Poverty segregation in nonmetro counties: A spatial exploration of segregation patterns in the US

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Introduction

One of the basic premises underlying most measures of residential segregation is the inherent spatial patterning of different groups in an urban environment (Cortese, Falk, & Cohen, 1976; Duncan & Duncan, 1955; D.S. Massey & Denton, 1988; D. S. Massey, White, & Phua, 1996). The majority of research exploring residential segregation and its potential impact on a variety of health, education, employment, inequality, crime, and other outcomes has focused on metropolitan areas as the unit of analysis, often defined as metropolitan statistical areas (MSAs) or labor market areas (Brown & Chung, 2006; Fischer, Stockmayer, Stiles, & Hout, 2004; Frey & Farley, 1996; Logan, Alba, & Zhang, 2002; Logan, Stults, & Farley, 2004; Douglas S. Massey, 1996; Wilkes & Iceland, 2004). However, recent work highlights the importance of considering segregation patterns in nonmetropolitan areas as well. In one of the few national studies available on the topic, Lichter and colleagues (D. T. Lichter, Parisi, Grice, & Taquino, 2007) explore racial residential segregation patterns for rural areas and small-town in the US from 1990 to 2000. One of the most important findings from this research was that similar racial residential segregation patterns and trends were observed over this period between both metropolitan and nonmetropolitan areas. In another study, Lichter, Parisi, Taquino, and Beaulieu (2008) found that rural poverty was highly concentrated spatially and that poor residents were segregated from non-poor residents in rural areas, particularly among poor rural minorities.

With more attention now devoted to the study of spatial inequality (Lobao, Hooks, & Tickamyer, 2007), it is important to identify why certain dimensions of segregation are spatially patterned and if these patterns have different correlates across metro and nonmetro locations. Individuals make decisions about where they want to live relative to resources (i.e., schools, employment, health care, environment, amenities) available in an area (Iceland, Goyette, Nelson, & Chan, 2010), and these decisions may differ for rural and urban residents. However, poor individuals in general can be less mobile and have fewer opportunities to live in wealthier neighborhoods, regardless of whether they live in a rural or inner-city urban area. Further rural residents do not select to live in rural or remote areas because they are poor or vice versa (Partridge & Rickman, 2008). Structural or place based arguments of poverty would argue that the spatial concentration of poor individuals in a local area is due to few economic opportunities and underinvestment in infrastructures (Tickamyer & Duncan, 1990; Voss, Long, Hammer, & Friedman, 2006). However little work has examined whether the spatial concentration of poverty in nonmetro areas is really a function of poverty segregation using a placed-based poverty argument and if a potential spatial mismatch exists to explain higher rural poverty and poverty segregation.

From a population perspective, the changing population composition of many rural areas elevates the importance of studying segregation in nonmetro and metro areas, particularly the economic aspects of segregation. This research starts to fill this gap by using regression based methods to document poverty segregation patterns across the United States. Additionally we assess correlates of poverty segregation in metro and nonmetro counties by measuring multiple dimensions of segregation. More specifically this research asks two questions. First, how is poverty segregation spatially distributed in the US? And second, are the determinants of place-based poverty segregation in metropolitan and nonmetropolitan areas different and do these patterns differ by region?

Spatial Mismatch in Nonmetro Poverty Segregation

Poverty rates decreased significantly from 1990 to 2000 (Jargowsky, 2003), and nonmetro areas experienced more of a decline in poverty than metro areas (Jolliffe, 2004). Yet even with declines in poverty rates over this period, the spatial concentration of poverty remained high for many areas in the US (Foulkes & Schafft, 2010; Jargowsky, 2003). Rural poverty has been shown to be more highly concentrated spatially than urban poverty (D.T. Lichter, et al., 2008), however patterns of metro and nonmetro poverty concentration differ based on the scale at which poverty is assessed (D.T. Lichter & Johnson, 2007).

Borrowing from the urban spatial mismatch literature, Partridge and Rickman (2008) argue that the location of rural populations relative to labor markets in more urban or suburban areas creates a distance based friction that may lead to higher rural poverty. Frictions are created when rural households are too far removed from labor markets that would allow residents of rural areas to maximize their employment opportunities and earn a wage to support their family. These authors also argue that the further a rural area is from a metro center that offers diverse employment opportunities the more likely this rural area is to be poor.

Commuting and migration barriers relative to labor markets creates the potential for a rural spatial mismatch and higher rural poverty (Blumenberg & Shiki, 2004). Transportation barriers create commuting problems for rural residents (Beale, 2004), making the possibility of traveling to another area for work more difficult and costly.

Therefore rural residents may have excess labor supply or underemployment in their local areas, which can translate to lower levels of employment, high unemployment, or higher underemployment and high rates of poverty (Partridge & Rickman, 2008). Additionally rural residents may enjoy the amenities present in their local area and depend on family and close social networks to assist each other during difficult economic times making the possibility of migration to an area with more employment opportunities less likely. Therefore non-monetary costs associated with transportation or migration create a distance based friction or spatial mismatch for rural areas.

Uneven regional development and economic restructuring presents unique barriers to developing the economic base of many rural areas as well (Bryden & Bollman, 2000; Lobao, et al., 2007; MacKay, 2003). These changes raise the importance of examining structural determinants of area poverty (D.T. Lichter, et al., 2008) and the patterns of poverty segregation that emerge as the result of labor market mismatches across diverse rural areas of the United States. In addition, it is the lower skilled workforce and less mobile population of rural areas that often face reduced employment opportunities due to these changes in local economic sectors (MacKay, 2003). These changes to local and regional economies makes it necessary to understand how poverty operates over space in order to offer sound structural policies to address the presence of nonmetro poverty segregation.

Data and Methods

Data for this analysis come from two sources: the 2000 U.S. Census of Population and Housing, Summary File 3 (block and county data) and the Economic Research Service (ERS) county typology codes for 2004. Patterns of residential poverty segregation were considered for all counties in the contiguous United States. For all segregation measures, each index was based on block group data within each county, which has been argued to be a better unit of analysis for detecting variation in segregation patterns across areal units (Lichter et al. 2007; Reardon and O'Sullivan 2004).

Massey and Denton (1988) outline evenness, exposure, concentration, centralization, and clustering as five dimensions of residential segregation. We measure poverty segregation using three indexes including: the dissimilarity index (*D*) to measure evenness, the interaction index (${}_xP_y{}^*$) to measure exposure, and the spatial proximity index to measure clustering (Massey and Denton 1988; Reardon 2006). These measures were selected since they compare two subgroups to each other when calculating the segregation measure instead of considering one group by itself. The three measures used here capture poverty segregation, where poverty is defined as the number of persons living below the federally designated poverty threshold in each block group. Measures for three of these dimensions (evenness, exposure, and clustering) were utilized to: 1) investigate the differences in residential segregation among metropolitan and nonmetropolitan areas of the United States, and 2) determine if any of the segregation measures offers support for a poverty segregation spatial mismatch in nonmetro areas.

The index of dissimilarity, the most widely used measure of residential evenness, measures the invariability of the distribution between two groups across a county. The dissimilarity index can be interpreted as the proportion of residents living below the poverty threshold that would have to move to a different block group in the county in order to produce an even distribution with those residents living above the poverty threshold. One formula for the index of dissimilarity is:

$$D = \frac{1}{2}\sum_{i=1}^{n}\left|\frac{x_i}{X} - \frac{y_i}{Y}\right|$$

where x_i is the number of residents in the ith block group in a county living below the poverty threshold, X is the total number of county residents living below the poverty threshold, y_i is the number of residents in the ith block group living above the poverty threshold, and Y is the total number of county residents living above the poverty threshold. This index varies between 0.0 and 1.0, with 0.0 corresponding to an even distribution amongst persons below the poverty threshold and persons living above the poverty threshold in a county and 1.0 corresponding to perfect segregation. A dissimilarity index score of 1 would therefore be interpreted as 100 percent of residents in a county living below the poverty threshold would need to change their block of residence in the county in order to achieve an even poverty distribution.

Residential exposure refers to the possibility of interaction between residents living below the poverty threshold and residents living above the poverty threshold within a county. Indexes of exposure measure the extent to which poor and non-poor residents come into contact with one another simply by sharing a common residential area. The interaction index measures the extent to which residents living below the poverty threshold are exposed to residents living above the poverty threshold. It has been denoted as ${}_xP_y{}^*$

$${}_xP_y^* = \sum_{i=1}^{n}\left[\frac{x_i}{X}\,\frac{y_i}{t_i}\right]$$

where x_i , y_i , and t_i are the number of residents living below the poverty threshold, the number of residents living above the poverty threshold, and the total population of block group i within a county, respectively. X represents the total number of residents living below the poverty threshold in the county. The index varies between 0.0 and 1.0 and can be interpreted as the probability a resident living below the poverty threshold shares an area with a resident living above the poverty threshold (Lieberson, 1980; Lieberson & Carter, 1982a, 1982b).

Spatial clustering refers to the extent to which population subgroups live next to other groups or cluster in space. The index of spatial proximity is adapted from White (1986) to measure the clustering of economic subgroups in space. To adequately calculate the spatial proximity index, the average proximity between members of the same group must first be calculated. The average proximity between members of an arbitrary group *Z* can by approximated by:

$$P_{xx} = \sum_{i=1}^{m} \sum_{j=1}^{m} \frac{z_i z_j c_{ij}}{Z^2}$$

where c_{ij} is a dichotomous variable with a value of one indicating block group i is continuous to block group j and zero otherwise, z_i is the subgroup population of the ith block group in a county, z_j is the subgroup population of the jth block group in a county, and Z is the total subgroup population of the county. The index of spatial proximity is simply the average of the intragroup proximities weighted by the fraction of each group in the population:

$$SP = \frac{XP_{xx} - YP_{yy}}{TP_{tt}}$$

where P_{xx}, P_{yy} and P_{tt} are the average proximity between residents living below the poverty threshold, the average proximity between residents living above the poverty threshold, and the average proximity between for the total population, respectively. X is the total number of residents living below the poverty threshold in the county, Y is the total number of residents living above the poverty threshold in the county, and *T* is the total population of the county. If there is no differential clustering between residents living below the poverty threshold and residents living above the poverty threshold, the spatial proximity index has a value equal to 1.0; it is greater than 1.0 when members of each group live nearer to one another than to members of the other group (higher levels of segregation). The ratio would be less than 1.0 in the event that residents living below the poverty threshold and residents living above the poverty threshold populations reside closer to each other than to members of their own group (lower levels of segregation).

Instead of estimating separate regression models for each of these measures of segregation, we aggregate the three measures into a single measure of intensity of segregation, or total segregation, in order to assess the degree of poverty segregation across metro and nonmetro areas. To construct this measure, quartiles of each segregation measure were calculated; then for each measure of segregation, a binary variable indicating if a particular county was in the highest segregation quartile was generated. For each measure of segregation each county would then have three 1/0 binary variables indicating whether that county was highly segregated along that dimension of segregation. These three indicators were then summed for each county, generating an ordinal variable with a range between 0 and 3 that measures on how many of the three dimensions of segregation were high in each county. Since this variable was ordinal and restricted to a finite set of categories, an ordinal logistic regression model was used to examine how the predictors affect the odds of a county being high on one or more dimensions of segregation.

Here we specify the ordinal logistic regression model using the proportional odds specification (Harrell, 2001; Powers & Xie, 2000):

$$\Pr[Y \geq j|X] = \frac{1}{1 + exp(-(\alpha_j + x'\beta))}$$

where j=1 to 3. This model fits j intercepts for each level of segregation and assumes homogeneity of the effect of the covariates on log odds of a county being high on 1 to 3 measures of segregation. Interpretation of the model results are the same as for the binary logistic regression model and is done using odds ratios or exp(β). Model estimation was done in R 2.11.1 (CRAN) using the rms library (Harrell, 2010; R Development Core Team, 2010).

The regression model was estimated to examine the effects of rurality, county economic sectors, racial minority concentration, and persistent poverty on poverty segregation. Racial concentration was measured by the proportion of the county population that was black and Hispanic in 2000. The proportion of the county population over the age of 65 and the proportion of the county population who moved into the county within past 5 years were two additional variables included in the models that have been linked to economic segregation and poverty concentration. Controls for the geographic characteristics of the counties were also included in the models. The regional divisions used by the United States Census Bureau were included as factors in the model with the "South" region retained as a reference; thus, the change in economic segregation levels for the other three regions (Northwest, Midwest, West) of the U.S. was compared to the South. The economic-dependence in a county serves as another set of indicator variables included from the Economic Research Service (ERS). These indicators denote the primary means of employment and economic earnings for each U.S. county, and the following economic-dependence categories are identified: farming, mining, manufacturing, federal/state government, services, or nonspecialized. For this analysis, manufacturing-dependent counties were considered the reference group. As such, measured coefficients for the other five economic-dependence indicators along with their interpreted segregation level changes will be compared to manufacturing-dependent county-level segregation. Additional predictors were used to control for variation in county level measures of education, unemployment and social service use. The percentage of the population 25 years of age and older with a college or professional degree captures the educational level of each county. County unemployment was measured as the percentage of residents out of work or looking for work among those county residents of working ages. Social service use patterns were measured with two variables: the percentage of households receiving Supplemental Security income and the percentage of households receiving any public assistance income.

Other indicator variables included in the models were a measure of persistent poverty, the percentage of the workforce working elsewhere, and county metropolitan status. Counties were considered persistently poor if the proportion of the population living in poverty over the last 30 years (measured by the 1970, 1980, 1990 and 2000 decennial censuses) was 20 percent or more. The percentage of workers working elsewhere was taken from the census and represents the proportion of workers over age sixteen that worked in a county other than the one in which they reside. The nonmetropolitan classification for each county was taken directly from the resources available from ERS as both a dichotomous measure and as a classification measure based on the rural-urban continuum codes. Finally, a measure that controlled for the size of the block groups within each county was included in the models. This measure was calculated as the area of the county (in square miles) divided by the number of block groups within the county.

Results

Descriptive statistics for the segregation indices and the predictor variables are presented in Table 1. In addition, maps of the three segregation measures are presented in Figure 1.

[Table 1 here]

[Figure 1 here]

The dissimilarity index shows that almost 24 percent of U.S. county residents would have to move to a different block group in the county in order to produce an even distribution of residents living above the poverty threshold. Figure 1 shows that high values of the dissimilarity index are concentrated in the Northeastern seaboard, Midwest and Southwest, with various pockets of high clustering surrounding metropolitan areas in the South. The interaction index has an average value of 0.81, suggesting a relatively high probability of a resident of a county living in poverty running into a resident not it poverty. Figure 1 shows the highest values of this index occur in Midwestern counties, and the lowest values typically occur in the South and Southwest. The spatial proximity index shows less general spatial clustering than the other two segregation measures, with counties in the Northeast having a mean of 1.03, which suggests that people in poverty live closer to people in poverty, while the South has a mean of 0.977, suggesting that people in poverty live in closer proximity to people not in poverty. The other regions (Midwest and West) both have mean values of .99, indicating that there may be no discernible pattern of poverty segregation on average in these regions for this measure. Despite the aggregate measure not showing much differentiation, based on Figure 1, parts of southern California and Arizona show high (>1) values on the spatial proximity index, suggesting that people in poverty live closer to other people in poverty in these areas, while in places such as Nevada, the opposite is true. All of these measures show significant values of Moran's I, which suggests some average clustering among neighboring counties across the U.S., although the values of the statistic are not high. While these spatial displays are instructive to the nature of the spatial clustering of these indices, when these indices are compared across the categories of the rural-urban continuum codes (RUCC), other trends are apparent.

[Figure 2 here]

Figure 2 shows box and whisker plots of the distribution of the three indices by the RUCC classification scheme, in which higher values of the RUCC are more rural and lower values more urban/metropolitan. The dissimilarity index showed a strong negative association across these codes, with larger metropolitan areas showing higher values of the dissimilarity index, suggesting more segregation, while in more rural areas segregation is not as prevalent. There was significant variation in the poverty dissimilarity index across these codes using the Kruskal-Wallis test (χ^2=1,389, df=9, p=<0.0001). The poverty interaction index showed the highest value in medium sized metro areas, and the lowest values in small urban areas. Of the three poverty segregation measures, the poverty interaction index witnessed the highest values across the different types of nonmetro counties. However, in general the value for this measure was higher across all counties compared to the patterns for the other two segregation measures.

There was significant variation across these codes using the Kruskal-Wallis test (χ^2=202, df=9, p=<0.0001). The spatial proximity index showed patterns very similar to those of the dissimilarity index: higher values were observed in metropolitan areas (>1, suggesting higher levels of poverty segregation), while lower values were observed in nonmetro areas (<1, suggesting lower levels of poverty segregation). There was significant variation across these codes using the Kruskal-Wallis test (χ^2=1,261, df=9, p=<0.0001). These results suggest that the level of segregation varied between different types of metro and nonmetro counties. While there were differences in the central tendency as revealed by the results of the Kruskal-Wallis tests, another notable pattern in the spatial proximity index was the dramatically different levels of variation between the more rural, nonmetro counties and the metropolitan counties. The nonmetro counties had much lower levels of variation than the metropolitan counties on this measure (the boxes in Figure 2 are the interquartile range), and a similar pattern is not observed for the poverty dissimilarity or interaction indexes. This point is discussed further in the discussion section below.

Table 2 shows the results of the ordinal logistic regression model for the segregation intensity measure discussed above. It is important to note that the model parameter estimates are expressed as odds ratios of standardized β's, as the continuous variables in the model were z-scored prior to model estimation.

[Table 2 here]

Nonmetro counties had much lower odds of having high levels of poverty segregation compared to metro counties, this supports the findings from the illustrations in Figure 2. Counties with above average proportions of Black and Hispanic residents had higher odds of having higher general levels of poverty segregation, although the effect of the

Hispanic population was not as large as the Black population. Higher proportions of the population age 65 plus and higher proportions of migrants in counties lowered the odds of experiencing higher levels of poverty segregation.

Several of the economic indicators were significant in the model. Counties with economies specializing in federal or state government or counties with non-specialized economies had higher odds of experiencing more poverty segregation than counties with a manufacturing as the primary economic sector. Also counties that were persistently poor had dramatically higher odds of being more segregated. The proportion of workers who leave the county for work showed a negative association with higher intensity of poverty segregation, where counties with above average levels of this variable had lower odds of being more segregated. As the regional variables have significant interactions with nonmetro status, they are not interpreted directly. Counties with large average block groups had lower odds of being more segregated.

The proportion of the population with a college degree, the percentage of the county working age population that was unemployed, and the percentage of the county population receiving public assistance all increased the odds of poverty segregation intensity for those counties. The interaction terms between nonmetro county status and each of the three census regions (Northeast, Midwest, West) showed significant reduction in the odds of experiencing higher intensity of poverty segregation, compared to nonmetro counties in the South, with the highest reduction in odds being in the nonmetro counties in the Northeast. While the ordinal logistic model does not have a true R^2 measure because it is fit with maximum likelihood, the deviance R^2 suggests that the model is fitting the data fairly well, with a value of 54.3% of residual deviance explained.

To visualize the results of the original logistic regression model, two probability maps were created based on the cumulative probabilities generated from the regression model. The two probability maps are presented in Figure 3 and Figure 4. Figure 3 shows the predicted probability that no more than 1 dimension of segregation was high in a particular county.

[Figure 3 here]

For example it is evident that many areas of the Midwestern US, Northern Plains and Mountain West have relatively high probabilities of experiencing low levels of poverty segregation on multiple dimensions. On the other hand, many areas of the South, the Southwest and metro areas of the Northeast have low probabilities of only experiencing 1 or less high values of poverty segregation on any one dimension of poverty segregation used. Figure 4 represents the compliment in probability terms to Figure 3, where the probability being mapped is whether the counties had 2 or 3 of the poverty segregation measures that were high.

[Figure 4 here]

Since Figure 4 is the compliment of Figure 3, the areas that were lightly colored in Figure 3 (meaning low probability) are now darker (meaning high probability). Areas of the South, the Southwest and metro areas of the Northeast, as well as other metro areas in the Midwest and Northwest have high probabilities of being highly segregated along at least two dimensions of poverty segregation.

Discussion

Significant spatial patterns of poverty segregation were observed for all three measures in this analysis, including the dissimilarity index, the interaction index, and the spatial proximity index. Clear regional differences were also noted for each other these measures of poverty segregation. Further, the degree of segregation was found to differ across metro and nonmetro counties in the bivariate analyses, with nonmetro counties experiencing lower levels of poverty segregation than the most metro counties. This pattern was particularly evident for the dissimilarity and spatial proximity indexes. Less variation was noted between the level of poverty segregation based on the interaction index between metro and nonmetro counties, even though statistically significant differences were noted across county designations.

The low variation in the spatial proximity index across different nonmetro counties presents an interesting finding about the potential interaction between poor and non-poor residents of nonmetro counties. While the mean value for this index across the most metro counties had a value of 1, indicating that poor residents are spatially segregated from non-poor residents, the small variation in these values may be due to the larger block-group sizes assigned in nonmetro counties making it more difficult to isolate distinct spatial patterns in nonmetro counties. Alternatively, values of poverty segregation measured by the spatial proximity index in nonmetro counties indicate that the poor are spatially segregated from the non-poor, which was explored in more detail in the regression models used to assess the potential of a spatial mismatch in poverty segregation patterns in nonmetro counties in the U.S.

Nonmetro counties experienced lower levels of poverty segregation than metro counties on the measure of total segregation in the ordinal logistic regression model. However, significant nonmetro regional effects were also noted in the models. In most instances, nonmetro counties in the Northeast and West experienced different poverty segregation patterns than nonmetro counties in the South. Yet, poor residents in nonmetro counties in the South had less interaction with non-poor residents than residents of other nonmetro counties in the other three regions. This finding deserves further attention since less variation in general was noted in the value of the interaction index in different types of nonmetro counties based on the bivariate tests. True regional variations are masked in this measure of poverty segregation without considering structural conditions and locations of counties.

Some support exists for the potential spatial mismatch argument presented above, in that counties with larger proportions of residents traveling to other counties for employment experience lower levels of poverty segregation as measured by the total segregation index, or intensity of poverty segregation in a county. If people are able to secure employment outside of their local area, their chances of being poor are likely to decrease. Likewise a county's main form of economic dependence is associated with poverty segregation for all three measures. Of each of the economic dependence categories, only counties dependent on government or non-specialized economic sectors witness a positive effect on segregation, and no economic sectors appear to reduce poverty segregation intensity in and of themselves. Since rural areas have traditionally been more dependent on agriculture, mining, and manufacturing, the restructuring of service based industries in more metro areas may contribute to distance based friction and increased intensity of poverty segregation for certain nonmetro counties, particularly in the South. This finding deserves more exploration based on potential economic dependence nonmetro interactions and their impact on poverty segregation.

In the regression model, a statistically significant association was observed between the percentage of the county population that was Hispanic and intensity of poverty segregation. For the total segregation measure, a county with a higher proportion of Hispanics in the population witnessed higher odds of being more segregated. With increasing Hispanic migration into nonmetro areas (Johnson & Lichter, 2010; Kandel, 2005; Kandel & Cromartie, 2004), this association may indicate that nonmetro areas may experience high intensity of poverty segregation than comparable metro counties. It will be important to document this finding over time as the Hispanic population continues to grow in less traditional nonmetro areas.

Limitations

First, this analysis was based on cross-sectional aggregate data only. Therefore we are cautious when interpreting the associations between county contextual variables and the intensity of poverty segregation for each county. As an aggregate analysis, there was also attention given to the interpretation of associations noted in the results, as to not make erroneous claims that make generalizations to individuals within counties.

Second, in an effort to streamline the analysis and results presented, we decided to create an ordinal measure of poverty segregation intensity for each county in the contiguous United States. While each of the initial poverty segregation measures used were based on different dimensions of segregation, we were most concerned with presenting the overall intensity of poverty segregation in a particular county. This measure should not be interpreted as a true index or scale of poverty segregation, because each segregation measure used to construct this ordinal measure has unique properties in determining the level of segregation in the area.

Lastly, standard measures of residential segregation are based on the examination of residential patterns in metropolitan statistical areas (MSA) or central cities (Massey, 1996, Massey and Denton, 1988, Massey and Denton, 1989). In this paper, we constructed a measure of poverty segregation intensity for all counties in the U.S. based on three different dimensions of segregation. It is not clear if the interpretation and application of residential segregation indices operate in the same way between metropolitan and non-metropolitan locations in the United States. However, we feel more confident in the associations noted in the ordinal logistic regression model, since we allow for potential metro/nonmetro interaction based on region, and these nonmetro-region interactions were statistically significant.

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Table 1. Descriptive Statistics for Poverty Segregation Measures and Predictors

Variable	Mean or Proportion	Std.*	Moran's I**
Dependent Variables			
Dissimilarity Index	0.237	0.099	0.325
Interaction Index	0.805	0.120	0.338
Spatial Proximity Index	0.988	0.149	0.308
Sociodemographic Variables			
Nonmetro Status (Nonmetro=1)	0.727	-	0.418
% Black	0.088	0.146	0.792
%Hispanic	0.061	0.121	0.812
% Aged 65 +	0.146	0.044	0.513
% Population Moved Last 5 Years	0.213	0.073	0.426
Economic Dependence Variables			
Manufacturing	0.285	-	0.308
Farming	0.142	-	0.407
Federal/State Government	0.114	-	0.096
Mining	0.040	-	0.288
Service	0.107	-	0.227
Nonspecialized	0.299	-	0.111
Persistent Poverty	0.123	-	0.468
% of Workers Not Working in County	0.329	0.178	0.249
Regional Variables			
South	0.445	-	-
Northeast	0.070	-	-
Midwest	0.339	-	-
West	0.133	-	-
Other Predictors			
Mean Size of Block Group (mi^2)	82.170	185.400	0.481
% of Population Age 25+ with College Degree	0.018	0.0123	0.288
% Unemployed	0.058	0.027	0.422
% of Households Receiving SSI	0.051	0.027	0.683
% of Households Receiving Public Assistance Income	0.033	0.019	0.439
% of Households Receiving Social Security Income	0.306	0.063	0.496

*No standard deviations for proportions are reported.

**All values of Moran's I are significantly different from zero using a Monte Carlo hypothesis test at α=.001. No Moran's I values are reported for the regional indicator variables, as these will of course have spatial structure.

Table 2. Results of Ordinal Logistic Regression Model for Poverty Segregation Intensity

Parameter	exp(β) (95% CI)
Sociodemographic Variables	
Nonmetro Status (Nonmetro=1)	0.167*** (0.298 – 0.516)
% Black	1.485*** (1.349 – 1.634)
%Hispanic	1.151** (1.056 – 1.253)
% Aged 65 +	0.705*** (0.631 – 0.789)
% Population Moved Last 5 Years	0.867* (0.771 -0.975)
Economic Dependence Variables	
Manufacturing (Ref)	1.00
Farming	0.939 (0.673 – 1.310)
Federal/State Government	1.415* (1.051 – 1.907)
Mining	1.296 (0.844 – 1.988)
Service	1.094 (0.809 – 1.478)
Non-specialized	1.267* (1.023 – 1.569)
Persistent Poverty	4.136*** (3.024 – 5.657)
% of Workers Not Working in County	0.424*** (0.383 – 0.470)
Regional Variables	
South (Ref)	1.00
Northeast	2.301** (1.511 – 3.503)
Midwest	1.901** (1.365 – 2.647)
West	1.521 (0.958 – 2.414)
Other Predictors	
Mean Size of Block Group (mi^2)	0.754** (0.644 – 0.883)
% of Population Age 25+ with College Degree	1.754*** (1.568 – 1.962)
% Unemployed	1.266** (1.121 – 1.431)
% of Households Receiving SSI	0.904 (0.785 – 1.039)
% of Households Receiving Public Assistance Income	1.193** (1.063 – 1.339)
Interaction Terms	
Nonmetro*Northeast	0.261*** (0.138 – 0.496)
Nonmetro*Midwest	0.304*** (0.202 – 0.458)
Nonmetro*West	0.291*** (0.165 – 0.514)
Intercepts	
α_1	0.902***
α_2	-0.935***
α_3	-2.686***
Pseudo R^2	0.543
N = 3,109	

*=p≤.05, **=p≤.01, ***p≤.0001

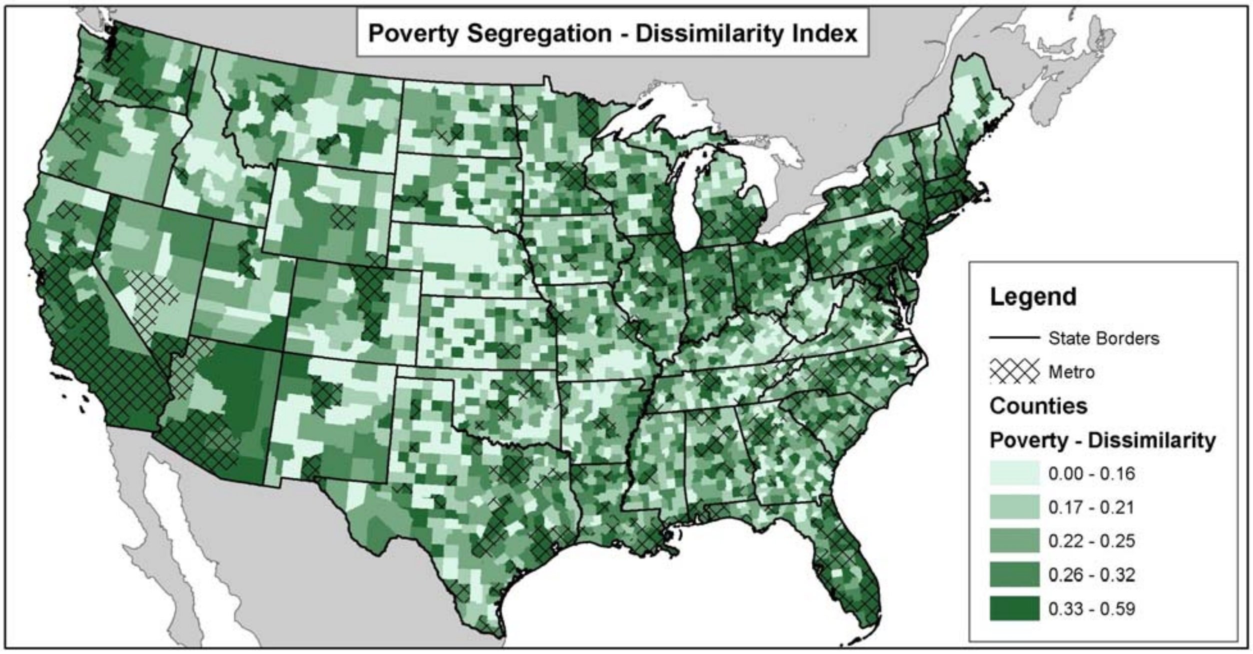
Figure Titles (Figures are presented in correct order below.)

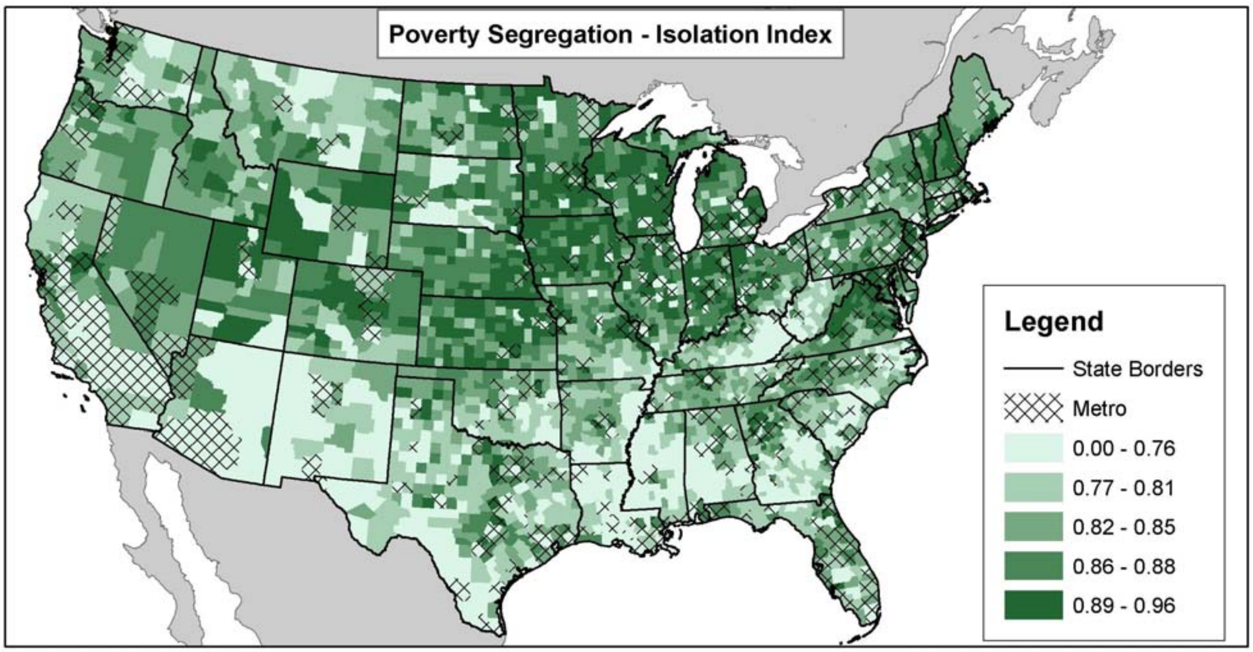
Figure 1. Spatial distribution of the three poverty segregation indices in US counties and metro/nonmetro status

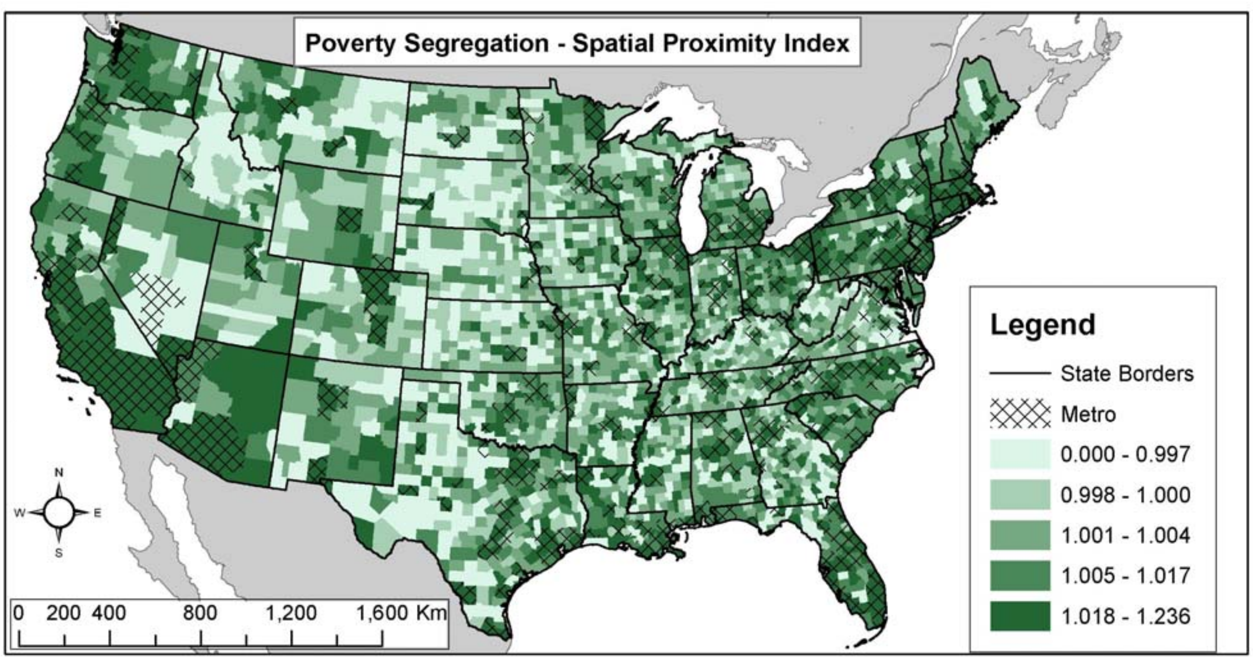
Figure 2. Boxplots of the three poverty segregation measures by level of the USDA Urban-Rural Continuum Codes

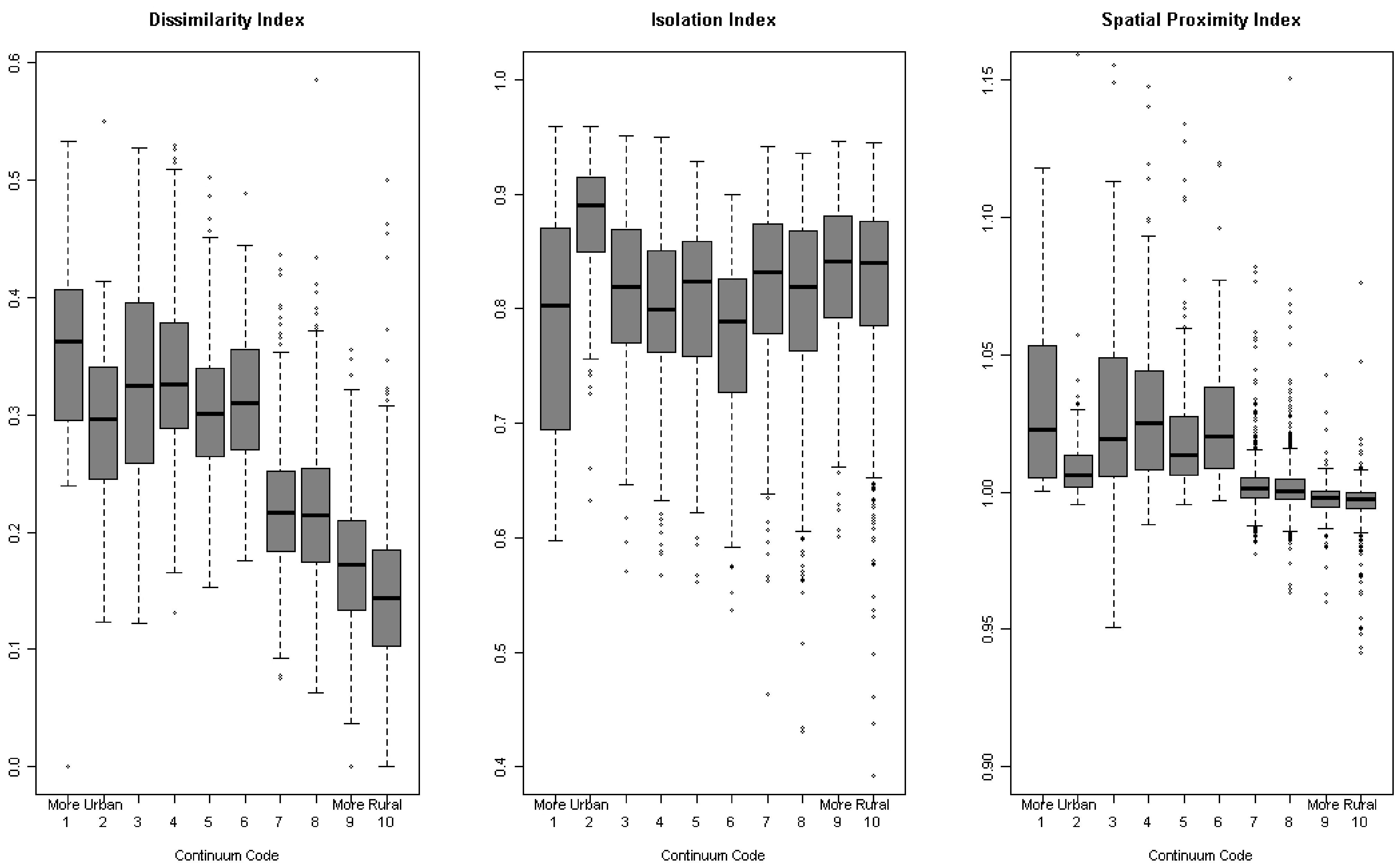
Figure 3. Predicted probability map of US counties showing probability of being high on zero or one of the dimensions of poverty segregation

Figure 4. Predicted probability map of US counties showing probability of being high on two or three of the dimensions of poverty segregation

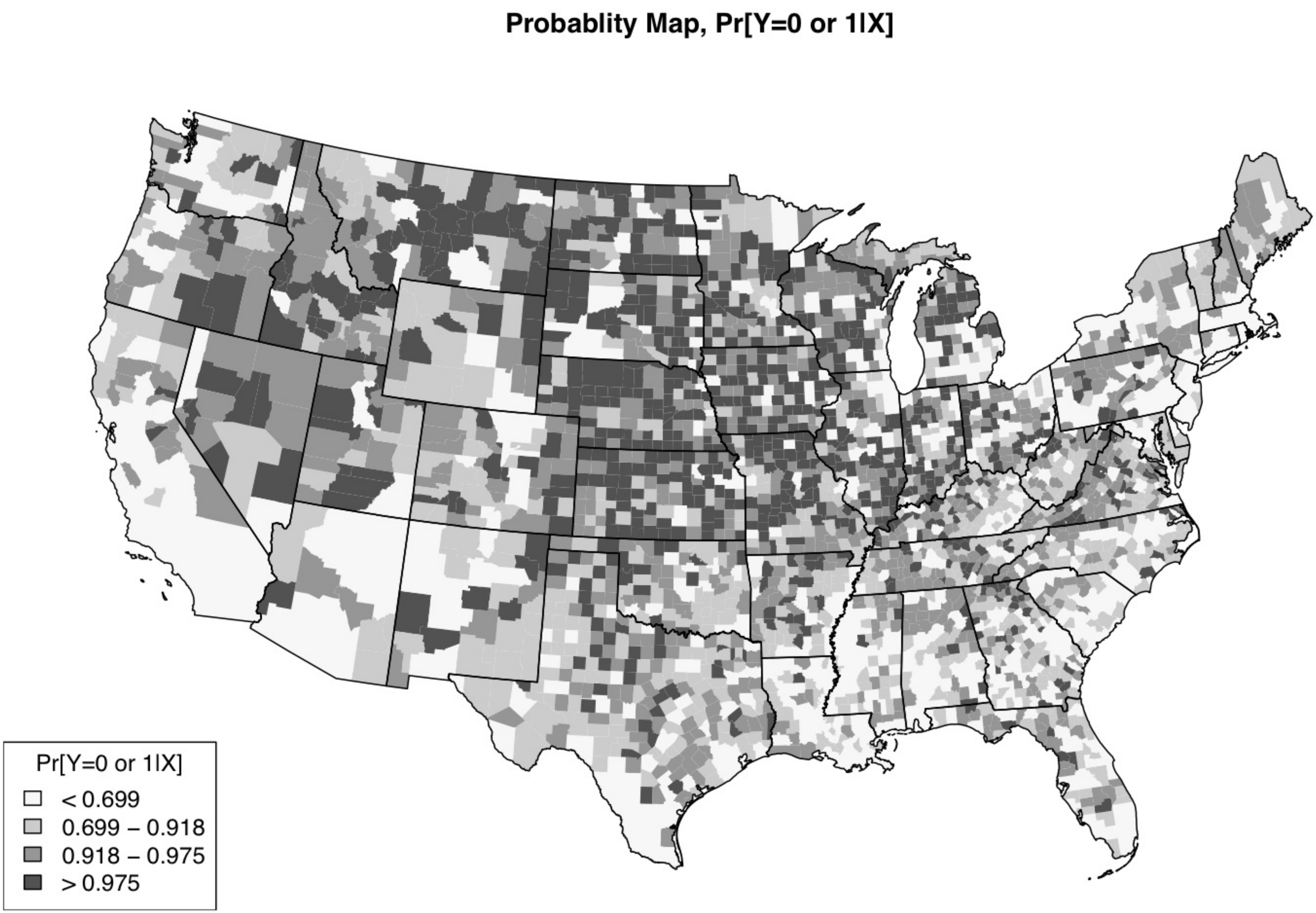

Poverty Segregation - Dissimilarity Index
Legend
State Borders
Metro
Counties
Poverty - Dissimilarity
0.00 - 0.16
0.17 - 0.21
0.22 - 0.25
0.26 - 0.32
0.33 - 0.59


Poverty Segregation - Isolation Index
Legend
State Borders
Metro
0.00 - 0.76
0.77 - 0.81
0.82 - 0.85
0.86 - 0.88
0.89 - 0.96


Poverty Segregation - Spatial Proximity Index
Legend
State Borders
Metro
0.000 - 0.997
0.998 - 1.000
1.001 - 1.004
1.005 - 1.017
1.018 - 1.236
N
W
E
S
0 200 400 800 1,200 1,600 Km



Dissimilarity Index
Isolation Index
Spatial Proximity Index
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.4
0.5
0.6
0.7
0.8
0.9
1.0
0.90
0.95
1.00
1.05
1.10
1.15
More Urban
More Rural
1
2
3
4
5
6
7
8
9
10
Continuum Code


Probablity Map, Pr[Y=0 or 1|X]
Pr[Y=0 or 1|X]
< 0.699
0.699 – 0.918
0.918 – 0.975
> 0.975

Probablity Map, Pr[Y=2 or 3|X]