Analysis of Factors Influencing U.S. Manufacturing Growth

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Abstract

Manufacturing is often seen as a potential source of growth for rural areas. This paper examines the influence that agglomeration, labor, input supply, infrastructure, and government fiscal attributes have on manufacturing investment flows in Indiana, USA, between 2000 and 2004. A Poisson regression was used to estimate the impact of location determinants at the county level. Because of the spatial nature of the data, a geographically weighted regression was used to test for parameter stability across space. Counties with access to product markets, relatively more available labor, a high quality workforce, and transport infrastructure were more likely to attract manufacturing investment.

Key Words: manufacturing site selection, location theory, spatial analysis, location determinants

JEL Classification: R1, R3

Introduction

The Indiana economy had a net loss of over 100,000 manufacturing jobs over the 2000-2004 period, or roughly 16 percent of the state's manufacturing employment (Bureau of Labor Statistics, 2004). The national economy has shown signs of recovery, but employment has yet to respond. The rate and distribution of employment growth as the economy continues to recover is a critical issue for state and local policy. Globalization, however, has seen low-tech manufacturers seek low-wage workers at off-shore sites while other U.S. manufacturing investment has sought locations that offer access to skilled labor, business services, markets, and the information highway.

Restructuring and recession have influenced Indiana economic performance over the past several years. While 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 has had 201 manufacturing closures from January 2000 though March 2004. Closings were distributed geographically across the state (Figure 1). Over the same period the Chamber identified 273 new manufacturing facilities that located in the state. These new investments were located in 71 of the state's 92 counties, primarily in urban and suburban areas, and in counties on major interstate highways. A key question or concern 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 useful for 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 and can be tested using spatial econometrics. When these spatial relations are appropriately modeled, more efficient and accurate estimates about which local factors influence firm location choice are obtained.

This analysis proceeds as follows. First, a conceptual model framing location theory is described. Next, the data used in the analysis is described, followed by a section outlining the empirics and estimation procedures used in the analysis. Because the data used in this analysis is count data, a Poisson regression model is used to estimate the marginal effects of location determinants on firm site selection. Because of the spatial attributes of the data, a regression technique relatively new to the spatial econometric literature – geographically weighted regression (GWR) – is described in the empirics section. The approach is applied to test the structural stability of the explanatory variables over space because data non-stationarities can compromise global results. Conclusions follow discussion of the results.

Conceptual Model

Plant location choice is a two-stage process (Woodward 1992, Bartik 1989, Henderson and McNamara 1997). In the first stage firms select the region for their investment based on broad company objectives such as raw materials access, entrance into product markets, increasing market share, or other criteria in firms' objective function. Firms seek a minimum cost site within a selected region for their investment in the second stage of plant location choice (Kriesel and McNamara 1991; Henderson and McNamara 1997). Firms evaluate potential sites on the basis of state, local, and site-specific attributes (Henderson and McNamara 1997). The second stage of the location decision is $\ell = g(\mathbf{A}, \mathbf{S}, \mathbf{L}, \mathbf{I}, \mathbf{F})$, where ℓ is the specific site choice and **A**, **S**, **L**, **I**, and **F** are county attributes representing market structure (**S**), agglomeration (**A**), labor (**L**), infrastructure (**I**) and fiscal (**F**) attributes that influence firm cost structure. The first and second stages of the location choice process are assumed to be independent of each other.

Market Structure (**S**) and Agglomeration (**A**)

Product Markets

Plant investment decisions are influenced by access to product markets because these markets are the source of final demand (Henderson and McNamara 1997). Firms enter product markets to distribute final products to minimize distribution costs. Firms choose to locate near product markets to reduce the cost and time of transporting final products thereby enhancing competitiveness (Wheat 1973). Bartik (1989) and Woodward (1992) that found access to markets had a positive effect on manufacturing location at the state level. Market potential captures effective demand relative to supply of competing manufactured goods. These larger markets can be served by taking advantage of lower transportation costs.

Agglomeration Economies

Agglomeration is the accumulation of business activity in and around a specific geographic area. 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 locating in a community where there is relatively more manufacturing activity. One by-product of agglomeration economies are information spillover effects between firms (McNamara et al., 2004). Other effects include reduced transportation costs of inter-firm trade, increased firm diversity, and product differentiation (Henderson, 1994). Businesses agglomerate to access external business services at lower costs, gain access to a base of workers with specialized skills, and reduce costs of infrastructure provision (Wheat 1973; Richardson 1969; Henderson and McNamara 1997). The concentration of activity in a particular area should lead to a larger labor pool with skills needed by that industry (Rainey and McNamara 1999). Agglomeration economies represent the cost savings that accrue to firms that locate in communities with relatively large concentrations of other firms (Richardson 1973; Kriesel and McNamara 1991; McNamara, Kriesel, and Rainey 1995; Henry and Drabenstott 1996; Rainey and McNamara 1999).

Spatial proximity of establishments in an industry may result in significant agglomeration economies for firms. One by-product of agglomeration economies are localization economies. Localization economies are externalities in a static context and result from the current scale of industry agglomeration. Henderson (1986) attributed static localization economies to: (i) Economies of intra-industry specialization where increased industry size permits greater specialization among industry firms in addition to a greater availability of specialized intermediate input suppliers, business services, and financial markets; (ii) Labor market economies resulting from a larger pool of trained, specialized workers and reduced search costs for firms looking for workers with specific skills; (iii) Scale networks of communication among firms to take advantage of complementarities, exploit new markets, integrate activities, and adopt new innovations; and (iv) Scale with respect to providing public goods and services tailored to the needs of a specific industry.

Median household income (in thousands of dollars, MEDINC) and county total population (POP, in thousands) are used to capture product market effects on firm location choice. Population is also used to proxy industry agglomeration effects. Job losses (JOBLOSS) due to firm closures between 2000 and 2004 are used to measure local restructuring since 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 dependant 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 a manufacturer's probability 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 (Wheat 1973). 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 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 2000).

Labor quality affects manufacturing productivity (McNamara, Kriesel, and Deaton 1988). Higher quality workers are more productive. Increased productivity leads to higher output at lower costs thus increasing plant profitability. It is hypothesized that in light of the new economy and increased demand for labor skill sets, high labor quality is expected to have a positive influence on manufacturing location.

Four variables were used to capture effects of labor availability, labor quality, information technologies, and labor cost (Table 1). The annual manufacturing wage per worker in 2000 was used to capture the impact of labor costs on location choice (MWAGE, in thousands), and the county-level unemployment rate in 2000 was used to proxy the available labor pool (UNEMP). The percent of individuals over the age of twenty-five with a high school diploma in each county was used to capture labor quality effects on manufacturing location (EDUC). To capture the effects of the impact of information technology on the new economy, the percent of the labor force employed in the technology or professional sectors in a given county was used (EMP54).

Infrastructure Determinants (**I**)

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 probability of a plant locating in a given county.

Infrastructure has been commonly researched in manufacturing location studies. Smith, Deaton, Kelch (1978), Woodward (1992), and Rainey and McNamara (1999) looked at infrastructure effects at the county and small community level all finding it to be a significant and positive determinant. Bartik (1985 and 1989), Glickman and Woodward (1988), and Coughlin, Terza, and Arromdee (1991) found infrastructure effects on manufacturing location at the state level to be significant and positive. Goetz (1997) found infrastructure to be a significant and negative determinant at the county level. Henderson and McNamara (2000) found infrastructure at the county level to be a positive and significant factor affecting food processing plant location. The presence of an interstate in a county (INTER) is used to capture infrastructure effects on firm location.

Fiscal Determinants (**F**)

Fiscal policy includes the tax policies and expenditure patterns of state and local areas. Fiscal policy influences plant locations 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 1997). 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 1991, Smith, Deaton and Kelch 1978, and Henderson and McNamara 1997). Bartik (1985 and 1989) measured fiscal policy affects at the state level finding them to be negative and significant. Kriesel and McNamara (1991) and Rainey and McNamara (1999) found fiscal policy factors at the county level to be significant and negative. Coughlin, Terza and Arromdee (1991) and Woodward (1992) assessed fiscal policy factors at the state level for foreign direct investment. Both of these studies also found fiscal policy to be a negative and significant determinant of plant location. The county-level net tax rate is used to capture fiscal effects (TAXRATE) (Table 1). It is expected that this variable will have a negative affect on firm location choice.

Data Used in the Analysis

Indiana manufacturing plant announcement data were used to measure industry investment. County-level data for Indiana plant locations over the 2000-2004 period were obtained from the Indiana Chamber of Commerce (Table 1). Indiana had 199 new plant locations over the four year period with plants locating 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 2000-2004 across all counties was 73, with a mean of 642 (1433, standard deviation). The most jobs were lost (8115) in Howard County (metropolitan area, Kokomo), a major automobile manufacturing location. The mean and median percent employed in manufacturing was 21% (10%). Noble County had the highest percent employed in manufacturing (46%), while only 1% of the population in Ohio County was employed in the manufacturing sector. Eighty-one percent of persons over the age of 25 held a high school diploma. The average manufacturing wage was $34,600/year ($11,400), with the highest wage earnings observed in rural Vermillion County, home to a pharmaceutical manufacturing facility ($74,000/year). The lowest manufacturing wage rate ($3,200/year) was observed in Ohio County, where manufacturing employment is predominantly part-time. Net county tax rates were highest in Lagrange County (17%), while the average tax rate was 8% (2%).

Empirical Model and Estimation Techniques

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:

(1) $NEW0004_i = \beta_0 + \beta_1 JOBLOSS_i + \beta_2 POP_i + \beta_3 MEMPL_i + \beta_4 MEDINC_i + \beta_5 INTER_i + \beta_6 UNEMP_i + \beta_7 EDUC_i + \beta_8 MWAGE_i + \beta_9 EMP54_i + \beta_{10} TAXRATE_i + u_i$

where NEW0004 is the number of new manufacturing plants established in county *i* between 2000 and 2004 and *u* is a random 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 appropriate than OLS because firm location decisions are strictly positive, discrete events. But in general OLS and Poisson estimates should be similar, and OLS is only applied 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 used to determine the strength of the relations between the explanatory variables. A VIF value of 1 indicates that the variable in question is orthogonal to the other variables (that is, no collinearity). In the case of overdispersion of the Poisson model the covariance matrix was scaled by Pearson's Chi-squared residuals divided by the model degrees of freedom (SAS, 2000).

Spatial Analysis Using Geographically Weighted Regression

Tobler's (1970) proposition that everything is related to everything else in geography, but that near things are more related than distant things, is relevant to location studies. Location determinants are conditional upon geography, and the firm site-selection process occurs in a spatial context. Counties compete for firm investment, and the success of one (or a group) of counties may spill over and positively (or negatively) influence the competitiveness of another county. There are a myriad of spatial econometric tools available to model spatial linkages and numerous methods useful for testing the significance of these connections (see Anselin et al., 2004 for a recent review of these techniques). One relatively new approach is geographically weighted regression (GWR) (Brundson et al., 1996; Fotheringham et al., 2002). GWR has been used to model real estate values in Ireland (Fotheringham et al., 2002), convergence in Western Europe (Bivand and Brunstad, 2002), and regional industrialization patterns in China (Huang and Leung, 2002). The purpose of GWR is to identify spatial non-stationarity of regression coefficients across space. When equation 1 is considered as a global model it is assumed that the marginal effects are universal across the region. With spatial data this may not be the case, and in some circumstances it may be reasonable to assume that the marginal effects of an explanatory variable are conditional upon localized, unobserved factors such as local knowledge or policy, customs, or social networks. For example, the impact of education on firm site selection may be stronger in regions where unemployment is high, but this relation may not hold in more rural locations.

Put another way, the measurement of an explanatory variable depends to some extent where and when that measurement is taken. Measurement error may be attributed to sampling error or social context effects where persons respond differently to the same stimuli (for example, political advertisements or news). Spatial non-stationarity in regression models may also be caused by omission of important information or model misspecification. These last two cases oftentimes cause spatial error autocorrelation (Anselin, 1988). When processes are not constant over space global models may not adequately explain local processes. In this sense GWR is useful with respect to diagnosing non-stationarity problems that may compromise inference drawn from global models. By testing how these local parameters covary over space, insight is gained as to which attributes might be the cause of spatial non-stationarity.

The GWR method uses distance weighting functions to generate sub-samples of spatially connected observations. These sub-samples are the data used to produce regression estimates at every location. In this analysis, an exponential spatial decay function is used to assign weights (w_i) to counties as $w_i = \exp\left(-\|d_i\|/\theta\right)$, where θ is a bandwidth parameter and $\|d_i\|$ is the Euclidean distance vector between all other counties. The exponential function was used because the Akaike information criterion for Gaussian decay functions and tri-cube weighing scheme (LeSage, 1999) were larger than the AIC produced using the exponential specification. In the geostatistics literature, θ determines how far any particular observation influences other observations over space (Cressie, 1993). The bandwidth parameter is estimated using a non-parametric cross-validation procedure (Brundson et al., 1996). A set of local parameters is estimated for each observation using the bandwidth using the linear specification: $y_i = \beta_{i0}(w_i) + \sum_{l=1}^{k} \beta_{il}(w_i) x_{il} + u_i$ where y_i, $i = 1,\ldots,n$ are the dependent variables, x_{il}, $l = 1,\ldots,k$ are observations of the kth explanatory variable, u_i are disturbance terms, and $\mathbf{\beta}(\mathbf{W}(i))$ is a vector of location-specific parameters conditional upon the decay function. Note that $\mathbf{\beta}(\mathbf{W}(i)) = (\mathbf{X}'\mathbf{W}(i)\mathbf{X})^{-1}\mathbf{X}'\mathbf{W}(i)\mathbf{y}$ solves for the k x 1 vector of estimates associated with county i and that $\mathbf{W}(i)$ is a n x 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, 2003). Maximum likelihood (ML) was used to estimate location-specific Poisson likelihood functions in the GWR specification.

Results and Discussion

Global Poisson Regression

As a starting point of comparison, 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). Although the R^2 was modest, population, labor quality (EDUC) and labor availability (UNEM), and infrastructure (INTER) had a positive impact on the number of firms that located in a given county during the period sampled. Manufacturing wage (MWAGE) had a negative impact on the likelihood of a county attracting manufacturing investment. The impact of skilled professionals (EMP54) on attracting manufacturing investment was not significant, and job loss was also not a significant factor with respect to attracting investment.

The global Poisson regression parameters were similar in sign and magnitude to the OLS results (Table 2), but the importance of some 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, 2000, page 884, T-test = 3.37) was rejected at the 5% level. Therefore, the

Poisson covariance matrix was rescaled using Pearson's chi-square statistic divided by the model degrees of freedom (Wooldridge, 2000).

The impact of total job loss between 2000 and 2004 significantly influenced firm site-selection at the 10% level in the Poisson regression, indicating plant closings that displace workers are attractive sites for firms seeking sites for new investment. Population also significantly increased the likelihood of a county attracting manufacturing investment at the 5% level indicating that counties with access to agglomeration economies and product markets are more competitive with respect to attracting manufacturing investment.

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. Likewise, counties with more educated individuals influenced the likelihood of attracting manufacturing investment.

Manufacturing wage had a negative, but not a significant impact on county competitiveness. Twenty-five years ago wage levels may have been an important consideration with respect to firm cost minimization, but today wage levels are not a binding constraint with respect to site location. In today's context labor productivity has increased with the widespread use of information technologies. Firms seeking low-skill labor are more inclined to look offshore.

Labor availability (UNEM) was also an important determinant with respect to location choice indicating that firms seek locations with available labor. During the late 1990s the lack of available labor throughout Indiana, especially in rural areas, created staffing problems for firms. 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. The percent of skilled professionals (EMP54) 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 the influence that information technology has on plant location seems warranted.

Comparison of the GWR and Global Results

The corrected Akaike's Information Criterion (AICc, Hurvich et al., 1998) for the GWR specification (346, with a log likelihood score of 5.29) was lower than the global specification (428). The optimal bandwidth for the GWR model was 4.47 (Figure 2). At this magnitude counties within a 55 mile radius of one another are assigned connectivity weights of 0.80 (Figure 1, 2). In the context of GWR this means that for any given county attributes associated with its neighboring counties will be given more weight in the estimation of the impact of firm location determinants for that county's competitiveness. Conversely, counties farther away have less of an influence on parameters explaining firm location in that county.

The distance weights network provides a context wherein hypotheses about the structural stability of explanatory variables over space can be tested. Leung et al.'s (2002) F-test for parameter stability indicated that the location determinants were stationary at the 5% level (Table 3), signifying that the explanatory variables are globally fixed and that the usual effects of spatial dependence do not compromise the global Poisson ML estimates. In sum, the explanatory power of both regression techniques is comparable, with slight improvement with the GWR model according to the AIC criterion. These results are consistent with the similarity observed between the influence measures (Figure 3).

Cook's distance (Cook's D) statistics for each county estimated with the global and GWR residuals are presented in figure 3. Cook's D measures the change to the estimates that results from deleting each observation and is estimated as $D_i = r_i^2 h_{ii} \big/ k\sqrt{1 - h_{ii}}$, with k the number of parameters, r_i the studentized residual of the ith observation, and h_{ii} the leading diagonal of the hat matrix, $\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'$ (Fotheringham et al., 2002). In general, the GWR influence measures were larger than the global influence measure 73% of the time, but GWR residuals were less than the global residuals 65% of the time. This effect is mainly attributed to the difference in the elements of the GWR and global hat diagonals. Every element of the GWR hat diagonal was larger than the global elements. This reflects the impact of including distance information into the design matrix. When GWR influence statistics were smaller than the global statistic, the residual value of the global model was smaller than that of the GWR model, and the difference between the hat matrix diagonals was negligible. When the global residual was larger than the GWR residual and the difference between the hat matrix diagonals was small, the GWR influence statistic was larger than the global influence statistic. Because the F-test for structural stability was not rejected, the observed differences between the influence statistics are negligible. However, these measures are still useful for understanding inter-county competitiveness with respect to attracting manufacturing investment.

Competitive counties are apparent along the northern part of Indiana, particularly around the Chicago metropolitan area (Lake, Porter, La Porte, Allen, and De Kalb). Elkhart, St. Joseph, and La Porte counties are located around the South Bend area, adjacent to the Chicago metropolitan area. Two obvious observations include Clay and Allen counties. Allen County is home to several automotive and recreational vehicle manufacturers. The county also has a diversified large, non-manufacturing sector. Clay County is adjacent to Vigo County, where Terre Haute (a large metropolitan area) is located. Additionally, interstate 70 (I-70) passes through these counties providing easy access to regional and national transportation infrastructure. Hendricks, Marion, and Shelby are all part of the Indianapolis metropolitan area with related agglomeration and market attributes.

Correlating the county-level marginal effects of location determinants provides insight into how the impact of location determinants covaries over space (Table 5). For example, the localized effects of the agglomeration/product market variable POP and the structural variable JOBLOSS were negatively and significantly correlated (r = -0.54, P < 0.0001). Therefore, in counties where the marginal impact of population increased county competitiveness, the marginal effect of job loss was less. The localized marginal effects of population and labor availability (UNEM) were also significantly and negatively correlated, suggesting that counties with large populations are generally not constrained by labor availability related to attracting outside manufacturing investment. Additionally, in counties where the competitive edge is attributable to labor quality, the marginal contribution of the percent employed in manufacturing was less

The GWR predicted values of manufacturing location choice are mapped in figure 1. In general the GWR location estimates correlated well with the actual data (Pearson's $r = 0.59$). Firm location frequency was slightly underestimated along the I-80 corridor and the counties surrounding the Fort Wayne area, and the counties surrounding the Indianapolis metropolitan area. Frequency of firm location between Indianapolis-Chicago I-65 and Indianapolis-Cincinnati I-74 corridor was slightly overestimated.

Conclusions

This paper estimated the impact of location determinants on plant site selection in Indiana. Indiana is the leading manufacturing state in the U.S., where manufacturing contributes roughly 27% of the state gross state product. Following the 2000 recession Indiana's manufacturing sector was forced to readjust. Jobs were lost, manufacturing plants closed, and the percent unemployed in the workforce grew. Four years of data including firm closures and start-up announcements and county-level demographic attributes were available to estimate which county-level attributes contribute most to county competitiveness with respect to attracting manufacturing investment. 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 the general agglomeration of activity in a locality, labor quality and availability, and transportation infrastructure are the key location choice determinants. Job loss caused by plant closures also increased county competitiveness with respect to attracting manufacturing investment.

Spatial analysis using GWR indicated that variables explaining plant location choice were stationary. This implies that inference of the global regression model hold across all spatial units. However, the spatial analysis did reveal patterns that identified the variability of the marginal effects of location determinants. For example, in counties where labor quality was important with respect to increasing competitiveness, population and the percent of share employed in manufacturing had less of an impact. This has important policy implications for more remote, rural counties hoping to attract firm investment.

In this analysis the impact of county proximity with respect to explaining manufacturing location choice was negligible, perhaps because of the relatively small sample size used in the analysis. Because non-stationarity was not an issue, more confidence is gained with respect to generalizations about firm manufacturing location based on the global Poisson regression estimates. Influence diagnostics signal competitive counties. Analysis of these measure indicate that counties endowed with product market attributes, agglomeration economies, and infrastructure, labor availability, and educated persons have impact the results of the global and local models more than counties lacking these attributes. Although the size of the influence statistic changes in some cases after including distance information in the regression model, the qualitative results are not different compared to the global model. If spatial relations mattered more, then the frequency of differences between the local and global influence diagnostics would be anticipated.

Table 1. Descriptive statistics for Indiana manufacturing, 2000-2004.

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

Source: † US Census Bureau; ‡ Bureau of Labor Statistics; ¶ ESRI; #Indiana Legislative Services Agency, Handbook of Taxes, Revenues and Appropriations; ** Indiana Chamber of Commerce.

Table 2. Ordinary least squares (OLS) and Poisson regression estimates (T statistics in parentheses).

Dependent Variable	*OLS*		*Poisson‡*	
NEW0004 (n = 92)				
Variable	Estimate+		Estimate	
INT	-8.430	***	-6.173	**
	(-1.66)		(-2.09)	
JOBLOSS	0.0003		0.0001	***
	(1.30)		(1.66)	
POP	0.012	*	0.003	*
	(3.03)		(3.13)	
MEMPL	2.687		1.688	
	(1.04)		(1.32)	
INTER	1.618	*	0.865	*
	(2.55)		(3.27)	
UNEM	39.0	*	17.3	**
	(2.31)		(2.02)	
EDUC	10.955	***	7.416	**
	(1.80)		(2.12)	
MWAGE	-0.039	***	-0.015	
	(-1.74)		(-1.13)	
EMP54	-28.782		-11.005	
	(-1.37)		(-0.77)	
TAXRATE	-11.177		-5.256	
	(-0.77)		(-0.57)	
MEDINC	0.006		-0.001	
	(0.10)		(-0.06)	
Scale parameter			1.951	
Adjusted R^2	0.34			
Log Likelihood			3.22	

+T-tests based on White's (1980) heteroskedastic robust standard errors.

*, **, ***, significant at the 1%, 5%, and 10% levels.

‡The marginal effects of the independent variables on the likelihood of a firm locating in a given county are estimates as $\beta_i \exp(\mathbf{x\beta})$. Estimated at the means of the explanatory variables, the mean value is $\exp(\bar{\mathbf{x}}\boldsymbol{\beta})$ = 1.77. The marginal effects of the explanatory variables are calculated multiplying the estimates by this factor.

Table 3. Quartiles of GWR estimates and F-test results for non-stationarity of explanatory variables.

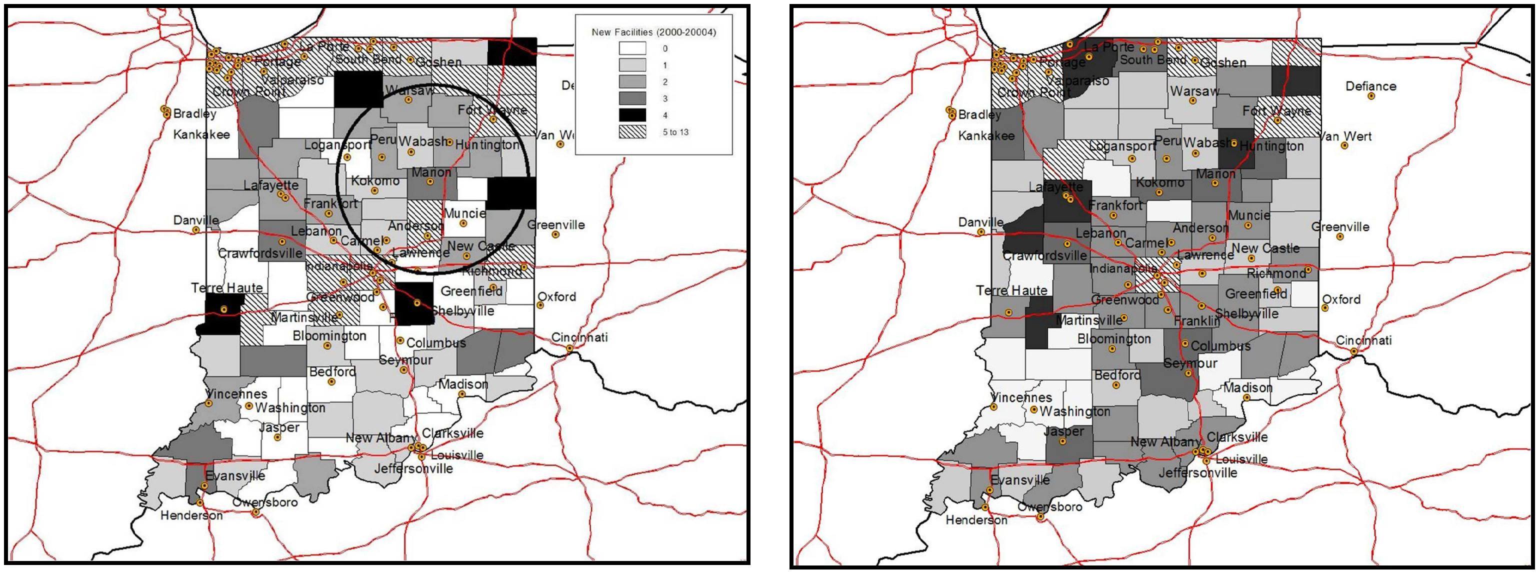
Variable	*25th Pctl*	*50th Pctl*	*75th Pctl*	*F-test*	*P-value*
JOBLOSS	1.2675E-04	1.2881E-04	1.2958E-04	3.03	0.09
POP	2.5422E-03	2.5655E-03	2.5865E-03	1.44	0.23
MEMPL	1.6111	1.6879	1.7899	0.43	0.51
INTER	0.8914	0.9091	0.9282	0.79	0.38
UNEM	17.7855	18.4750	18.9940	0.18	0.67
EDUC	7.5320	7.7230	7.9138	0.17	0.68
MWAGE	-0.0157	-0.0154	-0.0150	0.30	0.59
EMP54	-11.9720	-11.7790	-11.6665	0.03	0.86
TAXRATE	-5.7843	-5.4590	-5.2225	0.06	0.81
MEDINC	-0.0017	-0.0007	0.0003	0.10	0.75

Table 4. Pearson's correlation of the location determinants. (Probability values are in parentheses.)

	JOBLOS	POP	MEMPL	INTER	UNEM	EDUC	MWAGE	EMP54	TAXRATE
POP	0.55								
	(<.0001)								
MEMPL	0.09	-0.16							
	(0.4033)	(0.1341)							
INTER	0.10	0.28	0.06						
	(0.3481)	(0.0067)	(0.5723)						
UNEM	-0.04	-0.08	0.14	-0.34					
	(0.7045)	(0.4222)	(0.1749)	(0.0009)					
EDUC	0.22	0.19	-0.17	0.20	-0.43				
	(0.0383)	(0.067)	(0.1059)	(0.0566)	(<.0001)				
MWAGE	0.47	0.41	0.10	0.39	-0.09	0.29			
	(<.0001)	(<.0001)	(0.3228)	(0.0001)	(0.378)	(0.0057)			
EMP54	0.15	0.37	-0.31	0.32	-0.35	0.54	0.24		
	(0.1403)	(0.0003)	(0.0023)	(0.0019)	(0.0005)	(<.0001)	(0.0198)		
TAXRATE	0.10	0.19	0.05	0.11	0.07	-0.36	0.17	-0.13	
	(0.3338)	(0.0771)	(0.6271)	(0.2937)	(0.5129)	(0.0004)	(0.1071)	(0.2217)	
MEDINC	0.09	0.14	0.02	0.34	-0.48	0.57	0.22	0.57	-0.18
	(0.4201)	(0.1808)	(0.8652)	(0.0009)	(<.0001)	(<.0001)	(0.0394)	(<.0001)	(0.081)

Table 5. Pearson's correlations between local marginal effects estimated with GWR. (Probabilities are in parentheses.)

	JOBLOS	POP	MEMPL	INTER	UNEM	EDUC	MWAGE	EMP54	TAXRATE
POP	-0.54								
	(<.0001)								
MEMPL	-0.93	0.74							
	(<.0001)	(<.0001)							
INTER	0.92	-0.44	-0.88						
	(<.0001)	(<.0001)	(<.0001)						
UNEM	0.89	-0.58	-0.88	0.96					
	(<.0001)	(<.0001)	(<.0001)	(<.0001)					
EDUC	0.89	-0.32	-0.84	0.98	0.90				
	(<.0001)	(0.0016)	(<.0001)	(<.0001)	(<.0001)				
MWAGE	-0.80	0.28	0.77	-0.69	-0.54	-0.77			
	(<.0001)	(0.0073)	(<.0001)	(<.0001)	(<.0001)	(<.0001)			
EMP54	-0.39	0.29	0.40	-0.08	0.00	-0.12	0.65		
	(0.0001)	(0.0045)	(<.0001)	(0.4308)	(0.9901)	(0.2681)	(<.0001)		
TAXRATE	0.50	-0.17	-0.50	0.30	0.13	0.41	-0.87	-0.78	
	(<.0001)	(0.1103)	(<.0001)	(0.0032)	(0.2165)	(<.0001)	(<.0001)	(<.0001)	
MEDINC	-0.74	0.35	0.72	-0.93	-0.92	-0.91	0.45	-0.26	-0.04
	(<.0001)	(0.0006)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.013)	(0.6902)



Actual firm location announcements

GWR predicted values

Figure 1. New manufacturing facilities established in Indiana, 2000-2004, and GWR-Poisson predicted firm locations. The 55-mile radius of the circle corresponds with an inter-county spatial weighting of 0.80 (see Figure 2).

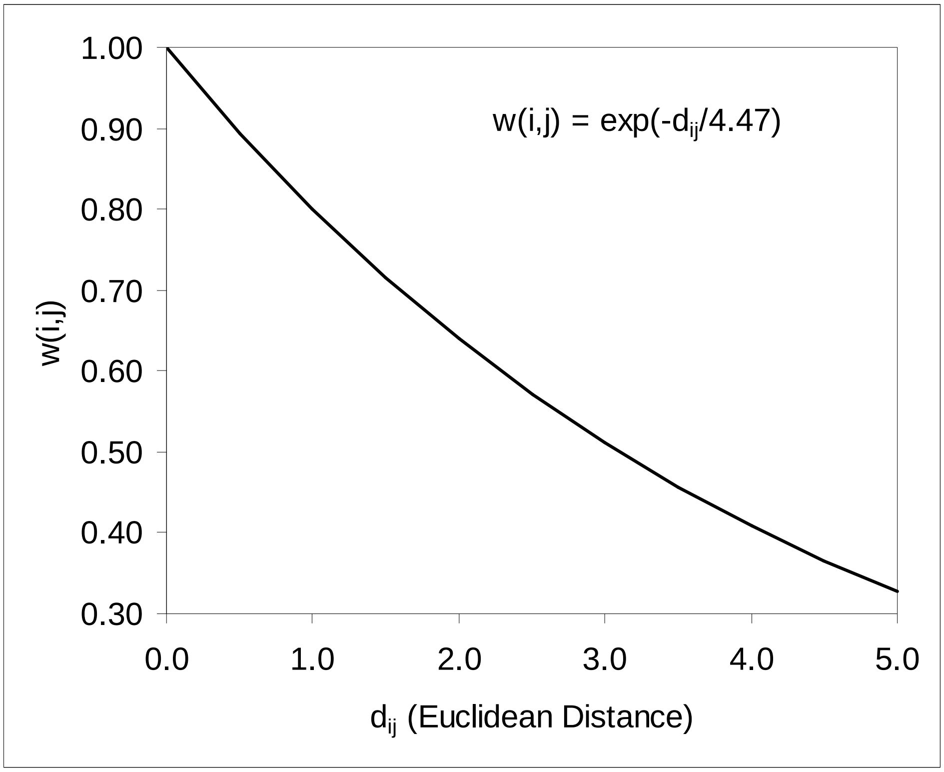


Figure 2. Exponential decay of spatial weights used in the geographically weighted regression. The distance of 1 is approximately 55 miles while 5 is 250 miles.

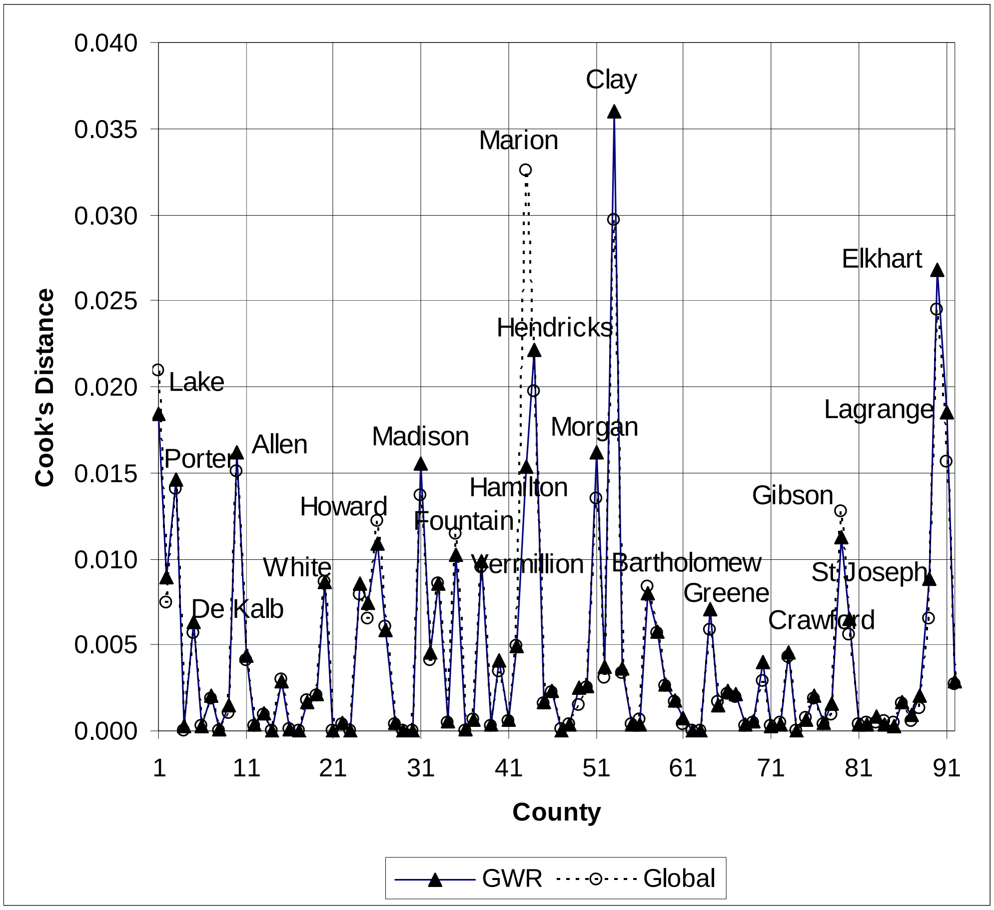


Figure 3. Cook's distance measure of county influence on GWR and global model estimates.

Acknowledgements

The views and opinions expressed in this manuscript to not necessarily reflect those of the United States Department of Agriculture, or the Economic Research Service. The usual caveats apply.

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