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Spatio-Temporal Dimensions of Child Poverty in America, 1990–2010

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Abstract

The persistence of childhood poverty in the United States, a wealthy and developed country, continues to pose both an analytical dilemma and public policy challenge, despite many decades of research and remedial policy implementation. In this paper, our goals are twofold, though our primary focus is methodological. We attempt both to examine the relationship between space, time, and previously established factors correlated with childhood poverty at the county level in the continental United States as well as to provide an empirical case study to demonstrate an underutilized methodological approach. We analyze a spatially consistent dataset built from the 1990 and 2000 U.S. Censuses, and the 2006–2010 American Community Survey. Our analytic approach includes cross-sectional spatial models to estimate the reproduction of poverty for each of the reference years as well as a fixed effects panel data model, to analyze change in child poverty over time. In addition, we estimate a full space-time interaction model, which adjusts for spatial and temporal variation in these data. These models reinforce our understanding of the strong regional persistence of childhood poverty in the U.S. over time and suggest that the factors impacting childhood poverty remain much the same today as they have in past decades.

Keywords

poverty; spatial econometrics; space-time modeling

1. Introduction

We present in this paper an incrementally sophisticated approach to an examination of poverty in the United States. The methodology permits a careful and rigorous examination of the unequal geographic distribution of poverty and the changes in poverty over time, as well as a fully interactive approach which deals jointly with spatial clustering of poverty and change in such spatial clustering over time. The approach addresses, and is motivated by, concern over one of the most difficult and intractable problems facing the social and economic landscapes of the country.

In recent decades, the United States has emerged as one of the few developed countries where high per capita income is juxtaposed with a persistently high rate of poverty (Smeeding, 2006). While definitions of poverty vary among nations, a recent international comparison of 157 countries reveals that the U.S. has the 123rd highest poverty rate, higher than most wealthy western nations and, at 15.5%, situated between Chile and Morocco (CIA Factbook, 2012). Even more striking than the overall poverty rate is the current *child* poverty rate. A recent United Nations Children's Fund report on the well-being of children in 29 developed nations ranks the U.S. as 28th, above only Romania (UNICEF, 2013). Presently, 16 million children live in families with incomes below the federal poverty level (National Center for Children in Poverty [NCCP], 2013). Although children comprise only 24% of the total population, a disproportionate 34% of all individuals living in poverty in the U.S. are children (NCCP, 2013). It is remarkable that, while the U.S. is currently in a period of economic recovery, a larger number (and *proportion*) of children live in poverty today than in 2010, at the height of the recent recession (Bishaw, 2012). The reasons for the continued increase in child poverty during economic recovery are poorly understood, suggesting that there continues to be much we do not know about the underlying drivers of child well-being in this country. Many theories have been advanced to explain these processes, including increasing wage inequality, industrial restructuring, family compositional changes, and reduced community fiscal capacity (Lesthaeghe & Neidert, 2006; Goldin & Katz, 2007; Dorling et al., 2007; Fong & Chan, 2008). A stronger examination of the correlates of poverty is called for, to investigate the persistence of high poverty rates despite overall economic growth and an uptick in the business and market cycles.

Another hallmark of poverty in the U.S. is the persistent imbalance across regions of the country in terms of the aggregate burden of poverty. Indeed, the *spatial* aspect of child poverty appears to be as stubbornly resistant, and perhaps more so, than the unwavering *temporal* persistence (Labao & Saenz, 2002). For many decades, large regions of high child poverty rates in the U.S. have remained along the Mississippi Delta, Appalachia, southwest Texas and New Mexico, several Native American tribal lands in South Dakota and Nebraska, and the crescent of counties marking the old "Cotton Belt" (Friedman & Lichter, 1998; Dunning, Ledbetter & Whorton, 2002). These large regions of persistent poverty seem immune even to targeted efforts to raise the economic fortunes both of families and economically impoverished areas. Previous studies of child poverty have explored these topics both through regional-specific analyses (e.g., Dunning, Ledbetter & Whorton, 2002; Rae, 2012) and national studies (e.g., Cotter, 2002; Dorling et al., 2007). The overwhelming conclusion has been that childhood poverty remains strongly and persistently clustered across the U.S. landscape. Can a carefully structured analysis that simultaneously includes both spatial and temporal variations in child poverty contribute to an improved understanding of these issues? This question motivates the choice of analyses presented in this methodologically-focused paper.

Substantively, we seek to understand the impact of time, viewed here as a proxy for the profound cultural and demographic shifts that have occurred in recent decades, on known correlates of child poverty at the county level. We look, as well, to the spatial patterns and

potential drivers of variation in child poverty across U.S. counties. Methodologically, the spatial nature of child poverty requires the use of spatially informed modeling strategies to correctly estimate model parameters (Orford, 2004; Voss et al., 2006; Rae, 2012). Even recent spatial econometric studies have ignored the temporal aspect of aggregate poverty trends, focusing instead on cross-sectional analyses. An exception is Curtis et al. (2013). Temporally-driven research, on the other hand, generally lacks an explicitly spatial dimension. However, the field of spatial econometrics has matured considerably over the past three decades (Anselin, 2010). Recent methodological advances include spatio-temporal econometric modeling (LeSage & Pace, 2009: Chapter 7; Elhorst, 2003) and formal panel studies explicitly incorporating spatial effects (Baltagi, Song, & Koh, 2003). These developments are the methodological focus of the present analysis. A simple illustration of the methods is important, as the literature, especially in the area of panel models incorporating spatial effects, is often inaccessible to readers not deeply familiar with econometric theory and method.

In this paper, we demonstrate the use of spatial regression, panel regression, and spatial panel regression to explicitly analyze the spatio-temporal elements of county-level child poverty in the U.S. over the past two decades. For each reference year, we hypothesize a positive relationship between child poverty rates and low educational levels, high unemployment rates, and a high proportion of female-headed households. As a consequence of demographic and economic restructuring over the past two decades, we further hypothesize that the relationship between poverty and industrial structure variables will shift over time. In addition, as a result of the persistent geographic distribution of poverty, we hypothesize that temporal effects will not strongly impact the relationships between the childhood poverty and our principal variables of interest even when controlling for behavioral and structural characteristics and spatial heterogeneity.

2. Background

Since the 1990s, the U.S. has experienced major social, economic, and demographic upheavals, though, of course, these changes have not been spatially homogeneous. One notable demographic shift in the past two decades has been the rapid change in the racial and ethnic composition of the youth population. Today, nearly 30% of children are Hispanic, Asian, Black, or of mixed-race. A quarter of all children are either immigrants themselves or born to foreign-born parents (Passel, 2011). These changes have altered both the ethnicities of children living in poverty, and shifted the geographic distribution of child poverty in the U.S. Immigrants remain much more concentrated spatially in metropolitan areas and specific regions of the country than other groups (Lichter & Johnson, 2006).

In recent decades, the American household has also undergone changes in structure. Between 1990 and 2010 the share of all households consisting of a mother with children (but no spouse) increased from 11.6% to 12.9%. This shift, coupled with the movement of more women into the workplace, may also have influenced the household income distribution and altered child poverty rates (Bishop et al., 1997; Bradbury, 1996; Cancian & Reed, 1999; Chevan & Stokes, 2000; Karoly & Burtless; 1995). Other socio-cultural changes including increased cohabitation, same-sex unions, and extramarital childbearing have further altered

the traditional notion of the "American family" (Lesthaeghe & Neidert, 2006; Cherlin, 2004).

In addition to these socio-cultural and demographic shifts, large and prolonged swings in the business cycle, a significant upheaval in the housing market, and regionally variable economic fortunes may have changed the influence of factors associated with child poverty. The discovery and exploitation of the oil-rich Bakken geological formation in western North Dakota, and the consequent oil boom prosperity on employment and state GDP, is a recent, if extreme, example. Evidence indicates that places with homogenous economies are most impacted by economic shocks, including outsourcing of manufacturing jobs to overseas locations (Lynch, 2003; McLaughlin, 2002).

America has also transitioned into an information-dominated society over the past several decades. As a result, there have been in substantial changes in the workforce, occupational markets, and productivity. Workers have been forced into contingent work or nonstandard employment as livelihood strategies (Barker & Christensen, 1998; Freedman, 1985; Polivka & Nardone, 1989). Advances in technology and computerization have improved high-wage employment in some sectors of the economy while replacing many of the routine jobs that once were middle-wage job labor, such as factory work. Such shifts have further contributed to greater unemployment, poverty and income/wealth inequality (Goldin & Katz, 2007). Effects from computerization have, however, had only marginal influence on low wage manual labor jobs, such as janitorial work, which cannot be mechanized.

The past two decades have contained sufficiently strong social and economic change that our models should be able to detect the presence and strength of space-time interactions. While it might have been instructive to have a longer temporal dimension, pushing these data back in time creates comparability issues with several of our key variables as well as our units of geography. The data are sufficient to illustrate our methodological approach and address hypotheses specific to the period 1990 to 2010.

3. Theoretical Underpinnings

In our study, we focus on three reference dates (1990, 2000, and, approximately, 2010), represent roughly two decades. The word "approximately" is used because the U.S. 2010 Census discontinued a point-in-time collection of detailed social and economic characteristics – data formerly gathered by a large sample survey tied to the census. Following the 2000 Census, these data began to be collected in the U.S. as part of a large rolling sample survey of housing units. The data we refer to in this paper as applying to the terminal period were, in fact, gathered in 60 monthly household surveys spanning the period January, 2006, and December, 2010. The data collection window was centered on July, 2008, and for simplicity we refer to the terminal period in our time series as "2008".

Specifically, we examine the relationships between childhood poverty (observed as an aggregate summary measure for counties in the U.S.) and several related county-level characteristics: specifically, unemployment, female-headed households, and low levels of completed education. The measure of poverty in the U.S. is consistent over time in the sense that it is annually updated, using the official Consumer Price Index, to reflect the cost of a

minimum food diet for families of different sizes and composition. This "poverty threshold" does not vary geographically. In this paper, child (or childhood) poverty refers to children under the age of 18, living in a household where income falls below the poverty threshold. The appropriate measurement of poverty in the U.S. is a topic of considerable ongoing debate. One of the best overviews of the debate can be found in Citro & Michael (1995).

High levels of unemployment are hypothesized to increase childhood poverty rates because if at least one parent is unemployed, the overall earning potential for the household is reduced, sometimes drastically (Conger et al., 1990). In addition, certain regions of the country have a history of relatively poor prospects for employment. These often long-standing forces result in a mosaic of differential employment opportunities represented by clusters of "traditionally" low- or high-unemployment counties. Levels of poverty tend to follow this spatially clustered pattern.

Rates of female-headed households are hypothesized to relate directly to child poverty rates for reasons similar to unemployment. This relationship holds at the individual family level because female-headed households rarely include two wage earners. The evidence is clear that women also continue to earn less than men in identical jobs (National Commission on Children, 1991), contributing to the economic disadvantage of these households. County-level proportions of female-headed households have long been shown to have a strong positive association with county-level poverty rates (Voss et al., 2006; Curtis et al., 2012).

Low educational achievement is hypothesized to be related to childhood poverty levels because it is generally associated with reduced access to living wage employment and low earning potential. Counties with low educational achievement levels likely reflect some combination of high drop-out rates, shortage of educational opportunities, and selective out-migration of persons with higher educational achievement.

Previous research has investigated aggregate-level child poverty using both spatial cross-sectional and regional spatio-temporal analytic techniques. Using 2000 Census sample data, Voss et al. (2006) applied cross-sectional spatial regression models to examine the relationship between child poverty and socioeconomic characteristics for counties in the U.S. A follow-up analysis explored the importance of regionalism and regional variations in the social and economic processes by which poverty is generated and sustained over time. The study concluded that sub-regions in the U.S. have different poverty-generating processes based on regional differences (Curtis, Voss, & Long, 2012). Subsequent work by Curtis et al. (2013) evaluated the relationship between poverty, industrial structure, and racial/ethnic composition for counties in five states in the U.S. Upper Midwest between 1960 and 2000. The authors find that industrial structure, more so than racial/ethnic composition, can be linked to varying rates of county-level poverty in this region (Curtis et al., 2013). The results of the first study (Voss et al., 2006) confirm the validity (indeed, the necessity) of spatially explicit models for analyzing such data. The second study (Curtis, Voss, & Long, 2012) indicates that poverty generating processes are not the same across space, and adjustments to accommodate this variation are important. Finally, the third study (Curtis et al., 2013), using a novel penalized maximum likelihood estimator, reveals the importance of race and industrial structure across space and time, but other important

variables associated with poverty generation are omitted from the analysis. Our analysis in this paper extends these previous analytic strands by utilizing longitudinal data, spatially-temporally explicit modeling, and a geographically rich and detailed dataset.

In summary, for each reference year in this analysis we hypothesize a positive relationship between high child poverty rates and high unemployment rates, high proportions of female-headed households and low levels of educational attainment. Since we are using aggregated data, we exercise caution in using explanations originating in household attributes (Robinson, 1950). As a consequence of demographic and economic restructuring over the past two decades, we also hypothesize that the relationship between poverty and industrial structure variables will shift over time. Finally, as a result of the temporally persistent geographic clustering of poverty, we hypothesize that changing temporal influences will not strongly impact the relationships between childhood poverty and our principal variables of interest.

4. Construction of Dataset

To address our research questions, we use a county-level dataset that combines point-in-time survey-based estimates from the 1990 and 2000 U.S. decennial census sample data with estimates derived from a rolling monthly household survey. The terminal year in our analysis (referred to as "2008") was pooled from monthly surveys spanning the period January, 2006, to December, 2010. These pooled estimates from the American Community Survey (ACS) are centered on July 2008, but include data gathered as recently as December, 2010. This was a five year period marked by considerable social and economic change, and regrettably our variables for this period end up resembling something akin to a weighted average from 60 monthly surveys. Fortunately, one unplanned contribution of this study helps to shed some light on the effect of the changed methodology both in terms of the estimates of the variables as well as the relationships among them. We briefly address this topic when discussing the spatial cross-sectional models, Section 5.1. This critique of the data aside, there are advantages to the data chosen for this analysis. First, U.S. county boundaries are relatively stable over time, which reduces the introduction of error that results from attempting to reconcile smaller units of geography for temporal research. County-level data is also a rich source of temporally contiguous sociodemographic data in the United States, and has been used for previous analyses of this topic (Voss et al., 2006; Curtis, Voss, & Long, 2012; Curtis et al., 2013). Second, from a cultural change perspective, the two decades spanning 1990 and 2010 were a period of enormous shifts in socio-cultural, demographic and industrial structure. The Great Recession, which officially began in December 2007 and ended in June 2009 (National Bureau of Economic Research, 2014) represents one aspect of this change, only partly captured by the 2006–2010 ACS data. Nevertheless, we anticipate that factors underlying child poverty may have been sufficiently altered by changes over the period 1990 to 2010 such that the effects can be identified in our models. Though other time periods exist wherein changes have been more dramatic, we were mostly interested in examining the present state of affairs for child poverty in the United States taking an interesting methodological approach. We considered extending our analysis further backward in time, but quickly learned that county variability increased significantly with these changes, and some of the variables (such as Hispanic ethnicity) were

not available prior to 1990. Finally, counties are generally sufficiently large that estimates from surveys are relatively efficient (small margins of error). We acknowledge that there is considerable heterogeneity in population (as well as physical) size between counties in the U.S., with Los Angeles County, CA (population approximately 10 million) and Loving County, TX (approximately 80 persons) serving as two particularly extreme examples. However, most counties are large enough that estimates of our variables (here measured as proportions) are reasonably precise. Admittedly, this precision drops somewhat for the 2006–10 ACS period estimates due to somewhat smaller overall sample size and other data collection differences.

For a few counties, boundary changes shifted slightly over this time period. We adjust for this by combining areas of geography when necessary yielding a final dataset with 3,104 units of analysis (after excluding Hawaii and Alaska, which are not contiguous and introduce complications into the spatial analyses. In addition, we treat the District of Columbia as a county. Summary descriptive statistics for our variables are shown in Table 1.

The most interesting elements of Table 1 are the temporal changes in the proportions between 1990 and 2008 and the very high values of the Moran statistic (final column of Table 1). Moran's I is a measure of spatial clustering of an attribute (under an exogenously defined "neighborhood") and is interpreted much like a standard correlation coefficient (−1 to 1) with significant positive values signaling spatial clustering (Cliff & Ord, 1973). Variables with little apparent clustering (or inverse clustering) on a map would have a Moran statistic close to zero.

Our dependent variable, rate of childhood poverty, shifted over the course of the two decades, with a decrease between 1990 and 2000 followed by an increase in 2008 to levels slightly above those in 1990. Despite these temporal fluctuations, spatial clustering of child poverty remained consistently strong throughout the two decades.

Additional dummy variables were tested as control variables using the Rural-Urban Continuum Codes (RUCC) created by the U.S. Department of Agriculture (United States Department of Agriculture, 2013). These codes classify each county in the U.S. through a combination of population size, urbanity, and distance from a metropolitan area. They were eventually dropped from our analysis, as they failed to add anything of substance to any of the models tested (Tickamyer & Duncan, 1990; Wang et al., 2012).

5. Analytic Approaches

We begin by investigating cross-sectional spatial regression models for each of the three reference dates, 1990, 2000 and 2008. The purpose of estimating three separate cross-sectional models is to compare and interpret changes in parameter estimates (including spatial parameters) across a two-decade period of substantial social and economic change. These parameter estimates, and possible shifts in them over time, provide a baseline for better understanding the two other analytic approaches we apply. The cross-sectional spatial regression models correct parameter estimates for biasing forces arising from spatial autocorrelation (spatial clustering) in the dependent and independent variables. This stage of the analysis follows a tradition of spatial econometric development beginning perhaps with

Anselin's foundational textbook (Anselin, 1988). This early exposition has been significantly expanded more recently by LeSage & Pace (2009) and others (Elhorst, 2010; Golgher & Voss, 2015).

Following the cross-sectional spatial regression analyses, we turn our attention to explicitly incorporating time into the analysis by employing and exploring traditional panel model approaches (Baltagi, 2008). We use the results and inferences gleaned from the cross-sectional results to test our hypothesis regarding the likely weakness of temporal forces once other drivers of poverty are controlled. This part of the analysis explicitly allows for temporal changes in all variables across the three survey periods. While instructive, this approach fails, however, to acknowledge the high degree of spatial autocorrelation in the data – a statistical reality that renders the parameter estimates (and associated standard errors) from the standard panel model highly suspect. Finally, we incorporate both the spatial and temporal influences in these data in a formal spatial panel regression model. This model is used to understand the joint interplay of spatial patterning and temporal shifts in the data. All model estimation was carried out using the R programming suite (R Development Core Team 2014), in particular, package spdep (Bivand, 2014) for cross-sectional spatial regression models, package plm (Croissant & Millo, 2008) for the linear panel models and package splm (Millo & Piras, 2012) for the spatial-temporal models. Many models were specified and estimated in the course of this analysis, with the results of most of these models not reported here. We report only the most theoretically satisfying models and also models standing up to detailed examination of model residuals and other diagnostic tests. In addition, for models from each of three approaches, independent variables clearly not contributing to explained variance in child poverty were removed. Our data and R scripts are available by contacting the lead author.

5.1 Cross-Sectional Spatial Durbin Error Model

Our approach to cross-sectional model specification and diagnostic analysis follows the template outlined in the workbook and tutorial documentation for the GeoDa spatial software package (Anselin et al., 2006), although that particular package was not employed in our analyses. A Standard Linear Model (SLM) was first estimated for each of the three reference dates using the Ordinary Least Squares estimator to establish a baseline set of estimates and opportunities for full residual diagnostic testing. In the interest of parsimony, independent variables from a large set of potential predictors were pared down when it was apparent that some anticipated useful predictors were not contributing to explained variance of the county-level child poverty dependent variable, net of other predictors. In addition, we applied standard approaches to reducing multicollinearity.

We examined the residuals from the Standard Linear Model using the Moran's I statistic to test for spatial independence among residuals and Lagrange Multiplier statistics as a likely clue to the source of residual dependence. These examinations indicated that the SLM is a poor model choice, as the estimator leaves behind substantial dependence in the residuals. Further, the diagnostic tests strongly favored a formal spatial regression acknowledging spatial structure in the error term – the implication being that there remains unresolved spatial heterogeneity in the model errors.

Based on the results of the SLM, we examined several spatial regression models for our cross-sectional data. Among these, the relatively simple Spatial Error Model (SEM) behaved well, but economic theory and diagnostic analyses suggest a preference for a closely related, but less common, model: a Spatial Durbin Error Model (SDEM).

From a theoretical perspective the SDEM model is conceptually logical. It is among the family of Simultaneous Autoregressive Models (including SAR (Spatial Lag Models) and SAC Models) where, because of the inverse matrix in the reduced form specification, a shock to any county in the dataset affects the dependent variable in every other county, although the effect declines with distance (LeSage & Pace, 2009; Golgher & Voss, 2015). For example, these models suggests that a change in the unemployment rate in a county affects not only poverty in that county, and poverty among neighboring counties (to a lesser degree), but also poverty among counties hundreds of miles away. It becomes difficult to build the story about how change in an independent variable in one county would affect child poverty three or even more counties away. However, with the SDEM (which we use here), the joint simultaneity occurs only in the error term. The reach of changes in the independent variables in this spatial model goes only to the immediate neighbors as defined by the *W* spatial weights matrix (in this instance, a matrix defined using the so-called row-standardized 1st-order Queen convention). These immediate neighbor influences are indicated in the model by the spatially lagged independent variables. The impact of a change in unemployment, for instance, is theorized in this model to affect child poverty not only in the reference county but to have effects on child poverty in the proximal neighboring counties as well

Conveniently, the diagnostic analyses of the SAR and SAC models directed us away from these two specifications by supporting our conceptual reasoning that, for example, changes in unemployment in a county will affect the standard of living in surrounding counties due to employment opportunities in labor markets that extend beyond the boundaries of a single county. From a statistical perspective, the SDEM consistently outperformed the other spatial models examined. It provided better goodness of fit diagnostics than alternative spatial regression models; it did a superior job of purging the residuals of substantive spatial dependence; and it managed to pull in the tails of the residual distribution (fewer extreme residual outliers) better than alternative model specifications.

Specification details for this model are briefly discussed in the Appendix, and the results of the SDEM model fit for each of the three years are shown in Table 2. Further elaboration and examples using the SDEM can be found in LeSage & Pace (2009) and a helpful interpretation of spatial effects from the SDEM is found in Elhorst (2010) and Golgher & Voss (2014).

The cross-sectional datasets show a fair amount of stability in model coefficient estimates across the three years suggesting that the immense changes in the U.S. economy over these two decades did not much alter the fundamental relationships at work in our model. The model for 2008 is weaker in terms of model fit, and, generally speaking, the estimated parameters are not as strong or precise as the results for 1990 or 2000. We attribute this to the higher imprecision in the estimates from the American Community Survey data rather

than to substantive change in these relationships between 2000 and 2006–10, although we admit that support for this claim would be difficult to prove.

We save further discussion of the individual parameter estimates for the "Discussion" section to follow. Generally speaking, the SDEM approach appears to yield strong cross-sectional models for these data. However, in this approach, the effect of change in the variables over time is only implicitly apparent. Thus we turn next to a model which examines whether our tentative conclusion of little temporal effect holds up when specifying a model that explicitly incorporates time. In doing this, we maintain the basic specification structure of the cross-sectional SDEM, but we add the temporal effect.

5.2 Linear Panel Modeling

For our linear panel model, we maintain the basic model structure and variables chosen for the cross-sectional analysis, both with and without the inclusion of spatially lagged versions of the relevant independent variables. Our goal is to formally test one of the key findings of the cross-sectional analysis: despite the immense social and economic changes witnessed between 1990 and 2010, including a substantial dip, followed by an increase, in the rate of child poverty, these changes appear not to have much affected the relationships between poverty and several other variables known to be associated with poverty. Here we explicitly test the independent role of temporal change in child poverty across U.S. counties by controlling for key social and economic predictors of child poverty which are also permitted to change across the three time periods under study.

Panel data analysis is a timewise approach to examining change in a set of observational units. This analytic approach by now has a relatively strong history and well developed conceptualizations and methodologies (Baltagi, 2008). There are several types of panel analytic models, including constant coefficients (pooled) models, fixed effects models and random effects models. The latter two approaches adjust for the relationship between repeated observations over time. We tested several of these using the variables that emerged as important predictors in the cross-sectional analyses. Model details are addressed in the Appendix.

A simple pooled model predicting child poverty, with three observations per county (permitted to change across the three observational periods), yielded results similar to those from the cross-sectional analyses. As anticipated, a simple fixed effects model produced results that are considerably different from the pooled model since the model adjusts for correlation between observations for a county over time. This is a constant slope model but one which permits intercepts to differ among the 3,104 counties. The temporal effects (included in both PLM models), although small, are exactly as anticipated: all other things equal, child poverty levels dropped significantly between 1990 and 2000. Poverty rates in 2006–10 were, on average, slightly higher than 1990, but the difference is of weak significance. A formal Hausman test revealed that the county-specific effects are sufficiently correlated with the regressors, advising against the random effects model (Baltagi, 2008). Results of the fixed effects panel models are shown in Table 3. Model II differs from Model I only by the addition of the spatially lagged predictors.

Model I is a fixed effects panel model specified without any spatially lagged independent variables, the inclusion of which (in Model II) partially adjusts for local spatial clustering of the variables. Without adjustment for any spatial effects lurking in the error term (arising from spatially autococorrelated omitted variables), the panel models indicate that unemployment is very strongly related to child poverty at the county level. Temporal effects, while in the anticipated direction, are not statistically significant. Model II includes spatially lagged independent variables, adjusting for neighboring influences on poverty. The unemployment rate in a specific county, for example, may be similar to unemployment in neighboring counties (spatial clustering), and may also be related to income and poverty levels in neighboring counties (spatial spillover) since individuals can commute across county lines for employment. In the case of Model II, this appears to be true, since spatially lagged (neighboring) unemployment is positively related to child poverty in the neighboring county.

The panel data approach acknowledges unobserved heterogeneity in the data across time and provides a more accurate set of parameters, since panel datasets typically have more degrees of freedom and larger sample variability than cross-sectional or time-series data. Spatial panel data models, taken up next, also benefit from this advantage, but further adjust for spatial clustering of observed characteristics and also the related spatial clustering of unobserved effects in the errors. The specification of a full spatial panel data model is the third approach taken in this study.

5.3 Spatial Panel Model

The panel data models described in the preceding section acknowledge the clustering within and differences between counties in the dependent variable but do not permit estimation of unobserved spatial heterogeneity. Spatial panel data models, however, provide a substantially richer panel analytic repertoire by including the estimation of parameters of the independent variables but also permit expressing the strength of unobserved neighboring relations beyond those already explicitly in the model specification (i.e., the spatially lagged independent variables). The spatial approach chosen for a given panel dataset can be any method used in a traditional cross-sectional spatial model, including the Spatial Error model, the Spatial Lag model, the mixed-regressive-spatial autoregressive model with a spatial autoregressive disturbance (SARAR) model, and the Spatial Durbin Error model. In regard to the temporal aspect of these types of models, options include random, fixed effects, and pooled models, just as with typical panel data modeling. The estimation of models specifying both spatial and temporal effects has recently been strengthened in the R programming suite using the splm package (Millo & Piras, 2012). Based on the findings from the spatial and temporal models described above, it was clear that the type of spatial panel model appropriate for these data would be a fixed effects Spatial Durbin Error model. Results are shown in Models III and IV in Table 4.

Perhaps the most interesting aspect of Tables 3 and 4 from a substantive perspective is the comparison between Models II and IV. Both are fixed effects panel models with neighbor influences on poverty arising from changes in the independent variables explicitly. Parameter estimates for temporal changes are included in both models but while they shine

through with the anticipated correct sign they are (as discussed above) of little import statistically. In other words, the predictors and spatially lagged predictors overwhelm the model and remind us again that the temporal effect of poverty is primarily one of persistence.

Models II and IV are essentially the same, except that Model IV permits an explicit estimate of the combined effect of spatial clustering among omitted variables (under the particular spatial weights matrix employed). This is accomplished in the model specification by allowing for spatial structure in the error term (see Appendix). The spatial error parameter expresses the strength of unobserved spatial heterogeneity, which is revealed in Table 4 to be statistically significant (likely the result of our large sample) but substantively negligible. This outcome suggests that we have accommodated the spatial heterogeneity in the data and that the parameter estimates are consistent and efficient under the maximum likelihood estimator. The squared correlation between the observed and model-fitted estimates of child poverty (analogous to the R-squared statistic from the OLS estimator) for this model is 0.902, implying an exceptionally strong fit. It also means that Model IV, which includes a relatively parsimonious array of observed predictors (including temporal and spatial effects), provides the opportunity to interpret with confidence what the model suggests regarding the predictors of poverty. In the following discussion section, we will go into greater detail regarding our findings and the potential storyline behind the results, both substantive and methodological, of this, and the earlier, modeling approaches.

6. Discussion

We built our analytic approach incrementally, beginning first with a strong spatial model (SDEM) applied to the three cross-sectional datasets. We then extended these results by estimating linear panel models to identify the influence of temporal changes in the variable set (including neighboring influence predictors) over the three observation periods. Finally, we applied the lessons learned in the first two approaches to estimate a spatial panel model that augments the panel structure by explicitly estimating the strength of unobserved spatial heterogeneity.

We found that for spatio-temporal data, it is possible and highly desirable to specify and estimate a spatial panel model that accommodates both temporal change and spatial clustering. The final fixed effects space-time model (Model IV in Table 4) incorporates strong predictor variables, explicit neighboring effects, temporal change and an estimate of the strength of remaining unobserved spatial heterogeneity. This combination yields a very strong model fit. In addition, an incremental strategy that begins with estimation and interpretation of simple (but spatially appropriate) cross-sectional models is useful for understanding the strength of predictor variables and guides the path to more appropriate models that fully and properly exploit the data at hand.

Substantively, we provide further evidence for our hypothesized predictors of the rate of child poverty among counties in the U.S. On average, the unemployment rate in a county is a very strong predictor of poverty with marginal effects lying generally in the range of 0.6 to 0.9 when examining the cross-sectional and non-spatial panel data. These effects decrease to

0.3 (+− 0.03, p<0.001) once spatial effects are controlled for, but remain significant. This implies, across the data set, that a 1% increase in unemployment is linked to increases in child poverty in the range of 0.3% to 0.9% -- a strong effect, indeed. The unemployment rate in neighboring counties also reveals an upward force on poverty in each of our models, suggesting the influence of lowered opportunities for market work through inter-county commuting to counties with poor employment prospects.

Alongside unemployment, high proportions of female-headed households with children and lower aggregate educational achievement levels are also significant predictors of child poverty. In the final fixed effect spatial panel model, these two variables have predictive power similar to the unemployment rate, with marginal effects on the order of 0.3. We did not include a spatially lagged term for female-headed households, as there was not apparent theoretical justification for doing so. Our lagged term for low educational attainment, however, suggests that the neighboring effects of low educational achievement are positive, net of any other included predictive variables. These findings suggest that the influence of low educational attainment stretches beyond the bounds of a specific county, perhaps for socio-cultural reasons not captured by this model.

While the economic base variables were not as strong as the household characteristics, higher proportions of the employed labor force in extractive industries (e.g., farming, mining, fisheries) are related to higher child poverty rates, net of the other variables in all of the models. These effects increase with the adjustment for spatio-temporal effects. Conversely, higher proportions of the county labor force in manufacturing industries is predictive of a statistically significant lower rate of child poverty, across all models. Moreover, while most of the parameter estimates for spatially lagged industrial variables do not tell much of a story, the effect of high manufacturing employment in neighboring counties provides some relief to upward pressures on poverty. It is interesting to note that counties which neighbor a county with a high proportion of the labor force employed in an extractive industry are predicted to have lower, rather than higher, child poverty rates. This may arise because these are the counties wherein the manufacturing, sales, or other higher order services utilizing these extracted resources takes place. In addition, 80% of the United States can be classified as rural, where extractive industry (e.g., agriculture) is a common livelihood source. Those counties which are not rural are often wealthier, with lower child poverty, but are also adjacent to rural counties. Without the ability to include a satisfactory measure of rural/urban status in the model, we cannot know whether some of these relationships, such as the one between lagged extractive industry employment and child poverty, are because of the industry type itself or the characteristics of the places in which the industry typically takes place.

We included a race variable (proportion Black) and ethnicity variable (proportion Hispanic) in the models and show the results in the tables primarily because other research on this topic has drawn attention to these (Curtis et al., 2013). Race and ethnicity are related to other independent variables in the model – in particular, education, household structure and unemployment. The correlation between some of these characteristics supports our hypothesis that the inclusion of these variables will contribute little more to the analysis. While the proportion Black contributes nothing of significance to the models, net of these

latter variables, high proportions of Hispanic populations in counties is mildly related to higher levels of child poverty. It is unclear exactly why this is the case, once other factors have been controlled for in the models. Further research is necessary to delve deeper into the implications of this finding.

The parameters for the temporal dummy variables in the panel models have signs in the anticipated direction. Overall, poverty went down between 1990 and 2000 and then rose by 2010 to levels that are mostly indistinguishable from 1990. The effects of temporal change are weak, however, corroborating the inference made from the repeated cross-sectional analyses shown in Table 2. As hypothesized, the predictors included in the model (including spatially lagged predictors) explicitly account almost completely for spatial patterning in county child poverty. Estimation of unobserved spatial heterogeneity lurking in the error term reveals a small (but significant) spatial parameter -- approximately 0.05 in Model IV of Table 4.

Finally, in the cross-sectional explorations, the 2006–10 (2008) ACS data produce parameter estimates with generally higher standard errors and a lower goodness of model fit. We attribute this to a combination of smaller sample size and different sample design when compared with the 1990 and 2000 Census long form sample estimates. In addition, the fact that the ACS data were gathered in monthly surveys during a severe economic downturn should also be taken into consideration when interpreting the weaker results for 2006–10.

Limitations of our study include the short panel, with only three cross-sections, covering approximately two decades. This renders moot the question of longer-term temporal influences on childhood poverty. Further, our data are aggregated to the county level, meaning that it is impossible to generalize to individual or household behavior (Robinson, 1950). Finally, the data, as a matter of convenience, are applied here at the county level. The processes analyzed and perhaps even some of the inferences drawn likely would differ were the level of spatial support to change, for example using a finer spatial resolution such as census tracts. We are presently assembling the data necessary for examination at the subcounty level of geography.

7. Conclusions

The results of our analyses highlight the utility of a cautious incremental development and diagnostic evaluation of increasingly complex statistical models. They also reveal the importance of jointly acknowledging both temporal changes in variables and spatial clustering of these variables in regression models. When both temporal and spatial effects are included in proper space-time models, the conclusion is clear that spatial influences overwhelm temporal change or fluctuation. Even during the period of immense social and economic change represented in our data, the highly time-resistant strong spatial clustering of poverty and its related predictors in this country suggest the United States is making little progress over time in addressing this persistent social and ethical issue. The findings further confirm what already is a well-established consensus for poverty remediation programs in the U.S.: regardless of the effectiveness (or not) of public policy programs designed to reduce high levels of poverty by focusing on individual household assistance, place-based

policies focusing on such matters as job creation and amelioration of high unemployment must remain part of the policy mix.

Acknowledgments

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APPENDIX

For details regarding the specification and estimation of the cross-sectional spatial regression models, the reader is referred to LeSage and Pace (2009).

Standard Linear Model (SLM)

This model, fit using OLS, is the standard baseline approach to understanding the spatial processes apparent in a georeferenced data set. A variety of exploratory data analyses, in

particular examination of regression residuals is common. The model is discussed at length in elementary statistics textbooks.

$$y = X\beta + \varepsilon$$
$$\varepsilon \sim N_{iid}(0, \sigma^2 I)$$

Spatial Durbin Error Model (SDEM)

This model is among a powerful suite of spatial regression models commonly employed in the field of spatial econometrics. The model assumes a set of appropriate independent variables, *X*. The model has two other features. It acknowledges spatial spillover effects from the *X* variables by including in the model specification a set of spatially lagged variables, *WX*. By way of example using the independent variable x_1 (county unemployment rate), the model assumes that child poverty in County A is affected not only by unemployment in County A, but in neighboring counties B, C, and D. The rationale is that poverty is elevated not only in County A because of poor employment opportunities, but that unemployment in neighboring counties B, C and D further inhibit increased job holding in County A. This neighbor effect of unemployment is expressed by the vector of variables Wx_1, which expresses the average unemployment rate in neighboring counties for each county in the dataset. The spatial weights matrix, *W*, expresses the neighbor structure (in this instance using a 1st-order queen convention) and the weights (which sum to 1) assigned to each neighbors' unemployment rate.

The specification for the SDEM also relaxes the independence assumption for the error terms *u*, to acknowledge that there are missing variables in the specification that may have spatial structure – i.e., have significant spatial autocorrelation. The spatial structure for the error term, *u*, is expressed in the second of the two specification equations, where Σ is a nondiagonal error variance/covariance matrix:

$$y = X\beta + WX\gamma + u$$
$$u = \lambda W u + \varepsilon$$
$$u \sim N(0, \textstyle\sum), \quad \varepsilon \sim N_{iid}(0, \sigma^2 I)$$

In the above model specification, the ($p \times 1$) β vector represents the parameters for the independent variables *X* and ($q \times 1$) γ vector represents the parameters for the lagged independent variables *WX*. We allow that *p* is not necessarily equal to *q* (meaning that the set of predictors *WX* may be a subset of the predictors *X*. It also is not a requirement that *W* in equations 1 and 2 be the same, although in this paper we assume a row standardized 1st-order queen specification for each.

The models were estimated using the spdep package in R (R Development Core Team, 2014).

Panel Data Models

Panel data provide information on county-specific variables, both across counties and over time. That is, they have both cross-sectional and time-series features. Linear panel models permit the estimation of regressor parameters while separately permitting the decomposition of overall variance into pieces that represent the fact that counties are different from one another in their poverty levels (between variation) while poverty for each county is different across the time periods, controlling for other covariates (within variation). The estimator properties include consistency and efficiency, and tests for choosing among models (pooled, random effects, fixed effects) have been developed (e.g., Breusch-Pagan Lagrange Multiplier test and Hausman test). For 3,104 counties and three time periods, we have the basic linear fixed effects panel model:

$$y_{it} = \alpha_i + X_{it}^{'}\beta + u_{it}$$

where:

$i = 1, \ldots, 3104$

$t = 1, 2, 3$ (for 1990for 2000 and 2008)

α_i is the time invariant fixed effect representing the model intercept for each county ($\alpha_{it} = \alpha_i$)

β is the vector of constant slope parameters ($\beta_{it} = \beta$)

X_{it} is the matrix of regressor variable values, with a value for each x for each county in each time period; time dummies may be included among the regressors in X

u_{it} is the individual error component for each county at time t.

The dimensionality of element of the above equation is $(9{,}312 \times 1)$

Spatial Panel Model

The spatial panel approach is the same as the non-spatial panel approach, except it also includes parameters to account for spatially autocorrelated disturbance terms. As with the typical panel data model, these models can be specified either as pooled, random effects, or fixed effects. The model used for these data is a modified fixed effects spatial error model. The modification involves the inclusion of the lagged independent variables, as shown in the cross-sectional Spatial Durbin Error Model above. For these data, we specify the following model:

$$y = (i_T \otimes \alpha) + X\beta + WX\gamma + u$$
$$u = \lambda(I_T \otimes W_N)u + \varepsilon$$

where:

λ is the spatial autocorrelation coefficient

$i = 1,…,3104$

$t = 1,2,3$ (for 1990for 2000 and 2008)

α_i is the time invariant fixed effect representing the model intercept for each county ($\alpha_{it} = \alpha_i$)

β is the vector of constant slope parameters ($\beta_{it} = \beta$)

X_{it} is the matrix of regressor variable values, with a value for each x for each county in each time period; time dummies may be included among the regressors in X

u_{it} is the individual error component for each county at time t.

γ vector represents the parameters for the lagged independent variables WX

W is the spatial weights matrix (queen first order row-standardized matrix)

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Table 1

Descriptive Statistics

Year	Mean	Median	10% Quantile	90% Quantile	Standard Deviation	Moran's I
Childhood Poverty (children living in poverty over total number of children)						
1990	0.214	0.193	0.101	0.355	0.104	0.620
2000	0.184	0.168	0.084	0.303	0.090	0.604
2008	0.214	0.205	0.101	0.340	0.098	0.473
Female-Headed Households (female headed family households over total family households)						
1990	0.172	0.160	0.102	0.255	0.067	0.519
2000	0.205	0.191	0.130	0.297	0.072	0.533
2008	0.239	0.229	0.146	0.346	0.086	0.454
Unemployment (unemployed population16+ over total workforce 16+)						
1990	0.066	0.062	0.033	0.106	0.031	0.541
2000	0.058	0.053	0.030	0.089	0.027	0.418
2008	0.075	0.073	0.037	0.115	0.033	0.520
Less than High School Education (individuals 25+ with less than high school education over all individuals 25+)						
1990	0.305	0.287	0.182	0.447	0.103	0.686
2000	0.227	0.209	0.127	0.349	0.087	0.658
2008	0.170	0.155	0.087	0.271	0.073	0.616
Extractive (individuals employed in an extractive industry [e.g. mining or farming] over workforce)						
1990	0.104	0.071	0.019	0.244	0.096	0.625
2000	0.072	0.047	0.009	0.175	0.076	0.619
2008	0.069	0.043	0.007	0.176	0.076	0.603
Manufacturing (individuals employed in manufacturing industry over workforce)						
1990	0.254	0.244	0.116	0.401	0.107	0.724
2000	0.236	0.231	0.116	0.362	0.092	0.693
2008	0.207	0.204	0.117	0.306	0.073	0.576
Trade (individuals employed in trade industry over workforce)						
1990	0.196	0.197	0.152	0.240	0.035	0.167
2000	0.145	0.146	0.115	0.174	0.025	0.196

Year	Mean	Median	10% Quantile	90% Quantile	Standard Deviation	Moran's I
2008	0.141	0.142	0.107	0.171	0.028	0.143
Service (individuals employed in service industry over workforce)						
1990	0.445	0.440	0.348	0.553	0.080	0.438
2000	0.546	0.542	0.444	0.657	0.083	0.462
2008	0.583	0.580	0.486	0.686	0.079	0.372
African American/Black (black individuals over total individuals)						
1990	0.086	0.015	0.000	0.307	0.143	0.803
2000	0.088	0.017	0.001	0.307	0.145	0.789
2008	0.089	0.020	0.001	0.305	0.147	0.784
Hispanic/Latino (Hispanic individuals over total individuals)						
1990	0.045	0.008	0.003	0.110	0.111	0.856
2000	0.062	0.018	0.006	0.159	0.121	0.822
2008	0.079	0.030	0.008	0.201	0.129	0.798

Source: 1990 U.S. Census, 2000 U.S. Census, 2006–2010 ACS. N = 3,104

Table 2

Cross-Sectional Spatial Durbin Error Model Parameter Estimates (Std. Errors)

	1990		2000		2008	
Unemployment	0.886 (0.038)	***	0.693 (0.036)	***	0.745 (0.046)	***
Female-Headed Households	0.664 (0.024)	***	0.640 (0.021)	***	0.481 (0.019)	***
Less than High School Education	0.384 (0.016)	***	0.400 (0.016)	***	0.443 (0.025)	***
Extractive	0.279 (0.018)	***	0.302 (0.017)	***	0.115 (0.022)	***
Manufacturing	−0.105 (0.016)	***	−0.034 (0.014)	*	−0.035 (0.021)	+
Trade	−0.052 (0.030)	+	−0.012 (0.031)		−0.045 (0.038)	
Service	---		---		---	
African American/Black	−0.012 (0.013)		−0.081 (0.011)	***	−0.025 (0.013)	*
Hispanic/Latino	0.052 (0.012)	***	−0.031 (0.010)	**	−0.034 (0.012)	**
Lag of Unemployment	0.305 (0.070)	***	0.326 (0.069)	***	0.020 (0.079)	
Lag of Less than High School Education	0.085 (0.025)	***	0.080 (0.023)	***	0.106 (0.034)	**
Lag of Extractive	0.085 (0.032)	**	0.116 (0.028)	***	0.209 (0.037)	***
Lag of Manufacturing	−0.007 (0.029)		−0.051 (0.024)	*	0.069 (0.035)	*
Lag of Trade	0.159 (0.071)	*	0.260 (0.075)	***	0.125 (0.092)	
Lag of Service	---		---		---	
Intercept	−0.155 (0.024)	***	−0.152 (0.017)	***	−0.087 (0.019)	***
Spatial Error Parameter	0.577		0.523		0.375	
Pseudo-R²	0.866		0.853		0.702	
N=3104						

Significance codes: '***' 0.001 '**' 0.01 '*' 0.05 '+' 0.1

In each instance, "Lag" refers to a spatial lag computed using a row-standardized 1st-order Queen spatial weights matrix

Table 3

PLM Model Parameter Estimates (Std. Errors)

	I (Without inclusion of spatially lagged independent variables)		II (With inclusion of spatially lagged independent variables)	
Unemployment	0.669 (0.027)	***	0.373 (0.032)	***
Female-Headed Household	0.325 (0.018)	***	0.290 (0.018)	***
Less than High School Education	0.195 (0.015)	***	0.280 (0.024)	***
Extractive Industry	0.195 (0.023)	***	0.111 (0.027)	***
Manufacturing Industry	−0.155 (0.018)	***	−0.060 (0.022)	**
Trade Industry	0.166 (0.020)	***	0.055 (0.028)	*
Service Industry	---		---	
African American/Black	0.005 (0.034)		−0.022 (0.033)	
Hispanic/Latino	0.172 (0.021)	***	0.076 (0.024)	**
Lag of Unemployment	---		0.195 (0.052)	***
Lag of Less than High School Education	---		0.118 (0.034)	***
Lag of Extractive	---		−0.158 (0.050)	**
Lag of Manufacturing	---		−0.314 (0.036)	***
Lag of Trade	---		0.011 (0.058)	
Lag of Service	---		---	
1990	---		---	
2000	−0.003 (0.048)		−0.009 (0.005)	+
2008	0.005 (0.068)		0.012 (0.007)	+
Spatial Error Parameter				
Pseudo-R^2	0.895	0.902		
N=9312				

In each instance, "Lag" refers to a spatial lag computed using a row-standardized 1st-order Queen spatial weights matrix. Significance codes: '***' 0.001 '**' 0.01 '*' 0.05 '+' 0.1

Table 4

SPLM Model Parameter Estimates (Std. Errors)

	III (Without inclusion of spatially lagged independent variables)		IV (With inclusion of spatially lagged independent variables)	
Unemployment	0.449 (0.024)	***	0.379 (0.025)	***
Female-Headed Household	0.301 (0.014)	***	0.303 (0.014)	***
Less than High School Education	0.258 (0.018)	***	0.268 (0.019)	***
Extractive Industry	0.122 (0.021)	***	0.112 (0.021)	***
Manufacturing Industry	−0.132 (0.016)	***	−0.068 (0.017)	***
Trade Industry	0.042 (0.022)	+	0.054 (0.022)	*
Service Industry	---		---	
African American/Black	0.016 (0.027)		0.012 (0.027)	
Hispanic/Latino	0.123 (0.021)	***	0.107 (0.021)	***
Lag of Unemployment	---		0.137 (0.047)	**
Lag of Less than High School Education	---		0.094 (0.030)	**
Lag of Extractive	---		−0.136 (0.045)	**
Lag of Manufacturing	---		−0.283 (0.032)	***
Lag of Trade	---		0.021 (0.052)	
Lag of Service	---		---	
1990	---		---	
2000	−0.013 (0.003)	***	−0.011 (0.005)	*
2008	0.009 (0.004)	*	0.009 (0.007)	
Spatial Error Parameter	0.058 (0.002)	***	0.053 (0.002)	***
Pseudo-R^2	0.899		0.902	
N=9312				

In each instance, "Lag" refers to a spatial lag computed using a row-standardized 1st-order Queen spatial weights matrix. Significance codes: '***' 0.001 '**' 0.01 '*' 0.05 '+' 0.1