late 1990s and early 2000s. Although there is no centralized source reporting plant openings and closures, the Indiana Chamber of Commerce tracks manufacturer closure and investment activity through various sources, such as newspaper accounts. The Chamber's records indicate that Indiana had 229 manufacturing closures from January 2000 through March 2004. Closings occurred in 64 of Indiana's 92 counties (70%). During the same period, the

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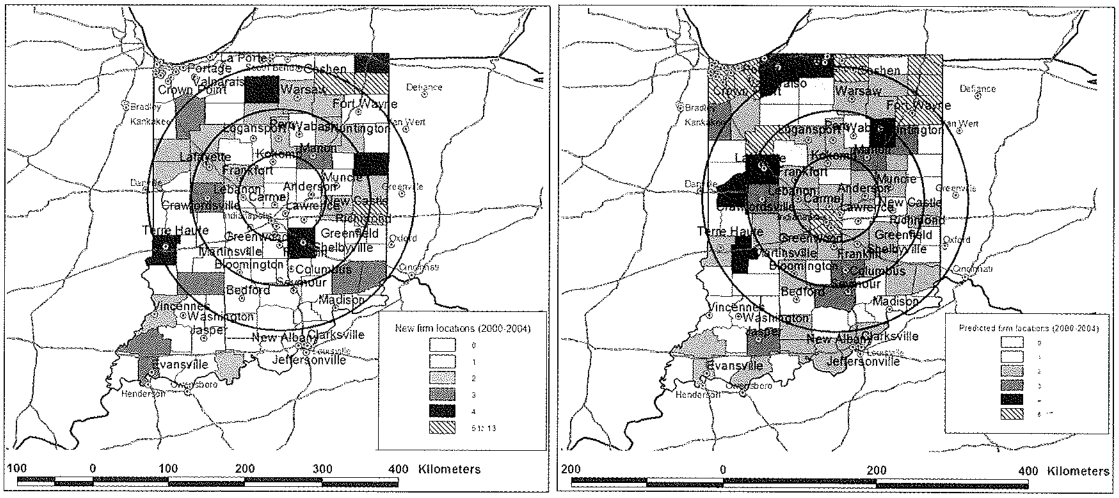

Figure 1. Spatial Distribution of New Firm Locations in Indiana, 2000–2004 (Left), and Predicted Values (Right)
Source: Authors' estimates.

Chamber identified 199 new manufacturing facilities that located throughout the state (Figure 1). These new investments were located in 63 of the state's 92 counties (68%), primarily in urban and suburban areas, and in counties with access to major interstate highways.

Attracting manufacturing investment is often seen as a potential source of growth for rural communities (McNamara, Kriesel, and Rainey). A central question for policy is whether Indiana's traditionally strong rural manufacturing environment will be able to retain existing manufacturing and attract new investment to sustain the rural manufacturing employment base.

Location theory is useful for understanding which local factors increase the likelihood of attracting firm manufacturing investment. This information could be valuable to policy makers planning to invest resources into local or regional projects designed to attract manufacturing investment. However, global models may not fully capture local attributes or economic spillover effects between neighborhoods of counties. This is an empirical question that can be tested using spatial econometrics. When spatial relations are appropriately modeled, more efficient and accurate estimates about which local factors influence firm location choice may be obtained.

This analysis proceeds as follows. First, a conceptual model of location theory is presented. Next, the data used in the analysis are described, followed by a section outlining the empirics and estimation procedures. Because firm location announcements are count data, a Poisson regression model is used to estimate the marginal effects of location determinants on firm site selection. Two spatial regression methods relatively new to the spatial economic literature are described in the empirics section. The first—geographically weighted regression (GWR)—is a local regression technique. This approach is applied to test the structural stability of the explanatory variables over space because data nonstationarities can compromise global results. Another advantage of this technique is that additional insight into the relation between firm site selection and the local factors explaining it may be gained by correlating GWR marginal effects at the regional (or state) level. Second, the global Poisson model is reestimated as a spatial generalized linear model (SGLM). This regression technique applies concepts originally developed in geostatistics, biometrics, and the soil sciences to model spatial correlation between observations. The advantage of this approach is that the magnitude and intensity of the influence of activities in a given location have on other locations can be empirically tested. Conclusions and policy implications follow discussion of the results.

Conceptual Model

Plant location choice is a two-stage process (Woodward; Bartik 1989; Henderson and McNamara 1997). Firms evaluate potential sites based on state, local, and site-specific attributes (Henderson and McNamara 1997). In the first stage, firms select a region for their investment based on broad company objectives, such as access to raw materials, entrance into product markets, increasing market share, and other criteria in the firms' objective function. In the second stage of plant location choice, firms seek a minimum cost site within a selected region for their investment (Kriesel and McNamara; Henderson and McNamara 1997; Henderson and McNamara 2000). This second stage of the location decision is represented as $\ell = Q(\mathbf{A}, \mathbf{S}, \mathbf{L}, \mathbf{I}, \mathbf{F})$, where ℓ is the site choice and **A**, **S**, **L**, **I**, and **F** are county attributes representing agglomeration factors (**A**), industry structure (**S**), labor (**L**), infrastructure (**I**), and fiscal (**F**) characteristics that influence firm cost structure. Q is a site location function assumed to minimize firm costs. The first and second stages of the site selection process are assumed to be independent of each other.

Agglomeration Economies (A)

Agglomeration is the accumulation of business activity in and around a specific geographic area. Some byproducts of agglomeration economies are information, own-industry, supply-side, and demand-side spillover effects between firms (McNamara, Lambert, and Garrett; Cohen and Paul). Other effects include reduced transportation costs of inter-firm trade, increased firm diversity, and product differentiation (Henderson). Agglomeration factors are hypothesized to have a positive influence on the location of new manufacturing at the county level. This is due to the agglomeration economies associated with a firm's locating in a community where there is relatively more manufacturing activity. There are typically two types of agglomeration economies: *urbanization economies* and *localization economies.* Urbanization economies are associated with size (i.e., population) or economic diversity (Viladecans-Marsal). Localization economies are associated with geographic specialization in specific activities and economies of scale arising from spatial concentration of activity within industries (Strange; Rosenthal and Strange).

Agglomeration economies represent the cost savings that accrue to firms locating operations in communities with relatively large concentrations of other firms (Richardson; Kriesel and McNamara; McNamara, Kriesel, and Deaton; Henry and Drabenstott; Rainey and McNamara). Businesses agglomerate to access external services at lower costs, gain access to a base of workers with specialized skills, and reduce costs of infrastructure provision (Richardson; Henderson and McNamara 1997). The concentration of activity in a particular area is expected to lead to a larger labor pool with skills needed by that industry (Rainey and McNamara).

Recent studies have used location quotients to measure agglomeration effects of localization economies (Gabe). Location quotients are a relative measure (e.g., a county's endowments of a particular attribute with respect to the state), whereas the percent employed in manufacturing is a measure of concentration with respect to workforce employment patterns (Smith and Florida). Location quotients in general, and for the manufacturing sector (*MLQ*) in particular, are commonly calculated as $MLQ_i = (E_i^{\text{Manufact}}/E_{\text{Manufact}}^{\text{Total}})/(E_i^{\text{Total}}/E_{\text{Indiana}})$, where E_i is employment in county i. Therefore, the *MLQ* is obtained by multiplying the share of employment in a given sector and county only by a constant. Without loss, agglomeration effects on the firm site selection decision due to localization economies were measured using the percent employed by the manufacturing sector (*MEMPL*). As used here, the percent employed in manufacturing in a given county measures the concentration of a particular economic sector in that given county, *inter alia* its competitive advantage with respect to workers employed by manufacturing in other counties. Agglomeration due to urbanization economies was measured using the 2000 total population per county (*POP*).[1]

Industry Structure (S)

Plant investment decisions are influenced by access to product markets because these markets are the source of final demand (Henderson and McNamara 1997). Market potential captures effective demand relative to supply of competing manufactured goods, and larger markets can be served by taking advantage of lower transportation costs. Firms choose to locate near product markets to reduce the cost and time of transporting final products, thereby enhancing competitiveness. Bartik (1989) and Woodward found that access to markets had a positive effect on manufacturing location at the state level. Median household income (in thousands of dollars, *MEDINC*) and county population (*POP*) were used to measure the effect access to product markets has on firm location choice.

Job losses (*JOBLOSS*) due to firm closures between 2000 and 2004 were used to control for local industry restructuring because they represent plant closings. In contrast to unemployment, a measure of persons without jobs actively seeking employment, *JOBLOSS* reflects the number of people who had been gainfully employed who are now seeking employment.

Labor Determinants (L)

Manufacturing productivity is dependent upon labor availability. A deep labor pool requires less recruiting and can provide a more diverse work force. A diversified, well-educated work force increases the likelihood of acquiring workers with the necessary skill sets to fill positions at all levels of manufacturing production. Plants in areas with small quantities of labor face more turnover and recruitment problems. It is hypothesized that a positive relationship exists between plant location and available labor.

Continued technological advances in the manufacturing sector coupled with economic globalization and rapidly evolving information technologies cast doubt on the viability of a low-wage manufacturing strategy for locations lacking quality education. Some newly adopted manufacturing technologies and management practices require more highly skilled production workers and larger professional and technical staffs. Low worker skill levels in a given location may decrease manufacturer competitiveness with respect to product quality and the ability to tailor production to individual customer needs. This "squeeze" scenario causes a shift away from manufacturing jobs in low-education rural areas (Wojan).

Labor quality also affects manufacturing productivity (McNamara, Kriesel, and Deaton). Higher quality workers are more productive, and increased productivity leads to higher output at lower costs, thus increasing plant profitability. It is hypothesized that in light of the increased demand for labor skill sets, the availability of high labor quality is expected to have a positive influence on manufacturing location.

Four variables were used to measure the effects of labor availability, labor quality, information technologies, and labor cost on manufacturing investment flows (Table 1). The manufacturing wage per worker in 2000 was used to capture the effect of labor costs on location choice (*MWAGE*, in thousands). The county-level unemployment rate in 2000 was used to proxy the available labor pool (*UNEMP*). The percent of individuals older than age 25 years with a high school diploma in each county was used to capture labor quality effects on manufacturing location (*EDUC*). To measure the effects of information technology on plant location choice, the percent of the labor force employed in the technology or professional sectors (i.e., "high-skilled" workers) in a given county was used (*EMP54*).

[1] Alternatively, the total workforce employed in the manufacturing sector could have been used to measure agglomeration effects due to localization economies. However, this measure is highly collinear with population, which was used to measure product market and agglomeration due to urbanization effects.

Table 1. Descriptive Statistics for Indiana Manufacturing, 2000–2004

	Variable	Description	Mean	Std. Dev	Median	Minimum	Maximum
Dependent variable	NEW0004[a]	New plant announcements (2000–2004)	2.16	2.68	1	0	13
Market structure (S)	JOBLOSS[a]	Number of jobs lost due to plant closings (2000–2004)	642	1433	73	0	8115
	MEDINC (000s)[b]	Median houshold income, 2000	41.99	6.47	41.06	32.45	76.48
Agglomeration, concentration (A)	POP (000s)[b]	Population, 2000	66.09	109.8	33.75	5.62	860.45
	MEMPL[c]	Percent of workforce employed in manufacturing, 2000	21.0%	10.0%	21.0%	1.0%	46.0%
Infrastructure (I)	INTER[d]	Presence of interstate (1 = yes, 0 = no)	59.0%	5.0%			
Labor (L)	UNEMP[c]	Unemployment rate, 2000	5.4%	1.5%	5.3%	2.6%	9.7%
	EDUC[c]	Percent of persons 25+ yr with a high school diploma, 2000	81.0%	5.0%	81.0%	60.0%	94.0%
	MWAGE (000s)[c]	Manufacturing wage, 2000	34.62	11.41	32.64	3.19	79.48
	EMP54[c]	Percent of labor force employed in skilled/technical profession, 2000	3.0%	1.0%	3.0%	0.0%	7.0%
Fiscal (F)	TAXRATE[c]	Net county tax rate, 2003	8.0%	2.0%	7.0%	6.0%	17.0%

Souce: [a] Indiana Chamber of Commerce. [b] U.S. Census Bureau. [c] Bureau of Labor Statistics. [d] ESRI. [c] Indiana Legislative Services Agency, Handbook of Taxes, Revenues, and Appropriations.

*Infrastructure Determinants (**I**)*

Counties of identical size may have different levels of productivity from agglomeration economies because of differences in the quality and size of their public infrastructure (Eberts and McMillen). Infrastructure consists of the physical components of an economy that support the surrounding community and business activities by creating access to regional, national, and international markets. Infrastructure includes transportation systems, land availability, and educational institutions. These attributes increase the attractiveness of a site and, thus, increase the likelihood of a firm's locating operations in a given county.

Infrastructure has been commonly researched in manufacturing location studies. Smith, Deaton, and Kelch; Woodward; and Rainey and McNamara looked at infrastructure effects at community and county levels, all finding it to be a significant and positive determinant. Bartik (1985, 1989); Glickman and Woodward; and Coughlin, Terza, and Arromdee found infrastructure effects on manufacturing location at the state level to be significant and positive. The presence of an interstate in a county (INTER) is used to measure infrastructure effects on firm location.

*Fiscal Determinants (**F**)*

Fiscal policy includes the tax policies and expenditure patterns of counties and states. Fiscal policy influences plant location by providing public service benefits and levying taxes to finance these benefits (Henderson and McNamara 1997). Higher state spending is a benefit, but manufacturers refrain from locating in states with high corporate taxes (Goetz). Fiscal policy expenditures directed to educational facilities, worker training, school systems, public services, and infrastructure developments can lower the costs of production and increase the prospect of plant profitability (Bartik 1989; Kriesel and McNamara; Smith, Deaton, and Kelch; Henderson and McNamara 1997). Bartik (1985, 1989) measured fiscal policy effects at the state level and found them to be negative and significant, while Kriesel and McNamara and Rainey and McNamara found fiscal policy factors at the county level to be significant and negative. The county-level net tax rate is used to capture fiscal effects (*TAXRATE*) (Table 1). The net tax rate is defined as the product of the gross county tax rate by 1 minus a state property tax replacement factor. The replacement factor determines how much the tax bill is lowered by fund transfers from the State of Indiana.[2] It is expected that this variable will have a negative effect on firm location choice.

Data Used in the Analysis

Indiana manufacturing plant announcement data were used to measure industry investment flow. County-level data for plant location announcements between 2000 and 2004 were obtained from the Indiana Chamber of Commerce (Table 1). During that time, there were 199 plant location announcements in 68% of the 92 counties. Explanatory variables were obtained from the Bureau of Labor Statistics, ESRI, the Census Bureau 2000 report, and the Indiana Legislative Services Agency (Table 1). The median number of jobs lost from 2000 to 2004 across all counties was 73, with a mean of 642 (1,433, standard deviation). The most jobs were lost (8,115) in Howard County (metropolitan area, Kokomo), a major automobile manufacturing location. The mean and median percent employed in manufacturing was 21. Noble County had the highest percent of the workforce employed in manufacturing (46%), while the percent employed in manufacturing was lowest in Ohio County (1%). Eighty-one percent of persons older than the age of 25 years had high school diplomas. The average manufacturing wage was \$34,600 year^{-1} (\$11,400), with the highest wage earnings observed in rural Vermillion County, home to a pharmaceutical manufacturing facility (\$74,000 year^{-1}). The lowest manufacturing wage rate (\$3,200 year^{-1}) was observed in Ohio County, where manufacturing employment is predominantly part time. Net

[2] For more details, see http://www.stats.indiana.edu/taxes_topic_page.html.

county tax rates were highest in Lagrange County (17%), while the average net tax rate was 8% (2%).

Empirical Model and Estimation

A linear model was specified to estimate the impact of product markets, agglomeration, labor determinants, infrastructure, and fiscal attributes on the establishment of new manufacturing firms in a county[3]:

$$(1)\quad NEW004_i = \beta_0 + \beta_1 JOBLOSS_i + \beta_2 POP_i + \beta_3 MEMPL_i + \beta_4 MEDINC_i + \beta_5 INTER_i + \beta_6 UNEMP_i + \beta_7 EDUC_i + \beta_8 MWAGE_i + \beta_9 EMP54_i + \beta_{10} TAXRATE_i + u_i$$

where *NEW0004* is the number of new manufacturing plant location announcements in county i between 2000 and 2004, and u is a disturbance term. The coefficients of Equation (1) were first estimated using ordinary least squares (OLS), then by a Poisson regression. The Poisson model is theoretically more appealing than OLS for two reasons. First, firm location decisions are discrete positive events (i.e., 0, 1, 2, . . .). Therefore, the usual distributional assumptions associated with OLS are not valid. Second, Guimarães, Figueiredo, and Woodward provide the theoretical underpinnings of how the Poisson specification of industrial site selection is linked to firm profit maximization and optimal strategies for site selection in particular and random utility models in general. Therefore, OLS is applied only as a reference. White's heteroskedastic-robust standard errors were used to test parameter significance of the OLS estimates, and variance inflation factors (VIF, SAS 2000) were estimated to assess multicollinearity. In the case of overdispersion in the Poisson model, the covariance matrix was scaled by the sum of squares of the Pearson's χ^2 residuals divided by the model degrees of freedom (Wooldridge, p. 549).

Geographically Weighted Regression

Location determinants are conditional upon geography because the firm site selection process occurs in a spatial context. There are numerous spatial econometric methods available for testing the significance of these linkages across space (Anselin, Florax, and Rey). A relatively new approach is GWR (Brundson, Fotheringham, and Charlton; Fotheringham, Brunson, and Charlton; LeSage 2004). GWR has been used to model real estate values in Ireland (Fotheringham, Brunson, and Charlton), convergence of agricultural productivity in Western Europe (Bivand and Brunstad), net primary productivity of forest ecosystems (Wang, Ni, and Tenhunen), election outcomes (LeSage 1999), and regional industrialization patterns in China (Huang and Leung). The purpose of GWR is to identify nonstationarity of regression coefficients across space. When Equation (1) is considered as a global model, it is assumed that the marginal effects apply universally across the region of interest. This may not be the case with spatial data. In some circumstances it may be reasonable to assume that the marginal effect of an explanatory variable is conditional upon localized, unobserved factors, such as local knowledge or policy, customs, and social networks. For example, the impact of education on firm site selection may be stronger in regions where unemployment is high in metropolitan areas, but

[3] The manufacturing sector is composed of many subsectors that are heterogeneous in terms of, for example, labor skill requirements, technologies, and transportation costs. But which subsectors the plants in this data set belong to cannot be determined. This poses potential model specification problems. For example, the effect of some of the explanatory variables used in the model might depend on the subsector in which the plant belongs (i.e., if the plant demands "high-skilled" or "low-skilled" workers). Given data limitations, this heterogeneity is difficult to completely model. However, we do include the percent of the workforce employed in the information technology sector (EMP54) in an attempt to control for differences in skill levels, as well as infrastructural determinants (i.e., interstate highways) to measure demand for lower transport costs. We also test whether job loss, the percent employed in manufacturing, manufacturing wage, and unemployment were exogenous. Although evidence that these variables are exogenous will not fix the problems with identification or omitted variables, it provides some modicum of confidence that the coefficients are consistent.

this relation may not hold in more rural locations.

Put another way, the measurement of an explanatory variable depends to some extent on where and when that measurement is taken. Measurement error may be attributed to sampling error or social contextual effects where persons respond differently to the same stimuli (for example, advertisements or news). Spatial nonstationarity in regression models may also be caused by omission of important information or model misspecification. These last two cases are often the cause of spatial error autocorrelation (Anselin). When effects are not constant over space, global models may not adequately explain local processes. In this sense, GWR may be useful with respect to identifying nonstationarity problems that might compromise inference drawn from global models. By testing how local parameters covary over space, insight may be gained as to which attributes might be the cause of spatial nonstationarity. Second, correlations between local GWR estimates across the region may be investigated, thereby adding another dimension to understanding which combinations of local attributes influence county competitiveness with respect to manufacturing investment.

The GWR method uses distance weighting functions to generate subsamples of spatially related observations. In this study, 92 data subsamples were generated for each county to produce county-specific estimates. An exponential decay function was used to assign weights (w_i) to each county ($i = 1, \ldots, 92$): $w_i = \exp(-\|\mathbf{s}\|_i/\alpha)$, where α is a bandwidth (or "range") parameter and $\|\mathbf{s}\|_i$ is a Euclidean distance vector between all other counties relative to county i. In the geostatistics literature, α determines the distance over which an observation (county) influences other observations over space (Cressie). In the GWR approach, the bandwidth parameter is determined using a nonparametric cross-validation procedure (Brundson, Fotheringham, and Charlton). A set of parameters is estimated for each county with the calculated bandwidth using the linear specification: $y_i = \beta_{i0}(w_i) + \Sigma_{l=1}^{k} \beta_{il}(w_i)x_{il} + u_i$, where y_i is the number of plant location announcements in county i during the study period, x_{il} ($l = 1, \ldots, k$) are observations of the kth explanatory variable, u_i are disturbance terms, and $\boldsymbol{\beta}(\mathbf{W}(i))$ is a vector of county-specific parameters conditional upon the decay function. The vector $\boldsymbol{\beta}(\mathbf{W}(i)) = (\mathbf{X}'\mathbf{W}(i)\mathbf{X})^{-1}\mathbf{X}'\mathbf{W}(i)\mathbf{y}$ solves for the $k \times 1$ estimates associated with county i, and $\mathbf{W}(i)$ is a $n \times n$ diagonal matrix of distance weights (w_i) for county i with respect to all other counties. The Matlab™ code for estimating GWR models is well documented and can be downloaded at www.spatial-econometrics.com (LeSage 2005). Iteratively re-weighted least squares (Maddala, p. 53) was used to sequentially estimate the 92 county-specific GWR Poisson regressions. Leung, Mei, and Zhang's F-test was used to test parameter stability over the study area. Rejection of one (or more) of the tests is sufficient evidence that one (or more) of the global parameters is nonstationary.

Spatial Generalized Linear Model

Counties compete for firm investment, and the success (failure) of one (or a group) of counties may spill over and positively (negatively) influence the competitiveness of another county. To model these potential effects at the global level, Equation (1) was re-estimated using a Poisson SGLM (Schabenberger and Pierce, pp. 684–692). The Poisson SGLM model is specified as $\mathbf{Y} = g^{-1}(\mathbf{x}\boldsymbol{\beta} + \mathbf{W}(\mathbf{s})) + \mathbf{u}$, $\mathbf{u} \sim (\mathbf{0}, \boldsymbol{\Sigma}(\boldsymbol{\mu}))$, with $\mathbf{Y}$ the vector of the number of new manufacturing plant location announcements in Indiana during the time interval, $\boldsymbol{\Sigma}$ a covariance matrix, and $g(\cdot)$ a log link function, with $g^{-1}(\mathbf{x}\boldsymbol{\beta}) = \boldsymbol{\mu}$. The expected value of $\mathbf{W}(\mathbf{s})$ is $\mathbf{0}$, and $\mathrm{Var}[\mathbf{W}(\mathbf{s}_i) - \mathbf{W}(\mathbf{s}_i + \mathbf{s}_j)]/2 = \gamma(\mathbf{s}, \boldsymbol{\theta})$. The vector $\mathbf{s}$ includes the Cartesian (x, y) coordinates for a given county, and γ is a semivariogram function explaining the strength of influence between observations across space (Cressie). The $\boldsymbol{\theta}$ parameters regulate the intensity and rate of spatial decay between counties. An exponential decay function is used to model the correlation between counties in the Poisson SGLM model: $\gamma(\mathbf{s}, \boldsymbol{\theta}) = \sigma^2_{\mathrm{Spatial}}\exp(-\|\mathbf{s}\|/\alpha)$, with $\boldsymbol{\theta} = [\sigma^2_{\mathrm{Spatial}}, \alpha]$. The kernels for the GWR and the SGLM are the

Table 2. Ordinary Least Squares (OLS), Poisson Maximum Likelihood, and Poisson Spatial GLM Regression Estimates (T statistics in Parentheses)

Variable	OLS Estimates[a]	Poisson ML Estimates	Spatial GLM Estimates
INT	−8.43 (−1.66)***	−6.173 (−2.09)**	−6.825 (−2.40)*
JOBLOSS[b]	0.0003 (1.30)	0.0001 (1.66)***	0.0001 (1.23)
POP	0.012 (3.03)*	0.003 (3.13)*	0.003 (3.34)*
MEMPL[b]	2.687 (1.04)	1.688 (1.32)	2.030 (1.64)
INTER	1.618 (2.55)*	0.865 (3.27)*	0.841 (3.40)*
UNEM[b]	39.040 (2.31)*	17.30 (2.02)**	18.791 (2.21)**
EDUC	10.955 (1.80)***	7.416 (2.12)**	8.124 (2.44)**
MWAGE[b]	−0.039 (−1.74)***	−0.015 (−1.13)	−0.015 (−1.23)
EMP54	−28.782 (−1.37)	−11.005 (−0.77)	−12.525 (−0.95)
TAXRATE	−11.177 (−0.77)	−5.256 (−0.57)	−4.627 (−0.55)
MEDINC	0.006 (0.10)	−0.001 (−0.06)	−0.004 (−0.18)
$\sigma^2_{spatial}$			0.33 (44.00)*
α			0.23 (0.79)
Pearson's χ^2 residuals		158.03	110.28
Adjusted R^2	0.34		
AIC[c]		429	

Source: Authors' estimates. *, **, ***, significant at the 1%, 5%, and 10% levels, respectively.
[a] T-tests based on White's (1980) heteroskedastic robust standard errors.
[b] The test that JOBLOSS, MWAGE, MEMPL, and UNEM were exogenous could not be rejected at the 10% level (χ^2 = 0.71, 0.38, 0.22, and 2.70, respectively. $\chi^2_{crit(10\%)}$ = 2.71).
[c] Corrected Akaike's information criterion.

same (i.e., exponential decay functions), but the SGLM kernel has a second parameter. At present, this second parameter cannot be estimated for the GWR approach using the cross-validation technique of Brundson, Fotheringham, and Charlton. The spatial covariance parameter $\sigma^2_{\text{Spatial}}$ and the influence range parameter α are interpreted as the magnitude of inter-county influences and the range (or intensity) these effects have across the geographic region, respectively (Dubin). The joint hypothesis, $\boldsymbol{\theta} = \mathbf{0}$, tests if spatial dependence between counties is significant. The Poisson SGLM model was estimated by quasi-maximum likelihood methods using a SAS™ macro provided by Schabenberger and Pierce.

Results and Discussion

Global OLS and Poisson Regression Results

The OLS-estimated model explained 34% of the variation in the data. The VIF values ranged between 1.34 and 2.20, suggesting that multicollinearity was not a serious problem. In general, the signs of the explanatory variables were consistent with the firm location literature (Table 2) Population, labor quality, labor availability, and infrastructure had a positive impact on the number of location announcements in a given county during the period. Manufacturing wage had a negative impact on the likelihood of a county's attracting manufacturing investment. The effect of skilled professionals on attracting manufacturing investment was not significant. The percent employed in manufacturing and local business restructuring effects were also not significant factors with respect to attracting manufacturing investment.

The global Poisson regression parameters[4] were similar in sign and magnitude to the OLS results (Table 2), but the importance of some

[4] The possibility that the percent employed in manufacturing, unemployment, manufacturing wage rates, and job loss were endogenous was tested using the method outlined by Wooldridge (p. 483). The null hypothesis that these variables were exogenous could not be rejected at the 10% level (Table 2).

explanatory variables changed. The likelihood ratio (LR) test that all coefficients were zero was rejected at the 1% level (LR = 30.65, df = 11). A regression-based test for overdispersion in the Poisson model (Greene, p. 884) was rejected at the 5% level (t-test = 3.37). Therefore, the Poisson covariance matrix was rescaled using the sum of squares of the Pearson χ^2 residuals normalized by the model degrees of freedom (Wooldridge, p. 459).

The effect of total job loss between 2000 and 2004 significantly influenced firm site selection at the 10% level in the global Poisson regression, indicating that in counties where workers were displaced by plant closures, there were attractive locations for firms seeking sites for new investment. Population also significantly increased the likelihood of a county's attracting manufacturing investment at the 5% level, indicating that counties with access to urbanization economies and product markets were more competitive.

Infrastructure is always a binding constraint with respect to firm location choice. County access to the interstate system positively increased county competitiveness with respect to attracting manufacturing investment.

Manufacturing wage had a negative, but insignificant impact on county competitiveness. Twenty-five years ago, wage levels may have been an important consideration with respect to firm cost minimization. Today, however, age levels may not be a binding constraint with respect to site location. In today's context, labor productivity has increased with advances in technology. Firms seeking low-skill labor may also be more inclined to look offshore.

Labor availability was also an important determinant with respect to firm location choice, indicating that a deep labor pool is a binding constraint with respect to manufacturing location decisions. Counties with higher unemployment rates are more likely to attract manufacturing investment.

Counties with a higher quality labor force had an increased likelihood of attracting manufacturing investment. Still, the percent of skilled professionals was not significant, failing to support the hypothesis that information technology service access influences manufacturing investment flows. Given the heightened importance of information technology in the manufacturing sector, further investigation of its influence on plant location seems warranted.

The parameter associated with county net tax rates was negative but not significant. This is not surprising because firms are likely to negotiate abatements with counties.

Industry concentration in manufacturing had no effects with respect to county competitiveness and firm location decisions. Apparently, other location determinants, such as access to product markets and urbanization economies, a deep, well-educated labor pool, and access to interstate highways, were given more weight in firms' location decision criterion during the study period.

Poisson GWR Results

The corrected Akaike's Information Criterion (Hurvich, Simonoff, and Tsai) for the Poisson GWR specification (346) was lower than the global specification (428). The sum of squares of the Pearson χ^2 residuals were 154 and 158 for the GWR and global Poisson models, respectively. According to these measures, the GWR produces a better fit than the nonspatial, global Poisson model.

The optimal bandwidth for the GWR model was 4.47 (Figure 2). At this intensity, the GWR bandwidth encompasses most counties in Indiana. Counties within an 89-km radius of one another were assigned connectivity weights of 0.80. Therefore, for any given county, attributes associated with its neighboring counties were given 80% more weight in the estimation of the effects of firm location determinants for that county's competitiveness in relation to surrounding counties. Conversely, counties farther away had less of an influence on parameters explaining firm location in that county. The squared Pearson correlation coefficient for the GWR actual and predicted values of firm location announcement was 0.35.

The structural stability of explanatory var-

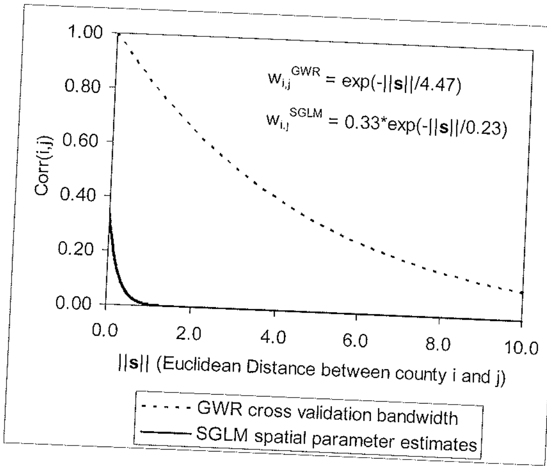

Figure 2. Estimated Inter-county Correlation
Source: Authors' estimates.

iables over space was tested using the GWR distance weights. Leung, Mei, and Zhang's *F*-test for parameter stability indicated that all location determinants were stationary at the 10% level, except for *JOBLOSS* ($F = 2.84$, numerator df $= 1$, denominator df $= 75$, $P = 0.096$). The spatial distribution of the marginal effects of business restructuring on manufacturing location decisions is represented in Figure 3. The marginal effects of jobs lost due to plant closings were lowest in the Northeastern portion of the state. This region has a traditionally strong manufacturing base producing plastics, automobiles, and recreational vehicles. The marginal effects decrease moving southwest. The southeastern portions of the state below Interstate 74 and inside the Interstate 64–65–70 triangle include counties where the manufacturing sector tends to be smaller relative to other counties in Indiana.

Correlating the county-specific marginal effects provides some insight into how the effect of location determinants covaries over space (Table 3). For example, the localized effects of the agglomeration/product market var-

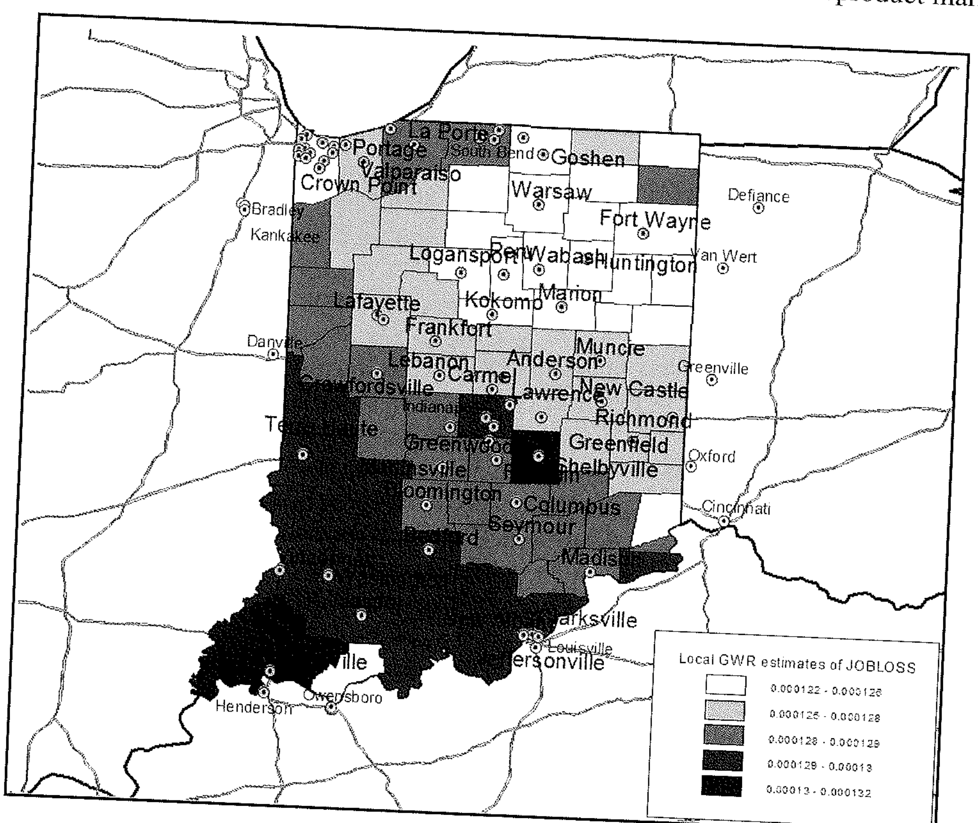

Figure 3. GWR County-specific Marginal Effects of Business Restructuring on Firm Manufacturing Investment Flow
Source: Authors' estimates.

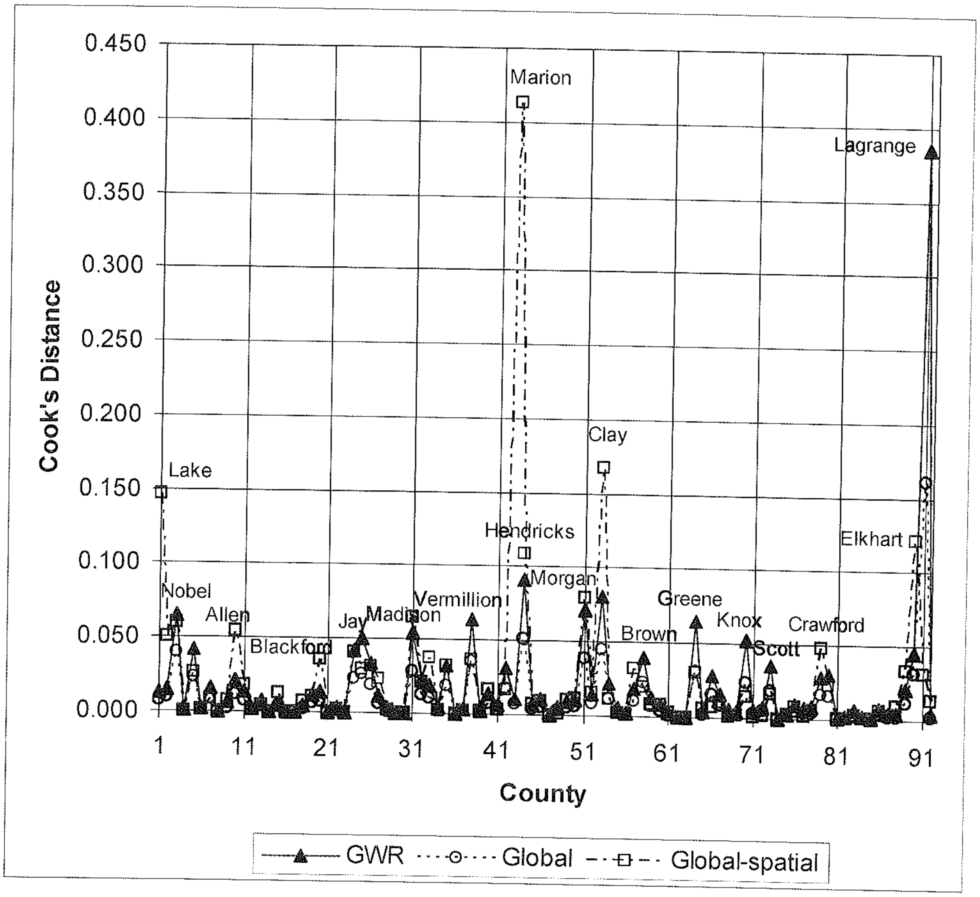

Figure 4. Cook's Distance Measure of County Influence on GWR, Global, and Spatial Global Model Estimates
Source: Authors' estimates.

through these counties, providing easy access to regional and national transportation infrastructure. Hendricks and Marion counties are part of the Indianapolis metropolitan area with related agglomeration and product market attributes. Allen County is home to several automotive and recreational vehicle manufacturers. This county also has a large diversified, nonmanufacturing sector.

Conclusions

About 27% of Indiana's gross state product comes from its manufacturing sector. After the 2000 recession, Indiana's manufacturing sector was forced to readjust. Manufacturing plants closed, jobs were lost, and the percent unemployed in the workforce grew. Four years of data regarding firm closures, start-up announcements, and county-level demographic and infrastructure attributes were available to estimate which county-level attributes contribute most to county competitiveness with respect to attracting new manufacturing investment. Spatial and nonspatial Poisson regressions were use to estimate the effects of location determinants. The most competitive counties are more likely to rebound more quickly with respect to new job creation and rejuvenated local economies.

Manufacturers tend to select plant locations in and around urban areas. Population, a measure of agglomeration due to urbanization economies and product markets, labor quality and availability, and transportation infrastructure are key location choice determinants.

These findings have policy implications for rural counties hoping to attract manufacturing investment. Counties with access to agglomeration economies, product markets, transportation networks, and a high-quality work force may be well positioned to use manufacturing recruitment as an economic development strategy. Counties not endowed with these attributes might consider alternative investment strategies. The prospects of attracting manufacturing investment depend on factors that may or may not be directly influenced by specific economic development strategies. Although proximity to urbanized areas or the presence of an interstate cannot be directly influenced, other factors can be adjusted. Community leaders might consider fostering environments that ensure a high-quality workforce. Policy makers might investigate public infrastructure financing and its relation to manufacturing activity. Local investors might reconsider plant investments in locations that lack attributes associated with manufacturing plant location.

Two relatively new spatial econometric approaches were used to model spatial dependency between counties and the manufacturing investment decisions of firms. Both methods accommodate count data. The GWR supplements global models by providing additional insight into how the effects of location determinants on manufacturing investment decisions vary over a region. Marginal effects of explanatory variables specific to a given county can be compared at a regional level. The GWR spatial analysis revealed patterns that identified the variability of the marginal effects of location determinants. The GWR approach is also useful for identifying which explanatory variables are spatially nonstationary. The SGLM approach is useful for modeling the influence of spatial effects at the global level. This regression technique provides an empirical mechanism whereby the magnitude and intensity of spatial dependence between counties can be tested. It is well known that inference about parameters drawn from GWR estimates is problematic because, by construction, the subsamples of observations drawn for each county are clearly no longer independent of one another (LeSage 2004). With this caveat in mind, the usefulness of the GWR approach is limited to exploratory diagnostics, revealing interesting relationships across space, and graphically portraying these relations. At present, the GWR approach supplements, but does not replace, conventional global regression models. On the other hand, the properties of the SGLM are better known. However, because the technique uses a quasi-maximum likelihood approach to estimate model parameters, the usual model selection criterion are not available. Despite these shortcomings, both methods provide means by which count data can be explained in a spatial econometric framework and applied to location studies.

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