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Spatial Variation in the Structural Correlates of Child Poverty in the United States

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A substantial literature in the social sciences affirms that poverty is non-randomly distributed across the United States (Weinberg 1987; Duncan 1992; O'Connor 2001; Cotter 2002; Glasmeier 2006; Voss et al. 2006). The present analysis of county level poverty builds on that extensive literature and is motivated both sociologically and methodologically. We aim to explain the non-random distribution by analyzing sociologically meaningful correlates of poverty through a spatially informed analytical approach. We begin with a geographically motivated model; that is, a model that identifies variation in the correlates of poverty between the South—a region historically known among scholars and policy makers for high and persistent poverty—and the non-South. While enlightening and useful in some instances (i.e., a regionally focused analysis), we argue that this approach fails to fully address the more sociological, or social structural, storyline generating the non-random distribution that shapes the face of poverty across the nation. Specifically, rather than modeling poverty within specific geographic sub-regions, we turn to models that analyze poverty across spatial units according to their structural characteristics, namely racial concentration and the type of economic dependence. We use a spatial regime approach to test for differences in the larger models as well as the chief correlates of poverty. Further, we simultaneously employ spatial error regression to remove the biasing effects of spatial autocorrelation both in the child poverty variable and the covariates.

This approach largely focuses on what is known as spatial heterogeneity. In general, spatial heterogeneity exists when the mean and/or variance and/or covariance structure "drifts" across our spatial region. Formally, spatial heterogeneity is addressed by the concept(s) of spatial stationarity (see Cressie, 1993). Quoting Anselin, spatial heterogeneity “follows from the intrinsic uniqueness of each location” (1996:112). Spatial heterogeneity is consistent with Doreen Massey’s description of how places are particular moments of intersecting social relations (1994:120). She argues that the unique combination of social forces “together in one place may produce effects which would not happen otherwise” (1994:156). These social forces include nonmaterial forces (i.e., cultural and/or historical processes) that cannot easily or always be quantified, yet these forces shape otherwise measureable social relationships. The spatial regime approach is one tool that permits the analyst to investigate the social relations of interest while accounting for the potential impacts of the generally quantitatively illusive nonmaterial forces.

In the current case, we ask whether the relationship between child poverty and the identified structural correlates of poverty are similar across all places within the United States, or whether it varies between particular sub-regions. If we find spatial variation in the relationship, then we are in a position to better understand the likely or dominant sources of child poverty and, therefore, policy strategies for ameliorating such poverty. Much can be gain by moving away from the perspective that theoretical assumption regarding stratification, and poverty in particular, can be generalized everywhere (Lobao 1993; Lobao et al. 2007). Indeed, theoretical advances can result from the analysis of the conditions under which different relationships emerge. These conditions are spatial units in the current context, but we emphasize that these spatial units embody social factors that contextualize sociological processes of inequality. In their contextual analysis of family poverty, Cotter et al. argues that “poverty happens to individual families, but it happens in contexts that shape the size and nature of each family's risk" (2007:163). We argue that poverty also happens to communities or places; the contexts that shape the individual family's risk are comprised of the structural factors that shape the poverty experienced by a place.

DATA AND METHODOLOGICAL APPROACH

Our data are taken from the 2000 U.S. Census of Population Summary Files 1 and 3 (U.S. Census Bureau 2002). The county serves as the unit of analysis. Specifically, we generated 3071 county/county equivalent dataset from a data set initially containing all 3109 continental US counties.[1] For the sake of comparability across geographies we dissolved "independent city" geographies. Independent cities are an anomalous political and census geography found mostly in Virginia.[2]

Our dependent variable is the log odds transformation of the proportion of children in poverty.[3] Covariates are included to address county racial concentration,

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[1] Hawaii and Alaska are exclude due to non-contiguity issues that affect the spatial analysis and, related, the extreme heteroskedasticity that is introduced in the data when the two non-contiguous states are included.

[2] For more information on independent cities see the Census Bureaus glossary (http://www.census.gov/geo/www/tiger/glossary.html). We removed these independent city geographies from the dataset by dissolving into adjacent geographies the independent cities of Baltimore, St. Louis and 36 other Virginia independent cities. We merged the polygons and associated data for these cities with their "parent" counties or, in a few cases, into other adjacent independent cities. One independent city, Carson, NV, had no obvious parent county, so we left it unchanged.

[3] According the 2000 Census, two counties, Hinsdale, CO and Loving, TX, had zero children in poverty. These counties were problematic not only because they were outliers in this respect, but also because the zero values in the proportion in poverty precluded log transformation of the child poverty proportion for use as our dependent variable. Our in depth investigation of these counties' social characteristics suggested that the zero values given for these counties was likely due a result of sampling error due, in part, to the very low population in these counties. In order to move our analysis forward without dropping these observations altogether, we elected to estimate the proportion of children in poverty based on shared characteristics of neighboring counties.

economic conditions, demographic structure and human capital. The racial concentration of the African American, Native American, and Hispanic population are measured as the proportion of the respective racial group relative to the total county population. Indicators of county economic conditions include the proportion of the working age population that is unemployed and the proportion of the male working age population that is underemployed, as well as county economic dependence. A county economic dependence typology code that designates the county economic dependence, designed by the USDA Economic Research Service (ERS), is appended to each county record. According to ERS the typology "captures differences in economic and social characteristics" in order to, "provide policy-relevant information about diverse county conditions to policymakers, public officials, and researchers."[4] An advantage of the typology is that is differentiates between the extractive industries which tend to dominate nonmetropolitan counties. Indicators of the demographic structure include the proportion of the household that are female-headed and the proportion of the population that is disabled, age 65 or older, and foreign-born. Finally, human capital is measured as the proportion of the county population age 25 and over that has attained a high school education or less.

The covariates have been identified in decades of research as having significant impacts on poverty. We anticipate that the generalized relationships between the covariates and child poverty, however, will systematically vary between regimes. That

[4] More information is available on the ERS website (http://www.ers.usda.gov/Data/TypologyCodes/). We appended to our 3071 records based on county fips subsequent to having dissolved the independent cities into parent counties. Thus the case of our dissolved geographies, county typologies reflect the characteristic of the "parent" counties.

is, for example, the association between racial concentration and child poverty may differ across economic dependence regimes; places with greater reliance on particular industries tend also to have larger or smaller concentrations of particular racial groups. For example, research has shown a high concentration of Hispanics in manufacturing, in terms of employment and settlement concentration (Kandel and Newman 2004).

We simultaneously employ a spatial regime (Anselin 1992:163) and spatial error regression (Anselin 1988:100-118) analysis to address the question of spatial variation in the associations between poverty and its correlates. The spatial regime addresses large-scale differences and, in essence, is akin to a fully interacted model—each of the variables in this case is interacted with the variable that designates the different regimes—with tests for stability in the specific estimates as well as the overall model fit. The spatial regime analysis is also a means of dealing with large-scale spatial heterogeneity and, thus, a means of ameliorating the fierce error heteroskedasticity common to ecological regression analysis. The spatial error regression component of the analysis addresses spatial autocorrelation (small-scale data dependence) not captured in the regime analysis that would otherwise bias model results. A first-order queen contiguity matrix is used for generating the spatial regression results.

RESULTS

Figure 1 shows a map of the dependent variable, county child poverty. The map affirms a long-standing reality: poverty is concentrated in particular geographic sub-regions of the United States, namely, Appalachia, the Mississippi Delta, the Borderlands, the Four Corners and Indian Reservations throughout the Northern Plains. The map also affirms that the South is a region of more extensive and more intense poverty than found in other large regions of the country. Thus, we begin the combined spatial regime and spatial error regression analysis by considering the South and non-South (as defined by Census Regions) as distinct spatial regimes.

[Figure 1 about here]

Regional Regimes. Results from the Southern regime analysis are reported in Table 1. There are significant differences between counties in the South compared to non-southern counties. For example, while there is a positive, statistically significant association between the proportion of the African American population and child poverty rates in non-southern counties, there is no evidence of a race effect in the South. In addition, economic conditions also have a weaker association with child poverty in the South relative to the non-South. The analysis provides evidence that the poverty process in the South is different from the process outside the South. While thought-provoking, these results do not give the analyst an understanding of what it is about the South, specifically and empirically, that distinguishes it from its non-Southern neighbors. That is, it is unlikely that race has no association with child poverty in the South but it is more likely that the statistical accounting of the South has explained the race association. Yet, claiming that the South is an explanatory variable for race is not a theoretically satisfying conclusion. We argue that the analyst would be better able understand the spatial patterning of poverty by moving beyond geography, per se, and toward social, economic and demographic factors—or, combined, sociological factors—that comprise the context of place.

[Table 1 about here]

Racial Regimes. Race is one sociologically compelling and meaningful factor, and is among one of the most influential correlates of poverty at both the individual level and aggregate level. For the analysis of racial concentration, we created two regimes; one representing high minority populated counties (those with 25% or more of the total population comprised of nonwhite residents) and one representing low minority population (those where the total population was comprised of fewer than 25% nonwhite residents). Figure 2 shows these two regimes along with (in outline) the counties with high poverty rates in 2000 (the upper quantile of poverty is highlighted in the figure). While not perfectly correlated, counties with high proportions of the population declaring a race other than white in the 2000 Census and high child poverty rate suggest a strong positive correlation. Indeed, the mean child poverty rate for high minority counties is 22% whereas the mean for low minority counties is 15%.

[Figure 2 about here]

Regimes Based on Economic Dependence. Economic conditions are also commonly investigated in studies of place level poverty. The updated county typologies from the ERS of the USDA are reported here. Like child poverty, and like race, economic dependence is spatially patterned (see Figure 3). Economic dependence does not appear to correlate as readily with child poverty as racial concentration, yet a notable pattern does emerge. Mining (the average child poverty rate is 23%), farming (21%), and federal/state government (20%) dependent counties are more greatly represented among counties with the highest levels of child poverty (highlighted in Figure 3) relative to nonspecialized (19%), manufacturing (17%) and services dependent (14%) counties.

[Figure 3 about here]

Sociological Regimes. The remainder of our analysis focuses on these two factors—racial concentration and economic dependence. We examine the spatial regime results with corrections for spatial autocorrelation where racial concentration and economic dependence are jointly considered to create sociologically motivated "spatial" regimes. This approach is intended to enable the analyst to address the "so what" question. That is, what is it about a place, in terms of child poverty, that distinguishes it from other places?

Beginning with racial concentration, evidence of structural variation was found for both the model and the separate correlates of poverty (see Table 2). Four variables most significantly varied in their association with child poverty between the two racial concentration types. Farming dependent counties were more likely to have higher rates of child poverty than non-specialized counties (the reference category), yet the relationship was lower among high minority populated counties. The same is observed for the proportion underemployed, disabled and foreign-born; a weaker or no association is observed among high minority counties relative to low minority counties. The findings show that economic and demographic factors do less to shape child poverty in places with high concentrations of minority groups. Instead, factors that produce racial inequalities, and are difficult to quantify, are likely at play in these places. High concentrations of nonwhite populations are dominant in the more southern counties of the U.S. extending along the eastern seaboard in addition to pockets in the Pacific Northwest and Northern Plains.

[Table 2 about here]

Evidence is also found for variation in the structural correlates of poverty according to county economic dependence (Table 3). Six regimes were examined, following the county typologies produced by the ERS. Farming dependent counties are the most distinct from the other regimes. Race has a notably larger association with child poverty in farming dependent counties relative to all other county types; race is more positively associated with child poverty in farm dependent counties which are predominantly located in the Great Plains (Native American) with some presence in the West and parts of the South (Native and African American). Demographic factors, however, have weaker associations with child poverty in farming dependent counties relative to other county types. The proportion of female-headed households and disabled are not associated with child poverty in farm dependent counties, although these factors, especially female-headed households, are consistently positively and strongly correlated with child poverty in all other economic types.

[Table 3 about here]

The proportion of the population that is disabled is especially correlated with child poverty among mining and manufacturing dependent counties whereas underemployment is relatively weakly associated. Mining dependent counties are largely found in the western part of the nation, especially in Texas, Nevada and among counties along the Rocky Mountains, in addition to Appalachia, the southern coast of Louisiana, and where the Illinois, Indiana and Kentucky borders intersect. Manufacturing dominates most of the eastern U.S., South and North. Our findings demonstrate that disability, perhaps attributable to employment in these more physically demanding and risky industries, is more of an issue for poverty in these areas than in others.

Services dependent counties show the strongest association between underemployment and child poverty of the economic regimes. These counties are found throughout the continental U.S. with the exception of the Great Plains region. Much of Florida, parts of the Northeast, Colorado and Arizona house the majority of services dependent county types. The proportion of female-headed households and Native American population are also more strongly associated with child poverty in these counties than in most other county types.

DISCUSSION

Our analysis is largely exploratory and very provisional at this time. What we have demonstrated is that racial concentration, economic conditions and demographic structure vary in their association with child poverty across U.S. counties. The only factor that did not vary in its association with child poverty across the racial and economic (or even geographical South/non-South) regimes was education—counties with lower proportions of low educated residents consistently had lower child poverty rates.

A greater understanding of the differences between regions and sub-regions in terms of the correlates, and ultimately the theorized causes, of child poverty has been gained through this analytical approach. Rather than concluding, for example, that the South is different from the non-South, the approach taken in this analysis empirically identifies the sociological factors underlying spatial variation in the rates of child poverty as well as the correlates of child poverty. Our results demonstrate how the structural correlates of child poverty vary according to area social, economic, and demographic characteristics—characteristics that are similarly non-randomly distributed across the nation.

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Figure 1. Log Odds of Proportion of Children in Poverty: 2000, U.S. Counties (excluding Alaska and Hawaii)

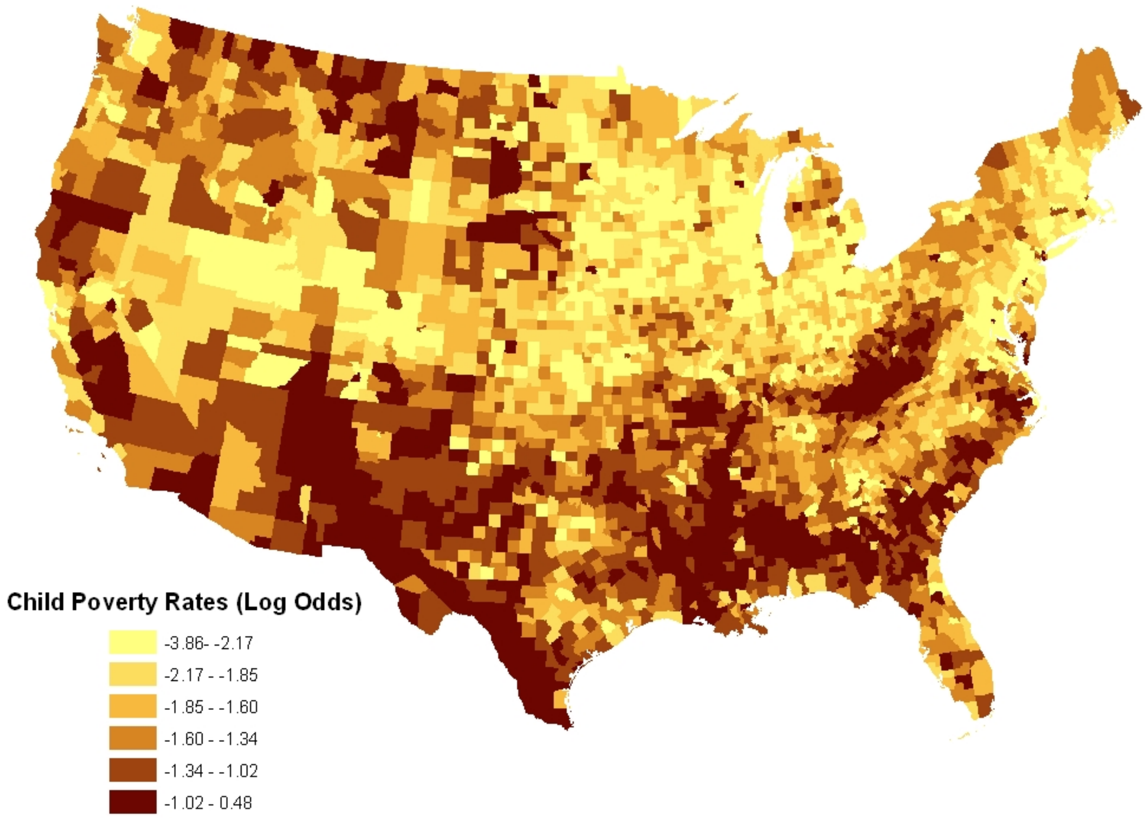

Figure 2. Regimes based on Percent Nonwhite and Counties with High Child Poverty in 2000.

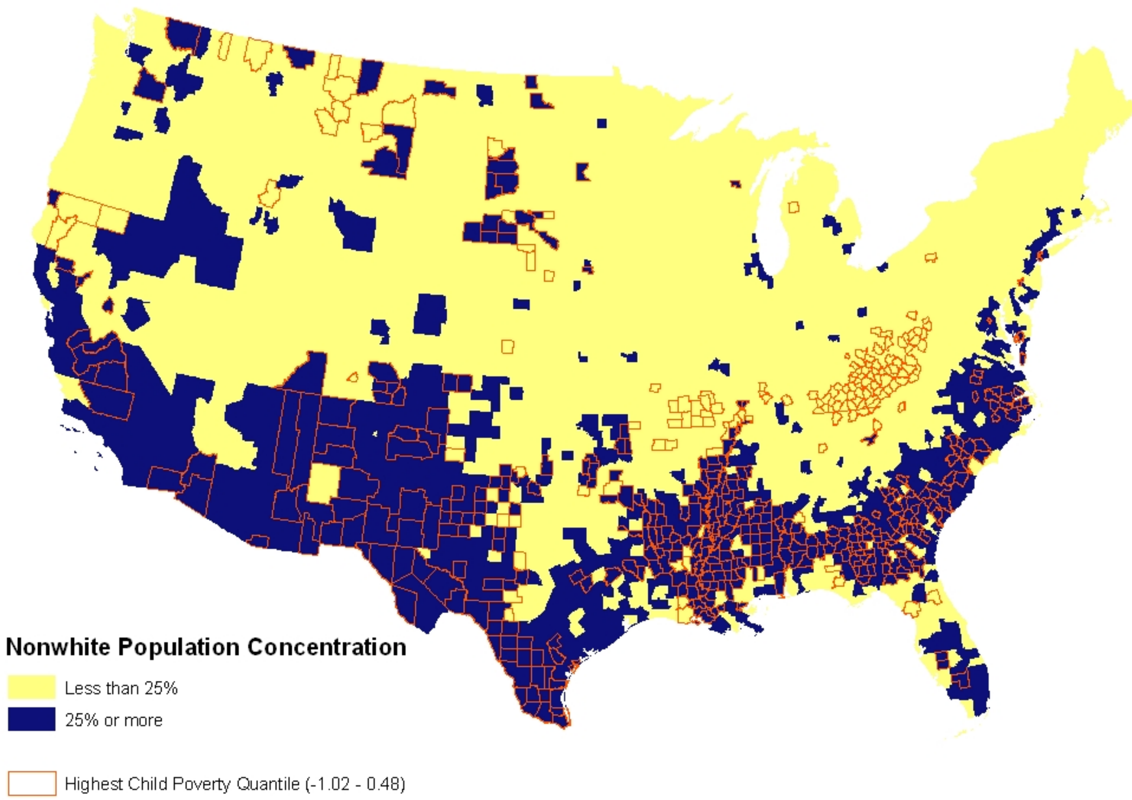

Figure 3. Regimes based on Economic Dependence and Counties with High Child Poverty in 2000.

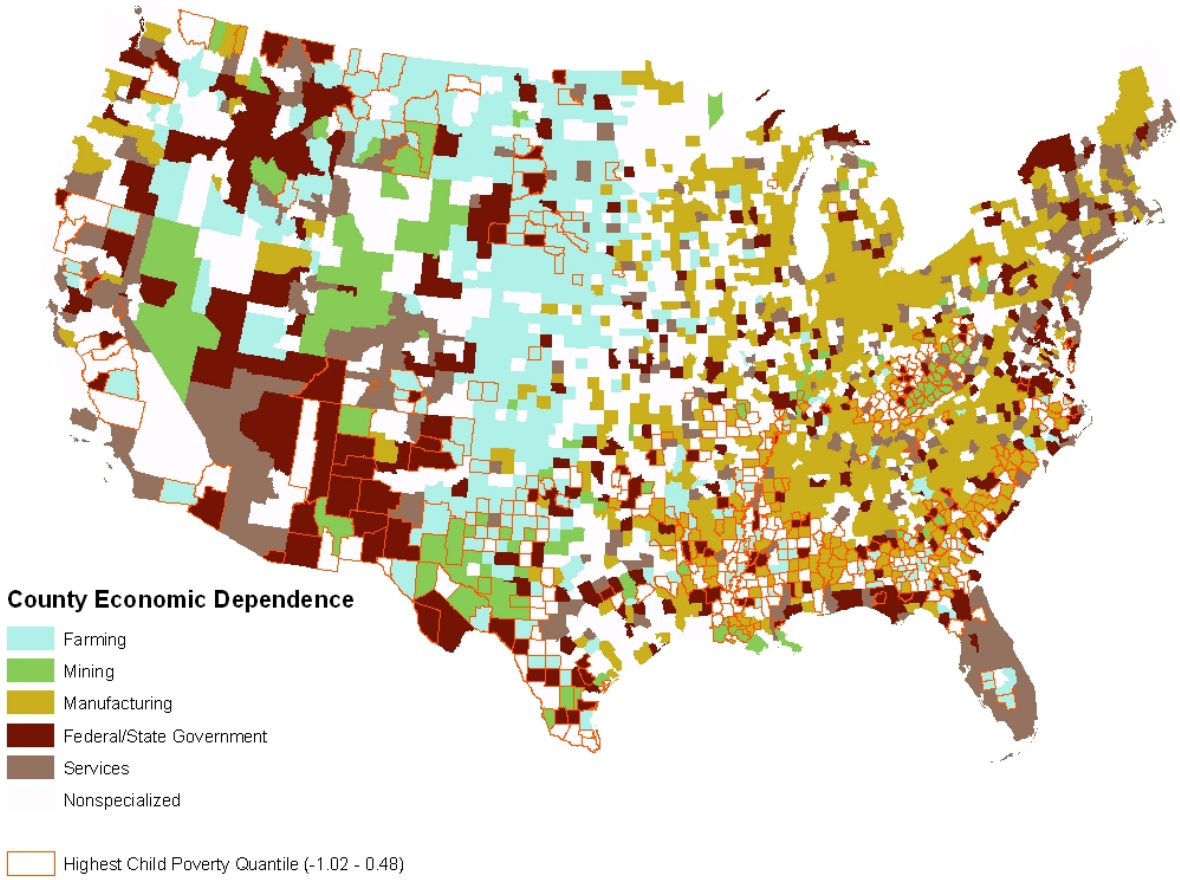

Table 1. Unstandardized Regression Coefficients from a Spatially Corrected Spatial Regime Analysis Testing for Structural Variation in the Predictors of Child Poverty Rates (log odds) for Southern and Non-Southern Counties (N=3,071)

	South (N=1,387)			Non-South (N=1,684)			Structural Differences in Correlates	
	β		SE	β		SE		
Racial/Ethnic Concentration								
Proportion African American	-0.22		0.12	0.77	***	0.23	14.69	***
Proportion Native American	0.54		0.32	0.54	***	0.13	0.00	
Proportion Hispanic	0.43	**	0.14	0.40	**	0.15	0.02	
Economic Conditions †								
Farming Dependent	0.12	***	0.03	0.27	***	0.02	16.67	***
Mining Dependent	0.03		0.04	-0.02		0.04	0.78	
Manufacturing Dependent	-0.02		0.02	-0.09	***	0.02	5.77	*
Federal/State Government Dependent	-0.02		0.02	-0.04		0.03	0.32	
Services Dependent	-0.04		0.03	-0.07	**	0.02	0.65	
Proportion Unemployed	3.51	***	0.46	2.77	***	0.46	1.31	
Proportion Underemployed	1.71	***	0.21	2.44	***	0.18	7.00	**
Demographic Structure								
Proportion Female-Headed Households	3.61	***	0.25	3.39	***	0.24	0.41	
Proportion Disabled	1.53	***	0.29	1.40	***	0.30	0.10	
Proportion Age 65 & Older	0.96	***	0.28	0.93	***	0.27	0.00	
Proportion Foreign-Born	0.90	**	0.31	0.94	***	0.28	0.01	
Human Capital								
Proportion High School Educated or Less	1.59	***	0.13	1.59	***	0.12	0.00	
Constant	-4.28	***	0.08	-4.52	**	0.08	4.19	*
Spatial Error Parameter (λ)	0.60	***	0.02					
Chow Test for Structural Instability across Regimes							112.04	***
Likelihood Ratio Test for Spatial Error	527.81	***						
LM Test on Spatial Lag	0.79							
B-P Heteroskedasticity	91.96	***						
-2 Log Likelihood	-276.25							

* p < .05, ** p < .01, *** p < .001

† Nonspecialized economic dependence is the reference category.

Table 2. Unstandardized Regression Coefficients from a Spatially Corrected Spatial Regime Analysis Testing for Structural Variation in the Predictors of Child Poverty Rates (log odds) for High (25% or more) and Low (less than 25%) Minority Populated Counties (N=3,071)

	High Minority Populated (N=876)			Low Minority Populated (N=2,195)			Structural Differences in Correlates	
	β		SE	β		SE		
Economic Conditions †								
Farming Dependent	0.13	***	0.03	0.26	***	0.02	11.04	***
Mining Dependent	-0.02		0.05	0.00		0.03	0.18	
Manufacturing Dependent	-0.03		0.03	-0.06	***	0.02	1.22	
Federal/State Government Dependent	-0.04		0.03	-0.05	*	0.02	0.11	
Services Dependent	-0.03		0.04	-0.05	*	0.02	0.14	
Proportion Unemployed	4.07	***	0.45	3.42	***	0.41	1.16	
Proportion Underemployed	1.51	***	0.25	2.49	***	0.16	10.78	**
Demographic Structure								
Proportion Female-Headed Households	3.21	***	0.18	3.41	***	0.19	0.58	
Proportion Disabled	0.32		0.35	2.29	***	0.25	21.00	***
Proportion Age 65 & Older	1.12	**	0.37	0.40		0.21	2.95	
Proportion Foreign-Born	0.76	***	0.19	2.18	***	0.36	11.91	***
Human Capital								
Proportion High School Educated or Less	1.54	***	0.15	1.76	***	0.11	1.53	
Constant	-3.74	***	0.10	-4.75	***	0.07	65.44	***
Spatial Error Parameter (λ)	0.62	***	0.02					
Chow Test for Structural Instability across Regimes							132.81	***
Likelihood Ratio Test for Spatial Error	622.71	***						
LM Test on Spatial Lag	46.48	***						
B-P Heteroskedasticity	33.00	**						
-2 Log Likelihood	-281.00							

* p < .05, ** p < .01, *** p < .001

† Nonspecialized economic dependence is the reference category.

Table 3. Unstandardized Regression Coefficients from a Spatially Corrected Spatial Regime Analysis Testing for Structural Variation in the Predictors of Child Poverty Rates (log odds) by Economic Dependence Typologies (N=3,071)

	Farming (N=440)		Mining (N=125)		Manufacturing (N=885)		Federal/State Government (N=356)		Services (N=331)		Nonspecialized (N=934)		Structural Differences in Correlates
Racial/Ethnic Concentration													
Proportion African American	1.16 ***	0.27	-0.17	0.51	-0.12	0.16	-0.31	0.21	0.16	0.29	-0.26	0.16	23.92 ***
Proportion Native American	1.86 ***	0.27	0.30	0.44	0.30	0.42	0.29	0.22	1.69 *	0.68	0.17	0.21	31.30 ***
Proportion Hispanic	0.61 *	0.24	0.21	0.30	0.60	0.47	0.57 **	0.19	0.19	0.37	0.15	0.18	4.29
Economic Conditions													
Proportion Unemployed	1.72 *	0.80	2.46 *	1.04	3.59 ***	0.78	2.81 ***	0.67	1.27	1.10	3.30 ***	0.62	5.51
Proportion Underemployed	2.00 ***	0.37	1.84 **	0.71	1.82 ***	0.33	1.36 ***	0.22	3.26 ***	0.45	2.27 ***	0.29	16.76 **
Demographic Structure													
Proportion Female-Headed Households	0.70	0.41	4.74 ***	1.01	3.83 ***	0.34	3.81 ***	0.42	4.57 ***	0.48	3.91 ***	0.32	56.41 ***
Proportion Disabled	-0.13	0.40	3.33 ***	0.74	3.80 ***	0.42	1.28 *	0.58	0.92	0.84	2.35 ***	0.35	54.12 ***
Proportion Age 65 & Older	0.42	0.43	-0.16	0.87	-0.11	0.45	0.91	0.58	0.22	0.48	0.64	0.34	3.10
Proportion Foreign-Born	1.01	0.53	1.90	1.15	1.12	0.74	0.76	0.50	0.69	0.42	1.49 ***	0.42	2.76
Human Capital													
Proportion High School Educated or Less	1.42 ***	0.25	1.49 **	0.46	1.29 ***	0.18	1.31 ***	0.22	1.72 ***	0.31	1.98 ***	0.16	10.62
Constant	-3.04 ***	0.17	-4.68 ***	0.32	-4.82 ***	0.13	-4.05 ***	0.13	-4.79 ***	0.12	-4.92 ***	0.10	114.20 ***
Spatial Error Parameter (λ)	0.56 ***	0.02											
Chow Test for Structural Instability across Regimes													603.95 ***
Likelihood Ratio Test for Spatial Error	583.32 ***												
LM Test on Spatial Lag	-10.33												
B-P Heteroskedasticity	341.04 ***												
-2 Log Likelihood	-149.05												

* p < .05, ** p < .01, *** p < .001