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Clustering of Auto Supplier Plants in the U.S.: GMM Spatial Logit for Large Samples

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Abstract

A linearized version of Pinkse and Slade's (1998) spatial probit estimator is used to account for the tendency of auto supplier plants to cluster together. By reducing estimation to two steps – standard probit or logit followed by two-stage least squares – linearization produces a model that can be estimated using large datasets. Our results imply significant clustering among older plants. Supplier plants are more likely to be in counties that are near assembly plants, that include interstate highways, and that are near other counties with supplier plants. New plants show no additional tendency toward clustering beyond that shown by older plants.

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1. Introduction

North American auto supplier plants have been remarkably concentrated for a long time (Klier 2004). However, since the mid-1970s the spatial configuration of the industry has been changing (Rubenstein 1992). Whereas the industry was concentrated in a corridor running from Chicago to New York, it now has a north-south orientation. The industry continues to be very spatially concentrated (Ellison and Glaeser 1997). Using county level data, Woodward (1992) and Smith and Florida (1994) find evidence that vertical linkages as well as the presence of highway infrastructure influence plant location decision of Japanese plants in the United States.

In this paper, we model the location decisions of auto supplier plants using probit models that take explicit account of the tendency for auto plants to cluster together. Despite the rapid change in the geographic configuration of the industry, we show that three salient features remain the same. First, Detroit remains the hub of the auto corridor, which now extends southward to Kentucky and Tennessee with fingers reaching into Mexico and Canada. Second, both supplier plants and assembly plants tend to cluster together. Third, plant locations seldom stray far from the network of highways running toward Detroit.

Spatial data increase the complexity of models of plant location decisions. We use a logit model and county-level data: what is the probability that a plant is located in a county given the locations of other plants and the characteristics of the county? Spatial data typically exhibit both autocorrelation and heteroskedasticity. Autocorrelation makes standard logit (or probit) estimates inefficient, and heteroskedasticity leads to inconsistent estimates. Several estimators have been proposed that are capable of producing consistent estimates when data are spatially autocorrelated and heteroskedastic – Case (1992), LeSage (2000), McMillen (1992), and Pinkse and Slade (1998). However, these estimators become infeasible for large samples because they require the inversion of nxn matrices, where n is the sample size. One objective of our paper is to propose a computationally feasible estimator for spatial discrete-choice models.

Our estimator is a linearized version of the generalized methods of moments (GMM) estimator proposed by Pinkse and Slade (1998). Linearization allows the model to be estimated in two steps. The first step is a standard probit or logit model, in which spatial autocorrelation and heteroskedasticity are ignored. The second step involves two-stage least squares estimates of the linearized model. The benefit of linearization is that no matrix needs to be inverted and estimation requires only standard probit/logit models and linear two-stage least squares. Thus, the model can be estimated even with very large sample sizes.

Our estimator extends the literature on spatial modeling by allowing a model with a spatially weighted dependent variable to be estimated in a discrete choice framework. For the case of continuous dependent variables, examples of this sort of model include Bordignon, Cerniglia, and Revelli (2003); Brett and Pinkse (2000); Brueckner (1998); Brueckner and Saavedra (2001); Case, Rosen, and Hines (1993); Fredriksson and Millimet (2002); Revelli (2003); and Saavedra (2000). The general model is written $Y = \rho WY + X\beta + u$, where Y is the dependent variable, W is the "contiguity matrix", X is a matrix of explanatory variables, u is an error term, and ρ and β are parameters whose values are to be estimated. Spatial effects are present if ρ is not equal to zero: values of Y are influenced by neighboring values of Y, where "neighbor" is defined implicitly by the pre-specified entries of the contiguity matrix. For example, Brueckner (1998) finds that California municipalities are more apt to have restrictive growth control measures if nearby municipalities are also highly restrictive. Current estimators for this class of spatial models are only suitable for models with continuous dependent variables. We extend these estimators to the case where the dependent variable of interest is discrete. Continuing with the example of growth controls, we re-interpret Y as the underlying latent variable showing the strength of the tendency to adopt growth controls, which then is translated into a discrete variable showing whether the municipality has measures to control growth.

We use the spatial probit model to analyze location decisions of both old (pre-1991) and new (1991-2003) auto supplier plants in the U.S. To capture the notion of clustering, we assume that the propensity to locate a plant in a given county depends on the propensity to locate plants in contiguous counties. Additional explanatory variables include characteristics of the county such as the presence of an interstate highway, distance from Detroit, population density, and crime rates. We also include as explanatory variables a count of the number of auto assembly plants located within 450 miles of the center of the county and the distance from there to the nearest assembly plant. Our results imply a strong tendency toward clustering among older plants. Supplier plants that were opened prior to1991 are far more likely to locate near other supplier plants and near interstate highways. They also are more likely to locate near counties with assembly plants. New plants also tend to cluster together. However, the focus of the industry has shifted southward. Once we control for proximity to existing plants, new plants show no additional tendency toward concentration. The auto region has shifted from an east-west to a north-south extension. It remains highly concentrated, and Detroit continues to be its hub. Supplier plants cluster near assembly plants and amongst each other.

2. Spatial Discrete Choice Models

The spatial model is written in matrix notation as

$$Y = \rho WY + X\beta + \varepsilon \tag{1}$$

The *n*x*n* matrix *W* is the "weight matrix." In the typical specification, $W_{ii} = 0$ and $\sum_{ji=1}^{n} W_{ij} = 1$ for $j \neq i$. This specification implies that each value of the dependent variable is a function of a group of explanatory variables, *X*, and a weighted average the values of the dependent variable for nearby observations. Counties are the unit of observation in our application. We follow common practice and impose that $W_{ij} = 1/n_i$ for all counties that are contiguous to county *i*, where n_i is the number of observations that are contiguous to county *i*. Under this specification, *W* is sometimes referred to as the "contiguity matrix." The coefficient ρ captures the spatial interaction effect. If $\rho > 0$, then high values of Y for nearby observations increase the value for observation *i*. In our formulation, $\rho > 0$ implies clustering: the probability of having an auto supplier plant in a county increases if there are plants in neighboring counties. In contrast, $\rho < 0$ implies dispersion as the probability decreases when there are plants in neighboring counties.

When the dependent variable is continuous, equation (1) is usually estimated by maximum likelihood methods. Under the assumption of normally and identically distributed errors, the log-likelihood function is

$$-\frac{n}{2}\ln(2\pi)-\frac{n}{2}\ln\sigma^2-\frac{1}{2\sigma^2}\left((I-\rho WY)-X\beta\right)'\left((I-\rho WY)-X\beta\right)+\ln\left|I-\rho W\right| \qquad (2)$$

where $\left|I-\rho W\right|$ is the Jacobian of the transformation from ε to Y. Common estimation procedures are reviewed in Anselin (1988). Alternatively, Kelijian and Prucha (1998) propose a GMM estimator for the model in which the spatial autoregressive term, WY, is replaced by an instrumental variable, which is the predicted value from a regression of WY on a set of instruments, Z. The GMM estimator has two advantages over maximum-likelihood estimation: (1) it does not rely on a potentially inaccurate assumption of normally distributed errors, and (2) by relying on two-stage least squares, estimation does not require calculating the determinants of nxn matrices.[1] The primary advantage of maximum-likelihood estimation is the potential for efficiency. However, the true structure of the model is rarely known. The specification of W is arbitrary, and researchers often try several different specifications to figure out which one best captures the spatial patterns evident in the data. GMM estimation is more robust than maximum likelihood to departures from the restrictive assumptions required by the maximum likelihood estimator.

When the dependent variable is discrete rather than continuous, maximum likelihood estimation is problematic because the likelihood function typically involves n integrals. Several authors have proposed estimation procedures that maintain the structure implied by maximum likelihood estimation for the spatial probit model. Case (1992) assumes a special, block diagonal structure for W, which simplifies the estimation

[1] Maximum-likelihood estimation can be simplified somewhat by calculating the eigenvalues of W, ω_i, since $\ln\left|I-\rho W\right|=\sum_{i=1}^{n}\ln(1-\rho\omega_i)$. After calculating ω_i, no further manipulations of large matrices are necessary. However, calculating the eigenvalues of an nxn matrix is itself problematic when the sample size is large.

procedure substantially. For example, we might assume that all observations within a state have a common spatial component: $W_{ij} = 1/n_s$ ($i \neq j$) for all observations in state s, where n_s is the number of observations in state s. However, this restrictive specification does not allow the weights to decline with distance within a state. McMillen (1992) and LeSage (2000) base their estimators directly on equations (1) and (2). McMillen uses an EM algorithm to estimate the model under the assumption of normally distributed errors, whereas LeSage uses a Bayesian approached based on Gibbs sampling to simulate the probabilities. Both approaches are limited to relatively small samples because they require the nxn matrix $(I-\rho W)^{-1}$ to be inverted in each iteration.

A variant of the Pinkse and Slade (1998) GMM estimator for a spatial probit model does not rely on the normality assumption. Their estimator is designed for a model with spatially dependent errors:

$$y = X\beta + e, \qquad e = \theta We + \varepsilon = \left(I - \theta W^{-1}\right)\varepsilon \tag{3}$$

where ε is a vector of independently and identically distributed errors. Equation (3) forms the basis for a probit model; the discrete variable, d, equals one if $y > 0$ and $d = 0$ otherwise. The covariance matrix is $V(e) = \left[(I-\theta W)'(I-\theta W)\right]^{-1}$. Thus, the model structure implies both heteroskedasticity and autocorrelation for e unless $\theta = 0$. Denoting the ith diagonal element of this covariance matrix by σ_i^2, the probability that $d_i = 1$ is given by $\Phi\left(X_i^*\beta\right)$, where $X_i^* = X_i / \sigma_i$. The generalized probit residuals are

$$u_i = \frac{d_i - \Phi\left(X_i^*\beta\right)}{\sqrt{\Phi\left(X_i^*\beta\right)\left(1-\Phi\left(X_i^*\beta\right)\right)}} \tag{4}$$

The GMM estimator is the value of θ that minimizes $u'ZMZ'u$, where Z is a matrix of instruments and M is a positive-definite matrix. An interesting application of the Pinkse and Slade estimator is found in Flores-Lagunes and Schnier (2005).

If $M = (Z'Z)^{-1}$, the GMM estimator reduces to nonlinear two stage least squares. The iterative procedure has the following steps:

1. Assume initial values for $\Gamma = (\beta, \theta)'$, Γ_0, and calculate u_0 and the gradient terms, $G = \partial u_0 / \partial \Gamma$.
2. Regress G on Z. The predicted values are $\hat{G}$.
3. Construct the new estimates as $\Gamma_1 = \Gamma_0 - \left(\hat{G}'\hat{G}\right)^{-1} \hat{G}' u_0$.
4. Iterate to convergence.

The covariance matrix is given by

$$\mathrm{var}(\hat{\Gamma}) = \left(\hat{G}'\hat{G}\right)^{-1} \left[\sum_{i=1}^{n} \hat{u}_i^2 \hat{G}_i' \hat{G}\right] \left(\hat{G}'\hat{G}\right)^{-1} \tag{5}$$

Note that a logit model involves no changes to this algorithm. The only difference is that we define the probability as $P_i = \exp\left(X_i^* \beta\right) / \left(1 + \exp\left(X_i^* \beta\right)\right)$ and $u_i = \dfrac{d_i - P_i}{\sqrt{P_i(1 - P_i)}}$.

This model extends readily to the spatial model. To do so, we must reinterpret equation (1) as the underlying latent variable explaining the *propensity* to have d =1. As the propensity to have d =1 increases (or decreases) for nearby observations, the propensity increases (or decreases) for observation i also. This assumption is different from a model in which the discrete variable d depends directly on neighboring values of d – $d = \rho W d + X\beta + \varepsilon$ – or in which the value of the underlying variable depends on neighboring values of d – $y = \rho W d + X\beta + \varepsilon$. These models are not algebraically consistent.

Following this interpretation of equation (1) as the underlying latent variable for the discrete choice model, we have

$$Y = (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1} \varepsilon \tag{6}$$

As in the Pinkse and Slade (1998) model, the covariance matrix is given by $\left[(I - \rho W)'(I - \rho W)\right]^{-1}$. The generalized probit error term is again given by equation (4), but we now define the transformed value of *X* as $X_i^* = H_i / \sigma_i$, where $H = (I - \rho W)^{-1} X$ and σ_i is the square root of the *i*th diagonal entry of the covariance matrix. The estimation algorithm is unchanged. All that changes is the gradient terms. As before, we have

$$\frac{\partial u_i}{\partial \beta} = -\left(\frac{\partial P_i}{\partial X_i^* \beta}\right) X_i^* \tag{7}$$

The gradient term for the spatial term is now:

$$\frac{\partial u_i}{\partial \rho} = -\left(\frac{\partial P_i}{\partial X_i^* \beta}\right)\left[X_i^* \beta - \frac{X_i^* \beta}{\sigma_i^2} \Lambda_{ii}\right] \tag{8}$$

where Λ is the *n*x*n* matrix $(I - \rho W)^{-1} W (I - \rho W)^{-1} (I - \rho W)^{-1}$. Under the probit model, $P_i = \Phi(X_i^* \beta)$, whereas $P_i = \exp(X_i^* \beta)/(1 + \exp(X_i^* \beta))$ for the logit model.[2] Note that $\Lambda_{ii} = 0 \;\forall\, i$ for the Pinkse and Slade (1998) version of the model, in which spatial dependence is only present in the error terms. However, $\Lambda_{ii} \neq 0$ when the autoregressive term *WY* is included as an explanatory variable. We exploit this fact in the next section to derive a linearized version of the spatial autoregressive probit model.

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[2] For completeness, note that $\partial P_i / \partial X_i^* \beta = u_i (u_i + X_i^* \beta)$ for the probit model, and $\partial P_i / \partial X_i^* \beta = P_i (1 - P_i)$ for the logit model.

3. The Linearized Spatial Probit Model

Although GMM estimation is robust to departures from the normality assumption that is explicit in maximum likelihood estimation, the spatial probit and logit models remain computationally burdensome. Each step of the iterative estimation procedures requires the inversion of the *n*x*n* matrix (I-ρW). Yet the spatial model given by equation (1) is generally viewed as an approximation. We seldom know the true structure of the spatial dependence; what is known is that the errors tend to be correlated over space. The models implied by equations (1) and (3) were developed for the relatively small data sets that were common in the past. Large data sets require less restrictive models that do not require inverting large matrices.

Since the model is already viewed as an approximation, a reasonable simplification is to make the approximation explicit and linearize the model around a convenient starting point (see Greene 2002). In this case, the starting point is obvious: when ρ=0, β is estimated consistently by standard probit or logit models. And when ρ = 0, no matrices need be inverted because $(I\text{-}\rho W)^{-1} = I$. The gradient terms simplify substantially because the error terms have constant variances and $X_i^* \beta = X_i \beta$. Recall that $u_i = \frac{d_i - P_i}{\sqrt{P_i(1-P_i)}}$ for either the logit or probit model. Linearizing this expression around the initial estimates $\Gamma_0 = (\beta_0, \rho_0)'$, we have $u_i \approx u_i^0 + G_0(\Gamma - \Gamma_0)$. Define $v_i = u_i^0 - G_0\Gamma_0 + G_0\Gamma$. Again letting $M = (Z'Z)^{-1}$, the objective function for the GMM estimator is $v'Z(Z'Z)Z'v$.

With the linearized model, estimation involves only three steps:

1. Estimate the model by standard probit or logit. The estimated values are $\hat{\beta}_0$. Calculate u_0 and the gradient terms, $G_\beta = \partial u / \partial \beta$ and $G_\rho = \partial u / \partial \rho$, where $\frac{\partial u_i}{\partial \beta} = -\left(\frac{\partial P_i}{\partial X_i \hat{\beta}_0}\right) X_i$ and $\frac{\partial u_i}{\partial \rho} = -\left(\frac{\partial P_i}{\partial X_i \hat{\beta}_0}\right) X_i \hat{\beta}_0$.
2. Regress G_β and G_ρ on Z. The predicted values are $\hat{G}_\beta$ and $\hat{G}_\rho$.
3. Regress $u^0 - G_\beta{}' \hat{\beta}_0$ on $-\hat{G}_\beta$ and $-\hat{G}_\rho$. The coefficients are the estimated values of β and ρ.

No large matrices have to be inverted in this algorithm. All it requires is standard probit (or logit) and several linear regressions.

The algorithm is closely related to the first step of the GMM estimator for the non-linearized model, which is a regression of u^0 on $-\hat{G}_\beta$ and $-\hat{G}_\rho$. Subsequent iterations of the full model would require calculating $(I\text{-}\rho W)^{-1}$. The spatial error model approach of Pinkse and Slade (1998) is not identified under the linearization approach because Λ_{ii} in equation (8) is equal to zero when ρ = 0. However, the first term in equation (8) allows ρ to be estimated under the spatial model. If the true structure of the model is given by equation (1), linearization will provide accurate estimates as long as ρ is small, and in general, the linearized model will provide a good approximation to an underlying unknown spatial model.

4. Data

We base our analysis on data acquired from ELM International, a Michigan-based vendor. Though not designed with research applications in mind, the intention behind the ELM database is to cover the entire North American auto industry. Data are available at the plant and company level. However, plants producing primarily for the aftermarket are not part of the database; nor are plants that produce machine tools or raw materials, such as steel and paint.[3]

The ELM database, which provides 3,542 plant-level records, was purchased at the end of 2003. The database includes information on a plant's address, products, employment, parts produced, customer(s), union status, as well as square footage. Several operations were necessary to clean up the data. First, records were crosschecked with state manufacturing directories to obtain information on the plant's age.[4] Information on captive plants was obtained from Harbour (2003). We also appended information on the nationality of the company to the record of each plant from the ELM company-level data. For the 150 largest supplier companies, the accuracy and completeness of ELM's plant listings – both the number of plants and their locations – was crosschecked with the individual company's website when possible.[5] The crosschecking resulted in a net addition of 335 records. Finally, the accuracy of the employment for the largest plants (more than 2,000 employees) was also checked with company websites or phone calls. After this preparation, the data set comprises 4,478 observations of auto supplier plants located in North America, of which 3,416 are located

[3] The data include information on "captive" supplier plants, which are parts operations that assemblers own and operate themselves, such as engine and stamping facilities.
[4] Plants for which no matching records were found were contacted by phone.

in the U.S., 461 in Canada, and 601 in Mexico. To our knowledge, this data set contains the most accurate description of the North American auto supplier industry currently available. The formal analysis draws only on the U.S. data.

One of our objectives in the empirical analysis is to determine whether recent plant location decisions differ from those of the past. Our definition of "new" is any plant that has opened since 1991. We refer to plants that began operations before 1991 as "existing" plants. The data is cross-sectional in nature. Hence, the age variable applies only to surviving establishments. This focus on survivors may lead us to understate the extent to which "old" plants are concentrated at the upper end of the auto corridor. Within the North American auto industry, we distinguish assembly and supplier plants. We focus on supplier plants as they represent by far the largest number of establishments in this industry. In so doing, we are able to capture the spatial extension of this industry quite well. Within the industry, the location of assembly plants matters as they often represent the delivery point for a supplier's output.

Figure 1 shows the location of existing (pre-1991) supplier plants in North America in 2003, along with the sites of assembler plants. The dominance of the East North Central region is striking. Detroit remains the core of the industry, with large numbers of counties occupied by supplier plants in Ohio and Indiana, also.[6] The locus of the industry has been moving southward over time. Though many plants are still evident in New England and the Middle Atlantic states, the East South Central and South Atlantic states have been adding plants recently. Very few plants are located in the western states. Figure 2 shows the location of supplier plants that have opened since 1991. Most of the

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[5] We thank Jim Rubenstein for sharing his plant-level data for the 150 largest supplier companies. The 150 largest supplier companies are listed annually in the industry weekly *Automotive News*.

new plants are located along a path running south from Detroit, although a respectable number of plants have opened in New England and the Middle Atlantic states. The tendency of supplier plants to locate near assemblers is clear in both Figure 1 and 2.

Table 1 presents descriptive statistics for the variables used in our analysis. Of the 3107 counties in the 48 contiguous states for which all data are available, 866 (27.87%) have plants that opened before 1990 and 245 (7.89%) have new plants. Most new plants are located in counties that already have an existing plant: only 37 counties have only a new plant. As shown in Figure 1 and 2, both new and existing plants are concentrated in the East North Central, South Atlantic, and East South Central census regions; these three regions account for more than two thirds (32.45%, 20.16%, and 16.06%, respectively) of the counties with auto supplier plants in 2003. The rotation of the auto corridor toward a north-south corridor running from Detroit is evident in the tendency for new plants to open up in the East North Central and East South Central regions. In fact, counties with new plants tend to be closer to Detroit on average than counties with existing plants – 407 miles compared to 494 miles. New supplier plants are also closer to assembler plants on average than are the existing suppliers: the centers of the counties in which new plants are located are 69.3 miles from the nearest assembler on average, compared with 104.5 miles for existing plants. The number of assembler plants within 450 miles of county centers is also higher for new plants than for existing plants – 36.547 versus 30.671. Overall, Table 1 suggests that the auto industry is re-trenching by drawing closer to Detroit along a north-south corridor.

Our empirical strategy involves estimating separate logit models explaining whether a county has an existing plant or a new plant. For the subset of counties that

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[6] For a map of plant density see Klier et al (2004)

have plants, we also estimate logit models explaining whether the county has a new plant. Our explanatory variables include the regional dummy variables and distance from Detroit. We include a dummy variable indicating whether an interstate highway runs through the county. Auto suppliers have increasingly been using just in time inventory systems, placing a premium on locations near highways running to assembler plants and to Detroit. To account for the tendency to locate near assembler plants, our explanatory variables include the distance to the nearest assembler and the count of the number of assemblers within 450 miles (an approximate one day's drive) from the center of the county. We also include some characteristics of the counties – population density, the proportion of the residents who are white, the proportion who have graduated from high school, the proportion of the employment in the county that is in manufacturing, and measures of the rates of violent and property crime.

We account for the tendency of supplier plants to cluster together in two ways. First, we include the spatial lag variable WY, which is a weighted average of the propensity for neighboring counties to have a supplier plant. The weight matrix, W, is a contiguity matrix. We construct the matrix by setting $W_{ij} = 1/n_i$ for counties that share a common border, where n_i is the number of observations that are contiguous to county i. $W_{ij} = 0$ for all other observations (including W_{ii}). A positive value for this variable's coefficient implies a county's probability of having a plant increases with the propensity for neighboring counties to have plants. Our second measure of the tendency to cluster is relevant only for new plants. For logit models explaining the probability that a county has a new plant, we include as explanatory variables the number of existing suppliers within 100 miles and between 100 and 450 miles of the center of the county. The results for these variables will help determine whether the location decisions for new plants simply mimic those of existing plants.

5. Logit Results

Our base model for counties with plants built prior to 1990 is shown in the first column of results in Table 2. The estimated logit model indicates that the presence of an interstate highway significantly increases the probability that a county will have an auto supplier plant. The probability of having an existing plant also increases if the center of the county is close to an assembly plant and if it is within a day's drive from a large number of assemblers. Not surprisingly, the probability of having an existing supplier plant is higher if the county has a high proportion of high school graduates and if it already has a high concentration of manufacturing employment. A somewhat surprising result is our finding that the probability of having a plant is higher in counties with high crime rates. This result holds even though we have controlled for the population density in the counties. A possible explanation is that high crime rates reduce land values in a county, and that auto plants substitute toward private security provision. Another possibility is that crime rates are correlated with urban locations in a way that is not captured by the population density variable. At any rate, the positive effect of crime on plant location is a robust result that holds up in subsequent models.

The tendency for auto supplier plants to cluster is evident in Table 2. Other regions of the country tend to have much lower probabilities of having a plant than the base location, the East North Central region, with significantly negative effects in the Middle Atlantic, West North Central, South Atlantic, West South Central, and Pacific regions. Although distance from Detroit is not a significant determinant of plant locations once other variables are taken into account, plants are much more likely to be located near assembly plants and in counties containing interstate highways. Since assembly plants are clustered in the auto corridor around Detroit, supplier plants tend to cluster together also.

The results for the linearized spatial logit model are presented in the last column of Table 2. Instruments for the GMM estimation procedure include all of the exogenous variables shown in Table 2. In addition, we include the weighted average of nearby values (*WX*) of those variables that vary significantly over space – the presence of an interstate highway, population density, crime rates, the proportion of employment that is in manufacturing, and the proportions of the county's residents that are white and who have high school degrees. Most of the results for the spatial version of the model are quite similar to those for the standard model. The significant changes are (1) the spatial lag variable (*WY*) is highly significant, and (2) distance to the nearest assembler is no longer a statistically significantly determinant of plant location. The positive coefficient for WY implies that the probability that a county has an existing supplier plant increases when neighboring counties have a high propensity to have plants also. These results suggest that existing plants cluster together closely, even beyond the extent indicated by the controls for regions, the presence of nearby assembly plants, highways, and other manufacturing establishments.

Table 3 shows the estimated results for two sets of models explaining the probability that a county has a supplier plant that has opened since 1991. The first set omits controls for the number of existing suppliers within 100 miles and between 100 and

450 miles of the center of a county, while the second set includes these two variables. Both models are estimated by standard logit and the linearized GMM spatial estimator. We use the same instruments for the new plants models as for existing plants.

The first two columns of results in Table 3 are directly comparable to the models estimated for existing plants. As was the case for existing plants, new supplier plants are more likely to be located in counties that contain a stretch of interstate highway, that have high proportion of high school graduates, that have a high proportion of their employment in manufacturing, and that have high property crime rates. In the base model, the coefficient for distance from Detroit is significantly negative, implying that new plants are more likely to be located closer to Detroit. However, this result disappears once we control for the spatial autoregressive term, *WY*. Table 3 suggests that new plants are somewhat less likely to be in the East North Central region, however. Controlling for distance from Detroit, new plants are significantly more likely to be located in the East South Central Region than in the base region surrounding Detroit. Thus, the auto industry is rotating toward the area south of Detroit.

The models presented in the first two columns of Table 3 suggest that the tendency toward clustering is somewhat less pronounced for new plants than was indicated for existing plants. Although distance from the nearest assembler has a significantly negative effect on the probability of having a new plants, neither this variable nor the number of assemblers within 450 has a statistically significant effect once we control for the spatial autoregressive term. The coefficient for the spatial autoregressive term, *WY*, is statistically different from zero at the 10% level but not at the 5% level, and its value is lower than was the case for existing plants (0.355 v. 0.542).

However, it is possible that part of the reason for this apparent lack of explanatory power of the variables that indicate clustering is due to the relatively small number of counties that have new plants. Overall, the results for the first two columns of results in Table 3 suggest that the location decisions of new plants are broadly similar to those of existing plants. New plants are more likely to locate south of Detroit, and exhibit a somewhat smaller tendency toward clustering, but otherwise the factors that influenced the locations of existing plants also affect new plants locations.

The last two columns of Table 3 add two variables to the models, the number of existing suppliers within 100 miles and between 100 and 450 miles of the county. The probability of having a new plant in a county rises significantly when older plants already exist in the area, with a pronounced effect if there already are plants within 100 miles of the county center. That effect diminishes in size for plants located within the larger radius. It is, however, statistically significant. The spatial autoregressive term is no longer statistically significant once these variables are added to the models. Though new plants have a tendency to cluster together, the tendency simply mimics the location pattern of existing plants. There is no increment to the clustering tendency among new plants.

Table 4 presents logit results for the subset of counties that have either an existing or a new plant. The dependent variable equals one if the county has a plant that has opened since 1990. The results directly capture the difference in location patterns between new and old plants. New plants are more likely than old plants to be in counties with a stretch of interstate highway. They are more likely to be in counties that are close to assemblers. New plants are also more likely to be in counties with high property crime rates, and in counties located in the East South Central, West South Central, Mountain, and Pacific Regions. They are less likely to be in counties in the Middle Atlantic States. Controlling for these regional fixed effects, new plants are likely to be closer to Detroit than existing plants. With the exception of the Middle Atlantic and Mountain regional effects, these results hold up once we control for the spatial autoregressive term.[7] The insignificant coefficient for *WY* suggests again that new plants have no additional tendency toward clustering once we control for the location of existing plants.

6. Conclusion

The spatial autoregression model is useful when individual decisions are mutually dependent and are influenced by proximity. Do tax rates in one jurisdiction depend on tax rates in nearby jurisdictions? Does the presence of growth controls depend on whether neighboring municipalities have growth controls? Does the sales price of a house depend on the prices paid for nearby homes? We show that the same class of model is useful for identifying clustering in the location decisions of auto supplier plants in the U.S. Does the presence of supplier plants in neighboring counties increase the probability that a county will also have a plant? We find strong evidence of clustering among plants that opened prior to 1991. Supplier plants are more likely to be located in counties that are near assembly plants, in counties that contain a stretch of interstate highway, and in counties that are near other counties with supplier plants. New plants also tend to cluster, but there is no additional tendency toward clustering beyond that shown by older plants.

[7] The set of instruments is the same as used in previous models.

We extend the literature on spatial modeling in two ways. First, we extend the standard spatial autoregression model to the case of a discrete continuous variable. Our model is appropriate if the *propensity* to have a value of one for the dependent variable depends on the propensity for nearby observations. Thus, the probability that an auto supplier plant is located in a county depends on the underlying latent variable determining the probability that nearby counties have assembly and/or supplier plants. The model can be estimated using a straightforward extension of the GMM estimator proposed by Pinkse and Slade (1998) for a spatial probit model. Our second contribution to the literature on spatial modeling is to show how a linearized version of the GMM approach can be used to estimate the spatial probit model when the sample size is large. Our approach involves only three steps. The first stage is a standard probit or logit estimator, while the second step is a standard two stage least squares estimation procedure. The linearized model can be estimated even for very large data sets.

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Table 1
Descriptive Statistics

	All Counties	Counties with Existing Plants	Counties with New Plants	New or Existing Plants
Existing plant located in county (%)	27.87	100.00	84.90	95.90
New plant located in county (%)	7.89	24.02	100.00	27.13
Interstate highway (%)	44.09	63.51	73.47	63.34
Distance to nearest assembler (100 miles)	1.880 (1.799)	1.045 (1.068)	0.693 (0.788)	1.041 (1.053)
Number of assemblers within 450 miles	19.467 (17.791)	30.671 (17.064)	36.547 (16.439)	30.573 (17.076)
Existing suppliers within 100 miles	0.487 (0.911)	1.129 (1.420)	1.815 (1.890)	1.110 (1.405)
Existing suppliers, 100-450 miles	7.811 (7.329)	12.129 (6.920)	14.303 (6.341)	12.120 (6.948)
Population density (1000s per sq. mile)	0.218 (1.434)	0.357 (1.315)	0.418 (0.782)	0.347 (1.289)
Proportion white	0.875 (0.153)	0.884 (0.133)	0.886 (0.118)	0.884 (0.133)
Proportion high school graduates	0.695 (0.103)	0.711 (0.096)	0.714 (0.091)	0.709 (0.096)
Proportion manuf. employment	0.186 (0.106)	0.245 (0.093)	0.256 (0.085)	0.245 (0.093)
Violent crime rate (1000s)	0.278 (0.320)	0.364 (0.394)	0.409 (0.378)	0.362 (0.389)
Property crime rate (1000s)	2.631 (1.983)	3.283 (2.111)	3.488 (2.078)	3.260 (2.094)
East North Central (%)	14.06	33.03	43.27	32.45
New England (%)	2.16	3.35	1.63	3.32
Middle Atlantic (%)	4.83	7.04	3.67	7.09
West North Central (%)	19.89	10.62	6.12	10.63
South Atlantic (%)	18.93	20.09	15.92	20.16
East South Central (%)	11.72	15.82	23.27	16.06
West South Central (%)	15.13	6.58	3.67	6.76
Mountain (%)	9.01	1.85	0.41	1.77
Pacific (%)	4.28	1.62	2.04	1.77
Distance from Detroit (100 miles)	7.395 (4.365)	4.942 (3.338)	4.073 (3.412)	4.978 (3.380)
Number of observations	3107	866	245	903

Note. Standard deviations are in parentheses for continuous variables.

Table 2
Logit Models: Existing Supplier Plants

Variable	Standard Logit	Spatial Logit
Constant	-8.333** (0.910)	-6.166** (1.059)
Interstate highway	0.725** (0.110)	0.584** (0.113)
Distance to nearest assembler (100 miles)	-0.183** (0.066)	-0.010 (0.072)
Number of assemblers within 450 miles	0.035** (0.008)	0.028** (0.008)
Population density (1000s per sq. mile)	-0.059 (0.036)	-0.061 (0.038)
Proportion white	0.095 (0.494)	0.113 (0.518)
Proportion high school graduates	5.330** (0.819)	2.990** (0.973)
Proportion manuf. employment	9.670** (0.698)	6.599** (0.931)
Violent crime rate (1000s)	0.582** (0.245)	0.472* (0.261)
Property crime rate (1000s)	0.323** (0.041)	0.302** (0.047)
New England	0.236 (0.346)	0.036 (0.329)
Middle Atlantic	-0.830** (0.225)	-0.426* (0.233)
West North Central	-0.546** (0.227)	0.049 (0.268)
South Atlantic	-0.787** (0.194)	-0.484** (0.205)
East South Central	-0.192 (0.215)	0.005 (0.220)
West South Central	-0.853** (0.303)	-0.354 (0.331)
Mountain	-0.851 (0.555)	-1.174** (0.590)
Pacific	-1.403* (0.788)	-1.961** (0.806)
Distance from Detroit (100 miles)	0.014 (0.058)	0.094 (0.059)
WY		0.542** (0.101)

Notes. Standard errors are in parentheses. Significance at the 5% and 10% level is indicated by "**" and "*".

Table 3
Logit Models: New Supplier Plants

Variable	Standard Logit	Spatial Logit	Standard Logit	Spatial Logit
Constant	-6.964** (1.576)	-6.029** (1.586)	-9.474** (1.647)	-9.207** (1.980)
Interstate highway	0.888** (0.179)	0.835** (0.186)	0.858** (0.183)	0.837** (0.193)
Distance to nearest assembler (100 miles)	-0.543** (0.140)	-0.203 (0.231)	-0.371** (0.135)	-0.182 (0.196)
Number of assemblers within 450 miles	0.016 (0.013)	0.013 (0.015)	-0.049* (0.029)	-0.046 (0.031)
Existing suppliers within 100 miles			0.709** (0.129)	0.675** (0.198)
Existing suppliers, 100-450 miles			0.229** (0.067)	0.214** (0.078)
Population density (1000s per sq. mile)	-0.058 (0.076)	-0.140** (0.055)	-0.021 (0.063)	-0.036 (0.039)
Proportion white	0.013 (0.856)	0.107 (0.742)	-0.765 (0.892)	-0.612 (0.784)
Proportion high school graduates	3.910** (1.259)	3.176** (1.319)	3.576** (1.298)	3.475** (1.347)
Proportion manuf. employment	6.681** (1.043)	5.605** (1.205)	5.628** (1.103)	5.073** (1.199)
Violent crime rate (1000s)	0.309 (0.332)	0.190 (0.289)	-0.063 (0.343)	-0.045 (0.308)
Property crime rate (1000s)	0.296** (0.059)	0.323** (0.052)	0.317** (0.059)	0.304** (0.053)
New England	0.514 (0.650)	0.222 (0.687)	1.561** (0.697)	1.122 (0.771)
Middle Atlantic	-0.998** (0.397)	-0.645 (0.425)	0.242 (0.462)	0.219 (0.468)
West North Central	-0.031 (0.408)	0.172 (0.435)	0.372 (0.418)	0.306 (0.425)
South Atlantic	-0.077 (0.296)	-0.023 (0.298)	0.296 (0.323)	0.218 (0.328)
East South Central	1.172** (0.305)	1.095** (0.366)	1.247** (0.306)	1.155** (0.354)
West South Central	0.505 (0.581)	0.540 (0.506)	0.346 (0.629)	0.109 (0.569)
Mountain	1.889 (1.475)	-1.545 (1.977)	-0.730 (1.519)	-2.152 (1.954)
Pacific	4.519** (1.552)	3.263 (2.320)	-0.125 (1.684)	-0.928 (2.016)
Distance from Detroit (100 miles)	-0.274** (0.108)	-0.194 (0.159)	0.114 (0.126)	0.149 (0.152)
WY		0.355* (0.181)		0.104 (0.195)

Notes. Standard errors are in parentheses. Significance at the 5% and 10% level is indicated by "**" and "*".

Table 4
Logit Models: New Versus Existing Plants

Variable	Standard Logit	Spatial Logit
Constant	-2.078 (1.761)	-1.880 (1.740)
Interstate highway	0.595** (0.193)	0.586** (0.192)
Distance to nearest assembler (100 miles)	-0.443** (0.152)	-0.408** (0.201)
Number of assemblers within 450 miles	0.008 (0.014)	0.008 (0.016)
Population density (1000s per sq. mile)	0.022 (0.068)	0.010 (0.048)
Proportion white	-0.280 (1.026)	-0.353 (0.923)
Proportion high school graduates	1.155 (1.401)	1.044 (1.386)
Proportion manuf. employment	1.927 (1.199)	1.895 (1.205)
Violent crime rate (1000s)	-0.123 (0.383)	-0.131 (0.361)
Property crime rate (1000s)	0.196** (0.073)	0.196** (0.070)
New England	0.337 (0.682)	0.448 (0.686)
Middle Atlantic	-0.860** (0.418)	-0.739 (0.456)
West North Central	0.440 (0.437)	0.461 (0.454)
South Atlantic	0.429 (0.342)	0.426 (0.379)
East South Central	1.351** (0.338)	1.264** (0.414)
West South Central	1.196* (0.616)	1.134** (0.570)
Mountain	3.156** (1.484)	2.947 (1.880)
Pacific	5.740** (1.661)	5.405** (2.262)
Distance from Detroit (100 miles)	-0.296** (0.114)	-0.282* (0.145)
WY		0.132 (0.193)

Notes. The dependent variable equals one if the county has a new plant. The data set includes the 903 counties that contain either a new or an existing plant. Standard errors are in parentheses. Significance at the 5% and 10% level is indicated by "**" and "*".

Figure 1
Counties with Existing Plants

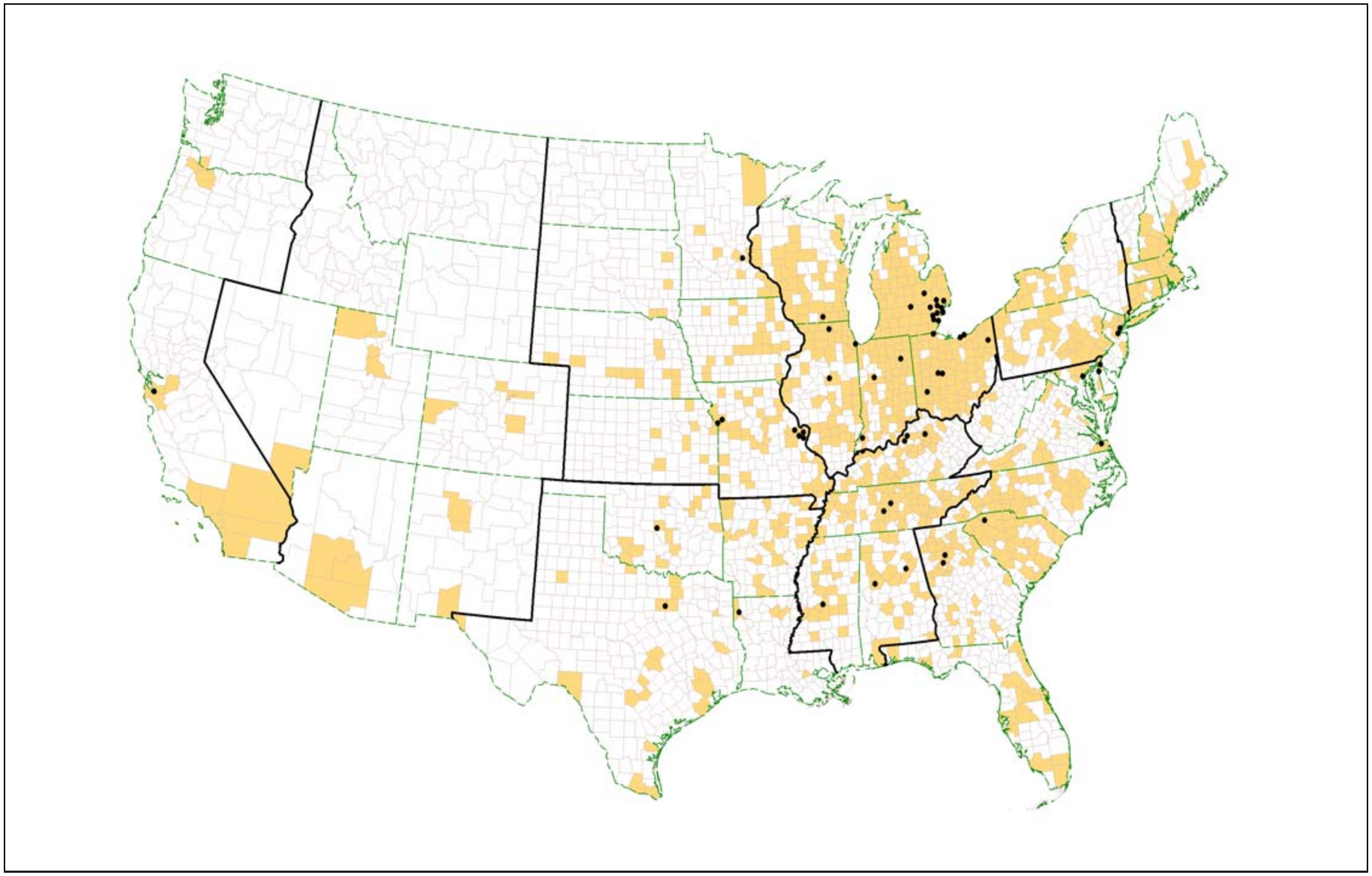
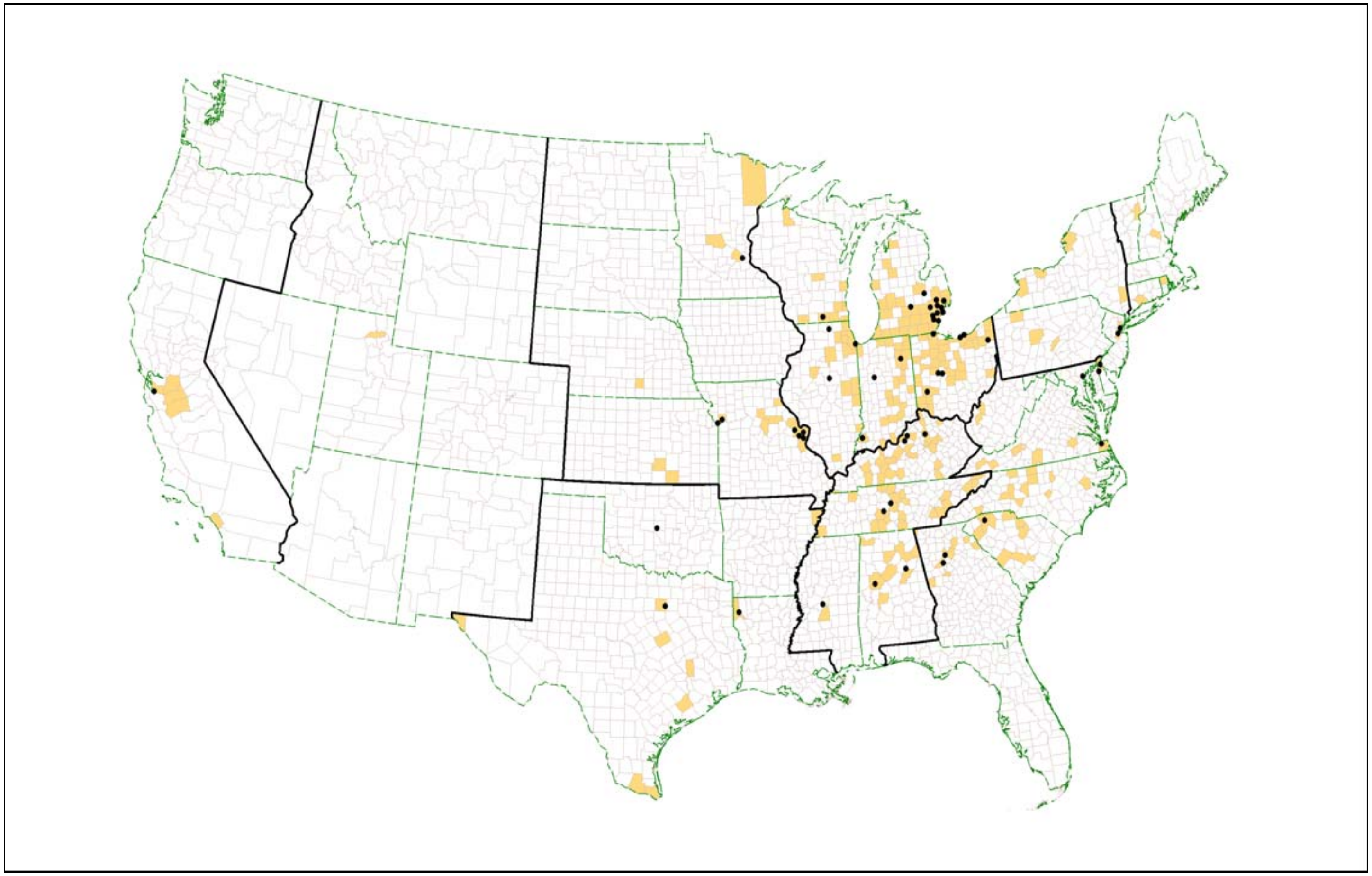


Figure 2
Counties with New Plants



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