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RESEARCH

A Study of County Child Poverty Rates in Puerto Rico: Does Space Matter?

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ABSTRACT

Previous literature on childhood poverty in Puerto Rico is sparse. This is surprising since Puerto Rico exhibits very high poverty rates as compared to the rest of the United States. In this paper, we apply a structural perspective and consider how economic characteristics, household structure and migration patterns influence child poverty rates in Puerto Rico. Data for this paper come from the 2006-2010 Puerto Rico Community Survey (PRCS) summary files. We apply methods of exploratory spatial data analysis and spatial regression models to understand how municipio (county equivalents) level child poverty rates are influenced by these factors. A spatial modeling methodology was deemed appropriate since significant spatial structure is found for the child poverty rate and residuals from the Ordinary Least Squares model. Household composition, as measured by the percent of female headed households and the percent of grandparents caring for their own grandchildren consistently showed positive associations with child poverty. In terms of the economic sector variables, the proportion of the workforce in agriculture and proportion without a high school education showed significant positive effects on child poverty. With respect to migration, we find little to no impact, but we do find that child poverty is concentrated outside of the region adjacent to the capital of San Juan.

KEYWORDS: child poverty rate, spatial analysis, spatial regression, spatial lag, spatial error, Puerto Rico

INTRODUCTION

Previous literature on childhood poverty in Puerto Rico is sparse. This is surprising since Puerto Rico exhibits very high poverty rates as compared to the rest of the United States. It was estimated from the American Community Survey, that for the period of 2006 to 2010, Puerto Rico's poverty rate for children under 18 years was of 56 percent (U.S. Census Bureau n.d.). Compared to the "mainland" US, the next highest rate was of 30 percent, belonging to Mississippi. For a place only slightly larger than Rhode Island and Connecticut, Puerto Rico's child poverty level is striking.

In his individual level analysis for Puerto Rico, Morales-González (2010) found that in 2000, poor family households with children under 18

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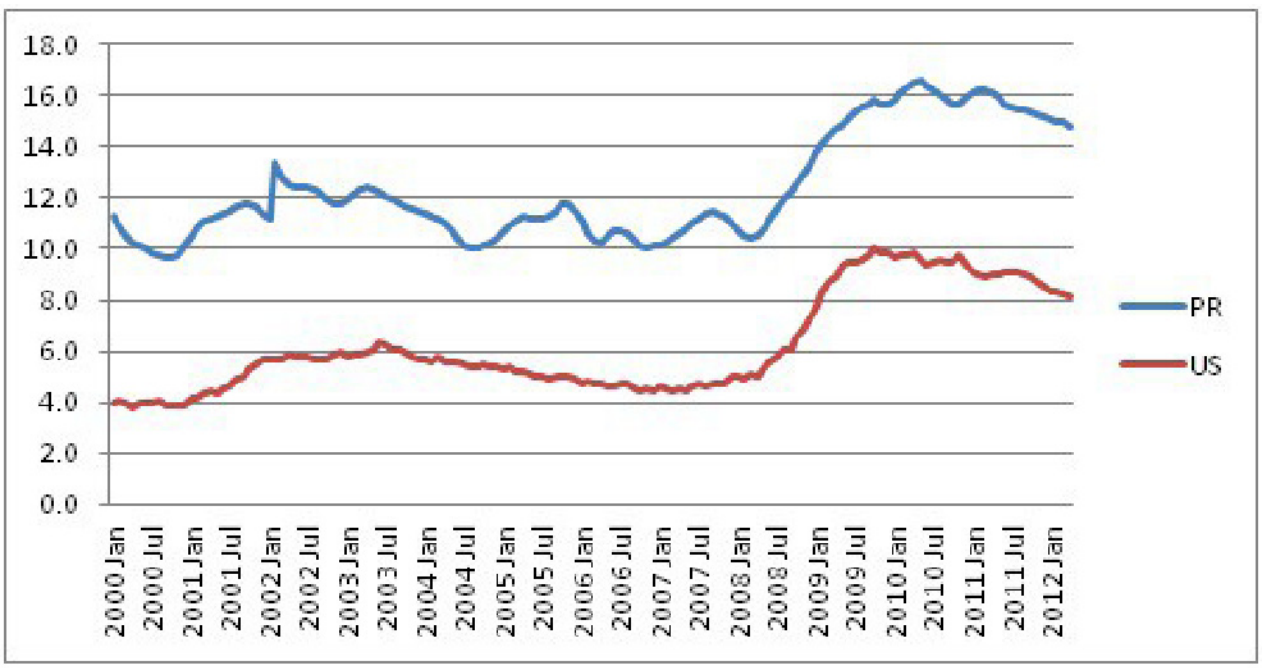
years were most closely associated with females without a husband present, and with uneducated householders. Households in poverty were also significantly associated with blue-collar, service occupations and particularly agriculture related occupations. However, this and other studies on Puerto Rican child poverty have been either primarily descriptive, or have focused on the effects of child poverty on other outcomes at the individual level (Galster and Santiago 1994; Morales-González 2010; Oropesa and Landale 2000).

Nonetheless, recent views on the subject tell us that both individual and structural factors play a role in the root causes of poverty (Cotter 2002; Voss, Long, Hammer, and Friedman 2006). In essence, the local labor market conditions are structural factors influencing poverty the most because they limit the employment of parents. This is disconcerting because Puerto Rico's unemployment rates were already above 10 percent at the beginning of the millennium, and were markedly higher than the rates in the nation (see figure 1) (U.S. Bureau of Labor Statistics 2012a; U.S. Bureau of Labor Statistics 2012b).

Child poverty in Puerto Rico is also worrisome because of the government's financial crisis, which hindered even more the island's economy and employment opportunities. For example, in May 2006, 100,000 public service employees went on a forced two-week, unpaid vacation because the government did not have enough money to pay their salaries. This was the beginning of the recession for Puerto Rico, which happened an entire year earlier than the start of the recession in the mainland. As a result, approximately 41,000 jobs were lost between April of 2006 and December of 2008 (Quiñones Pérez 2011). A second instance was in 2009, when the recently elected Governor Luis Fortuño announced that his plan to turn around the economy would begin with laying off 30,000 public service employees (Anonymous 2009). This second hit to the economy resulted in the loss of 91,000 jobs between the public and the private sector between December of 2008 and March of 2011, with a monthly average of 3,378 jobs lost over the period (Quiñones Pérez 2011).

Figure 1. Unemployment Rates for Puerto Rico and the United States, 2000-2012.

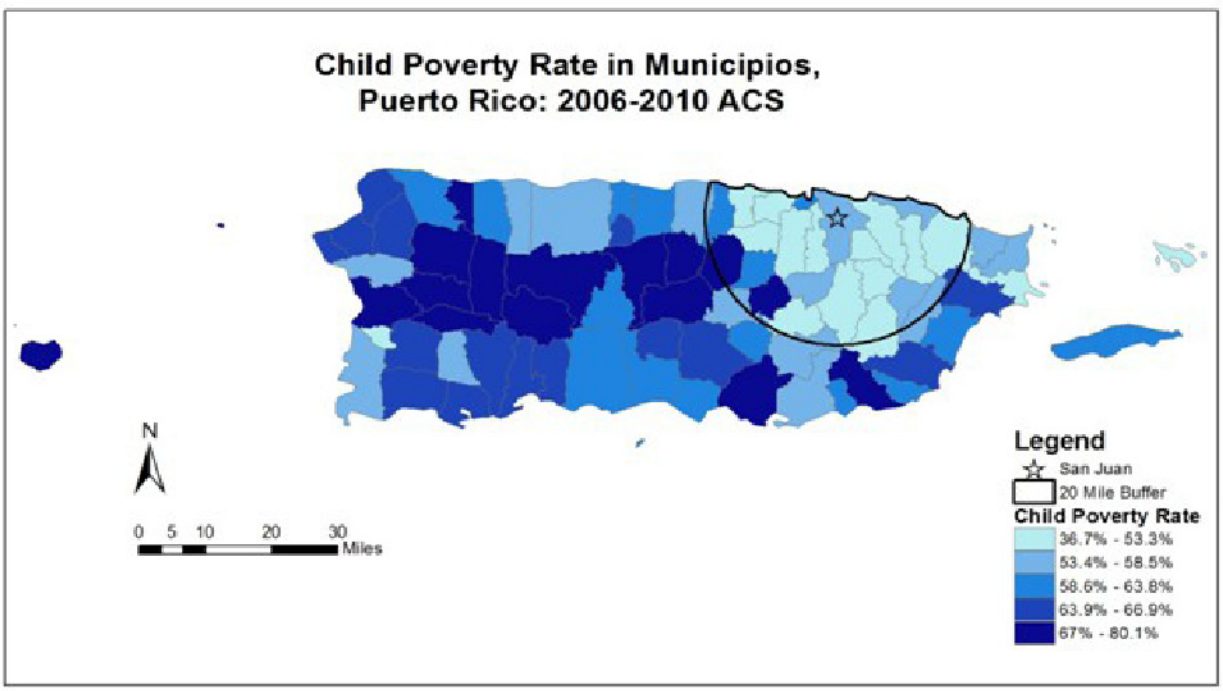


Source: U.S. Bureau of Labor Statistics [7].

In turn, unemployment rose to an all-time high of 16.6 percent on May of 2010, and has only decreased to 15 percent as of February of 2012 (U.S. Bureau of Labor Statistics 2012b). Morrison (2005) indicates that unemployment can mainly be explained in two ways. One view says that no matter how much employment is created, if the skill level of the unemployed does not meet the skills required by the labor market, then unemployment will permeate. However, a second view recognizes that unemployment can also be a result of localized demand for labor. This problem is also exacerbated when layoffs occur where local employers are limited, concentrating the population without a job in the area. Because children depend on their parents or main caregivers' income and employment status, and because neither people nor job offerings are homogeneously distributed, poverty is not a randomly distributed spatial process.

In the last decade, a number of demographers have started using the methods of exploratory spatial data analysis (ESDA) and spatial regression modeling to examine the variation of demographic characteristics across space. With respect to poverty specifically, Voss, Long, Hammer & Friedman (2006) have used these methods to study county child poverty rates for the United States. This paper will attempt to replicate the findings of Voss et al [5] within the island of Puerto Rico for two reasons. First, because of Puerto Rico's high poverty rate, and child poverty rate in particular and because of its weakened economic state, it is important to understand the associations between local labor market conditions and poverty within the Puerto Rican context. Secondly, because the literature for child poverty for Puerto Rico is limited and has not been examined using techniques from spatial statistics it makes an excellent case study of the power of these methods for understanding the influences of labor market conditions on poverty.

Figure 2. Child Poverty Rates in Municipios, Puerto Rico, 2006-2010 PRCS. Map shows the distribution of the poverty rate by quintiles. Source: Data comes from the 2006-2010 PRCS Summary File.



The purpose of this paper is to document spatial autocorrelation related to child poverty in Puerto Rico, use spatial regression models to estimate the socioeconomic variables associated with child poverty in the Puerto Rican context, and to examine the effects of the local industrial composition, employment composition, family structure and other control variables on child poverty rates at the county level (municipio). The paper will use the framework outlined by Voss et. al [5] for the US, and consider the relevance of their findings to the island of Puerto Rico.

BACKGROUND

Child poverty is a direct result of their parents' conditions and the circumstances that surround them. As Voss, Long, Hammer and Friedman (2006) explain, two schools of thought have dominated the literature on poverty. One focuses on the individual level determinants of poverty, while the other school of thought focuses on the structural forces that influence poverty. Past studies for both the United States and Puerto Rico have agreed that the changing family structure to single parent households, particularly female-headed households, has been strongly associated with changes in child poverty (Lichter and McLaughlin 1995; Morales-González 2010). After all, households with two income-earning parents are more likely to have more financial security than households with only one income-earning parent. In most cases, females are the ones typically leading single parent households.

In the structural perspective, skills and educational attainment of adults are not the only characteristics that influence people's access to employment opportunities. This view sees the local economic context as a main player in the development of poverty (Cotter 2002). The local labor market, an unstable economy, and unemployment are factors that individuals have little control over but, in great part, determine their employment opportunities.

While the causes of poverty differ between the individual and structural level determinant models, Cotter (2002) proposed that these two views are not necessarily competing with one another, but are actually complementary explanations of poverty. Friedman and Lichter (1998) had earlier considered this combined perspective for child poverty in the United States after acknowledging that risk of childhood poverty was not randomly distributed at the county level. They studied child poverty at level of analysis by using demographic and industrial composition variables of the labor force. Their focus was on industrial composition and they were attempting to estimate parents' employment characteristics on poverty, after noticing that counties with agricultural and extractive based economies were traditionally associated with high unemployment rates (Friedman and Lichter 1998). Unfortunately, even though they were making assumptions about spatial inequality in county-level child poverty and their discussion focused around the issue of about space spatial inequality in poverty (counties), their modeling strategy did not measure this directly since they relied on a weighted least squares (WLS) regression method that took into account space only in an indirect way.

In 2006, Voss et al. (2006) revisited the article by Friedman and Lichter (1998) and used both exploratory spatial data analysis (ESDA) and spatial regression models to account for spatial heterogeneity in poverty. Their approach was not intended to dismiss the weighted least squares regression approach that Friedman and Lichter (1998) originally used, but to strengthen their findings through the use of models that would explicitly take into account spatial autocorrelation to provide more support in favor of Friedman and Lichter's propositions. In their paper, Voss et al. (2006) explained that autocorrelated residuals occur in many standard regression analyses where the dependent variable is itself autocorrelated, poverty being one of them. In other words, poor counties are more likely to be surrounded by poor counties and non-poor or less poor counties are going to be surrounded by less poor counties. They go on to mention that autocorrelation is problematic because it violates the assumption of independence of errors from the classical linear regression models, and, in doing so, the estimates for the model's parameters are biased.

Wrigley, Holt, Steel, & Trammer (1998, as cited in Voss, Long, Hammer, and Friedman 2006) indicated four main reasons for why autocorrelation in poverty happens. The first is through feedback, which states that because individuals and households interact with each other, they are more likely to influence each other, and residential proximity increases these chances of interaction (Voss, Long, Hammer, and Friedman 2006). The second reason is that of grouping forces, meaning that individuals and households tend to be clustered together because of outside forces of the labor markers (Voss, Long, Hammer, and Friedman 2006) which limit their employment and housing options. Additionally, the amount of income made from employment limits the choice for housing as well. Therefore, people that are accessing similar sources of employment in a local area are often earning similar incomes, and living in close proximity to their employment and each other are also more likely to have similar characteristics. The third reason refers to grouping responses, and it refers to the capacity of people to respond to the structural forces that surround them (Voss, Long, Hammer, and Friedman 2006). In other words, people's skills, education, and other resources such as human capital will influence their capacity to overcome hardships brought by local unemployment and/or industrial restructuring that might limit employment choices. People with more human and social capital are more likely to overcome difficulties compared to people with lower levels of either human or social capital. A common response to the structural force of high unemployment rates in Puerto Rico has been to migrate to the United States. Oropesa and Landale (2000) found evidence that Puerto Rican migrants to the United States actually decreased the likelihood of living in poverty among their children because employment opportunities are more common in the US. Because past literature on Puerto Rican migration has indicated that Puerto Rican migrants tend to be selected from the middle of the skill pool (Senior 1953; Sotomayor 2009), and more recently among educated individuals (Meléndez and Visser 2011), it is suggested here, that outmigration will act to concentrate poverty in Puerto Rico. This is because the migrants that are leaving have better resources and may be able to counteract the costs of migration to escape poverty, but those that stay behind do so because of insufficient resources. Using spatial autoregressive models, Rupashinga and Goetz (2007) have already examined this concept for the United States, and found that non-movers contributed significantly to county level poverty. The last reason for autocorrelation is that of nuisance autocorrelation and it refers to what happens when the units of analysis are smaller than the spatial process itself, in this case poverty. As one can see from Figure 1, poverty is not restricted to a single municipio. It expands beyond this, creating regions or clusters, and so autocorrelation among neighbors happens.

In the current paper, spatial simultaneous autoregressive models (SAR) are used to estimate the effects of local labor market conditions and migration patterns on the childhood poverty rate, while directly taking into account the autocorrelation created from the influence of neighboring units of analysis on each other. This process can be approached in two ways, through either a spatial lag model or a spatial error model. The work by Voss et al. (2006) found that a spatial error better explained county child poverty rates in the United States. This paper examines both methods to determine if this is also how child poverty at the county level in Puerto Rico works.

DATA AND METHODS

Data

The data for this paper come from the 2006-2010 Puerto Rico Community Survey (PRCS) summary files. The Puerto Rico Community Survey is part of the American Community Survey operations. The summary files are a series of tables that present aggregated count data at different geographical levels. The level of analysis selected for this paper is the municipio, which is the equivalent of a county in the United States. The geographic data used for mapping the Puerto Rican municipios came from the U.S. Census Bureau's 2010 Census TIGER files (2011). ArcGIS 10 (ESRI Inc 2010) was used to produce all maps.

Following Friedman and Lichter [13], the dependent variable is the proportion of children in poverty. The poverty measurement was taken from the Census table that already has a predetermined threshold for poverty based on family income. To make it conform to a more normal distribution, the variable was transformed to a logit scale:

$$\log(p / (1-p))$$

where *p* is the proportion of children of people less than 18 years of age that were living below the poverty threshold.

Based on the work of Friedman and Lichter (1998), the independent variables of interest are local economic indicators of industrial composition, and employment opportunity structure that were considered to be positively associated with child poverty. The industrial composition consisted of the proportion of people, 16 years and older, in each county, that was employed in one of the following industries: agriculture (including forestry, fishing, hunting and mining); professional services (professional, scientific, management, administrative, waste management, educational, health care, social assistance related, and public administration); manufacturing, and other services (arts, entertainment, recreation, accommodation, food related, and other services). The employment opportunity structure is defined by unemployment and underemployment. Unemployment consists of the proportion of people 16 years and over in the labor force who were unemployed. Underemployment is identified by the proportion of people 16 to 64 years, who in the last 12 months usually worked less than 35 hours a week or those who worked less than 27 weeks.

The study also controls for family structure variables and other demographic variables. Family structure includes both the proportion of female headed households with children under 18 years, and the proportion of grandparents 60 years and older that were responsible for grandchildren under 18 years of age out of all the grandparents that lived with their grandchildren. This last variable was deemed important because previous literature has found that, after female headed households, a big proportion of children that live with their grandparents are poor (Baker and Mutchler 2010). We expect a positive relationship between both of these family structure variables and child poverty in our models.

The current analysis also considered the proportion of the population 18 years and older who had a High School Degree or less as a measure of labor force education. We believe that in areas with a lower educated population, we will see higher rates of child poverty. Finally, two measures of migration are considered; one for temporary labor force migration and the second a more typical measure of residential change. First, the proportion of people who worked outside the county of residence (commuters) is measured. Commuters are expected to have a negative association with child poverty, because they are people who will bring wages into their municipio of residence from another municipio, potentially reducing poverty on average in their home area. Finally, migration is considered by identifying the proportion of people who lived in the same house the year before. These are considered non-movers in the migration sense. We expect that in areas with high proportions of non-movers will be positively associated with poverty because they could lack the human capital it takes to move somewhere else.

Methods

The first step is to examine spatial structure of poverty in Puerto Rico through ESDA (Chi and Zhu 2008). First, the Global Moran's I statistic is used as a descriptive measure of overall spatial clustering of both the dependent and independent variables. In essence, the higher the value of Moran's I, the higher the indication of clustering of similar values (Voss, Long, Hammer, and Friedman 2006). The global Moran I statistic, however, is limited in the sense that it does not give more information about the individual units of analysis, the municipios in this case. For this reason the local version of Moran's I, the Local Indicator of Spatial Autocorrelation (LISA), is used to obtain a measure of autocorrelation for each municipio (Anselin 1995). This statistic is interpreted the same way as the global statistic, and for both, the statistical significance is tested through the randomization of the observed clusters (Anselin 1995). As part of the LISA analysis, adjustments for multiple comparisons were done using the False Discover Rate procedure (Benjamini and Hochberg 1995).

The second step is to use spatial regression models to examine the relationship between the child poverty rate and the independent variables. Following Voss et al. (2006) this is done by using alternative model specifications, beginning with an ordinary least squares (OLS) model and progressing through alternative specifications of spatially simultaneous autoregressive (SAR) models. The OLS model is defined by:

$$y = X'\beta + \epsilon$$

where y is the logit transform of child poverty, X is the matrix of independent variables, β is the vector of the estimated coefficient for the X variables, and e are the model's residuals, with a mean of zero and a constant covariance matrix, Σ.

The second model estimated is a weighted version of the OLS. A weighted least squares (WLS) regression model takes into account the variability in the size of the municipio populations and the variability in the poverty rate. The weighting variable for this model is specified as:

$$np\,(1\text{-}p)$$

where n is the total number of children in each county, and p is the proportion of poor children (Friedman and Lichter 1998).

Table 1. Descriptive statistics for all variables used in the regression models

Variable	Mean	Std.	Moran's I
Child Poverty Rate	0.59	0.09	0.46*
Logit of Child Poverty Rate	0.39	0.39	0.45*
% Female householders	0.37	0.06	0.08
% Grandparents with grandchildren	0.19	0.06	0.12*
% Professional services	0.39	0.04	0.19*
% Agriculture	0.02	0.03	0.48*
% Manufacturing	0.13	0.05	0.28*
% Other services	0.12	0.03	0.40*
% High School or less	0.61	0.06	0.37*
% Unemployed	0.17	0.06	0.40*
% Underemployed	0.17	0.04	0.28*
% Non-movers	0.97	0.02	0.37*
% Commuters	0.52	0.18	0.19*

*p ≤ .05 by randomization based on 999 Monte Carlo replicates.

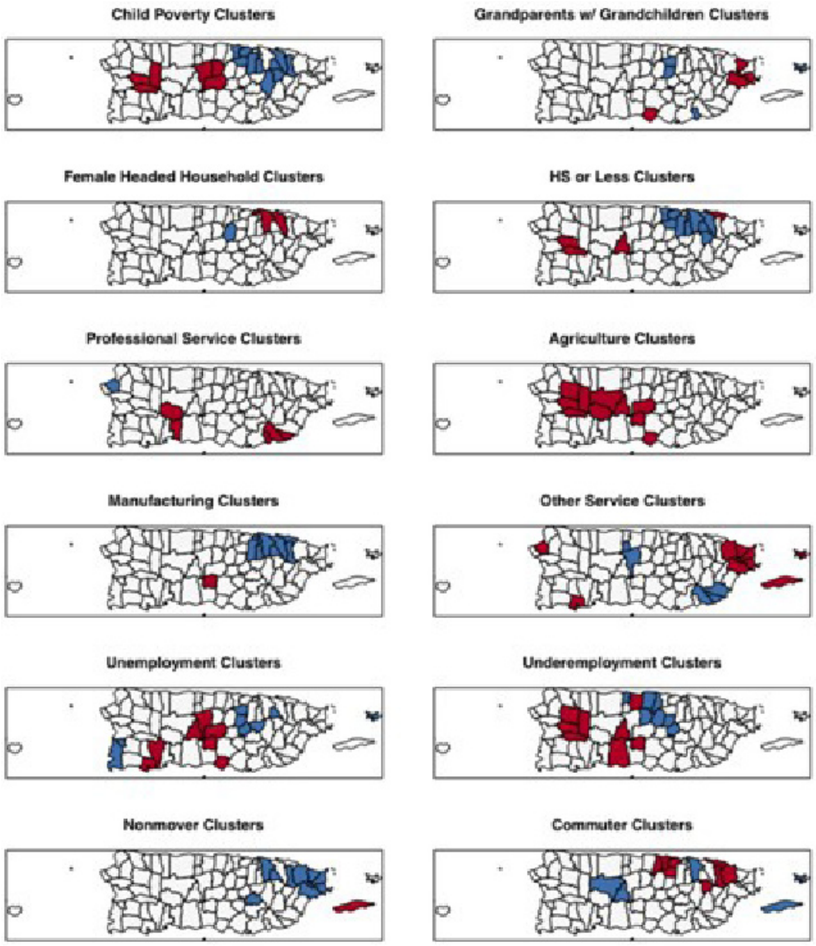
After specifying the OLS and WLS models, the spatial autoregressive models follow. First, the spatial error model is considered, which is defined by adding a spatial structure term to the OLS model's residuals, e:

$$y = X'\beta + \epsilon$$
$$\epsilon = \rho We + u$$

where u is an uncorrelated and homoskedastic error term, and W is a matrix of row-standardized[1] spatial weights and ρ is the spatial dependence parameter (Anselin and Bera 1998; Schabenberger and Gotway 2005). In essence, the weight matrix accounts for the total number of neighbors that a municipio has, and it assigns a value of 1 whenever two municipios are

1 Row-standardizing refers to the process of weighting by assigning an average from the neighboring values, giving each row a value between 0 to 1 until they sum to 1 Anselin, Luc. 2002. "Under the Hood. Issues in the Specification and Interpretation of Spatial Regression Models.", GeoDa Center for Geospatial Analysis and Computation. n.d. "Glossary of Key Terms." vol. 2012..

Figure 3. Univariate Local Autocorrelation (LISA) Cluster Maps. Red indicates a high-high cluster, while blue represents a low-low cluster. Clusters are significant at α ≤ .05.



neighbors, and 0 otherwise (Anselin 2002; Bivand, Altman, Anselin, Assunção, Berke, Bernat, Blanchet, Blankmeyer, Carvalho, Christensen, Chun, Dormann, Dray, Halbersma, Krainski, Legendre, Lewin-Koh, Li, Ma, Millo, Mueller, Ono, Peres-Neto, Piras, Reder, Tiefelsdorf, and Yu 2011). By row-standardizing the matrix, each row sums to one, which removes effects of municipios with a large number of neighbors (Tiefelsdorf and Griffith 1999).

The second spatial regression model specification is the lag spatial lag model, specified as:

$$y=\rho Wy+X'\beta+\epsilon$$

where the spatial component (ρWy) is specified on the model intercept. In doing so, the model's intercept dependent variable of child poverty is lagged across neighbors.

The next model is a modification of the basic spatial lag model, called the spatial Durbin model (SDM) which attempts to model the spatial heterogeneity in the data by introducing lagged predictor variables into the model. This model is a more proper specification of the spatial data generating process assumed in the error model, where we are basically modeling missing spatial covariates. The SDM enters these directly into the model. This model is specified as:

$$y=\rho Wy+X'\beta+WX'\gamma+\epsilon$$

Where the *g* parameters are regression effects of the lagged predictors.

To aid in model specification, Lagrange multiplier statistics were used (Anselin 2002; Chi and Zhu 2008). This is done to assess which of the lag or error models seems most appropriate for the outcome variable and the substantive model specified. Both the general and robust forms of the Lagrange multiplier tests were examined.

Table 2. Results of the OLS and WLS models for municipio child poverty, PRCS: 2006-2010

OLS Model	Estimate (95% CI)
(Intercept)	0 (-0.14 - 0.14)
% Female householders	0.11 (-0.05 - 0.28)
% Grandparents with grandchildren	**0.16 (0.01 - 0.30)**
% Professional services	0.09 (-0.10 - 0.28)
% Agriculture	**0.25 (0.05 - 0.46)**
% Manufacturing	0.08 (-0.12 - 0.28)
% Other services	0.03 (-0.18 - 0.25)
% High School or less	**0.5 (0.3 - 0.69)**
% Unemployed	**0.19 (0.03 - 0.35)**
% Underemployed	-0.05 (-0.23 - 0.13)
% Non-movers	0.13 (-0.04 - 0.30)
% Commuters	-0.04 (-0.22 - 0.13)
Adjusted R^2	0.637
AIC	155.21

WLS Model	Estimate (95% CI)
(Intercept)	0 (-0.12 - 0.13)
% Female householders	**0.16 (0.01 - 0.31)**
% Grandparents with grandchildren	0 (-0.14 - 0.15)
% Professional services	0.08 (-0.11 - 0.26)
% Agriculture	**0.21 (0.01 - 0.41)**
% Manufacturing	0 (-0.19 - 0.2)
% Other services	0.09 (-0.1 - 0.27)
% High School or less	**0.49 (0.34 - 0.64)**
% Unemployed	**0.22 (0.05 - 0.39)**
% Underemployed	-0.12 (-0.28 - 0.03)
% Non-movers	0.12 (-0.03 - 0.27)
% Commuters	**-0.28 (-0.41 - -0.14)**
Adjusted R^2	0.794
AIC	180.95

*Bold text indicates a parameter with a confidence interval that does not contain 0 with 95% confidence

Prior to model estimation, the dependent variable and all predictors were z-scored to facilitate comparison of model coefficients. Model fit was assessed by examining the Akaike Information Criteria (AIC) for each of the models, with the model with the minimum AIC value described as the "best" fitting model, considering the model likelihood and the number of estimated parameters.

The data management was undertaken with SAS (SAS Institute Inc. 2010), and the regression analysis was done with R (R Development Core Team 2011). The spdep package (Bivand et al. 2011) and maptools package (Lewin-Koh, Bivand, Pebesma, Archer, Baddeley, Bibiko, Callahan, Dray, Forrest, Friendly, Giraudoux, Golicher, Rubio, Hausmann, Hufthammer, Jagger, Luque, MacQueen, Niccolai, Short, Snow, Stabler, and Turner 2012) were also used through R as part of the spatial analysis. The criteria selected for spatial contiguity was the k nearest neighbors form, where two observations are considered neighbors when they form part of the k nearest municipios based on the distance between the municipios centroids (Anselin 2002; Chi and Zhu 2008). The current analysis uses k=4. This weighting scheme is chosen because there are several islands in the data and if a contiguity based weight scheme were used, these would be given zero weight in the analysis. The results from this model were not substantively different from a Queen neighbor specification, which was the neighbor specification chosen in the analysis by Voss et al. (2006), or a k=2 specification.

Finally, a simple descriptive analysis of the child poverty rate is conducted, where a GIS is used to examine the poverty rate in the municipios surrounding the capital municipios, San Juan. In this analysis, a 20-mile buffer is generated around the San Juan municipio and compared the child poverty rates of the municipios within this buffer to those outside of the buffer. The idea being examined is whether child poverty is concentrated outside of the capital region of Puerto Rico. A linear model is used to examine the degree to which the poverty rate is affected only by this simple function of distance to the capital.

It deserves to be noted that, the results of this analysis could be affected by the phenomena in spatial analysis known as the modifiable areal unit problem or MAUP, which has been described in a demographic modeling context elsewhere (Chi and Zhu 2008). The MAUP is basically the effect of the chosen unit of geography on the results from a statistical test, where the results could change if the variables were measured at a higher or lower level of geography.

RESULTS

First, descriptive statistics for both the outcome and all of the predictors used in the regression models are presented in Table 1.

Also presented are the values for the global Moran's I statistic for each variable. Statistical significance of all Moran's I values was judged by using a Monte Carlo randomization of the municipios. The Global Moran's I statistic for the dependent variable was 0.45, which was a high positive value indicating clustering of child poverty in the municipios, and on average municipios had a poverty rate of nearly 60 percent.

Thirty seven percent of households were headed by female heads, but this variable showed no evidence of spatial clustering. On average, municipios had 19 percent of grandparents residing with their own grandchildren, which showed modest spatial clustering. The economic sector variables showed higher levels of spatial clustering, with service industries dominating the labor force with a 39 percent average. In terms of education, 61 percent of municipio residents over

Table 3. Results of the spatial regression models for municipio child poverty, PRCS: 2006-2010

	Error Model	**Lag Model**	**Spatial Durbin Model**
	Estimate (95% CI)	**Estimate (95% CI)**	**Estimate (95% CI)**
(Intercept)	-0.02 (-0.17 - 0.13)	-0.01 (-0.13 - 0.11)	0.01 (-0.1 - 0.13)
% Female householders	0.13 (-0.02 - 0.28)	**0.16 (0.01 - 0.31)**	**0.17 (0.03 - 0.31)**
% Grandparents with grandchildren	**0.17 (0.04 - 0.31)**	**0.16 (0.03 - 0.29)**	**0.17 (0.04 - 0.3)**
% Professional services	0.08 (-0.1 - 0.25)	0.05 (-0.12 - 0.22)	0.09 (-0.08 - 0.25)
% Agriculture	**0.25 (0.06 - 0.43)**	**0.24 (0.06 - 0.41)**	**0.27 (0.1 - 0.44)**
% Manufacturing	0.06 (-0.12 - 0.24)	0.02 (-0.17 - 0.2)	0.07 (-0.11 - 0.25)
% Other services	0.01 (-0.18 - 0.21)	0.01 (-0.17 - 0.2)	0.1 (-0.09 - 0.29)
% High School or less	**0.48 (0.3 - 0.66)**	**0.49 (0.32 - 0.66)**	**0.52 (0.35 - 0.68)**
% Unemployed	**0.19 (0.04 - 0.35)**	0.14 (-0.02 - 0.29)	0.11 (-0.03 - 0.26)
% Underemployed	-0.05 (-0.22 - 0.12)	-0.07 (-0.23 - 0.09)	-0.09 (-0.24 - 0.07)
% Non-movers	0.13 (-0.03 - 0.29)	0.10 (-0.05 - 0.26)	0.03 (-0.13 - 0.19)
% Commuters	-0.05 (-0.20 - 0.11)	0.00 (-0.16 - 0.16)	0.01 (-0.15 - 0.16)
Lagged % Grandparents with grandchildren	--	--	**-0.34 (-0.6 - -0.08)**
Pseudo R^2	0.692	0.702	0.725
AIC	156.54	153.84	149.71
ρ	0.183	**0.232**	**0.253**

age 25 lacked a high school education, 17 percent were unemployed, and a further 17 percent were considered underemployed. All of these variables showed significant spatial clustering. Finally, the two migration variables are considered. Ninety seven percent of municipio residents were non-movers from three years before, suggesting a high degree of household persistence, while over 50 percent of workers commuted to another municipio for work. Both of these variables show significant spatial clustering. These figures also describe a situation where it may be easier to maintain ones residence and commute to a nearby municipio for work, especially if there is a large service sector in the neighboring area.The next method of the ESDA is the local Moran's I analysis of the variables discussed above. Figure 3 presents the maps for the Local Moran clusters. In each map, the municipios in red indicate spatial clustering of higher than average child poverty rates. In other words, they are municipios with high values of child poverty surrounded by municipios with higher than average values of poverty as well (often called high-high clusters). Municipios with a dark blue color indicate municipios with lower than average values of child poverty surrounded by municipios with likewise lower than average child poverty rates (low-low clusters). In the child poverty clusters map of Figure 3, one can see that while the area of San Juan and its neighboring counties constitute a low cluster, the municipios toward the western-central portion of the island have high-high clusters showing municipios with high poverty with neighboring municipios that also have high proportion of child poverty. With respect to the other maps in Figure 3, some variables show higher local clustering than others. For example, the maps of the proportion in agriculture, proportion with high school education or less, proportion of unemployed, and proportion of underemployed show similar high-high clusters of these variables in similar municipios as the high-high clusters from the variable of child poverty. On the other hand, variables such as proportion of female householders alone with children, proportion of grandparents responsible of grandchildren, and proportion of commuters did not seem to present overlapping municipios of high-high clusters with poverty. Finally, for non-movers, no real high-high clusters exist, but several municipios in the northeastern section of the island overlapped the low-low child poverty clusters.

Table 2 presents the results for the ordinary least squares (OLS) and weighted least squares (WLS) models. Model coefficient estimates and 95% confidence intervals for each parameter are presented along with model fit statistics for each of the models. Overall, the OLS model R^2 was over 60%, suggesting that the model fit the data fairly well. Indeed the model showed signs of being homoskedastic and having well behaved, very normally distributed residuals. The residuals did show significant spatial autocorrelation, with a Moran's I value of 0.11 (p=.009), which suggests that some form of spatial model should be more informative to this process. We used a Lagrange multiplier test for the model and it suggested a spatial lag model would more appropriately fit this particular model specification. The lag model was preferred over the error model based on the values of the LM tests (LM lag= 4.5, p= 0.03, LM error= 2.1, p= 0.15). The WLS model, which took into account the municipios different population sizes of children, fit the data better than the OLS model according to its higher R^2 of 78 percent; the AIC value was much higher, although since this is a weighted model the AIC is not strictly comparable to the OLS model. This suggests that accounting for heterogeneity in population size can greatly improve the model performance in this setting. Since spatial dependence is present in the model it is not appropriate to discuss the model results, as they will be affected by the spatial structure in the data.

Next, we discuss the spatial regression models presented in Table 3. The first model was the spatial error model. Four of the predictors showed significant associations with the dependent variable. These were the same effects as were observed in the first OLS model, where the proportion of grandparents responsible for grandchildren, the proportion of the workforce employed in agriculture, the proportion of those with high school or less and the unemployment rate all had significant positive relationships with the child poverty rate. However, after comparing this model to the baseline OLS model, no significant improvement in the model's fit was found, as the error model's AIC was slightly higher than the OLS model. We also see an insignificant spatial autoregressive parameter (ρ), suggesting no autocorrelation to the model residuals. The spatial lag model also showed four significant predictors. With the exception of percent of female-headed households and the unemployment rate, the same variables that were significant as in the error model were also significant in this one. All significant effects were positively associated with child poverty. Unlike the spatial error model, the AIC that compared it to the OLS model revealed that the lag model was an improvement, but only a slight one, with an AIC change of only 1.37, which is generally not considered to be strong evidence for the more complicated model. The SDM was the final model considered. This model was first constructed using spatial lags of all predictors, and only the significant lagged effect was kept in the final model, akin to a backward selection process. The only significant lagged variable is the percent of grandparents with grandchildren, which showed a negative association with child poverty. This suggests that municipios that are surrounded by other municipios with a high proportion of grandparents caring for their grandchildren, the poverty rates are lower. Otherwise, the same pattern of significant predictors is observed in this model, with the percent of female-headed households, the proportion of grandparents responsible for grandchildren, the proportion of the workforce employed in agriculture, the proportion of those with high school or less showed positive associations with child poverty. The SDM shows the best model fit of any of the models considered with an AIC of 149.7, a decrease of over five AIC points, which gives some evidence that the model is fitting better, although not by any means overwhelming.

Lastly, the results from our GIS buffer analysis around the capital municipio of San Juan showed that the mean child poverty rate within the buffer zone is 51.0 percent, while outside of it is 62.6 percent. This is easy to assess by looking again at Figure 2, where the rates around San Juan are much lower than most other municipios. In the statistical model considered for this analysis, the buffer effect explains 37 percent of the variation in the dependent variable.

DISCUSSION

This paper had two goals. First was to document spatial clustering of child poverty rates and factors associated with child poverty in Puerto Rico. The second goal was to use spatially explicit regression models to estimate the effects of several key economic, household composition and migration variables on child poverty at the municipio level.

The results revealed that child poverty in Puerto Rico is not randomly distributed across space. The local autocorrelation cluster map for child poverty (Figure 3) revealed two clusters of municipios whose child poverty rates are similarly high. Near the center of the island the municipios of Jayuya, Ciales, Morovis, Orocovis, Villalba, and Juana Díaz, represented one pocket of high poverty rates. The second cluster was located toward the west, where a series of municipios that go from one end of the coast to the other, form a bigger pocket where child poverty is concentrated. These municipios were: Isabela, San Sebastián, Lares, Las Marías, Maricao, Adjuntas and Yauco.

After comparing the different regression models used in this analysis, we found that several variables consistently act to increase child poverty. Household composition, as measured by the percent of female-headed households and the percent of grandparents caring for their own grandchildren consistently showed positive associations with child poverty. The positive association with female householders alone with children is a common finding for child poverty, and was also present in Voss et. al.'s (2006) analysis of US county poverty. Both of these effects, female householders and grandparents, most likely stem from the lower wages of such households, where more people are trying to exist off of fewer (for female-headed households) or lower (grandparents, most likely) wages.

In terms of the economic sector variables, the proportion of the workforce in agriculture, the unemployment rate, and the proportions without a high school education showed significant effects on child poverty. This suggested that areas that are more agricultural, have more unemployment, and areas that have a less educated work force on average, have higher levels of child poverty. Again Voss et al. (2006) found similar effects of extractive industrial structures, unemployment, and education county characteristics for child poverty.

Our hypotheses related to migration were only given partial support from one of the models considered. The WLS model showed a negative effect of commuters on child poverty, but this effect was not found in any of the spatial models. Also, the proportion of non-movers showed no effect on the poverty rate, giving no support for our expected effect. These findings are both suggestive that migration, as measured by the current ACS data, have no impact on child poverty. Perhaps in future work, a time-lagged migration variable should be considered to investigate the ideas that high levels of emigration concentrate poverty.

In terms of the modeling approach used in the present paper, the spatial lag model and its associated form, the spatial Durbin model seemed to best fit the data, when all models are compared. Following this, it seems that child poverty in Puerto Rico appears to be more of a diffusive process more than an error-based process as found for the continental US (Voss et. al., 2006). This suggests that poverty rates of neighboring municipios appear to be influencing the rates of its neighboring municipios, on average. This makes sense in the light of the ESDA analysis presented, where we see that several of the factors that showed significant effects in the model are concentrated themselves (see Figure 3) in the same areas.

As a final exploration of the data, we conducted a simple descriptive analysis using a GIS. Again, if we consider this context by examining Figure 3, we see that this area also has low proportions of grandparents with grandchildren, uneducated, manufacturing,unemployment,underemployment , and non-movers, while having high proportions of commuters. This result in and of itself points to the need for increased development in areas outside of the municipios immediately surrounding San Juan.

In conclusion, child poverty is not a randomly distributed process, and in Puerto Rico, municipio characteristics seem to interact strongly with their neighbors. Still, with a total poverty rate of 45 percent, poverty in Puerto Rico is a big problem, not just for children, but for everyone else as well. In brief, it is incredibly important to continue exploring the determinants of this process, in the hopes of recognizing solutions that can redefine it. Furthermore, by using the tools of spatial analysis we can not only properly model, but also visualize the processes we study better, and sometimes even reveal simple conclusions to complex phenomena.

Endnotes

1.For example see http://www.census.gov/did/www/sahie/methods/2000/estimates.html.

2.For example see http://www.census.gov/did/www/sahie/methods/2000/estimates.html

3.Further information on ACS PUMS data is provided on the Census Bureau website: http://www.census.gov/acs/www/Downloads/handbooks/ACSPUMS.pdf.

4.Further details available at : http://www.census.gov/ popest/data/historical/challenges.html.

5.Further details at Census Bureau website: http://www.census.gov/did/www/saipe/.

6.Further information about PUMS is provided on the Census Bureau website: http://www.census.gov/main/www/pums.html.

7.Information on PUMA delineation criterion can be found at: http://www.census.gov/geo/puma/2010_puma_guidelines.pdf.

8.The information in this paragraph was sourced and adapted from email correspondence with Vince Osier, the Brach Chief of the Geographic Standards & Criteria Brach in the Geography Division of the U.S. Census Bureau, Washington, DC.

9.Particulars on 2000 PUMA criteria can be found at: http://www.census.gov/geo/puma/puma_guide.pdf.

10.For a full history PUMS and PUMAs please visit: http://www.census.gov/geo/puma/puma_history.pdf.

11.Details on geographic terms and concepts are provided at: http://www.census.gov/geo/www/2010census/GTC_10.pdf.

12.Discussion available at: http://www.census.gov/geo/ puma/FAQ_version2.pdf.

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