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County child poverty rates in the US: a spatial regression approach

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Abstract We apply methods of exploratory spatial data analysis (ESDA) and spatial regression analysis to examine intercounty variation in child poverty rates in the US. Such spatial analyses are important because regression models that exclude explicit specification of spatial effects, when they exist, can lead to inaccurate inferences about predictor variables. Using county-level data for 1990, we re-examine earlier published results [Friedman and Lichter (Popul Res Policy Rev 17:91–109, 1998)]. We find that formal tests for spatial autocorrelation among county child poverty rates confirm and quantify what is obvious from simple maps of such rates: the risk of a child living in poverty is not (spatially) a randomly distributed risk at the county level. Explicit acknowledgment of spatial effects in an explanatory regression model improves considerably the earlier published regression results, which did not take account of spatial autocorrelation. These improvements include: (1) the shifting of "wrong sign" parameters in the direction originally hypothesized by the authors, (2) a reduction of residual squared error, and (3) the elimination of any substantive residual spatial autocorrelation. While not without its own problems and some remaining ambiguities, this reanalysis is a convincing demonstration of the need for demographers and other social scientists to examine spatial autocorrelation in their data and to explicitly correct for spatial externalities, if indicated, when performing multiple regression analyses on variables that are spatially referenced. Substantively, the analysis improves the estimates of the joint effects of place-influences and family-influences on child poverty.

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Introduction

In the past two decades, developments in the field of spatial econometrics (Anselin 1988, 2001a) have resulted in two important outcomes. First, studies in a variety of social science disciplines have demonstrated the value gained by explicitly acknowledging spatial effects in explanatory statistical models. Such studies can be found in criminology (Baller, Anselin, Messner, Deane, & Hawkins, 2001), economics (Case, Rosen, & Hines, 1993; Holtz-Eakin, 1994), agricultural economics (Nelson, 2002), land use and land cover change (Bell & Irwin, 2002; Mertens, Poccard-Chapuis, Piketty, Lacques, & Venturieri, 2002; Müller & Zeller, 2002; Munroe, Southworth, & Tucker, 2002; Nelson & Geoghegan, 2002; Vance & Geoghegan, 2002), environmental and resource economics (Anselin, 2001b; Bockstael, 1996; Walker, Moran, & Anselin, 2000), adoption/diffusion studies (Case, 1992), geographic patterns of suicide (Baller & Richardson, 2002), and real estate analysis (Can & Megbolugbe, 1997; Pace, Barry, & Sirmans, 1998). A second outcome is the theoretical refinements and software developments that have grounded new analytical tools in theory and made them reasonably accessible to data analysts not specifically trained in the geosciences (Anselin, 1999; Goodchild, Anselin, Appelbaum, & Harthorn, 2000).

However, while the studies cited above demonstrate that these approaches have been adopted by a variety of researchers working in different substantive areas across the social sciences, outside of human geography and regional science, adoption has not been widespread. The explicit consideration of spatial externalities in much of the sociological literature is a very recent phenomenon (Anselin, 2000, p. 11). Some disciplines in the social sciences (e.g., demography) have largely ignored these developments (Tiefelsdorf, 2000, p. 151; Voss, White, & Hammer, 2004). This is ironic, since maps of various social and economic attributes from the census at differing levels of census geography immediately and clearly demonstrate that low attribute values tend to cluster together in space, as do high values—patterns suggesting the presence of positive spatial autocorrelation (Brewer & Suchan, 2001).

The irony is further heightened because it has long been understood that regression analysis of spatially distributed variables can lead to incorrect statistical inference (a result of inefficient or biased parameter estimates) when spatial autocorrelation exists and when model specifications fail to incorporate proper corrections for such spatial effects (Cliff & Ord, 1973). To our knowledge, however, no existing statistical investigation into the spatial distribution of poverty has adopted spatial econometric methods.

This paper uses spatial econometric methods to re-examine place and family effects on child poverty. Specifically, we demonstrate how regression models can be tested for spatial effects, evaluate the results of failing to account for these effects in models of child poverty in the US, and correct for such effects in more properly specified models. We accomplish this by revisiting an article, published in this journal, that explores the determinants of geographic variability in county-level child poverty rates (Friedman & Lichter, 1998).

In the following section we briefly review the theoretical and empirical research addressing the causes of poverty. Since our goal is to use this substantive issue to demonstrate the appropriate integration of spatial effects in regression models, this overview of spatial inequality in child poverty is deliberately brief and is included primarily to contextualize our analysis. Next we review the findings from the Friedman and Lichter article and examine the important contributions their research made to the poverty literature. Following this, we reanalyze their data, demonstrating how and why their model can benefit from modifications that incorporate spatial process effects. This section addresses an important emergent issue and therefore assumes a somewhat (hopefully useful) didactic structure. In the fifth section, we describe our research strategy, and, in a sixth section, we comment briefly on our results and compare these to the original findings. Finally, in a concluding section, we discuss the importance of this research as an example for demographers and others concerned with poverty who are undertaking analyses of geo-referenced data.

Background

Over the past 40 years, the causes and consequences of poverty, and changes in poverty over time, have been the subjects of much academic research and social policy debate. In large measure, two schools of thought have dominated this research and debate. One attributes the causes of poverty primarily to individualistic or family compositional forces. Sometimes referred to as ''people poverty,'' this line of reasoning points to such underlying causes as a ''breakdown'' of traditional American family norms, high levels of teenage and non-marital childbearing, and the rise of a permanent urban underclass caught up in a culture of poverty from which escape is difficult (for a review, see Wilson, 1987). Extensions of this general view see *child* poverty in the US as a by product of predisposing family structures: children born to single mothers and children of divorced parents (Rainwater & Smeeding, 1995; Smeeding & Torrey, 1988; Espenshade, 1985). The argument often is grounded in the empirical observation that families headed by a single parent are several times more likely to be poor than are married-couple families with children (National Commission on Children, 1991).

Another school of thought focuses on contextual or structural forces, sometimes referred to as ''place poverty.'' These include issues such as urban economic dislocations, faltering regional economies, high unemployment, poor and often disorganized local employment opportunity structures—all forces over which the individual has little or no control (Massey & Denton, 1993; Pebley & Sastry, 2003; Rexroat, 1989; Tickamyer & Duncan, 1990; Tigges, 1987; Tomaskovic-Devey, 1987; Weinberg, 1987; Wilson, 1996).

That said, there are examples of poverty research that have sought to transcend the debate between people-poverty and place-poverty and to view both of these underlying causes as contributory factors in explaining poverty—and, in particular, child poverty—where the influences of industrial and local opportunity structures are mediated through family structures (Conger et al., 1990; Easterlin, 1987). More recently, Cotter (2002) has argued that the industrial and family structural approaches to understanding poverty need not be viewed as competing explanations. Building on the work of Schiller (1980), Cotter argues for a complementary approach that views "structural factors determining the *level* of poverty in a social aggregate (establishing the number of poverty positions), and individual factors determining the *distribution* (providing the criteria for the sorting)..." (2002, p. 537). Cotter blends place and person influences by taking a multilevel modeling approach. Our analysis takes a different approach by examining the spatial variation in child poverty using spatial econometrics.

Findings of Friedman and Lichter

It is into this debate about the causes of poverty—specifically child poverty—that Friedman and Lichter (1998) (henceforth FL) make their contribution. Using county-level data from the 1990 decennial census, they review the familiar and persistent geographic concentrations of child poverty in the US. We replicate their map revealing concentrations of higher child poverty in Appalachia, the Mississippi Delta, the lower Rio Grande Valley, and the historical "black belt" that sweeps across southern states in an arc from east Texas to North Carolina (Fig. 1). Other concentrations are apparent in central city counties of major metropolitan areas and in rural counties with Indian reservations. Large expanses of relatively low child poverty also are evident, especially (1) in a near-contiguous band of counties sweeping south from New England through the southern Piedmont region of central Virginia and North Carolina and (2) in large portions of the central Midwest. The principal research issue for FL was "how industrial structure affects spatial variation in county-level poverty rates for children... and how these effects are mediated by employment opportunities and family structure" (1998, p. 93). This statement acknowledges the validity of both schools of poverty study and subscribes to a mediation process. With that framework, FL set out to "estimate multivariate models that assess the direct and indirect effects (through family structure) of local labor market conditions and employment opportunities on county child poverty rates" (1998, p. 94).

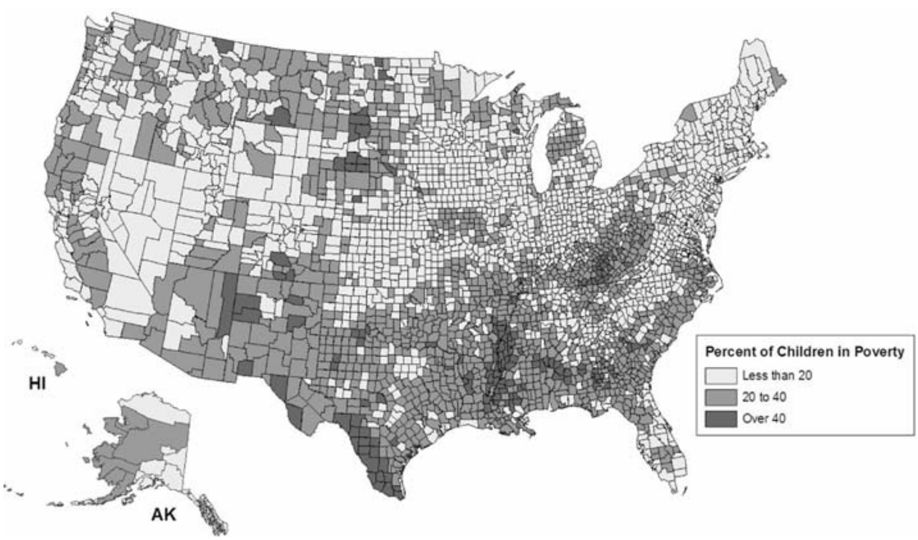

Fig. 1 Percentage of children in poverty: 1990

Data and variables

Data for the FL analysis came from the 1990 US decennial census, Summary Tape File 3C (US Bureau of the Census, 1992). Variables selected for their models are shown in Table 1. For details regarding their choice and operationalization of variables and their model specification, the reader is referred to the original article (Friedman & Lichter, 1998).

Findings

Using a sequence of weighted logistic regression models (Table 2), FL concluded that:

1. Most of the effect of industrial structure on child poverty in the US is mediated through local employment opportunity structures (1998, p. 97).
2. The effects of industrial structure and employment opportunity structure are mediated through family structures—but only partly. ‘‘[E]mployment dislocations contribute to the child poverty problem by undermining the formation and stability of ‘low risk’ two-parent families’’ (1998, p. 99).
3. The effect of family structure on child poverty is important but is smaller than the effect of the county unemployment rate (1998, p. 100).
4. ‘‘[T]he current industrial mix and the lack of employment opportunities place non-metro children at a comparative economic disadvantage and exacerbate the child poverty problem’’ (1998, p. 104).

Table 1 Variables used in the Friedman and Lichter models

Dependent variable: $\log(p/1 - p)$ where p = proportion of children <18 considered poor in 1989	
Hypothesized association	Independent variables
Industrial structure variables	
+	Proportion of employed persons in extractive industries
+	Proportion of employed persons in non-durable manufacturing
+	Proportion of employed persons in miscellaneous services
+	Proportion of employed persons in professional services
Employment opportunity structure variable	
+	Unemployment rate (in 1989; all workers aged 16+ in civilian labor force)
+	Underemployment rate (male workers aged 16+ who worked <35 h/week and/or <27 weeks during 1989)
Family structure variable	
+	Proportion of families with children headed by females (no husband present)
Control variables	
+	Proportion non-Hispanic black in population
+	Proportion Hispanic in population
+	Proportion of adults (18+) with completed education H.S. or less
+	Live in south dummy variable (South = 1)
–	Live in metro area dummy variable (Metro = 1)
–	Proportion of workers (16+) employed in county of residence

Source: All variables from the 1990 US Census of Population, STF3C. See Friedman and Lichter (1998, p. 98).

Table 2 Friedman and Lichter logit regression findings (N = 3,136)

Variable	(1)	(2)	(3)	(4)
Proportion black (non-Hispanic)	1.830 (0.050) a	1.475 (0.040)	–0.091 (0.066) ns	0.212 (0.054)
Proportion Hispanic	1.380 (0.042)	0.831 (0.035)	1.151 (0.036)	0.778 (0.031)
Proportion with a high school education or less	3.268 (0.076)	1.954 (0.069)	2.190 (0.069)	1.460 (0.063)
Proportion of workers (16+) employed in county of residence	1.028 (0.036)	0.702 (0.028)	0.782 (0.030)	0.596 (0.025)
South dummy variable	0.049 (0.013)	0.089 (0.010)	0.192 (0.011)	0.180 (0.009)
Metro dummy variable	–0.139 (0.018)	–0.006 (0.014) ns	–0.179 (0.015)	–0.061 (0.013)
Proportion employed in extractive industries	0.568 (0.146)	0.557 (0.112)	1.614 (0.124)	1.287 (0.101)
Proportion employed in non-durable manufacturing industries	–1.593 (0.170)	–0.268 (0.136)ns	–1.154 (0.142)	–0.216 (0.119) ns
Proportion employed in miscellaneous service industries	–0.701 (0.267)	0.268 (0.204) ns	–1.831 (0.224)	–0.691 (0.182)
Proportion employed in professional services industries	1.562 (0.123)	0.077 (0.101) ns	0.150 (0.108) ns	–0.604 (0.091)
Proportion of labor force unemployed		7.378 (0.261)		5.984 (0.234)
Proportion of male working population underemployed		3.211 (0.132)		2.555 (0.118)
Proportion of female headed families with children			5.085 (0.135)	3.517 (0.115)
Intercept	–4.811	–4.77	–4.32	–4.435
Adjusted R^2	0.725	0.842	0.811	0.878

Source: Friedman and Lichter (1998, p. 99). a: numbers in parentheses are standard errors; ns: not significant at the 0.01 level

5. ‘‘Local industrial structure has direct effects on child poverty (presumably through parental wages), as well as indirect effects through parents’ ability to find work and to maintain a stable family life for their children. Children’s lives—and their economic circumstances—are tied to the fortunes of the communities in which they reside’’ (1998, p. 105).

Spatial data analysis

Since the visual message in Fig. 1 points so unambiguously to an uneven spatial distribution of child poverty in America, we anticipated that the residuals from the FL analysis would not be independent as required by the assumptions underlying classical regression. With the authors’ cooperation, we replicated the FL findings, focusing our initial attention on spatial autocorrelation in the residuals of their regression models. The comments that follow specifically address their final model (Table 2).

FL express their main variable of interest (proportion of children in poverty) in logit form to make the variable more closely conform to the assumption of normality and to improve linearity between the dependent variable and the independent variables (Aldrich & Nelson, 1984). They reduce their variable set to control the extent of multicollinearity, and they weight their model to accommodate heteroskedasticity. When conducting regression analyses with data aggregated to geographic areas such as counties (referred to in the spatial analysis literature as an irregular lattice), it is common to find spatially autocorrelated (i.e., correlated with themselves) residuals. More precisely, the residuals usually are spatially positively autocorrelated such that high residuals tend to cluster in space and low-valued residuals similarly tend to show geographic clustering. Although FL take pains to ensure the proper specification of their model, they do not address the issue of autocorrelated regression residuals.

Why do autocorrelated residuals occur?

Autocorrelated residuals are common, although not universal, in standard regression analyses of dependent variables that are themselves autocorrelated. Figure 1 strongly suggests that county-level child poverty is one such variable. Broad regions exhibit high child poverty, where any selected county and its neighbors likely share high levels of poverty. Similarly, other regions exhibit almost uniformly low levels of child poverty, where a selected county is likely to have a low rate of child poverty similar to that of its neighbors. (For the moment, we set aside the matter of how the term ‘‘neighbor’’ is defined.) Consider some of the mechanisms that can cause spatial autocorrelation (Wrigley, Holt, Steel, & Tranmer, 1996):

1. *Feedback*. For most social processes, individuals and households interact with each other and thereby influence each other. The influence of such interaction is likely to be stronger for those who are in frequent contact. Residential proximity generally increases the frequency of such interactions and the strength of the feedback. This process is formally based on adoption/diffusion theory (Rogers, 1962) or agent interaction theory (Irwin & Bockstael, 2004) and suggests models

commonly referred to as spatial lag models (explained below). Poverty is a condition of economic deprivation, however, and one that carries with it a certain amount of societal disapproval. Thus, we are disinclined to favor this hypothesis when accounting for spatial autocorrelation of child poverty among counties.

2. *Grouping forces*. Individuals and households with common characteristics sometimes are found clustered together either by choice or because they are constrained to co-locate by the coercive operation of social, economic, or political forces. Persons in poverty may well be subject to such forces, say, through the operation of local housing or labor markets. When this type of constraint *is* responsible for spatial autocorrelation in a dependent variable, it may be possible to identify the variable or variables involved in the process and operationalize them on the right-hand side of a regression specification. Sometimes the spatial autocorrelation in the dependent variable (and in the regression residuals) can be explained by autocorrelated covariates (independent variables), and standard regression approaches will work just fine. If a causal variable cannot be identified and operationalized, then the source of the autocorrelation will remain in the error term, necessitating what is referred to as a spatial error model and estimation procedures appropriate for such a model (Anselin, 1988, 2001a; Anselin & Bera, 1998).
3. *Grouping responses*. Individuals or households that share a common attribute or a set of common characteristics may respond similarly to external forces. Often there exist contextual forces (e.g., local industrial structure and labor practices, long-time cultural influences, or geophysical conditions affecting, say, soil fertility and profitable agricultural pursuits) that affect all individuals and households in an area. Different groups of people will possess varying capacities (e.g., the necessary human or social capital) to overcome these external forces. It is likely, we believe, that county-level child poverty is spatially autocorrelated because of the combined disposition of such contextual influences. Often a data analyst can deal with the spatial autocorrelation that emerges under the operation of such a process by identifying some of these contextual forces and declaring different "spatial regimes"—subregions revealing systematic differences in the relationships under investigation. Failing this, as with the grouping models discussed in the previous paragraph, the source of the spatial autocorrelation will remain in the regression error term, the result of an omitted variable in the specification, and spatial econometric approaches must again be considered.
4. *Nuisance autocorrelation*. Most commonly this occurs when the underlying spatial process creates regions of attribute clustering that are much larger than the units of observation chosen by (or available to) the analyst. Figure 1 reveals that the areas of high and low poverty generally are considerably more extensive than is the particular lens (counties) through which we are viewing the process. When units of analysis are much smaller than the regions of high or low attribute values, spatial autocorrelation in the observations is inevitable. As with substantive autocorrelation, nuisance autocorrelation must somehow be recognized and eventually brought into the formal analysis. Anselin (1988, p. 15) differentiates among these types of autocorrelation using the terms "apparent contagion" (spatial heterogeneity) and "real contagion" (spatial dependence).

Why do autocorrelated residuals cause problems?

Regression models with autocorrelated residuals violate the independence assumption for errors in the classical multiple linear regression model , an assumption embodied in the Gauss-Markov Theorem (see, for example, Fox, 1997; Greene, 2000). A more helpful answer, however, addresses the potential dangers of violating the independence assumption. Spatially autocorrelated residuals indicate that the errors are not independent and that the regression parameter estimates therefore are no longer "BLUE"—for Best Linear Unbiased Estimator. In particular, statistical inference is unreliable because (1) the estimated regression parameters are biased and inconsistent, or (2) standard errors of the parameter estimates are biased. For example, in the case of positively autocorrelated residuals (the most common situation with census data), if a spatial error model (defined below) is the "correct" specification, then estimated standard errors in OLS are too small—possibly resulting in a claim of statistical significance for a parameter estimate when in fact such a claim is unwarranted. Thus, even when the regression parameters are unbiased (not always the case), t-values generally are wrong (too large), p-values are too small, and the R^2 coefficient is overstated. The stronger the autocorrelation in the residuals, the greater is the loss of independent information in the process and the more likely are errors of inference.

How is autocorrelation measured?

Spatial autocorrelation has been recognized for many decades (Cliff & Ord, 1973, 1981), and various means of measuring it have been devised. The most common, a statistic called Moran's I (Cliff & Ord, 1981; Moran, 1950), is defined as follows:

$$I = \left(\frac{n}{\sum_i \sum_j w_{ij}} \right) \left(\frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \right)$$

where i and j index the areal units of which there are n, and w_{ij} is a spatial weight (≤ 1) defining the connection between areal unit i and areal unit j. w_{ij} is an element of an $n \times n$ spatial weights matrix, $\boldsymbol{W}$, defining the neighborhood structure within which spatial dependence is believed to operate. $\boldsymbol{W}$ often is row-standardized (each row summing to unity), in which case the denominator of the fraction in the first term sums to n, simply making the value of the first term equal to unity.

Positive values of Moran's I suggest spatial clustering of similar values. Negative values (infrequent in the social sciences) suggest that high values are frequently found in the vicinity of low values. The I statistic is similar to the familiar Pearsonian product-moment correlation coefficient, however, the maximum and minimum possible values of Moran's I are not constrained to lie in the (–1,1) range (Bailey & Gatrell, 1995, p. 270; Griffith, 2003, p. 5).

When significant spatial autocorrelation exists, what must be done to specify a proper regression model?

This question forms the basis of an extensive literature. Recent treatments include the work of Anselin (2000, 2001a, b, 2002), Anselin and Bera (1998), Getis and

Griffith (2002), and Kelejian and Prucha (1997). Spatial effects must explicitly be incorporated into the specification of the model and then the model must be estimated using appropriate estimation techniques (maximum likelihood or instrumental variable general method of moments). While methods for proceeding are not found in any sort of spatial analysis ‘‘cookbook,’’ one approach is reasonably well established: (1) If indicated, consider methods for removing large-scale trend or drift in the process (referred to as spatial heterogeneity) before advancing to spatial regression models (designed to deal with spatial dependence). The reason for this first step is that spatial regression and regression diagnostic statistics assume a stationary (homogeneous) spatial process. (2) Fit a standard OLS model to the data and examine the regression diagnostics. Special tools for obtaining and interpreting such diagnostics are found, for example, in Anselin's SpaceStat software. The software documentation can be found at http://www.terraseer.com/products/spacestat/docs/spacestat_tutorial.pdf. (3) Relying on some defensible theory concerning the presence of autocorrelation in the data, and using the diagnostic guides from the OLS regression, proceed to fit an appropriate spatial regression model. (4) If so indicated by the diagnostics from the spatial regression, it may be necessary to cycle back to step (1) to carry out further remediation with respect to large-scale spatial variation in the process and then proceed iteratively through the steps again.

Reanalysis of Friedman and Lichter

Our reanalysis of the FL study focuses particular attention to matters of exploratory spatial data analysis (ESDA) and spatial regression. The GIS software used in this analysis are two products of ESRI (Environmental Systems Research Institute Inc.): ArcView 3.2 and ArcGIS 8.1. The spatial regression software used is SpaceStat 1.91, GeoDa 0.9i, S-Plus 6.1 (S + SpatialStats), and the open source programming language R. The exploratory data analysis was carried out using SPSS for Windows 11.5.0 and GeoDa 0.9i.

Exploratory spatial data analysis

We began by testing the dependent variable for normality and the bivariate relationship of each independent variable with the dependent variable for linearity. Although some of the independent variables (e.g., % Black and % Hispanic) were not normally distributed, they were not transformed in order to replicate the original FL model. Thus, only improvements to that model derived from the addition of a spatial term to the original specification will arise. Figures 2 and 3 display, respectively, the Moran scatterplot (Anselin, 1996) and a localized version of the Moran statistic (Anselin, 1995), which are valuable for gaining a ‘‘local’’ understanding of the extent and nature of spatial clustering in a data set.

In the Moran scatterplot of the dependent variable (the logit transformation of the child poverty rate in 1990), the data are standardized so that units on the graph are expressed in standard deviations from the mean (Fig. 2). The horizontal axis shows the standardized value of the log odds for a county. The vertical axis shows the standardized value of the *average* log odds for that county's ‘‘neighbors’’ as defined by the weights matrix, described above for the Moran statistic. Neighbors for this illustration are defined under the ‘‘first-order queen’’ convention, meaning that the

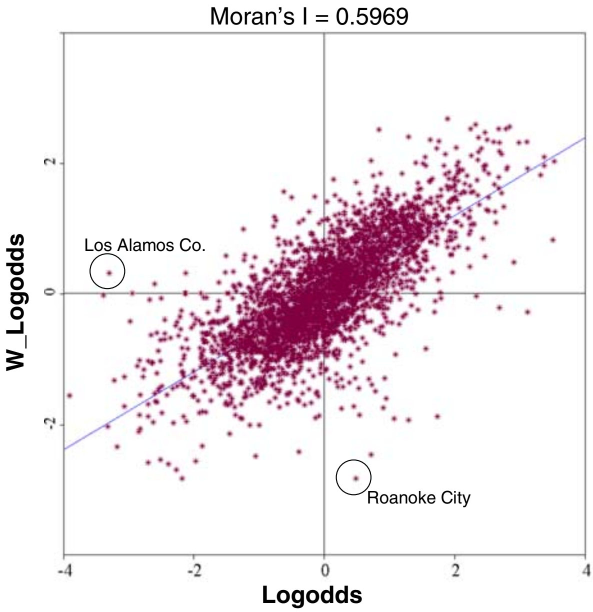

Fig. 2 Moran scatterplot of log odds child poverty

neighbors for any given county "A" are those other counties that share a common boundary (or single point of contact) with "A" in any direction. The upper right quadrant of the Moran scatterplot shows those counties with above average log odds that also share boundaries with neighboring counties that have above average values on the same variable (high-high). The lower left quadrant shows counties with below average log odds values and neighbors also with below average values (low-low). The lower right quadrant displays counties with above average log odds surrounded by counties with below average values (high-low), and the upper right quadrant contains the reverse (low-high). Anselin (1996) has demonstrated that the slope of the regression line through these points expresses the global Moran's *I* value which, for the log odds of child poverty is 0.597. This statistic is strongly positive, indicating powerful *positive* spatial autocorrelation (clustering of like values). It summarizes in a single number what we have already observed in the map of county-level child poverty (Fig. 1). Most counties are found in the high-high or low-low subregions of the country.

While there are several techniques for identifying potential outliers, the Moran scatterplot identifies observations that are very different from their neighbors. Based on the Moran scatterplot, we examined two observations in which the dependent variable is different (by several standard deviations) from neighboring values. In the lower right quadrant we identified Roanoke City, VA (child poverty rate = 24.9%, slightly above average). Due to the special nature of Virginia's independent cities, this observation has but one neighbor, Roanoke County (child poverty rate = 3.76%, far below average). In the upper left quadrant we identified Los Alamos County, NM, a low-poverty (2.8% child poverty) county surrounded by three neighbors with an average rate of child poverty of 23.5%, slightly above the national average. Other potential outliers were examined, but none were deemed to have qualities necessitating their exclusion from the analysis. However, the

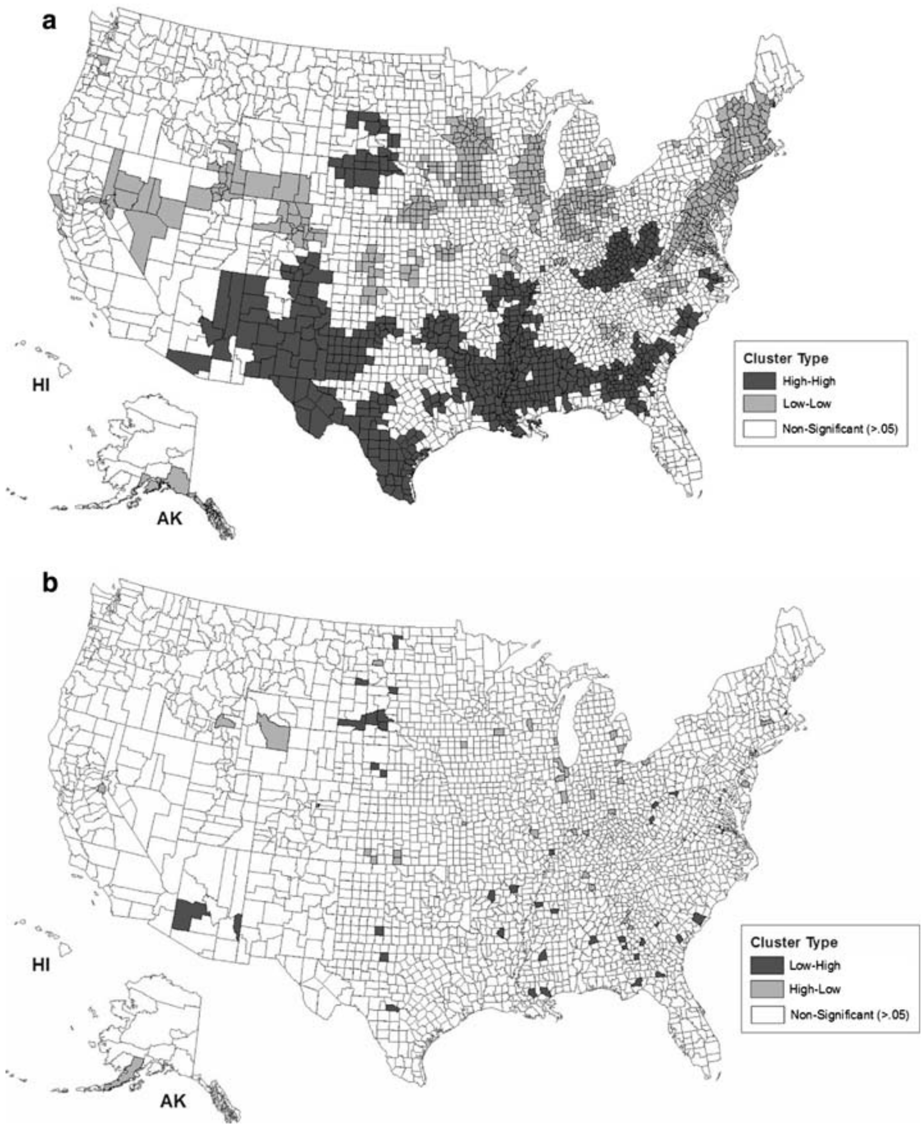

Fig. 3 (**a**) Log odds child poverty: local Moran cluster map (neighbors similar) and (**b**) log odds child poverty: local Moran cluster map (neighbors different)

illustration is useful in showing how this type of exploratory neighbor analysis can proceed. Such exploration is particularly aided by dynamic ''linking and brushing'' among windows—ESDA functionality that is accessible in the GeoDa software.

A map of the ''*local*'' Moran's *I* statistic for our dependent variable, a LISA map (for Local Indicators of Spatial Association), provides a corollary to the Moran scatterplot by displaying the same data in a different way (Fig. 3a, b). The LISA maps show the geographic distribution of the various value combinations (high-high and low-low in Fig. 3a and low-high and high-low in Fig. 3b) for counties across the

US. Counties where the local Moran statistic is not significant (at the 0.05 level, based on a randomization procedure) are not shaded on the map.

Hotspot clusters of high rates of child poverty (surrounded by neighbors with high poverty) are apparent in areas familiar from Fig. 1, including the Mississippi Delta region, the Black Belt, Appalachia, southwest Texas and New Mexico, and several counties with Indian reservations or proportionately large Indian populations in southern South Dakota and northern Nebraska. Coldspots include the large (low-low) cluster of non-central city counties in the Northeast and smaller clusters in Wisconsin & Illinois and Minnesota & Iowa. A band of low-low counties stretches westward from central Colorado to western Nevada.

Individual high-low counties (somewhat difficult to see at this scale) are mostly metropolitan central city counties. A few statistically significant (at the 0.05 level) low-high counties appear as islands here or there in Fig. 3b, but these defy easy summarization. Many of these low-high counties contain small/medium cities or are adjacent to such counties, perhaps suggesting the presence of suburban-type neighborhoods.

While this exploratory view of the data may suggest hypotheses to test in further analysis, the principal message is that, taken together, the maps in Figs. 1 and 3a, b confirm that child poverty is a highly clustered regional phenomenon. A combination of socioeconomic processes operating in space over time has somehow conspired to partition the country into large regions of high and large regions of low child poverty—with occasional "island" counties here and there that are very different from their neighbors.

Regression analysis

Using the variable specifications and transformations provided by FL we replicated, exactly, their WLS regression results using S-Plus (S + SpatialStats) software and the open source software, R. (The original FL analysis had been carried out using SAS.) Focusing specifically on the final and most fully elaborated FL model, we examined the regression residuals for spatial autocorrelation. A Moran's I statistic of 0.326 ($p < 0.001$) strongly suggests that standard regression estimates cannot be trusted, but, by itself, does not determine how we should proceed. We commenced the reanalysis by specifying and estimating a simple regression model using SpaceStat in order to obtain the useful diagnostic statistics that are part of the SpaceStat package. The model is faithful to the FL model except that it is fit using OLS rather than WLS—due to limitations of SpaceStat. The OLS diagnostics demonstrate the likely presence of a spatial error process in the child poverty data, although we will present the results of both a spatial error model and a spatial lag model.

A spatial error model commonly is specified (matrix notation) as follows:

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{u}$$
$$\boldsymbol{u} = \rho \boldsymbol{Wu} + \boldsymbol{\varepsilon}$$

where $\boldsymbol{y}$ is a $(n \times 1)$ vector representing the dependent variable, $\boldsymbol{X}$ is a $(n \times k)$ matrix representing the $k - 1$ independent variables (and an initial column of 1s to accommodate the regression constant term, $\boldsymbol{\beta}$ is a $(k \times 1)$ vector of regression parameters to be estimated, $\boldsymbol{u}$ is a $(n \times 1)$ vector of error terms presumed to have a covariance structure as given in the second equation, ρ is a spatial lag parameter to be estimated, $\boldsymbol{W}$ is a $(n \times n)$ "weights" matrix defining the "neighborhood" structure in the spatial process such that $\boldsymbol{Wu}$ is a $n \times 1$ vector of spatial lags of the model disturbance term $\boldsymbol{u}$; w_{ij} are elements of the $\boldsymbol{W}$ matrix and appear as terms in the (non-matrix notation) equation for Moran's I statistic, above, and, finally $\boldsymbol{\varepsilon}$ is a $(n \times 1)$ vector of independently (not necessarily identically) distributed errors.

Under this specification, spatial autocorrelation in the dependent variable results from exogenous influences. Portions of the spatial autocorrelation may be "explained" by the included independent variables (themselves spatially autocorrelated) and the remainder is specified to derive from spatial autocorrelation among the disturbance terms. The latter is assumed to occur because of one or more relevant spatially autocorrelated variables omitted from the design matrix, $\boldsymbol{X}$. Said another way, it is, in part, the error structure that is the vehicle by which spatial autocorrelation appears in the vector $\boldsymbol{y}$. In this analysis using a first-order queen convention, 10 counties have no neighbors (i.e., they are islands) and one county has 14 neighbors.[1] The modal number of neighbors is six, representing the situation for roughly one-third of counties in the US.

A spatial lag model commonly is given as follows:

$$\boldsymbol{y} = \lambda \boldsymbol{W} \boldsymbol{y} + \boldsymbol{X} \boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

where terms are the same or similar to those presented for the spatial error model. $\boldsymbol{Wy}$ is a $n \times 1$ vector of spatial lags of the dependent variable $\boldsymbol{y}$, and λ is a spatial lag parameter to be estimated.

Under this specification, the terms of vector $\boldsymbol{Wy}$ represent the weighted average of the dependent variable for neighboring locations. The specification assumes the existence of structured interaction among neighbors such that values of the dependent variable in one county are directly dependent, through some function (defined by $\lambda \boldsymbol{W}$), on the values of the dependent variable in neighboring counties. In both the error and lag specifications, $\boldsymbol{X\beta}$ (a $n \times 1$ vector expressing the conditional means of the random variable $\boldsymbol{y}$) represents the direct effects on $\boldsymbol{y}$ of the attribute values, $\boldsymbol{X}$, in a county. That is, $\boldsymbol{y}$ and $\boldsymbol{X}$ are attribute values drawn from the same county.

[1] One of the paper's reviewers requested information relating to our selection of a first-order queen specification for our weights matrix. Spatial weights matrices can specify a variety of configurations by which to capture neighborhood influences. We chose the common convention (first-order queen) for several reasons. First, after testing many alternatives, this specification was found to yield the highest Moran statistic (0.597) with strong statistical significance (z-value = 55.6) on the dependent variable. One weights matrix using a strong (order 6) inverse distance decay gave us a mildly higher Moran statistic (0.609) but with much weaker statistical significance (z-value = 41.8). We also believe the simple first-order queen is easy to explain to the reader and easy for the uninitiated reader to comprehend. Most important, however, we choose this convention because there is evidence when using county economic data that neighborhood influences extend out approximately 40–50 miles and then dampen appreciably (Wheeler, 2001)—quite unlike a smooth inverse distance decay. This distance (40–50 miles) will certainly include immediate neighbors for most counties in the US. In parts of the eastern US where counties are geographically small, this distance would occasionally pick up second-order neighbors as well (i.e., neighbors of neighbors), but in much of the western US a strict centroid selection rule of 50 miles would declare many counties to have no neighbors, whatever. Thus the first-order queen selection is deemed a useful compromise. The literature on this topic is growing. Two useful references include Griffith (1996) and Florax and Rey (1995).

Table 3 Regression results, county-level child poverty in US: 1990

	(1) F & L model S-Plus results (weighted) S-Plus & R	(2) Spatial error with original F&L model variables (weighted) S-Plus	(3) Spatial error with original F & L model variables (unweighted) & SpaceStat	(4) Spatial lag with original F & L model variables (unweighted) GeoDa & R & SpaceStat	(5) Spatial error model F&L model variables plus weight variable[a] GeoDa & R & SpaceStat	(6) Spatial lag model F&L model variables plus weight variable [a] GeoDa & R & SpaceStat
Control variables						
Proportion black (non-Hispanic)	0.212 (0.054) a	0.525 (0.127)	0.311 (0.081)	–0.052 (0.064) ns	0.289 (0.081)	–0.072 (0.013)
Proportion Hispanic	0.778 (0.031)	0.439 (0.107)	0.716 (0.083)	0.454 (0.050)	0.686 (0.081)	0.414 (0.051)
Proportion w/HS education or less	1.46 (0.063)	2.297 (0.101)	1.917 (0.085)	1.791 (0.076)	1.907 (0.085)	1.786 (0.076)
Employed in the county	0.596 (0.025)	0.287 (0.051)	0.335 (0.034)	0.283 (0.035)	0.317 (0.034)	0.259 (0.035)
South dummy	0.18 (0.009)	0.184 (0.031)	0.170 (0.023)	0.100 (0.014)	0.175 (0.023)	0.104 (0.013)
Met dummy	–0.061 (0.012)	–0.096 (0.036)	–0.029 (–0.015) ns	–0.021 (0.015) ns	–0.036 (0.015) ns	–0.040 (0.064) ns
Industrial structure						
Extractive	1.288 (0.101)	2.261 (0.108)	1.800 (0.097)	1.729 (0.082)	1.802 (0.097)	1.744 (0.082)
Non-durable manufacturing	–0.216 (0.119) ns	–0.395 (0.200) ns	–0.178 (0.140) ns	–0.265 (0.125) ns	–0.171 (0.140) ns	–0.253 (0.124) ns
Miscellaneous services	–0.691 (0.182)	1.924 (0.262)	0.210 (0.254) ns	–0.270 (0.237) ns	0.177 (0.254) ns	–0.325 (0.236) ns
Professional services	–0.604 (0.091)	–0.370 (0.176) ns	0.189 (0.134) ns	–0.124(0.118) ns	0.173 (0.134) ns	–0.116 (0.117) ns
Opportunity structure						
Prop of LF unemployed	5.984 (0.233)	3.862 (0.323)	3.694 (0.258)	2.907 (0.232)	3.700 (0.258)	2.863 (0.231)
Prop of males underemployed	2.555 (0.118)	1.627 (0.144)	2.022 (0.115)	2.054 (0.117)	2.035 (0.115)	2.074 (0.116)
Family structure						
Prop of fem-headed families with children	3.517 (0.115)	3.908 (0.205)	3.955 (0.154)	4.257 (0.156)	3.907 (0.154)	4.203 (0.155)
Weight variable					0.000002 (0.0000005)	0.000003 (0.0000005)
Intercept	–4.435 (0.069)	–5.076 (0.129)	–4.749 (0.099)	–3.971 (0.099)	–4.724 (0.099)	–3.938 (0.098)
Lag parameter	NA	0.080	0.612	0.305	0.614	0.312
Moran's I (residuals)	0.326	0.005 ns	–0.044	0.130	–0.044	0.126
R^2	0.878	M	0.666–0.843	0.811–0.818	0.660–0.844	0.813–0.82

Table 3 continued

	(1) F & L model S-Plus results (weighted) S-Plus & R	(2) Spatial error with original F&L model variables (weighted) S-Plus	(3) Spatial error with original F & L model variables (unweighted) & SpaceStat	(4) Spatial lag with original F & L model variables (unweighted) GeoDa & R & SpaceStat	(5) Spatial error model F&L model variables plus weight variable[a] GeoDa & R & SpaceStat	(6) Spatial lag model F&L model variables plus weight variable [a] GeoDa & R & SpaceStat
Residual sum of squares	308.02	1.08	203.92	236.99	202.75	234.46
Log-likelihood	−1,102	−10,970	−292	−428	−284	−412
AIC	2,235	M	616	887	599	856
Residuals						
Min	−95.12	−0.261	−1.540	−2.062	−1.533	−2.062
1Q	−5.293	−0.0018	−0.133	−0.146	−0.134	−0.142
Median	0.1	0.0028	0.018	0.014	0.018	0.014
3Q	5.564	0.0078	0.154	0.168	0.155	0.168
Max	65.99	0.261	1.796	1.765	1.790	1.754

a: standard errors; NA: not applicable; ns: not significant at $p = 0.01$; M: missing (unable to derive from output listfile) R^2 is adjusted R^2 for model 1; otherwise pseudo-R^2; for models (3)–(6) SpaceStat gave the smaller R^2 value

[a] Weight variable, defined as weight $= n \times p \times (1 - p)$, is used as an additional independent variable

Results and discussion

We accept on theoretical grounds, as well as on the basis of diagnostic statistics (not shown) from the OLS model run in SpaceStat, that a spatial error model is an appropriate alternative to standard regression approaches of county-level child poverty. Strong spatial autocorrelation (Moran's $I = 0.326$) in the residuals from the original FL model warrants this alternative. Our initial attempt to estimate a weighted spatial error regression model in S-Plus (S + SpatialStats) seemed very encouraging. In this run (column 2 of Table 3), three of the four "industrial structure" variables moved in a positive direction and for the Miscellaneous Services variable actually corrected an earlier "wrong sign." The residuals from the spatial error model (bottom of column 2), when compared with the FL residuals, were much reduced in size, and spatial autocorrelation among these residuals was essentially eliminated (Moran's $I = 0.005$). The apparent improvement in the model fit, compared to the original FL model, raised suspicions, however, and these were confirmed by a comparison of the log-likelihood figures. Despite the seeming improvements just mentioned, the log-likelihood (–10,970) alone indicated otherwise. This suggested the need for further exploration, and led to estimates of the model shown in column 3 of Table 3. While we were unable to run the *weighted* spatial error regression in any of the other software programs, the unweighted results from GeoDa, R, and SpaceStat were identical (except for SpaceStat's lower R^2 statistic and modestly different AIC score). The parameters in column 3 are changed in modest ways from those in column 2 (unweighted and weighted results, respectively). In particular, the effects of local industrial structure on child poverty are reduced. All four industrial structure parameters in column 3 shift in a positive direction (becoming more positive or less negative) when compared to the original FL non-spatial model shown in column 1. This is a welcome finding, as each of these variables was hypothesized by FL to be positive. The lag parameter in column 3 is much higher (when compared to model 2) suggesting stronger neighbor effects that likely come from a set of one or more spatially autocorrelated omitted variables. Recall that these results come from a spatial error specification where spatial autocorrelation in the dependent variable, net of the included independent variables, derives from spatial autocorrelation in the disturbance terms. The log-likelihood and AIC scores imply that the model in column 3 is a considerable improvement over both models shown in columns 1 and 2.

The results from the spatial lag model, shown in column 4, suggest that this model does not perform as well as the spatial error model in column 3. Here we get some help both from the error diagnostics produced by the software and from a consideration of the theoretical underpinnings of differential risks of child poverty. In column 4, the log-likelihood statistic is lower in value and the AIC score is higher (compared to column 3)—both signals that the spatial error model outperforms the spatial lag model. From a theoretical perspective, this is an anticipated finding. It would be difficult to defend "neighborhood" similarities in county-level poverty as arising from a spatial process akin to feedback or diffusion—that is, a spatial lag process in the classical meaning of that term (Rogers, 1962). Poverty is not a social condition arising from imitation of one's neighbors, as discussed earlier in the paper as a "feedback" process yielding spatially autocorrelated residuals. Rather, poverty seems to result from a complex mix of social, economic, and cultural factors, only a small number of which can be brought into a statistical model of the process. Much of it remains unaccounted for and summarized in the model's error term—a spatial effect we attempt to capture in column 3. Thus, a spatial lag specification (column 4) is deemed an unlikely data-generating model for these particular data. It (and later, the model in column 6) is included merely for didactic purposes.

Troubled by our inability to get properly weighted spatial process models to compare against the original weighted least squares model of FL, we carried out two more attempts to control heteroskedasticity by including the FL Weight variable as an independent variable in a spatial error model (column 5) and spatial lag model (column 6). While unorthodox, the models both seem to be very slight improvements over their counterparts in columns 3 and 4. Parameter values are not substantially altered in these final two runs, the residual sums of squares are nominally smaller, the log-likelihood statistics is higher, and the AIC scores are smaller.

When all the model diagnostics are considered, preference would be conferred on the spatial error model shown in column 5—i.e., a regression model incorporating a lagged error term, a spatial parameter, ρ, and the weight variable (not to be confused with the weight matrix) as an independent variable. We achieved consistent results (save for the R^2 statistic) from GeoDa, R, and SpaceStat. The statistically significant parameters all have the hypothesized sign (as originally posited by FL), the lag parameter, ρ, is registering the strong spatial autocorrelation among the disturbances, as anticipated, and the distribution of the model residuals seems quite good—certainly when compared with FL's original WLS model (column 1). With the exception of model 2 (which we are inclined not to trust for reasons stated above), the residual sum of squares for model 5 looks favorable when compared to the original model, and the residual Moran's I, while significant at $p = 0.01$ (and, surprisingly, negative), vanishes to inconsequence as a practical matter. Model 5 is preferred over model 6 for precisely the same reasons given above for preferring model 3 over model 4. The only feature in model 6 that merits special comment is that the parameter for the control variable, Proportion Non-Hispanic Black, becomes *negative* and statistically significant. The same unanticipated outcome is seen in model 4, but there the parameter fails to achieve significance. This finding suggests an unlikely inverse marginal relationship between proportion black and child poverty in the spatial lag model. We have encountered this interesting result in one other context. While exploring these data and model specifications using geographically weighted regression (Fotheringham, Brunsdon, & Charlton, 2002), we discovered that the FL model specification yielded large regions of the US where the marginal OLS parameter estimate for the variable, Proportion Non-Hispanic Black, was negative. These regions—with vast areas of rural populations—include (1) the states ranging from the Appalachian coal fields and westward across the lower Great Lakes industrial and corn belts, down to and including portions of the southern Great Plains, and (2) most of the lower 48 states in the Census Bureau's Pacific Census Division (Washington, Oregon, and California). Apparently in the spatial lag specification, the lagged dependent variable picks up the strong spatial clustering of poor African Americans in portions of the US (e.g., the Mississippi Delta region and the old coastal plain Cotton Belt or Black Belt) and leaves behind those rural areas with high rates of child poverty but low proportions of non-Hispanic Blacks.

Concluding comments

Awareness of the problems caused by spatial autocorrelation when using aggregated data in regression analysis is slowly spreading within the social sciences from the disciplines of geography, spatial econometrics, and regional science. Within sociology, for example, recent publications have emphasized the importance of space and place (e.g., Gieryn, 2000; Lobao, 2004; Lobao & Saenz, 2002; Tickamyer, 2000). In addition, a small number of sociologists have begun publishing research analyses where spatial processes have been brought into model specifications to correct for bias or inefficiency in parameter estimates that occur when spatial effects are ignored (e.g., Baller & Richardson, 2002; Baller et al., 2001; Deane, Beck, & Tolnay, 1998; Messner & Anselin, 2004; Sampson & Morenoff, 2004; Sampson, Morenoff, & Earls, 1999; Tolnay, 1995; Tolnay, Deane, & Beck, 1996). Unfortunately, however, this is still an emerging area where software developments have not kept pace with conceptual and theoretical advances—at least to the extent of making available relatively easy-to-use software. (GeoDa is emerging in ways that will soon contradict this statement, if it hasn't already.) For example, in our reanalysis of the FL data, despite the fact that we have been able to deploy several useful software packages with which to estimate spatial regression models, we were not able to fully implement the models we wished to estimate (e.g., properly weighted versions of models 3 and 4). As is evident from some "holes" (labeled "M") in Table 3, the kinds of regression diagnostics provided by the different packages differ (e.g., S-Plus did not provide a R^2 statistic or AIC score for the weighted spatial error model). Finally, even when everything else matched up, the R^2 statistic provided by SpaceStat differed from that reported by GeoDa and R, and the AIC score from SpaceStat also differed, but inconsequentially.

Yet, in the model shown in column 5 of Table 3, we likely have a reasonable re-estimation of the FL model, one that incorporates both the large-scale spatial heterogeneity (through the mean vector $\boldsymbol{X\beta}$) and the small-scale neighbor influences on child poverty (through the spatial lag process $\rho\boldsymbol{Wu}$). This model has all the advantages of model 3, but diagnostic statistics (log-likelihood and AIC score) suggest that it performs marginally better. It is important to say that this model does not alter in any substantial way the general findings of Friedman and Lichter in the original analysis. Their conclusions, presented early in this paper, do not change appreciably when corrected for spatial effects—but they might well have. Models 3 and 5 both appear to satisfactorily correct the problem of residual dependency (in the FL model) and are thus more reliable models on which to base those conclusions. Consequently, our reanalysis of these data provides a more secure understanding of the way in which this particular set of independent variables jointly determine the spatial distribution of child poverty in the US. The risk of a child living in a household with income below the officially established poverty threshold is not homogeneously distributed across the US. This is obvious from even a passing glance in Fig. 1. But model 5 in Table 3 provides us some clues about the spatial process yielding this outcome. As with the original FL regression results, model 5 tells us about the marginal influences of several important covariates. In addition, the model (as a spatial error specification) helps us better understand how a combination of "grouping forces" and/or "grouping responses" (discussed above) become strong participants in this process. In presenting this alternative to the original FL model, we have also re-emphasized the need for more sociologists to consider matters of spatial autocorrelation in analyses using aggregated data. That too is a modest contribution. Our reanalysis serves as an instructive example of how to approach the task of examining a structured socioeconomic process in the presence of strong spatial externalities. Such empirical re-examinations are necessary as new analytic methodologies emerge (see, for example, Doreian, 1980, 1981; Loftin & Ward, 1983). Indeed, Friedman and Lichter themselves invited and encouraged such activity vis-à-vis their own contribution when they wrote, ''...[O]ur study provides a point of departure for additional studies of child poverty and growing spatial economic differentiation'' (1998, p. 106).

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