A Spatial Analysis of Poverty and Income Inequality in the Appalachian Region

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RESEARCH PAPER 2010-15

Abstract

The Appalachian Region has made progress in the various measures of development but still lags behind other national counterparts. Understanding the relationship between poverty and income inequality is important to evaluate how a development strategy would benefit the region. This paper presents a spatial simultaneous equations approach to determine the relationship between poverty and income inequality. Cross sectional county level data from 1990 and 2000 for the 420 counties in the Appalachian Region are used to examine the determinants of poverty and income inequality. The empirical results suggest that poverty and income inequality are inversely related. If the policy objective is to alleviate poverty, then considering reducing income inequality at the same time, may prove to render ineffective conclusions. The result findings also suggest that the income inequality in the Appalachian Region may actually contribute to its economic growth and to poverty reduction in the Region.

Key Words: Poverty rate, Income inequality, Gini coefficient, Spatial Durbin Model

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The authors acknowledge and appreciate the review comments of Dale Colyer and Mulugeta S. Kahsai .

This research was supported by Hatch funds appropriated to the Agricultural and Forestry Experiment Station, Davis College, West Virginia University.

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Introduction

Poverty reduction has been one of the most challenging issues for economic development. Unlike the traditional presumption that economic growth alone could eliminate poverty, the role of income inequality of a region as a contributing factor to poverty has been recognized. Reducing poverty and income inequality have been taken to be the primary indicators of economic development in place of emphasis on economic growth. In the United States the poverty rate is relatively higher than the poverty rates in most of the other rich countries (Smeeding, 2006). The poverty rates for children and elderly and the population below poverty, especially for single parents, were seen to stand out distinctively relative to those of the nation's rich counterparts who worked more and received less in transfer benefits (Smeeding, 2006). Though this disparity in poverty rates still exists, strides towards poverty reform in the United states started with President Lyndon B. Johnson's declaration of a "War on Poverty" in 1964 (Brauer, 1982). The Appalachian Region was among the main focus of the poverty reform, depicted as a geographically isolated and rural region that lagged behind in the social and economic development from the rest of the nation (Pollard, 2003).

The Appalachian Region stretches from southern New York to northern Mississippi and includes 420 counties of 13 states as shown in Figure 1. It is characterized by high unemployment, deeply rooted poverty, low human capital formation, high out-migration, and a shrinking economic base (pollard, 2003). Efforts have been devoted through national and local policy programs to induce economic prosperity, curtail out-migration, and mitigate poverty and the region has shown a considerable improvement in its economic conditions over the past several decades. Isserman (1996) noted that the popular image of the Appalachian Region as "…*low income, high poverty, limited education, poor living standards, job deficits, high unemployment, outmigration, stagnation, and decline*" do not characterize the region as a whole. The gap in most of the economic, labor force and education measures of the region with the rest of the nation narrowed down from the period of 1990 and 2000. However, the region has yet to reach parity with the rest of the United States (Pollard, 2003). Considering the geographic concentration of population of poverty, it is indicated that poverty is greater in the non-metro counties than their counterpart metro counties across the region (Mannion, 2006).

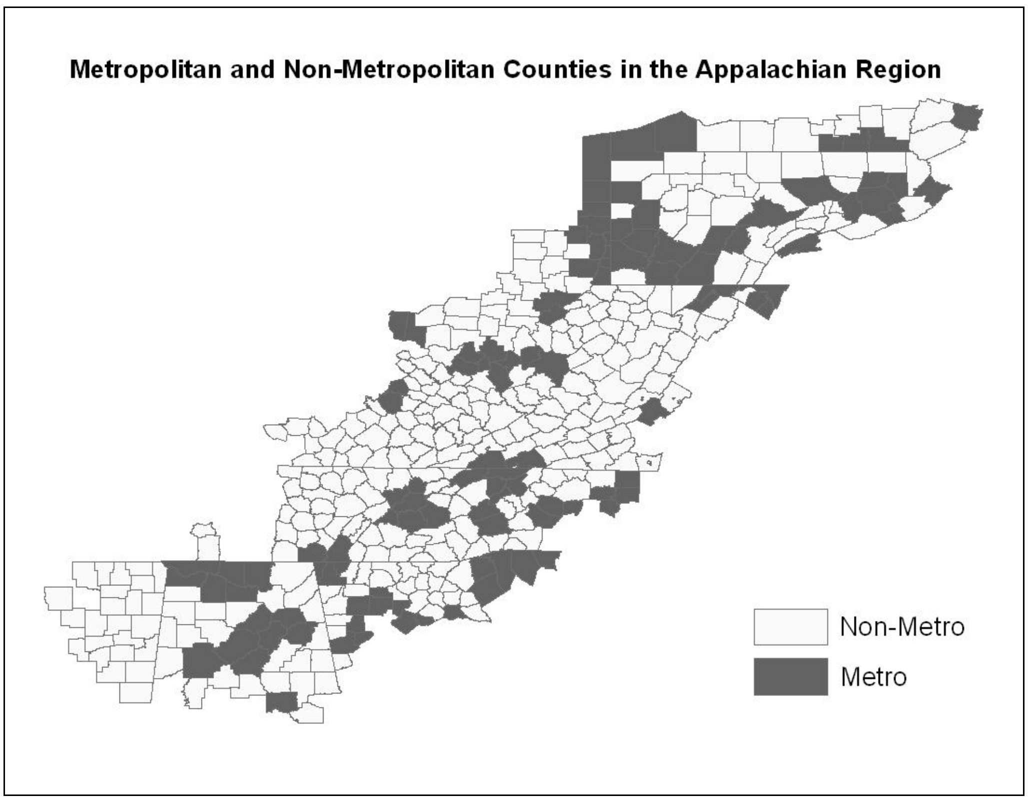


Figure 1. Metro and Non-Metro Counties in the Appalachian Region

With an increasing focus on addressing the issue of poverty and income inequality, there has been mixed suggestions from previous studies on the relationship between poverty and income inequality. Some studies show a positive relationship between poverty and income inequality (e.g., Persson & Tabellini, 1994; Allegrezza et al., 2004) while others show an inverse relationship (Williams, 1999; Kray, 2002; Nijhawan & Dubas, 2006). Bourguignon (2004) suggested that initial level of income and inequality determine the subsequent effect on poverty and that the effects are region specific. Analyzing the spatial context of poverty and income inequality is also becoming increasingly important with findings suggesting regional variations in their relationship. Therefore, a better understanding of the level of poverty and income inequality and their relationship with each other in the Appalachian Region is required in an effort to design sound development policies. Understanding whether income inequality hinders or actually helps in poverty reduction in the Appalachian Region would provide valuable insights for designing poverty alleviation strategies. This paper thus intends to evaluate the empirical relationship between poverty and income inequality in the Appalachian Region.

Literature Review

Poverty in its absolute sense is the proportion of population below a particular income line while income inequality is the disparity in the relative income after normalizing all observations to the population mean so as to make them independent of the scale of incomes (Bourguignon, 2004**)**. Bourguignon (2004) focused on the relationship between poverty, economic growth and income inequality and the change in the poverty as a function of economic growth, income distribution and change in the distribution of income is evaluated. The study also demonstrated the two-way relationship between economic growth and income distribution and applied it to hypothetical situations for countries like Ethiopia, Indonesia and Mexico. The study suggested that economic growth and income distribution need to be considered simultaneously and the study also showed that both income and distributional effects of poverty are positively dependent on the level of economic development and negatively dependent on the degree of income inequality.

Smeeding (1991) did a cross-national comparison of poverty and income inequality in 10 countries using the microdata made available from the database, the Luxemburg Income Study, from 1979 to 1983. The study used three measures of income inequality namely, the Atkinson inequality index, Gini coefficient and the Theil inequality index. The results showed that there were greater income inequality and poverty in larger countries like the US. The results also showed that children, elderly and single parents were mostly classified in the poverty to near poverty status. Janvry and Sadoulet (2000) conducted a causal analysis of urban and rural poverty and income inequality across different economic growth in 12 Latin American countries for the 1970-1994 period. The results showed that economic growth reduced poverty but not income inequality. Results also showed that economic growth reduced urban poverty in areas which had low income inequality and higher education.

Persson and Tabellini (1994) presented a theoretical politico-economic equilibrium growth model to suggest that income inequality has a negative impacts on economic growth. The study presupposed that since distributional conflict are given high importance; such policies discourage human and capital accumulation, which in turn deter economic growth. The study used empirical analyses with historical and postwar data from various countries in order to support their argument.

Ravallion (1997) used household survey data from 23 developing countries to understand the response to economic growth in high-income inequality developing countries versus the low-income inequality developing countries. The study indicated that economic growth has a small impact on reducing absolute poverty in high-income inequality countries. The study, however, also indicated that in cases of economic contraction, the poor in the high-income inequality countries tend to be less affected. Suryadarma *et al.* (2005) followed the model by Ravallion (1997) to evaluate if higher income inequality reduces the growth elasticity of poverty resulting from the low effect of economic growth on poverty reduction in Indonesia.

Nijhawan and Dubas (2006), on the other hand, explored the relationship between poverty and income inequality using cross-section data from 50 states within the United States. The study used multiple regression equations to test the hypothesis of inverse relationship between income inequality and poverty. The study used poverty gap as the index for income inequality and found that income inequality may cause income growth and therefore reduce poverty. The literature on the relationship between poverty and income inequality therefore leads to ambiguous conclusions. One possible reason for this variation suggests that regional variations exist in how poverty and income inequality are interrelated. Studies have shown that initial income inequality matters in how a region responds to economic growth in alleviating poverty (Ravallion, 1997; Alisjahbana et al., 2003; Bourguignon, 2004). A region specific study is therefore warranted in order to help develop effective development policies. This paper intends to evaluate the existing relationship between poverty and inequality in the Appalachian Region.

Empirical Model

A spatial simultaneous equations model is used in this study. Poverty and income inequality are influenced by a set of socio-economic variables. The control variables used for the models are extensively included in the studies that deal with poverty, economic growth and/or income inequality. The two dependent variables are compounded annual rate of change in the poverty rate (POVCHNG= $POV_{t+10}/POV_t{}^{1/10} - 1$) and the compounded annual rate of change in

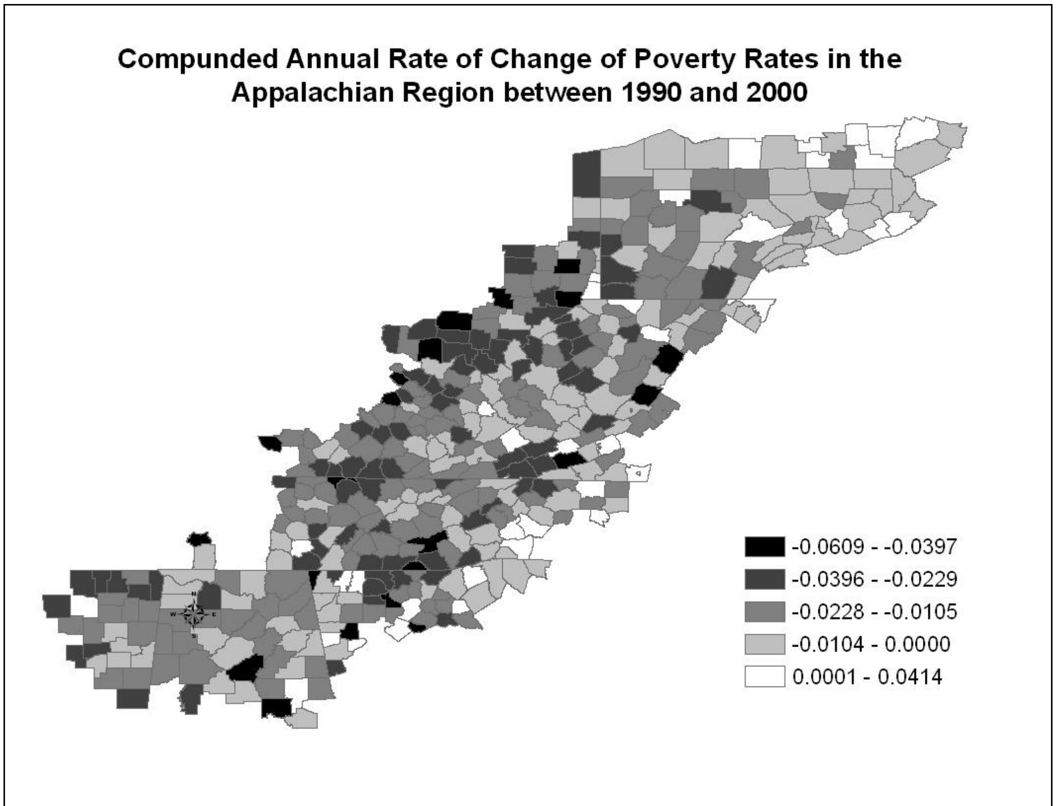
Gini coefficient (GINICHNG= $\left(GINI_{t+10}/GINI_t\right)^{1/10}-1$) from 1990 to 2000 for the two variables as shown in Figure 2. The empirical models are depicted as:

$$\begin{aligned}\text{POVCHNG}=&\beta_0+\beta_1\text{POV}+\beta_2\text{GINICHNG}+\beta_3\text{LN\_PERCAP}+\beta_4 AGE65+\beta_5 HSCD\\&+\beta_6 FEMHH+\beta_7 BLACK+\beta_8 UNEMP+\beta_9 WELFARE+\beta_{10} AGRI\\&+\beta_{11} CONSTR+\beta_{12} MANUF+\beta_{13} METRO+\varepsilon\end{aligned}$$

$$\begin{aligned}\text{GINICHNG}=&\beta_0+\beta_1\text{GINI}+\beta_2\text{POVCHNG}+\beta_3\text{LN\_PERCAP}+\beta_4 AGE65+\beta_5 HSCD\\&+\beta_6 FEMHH+\beta_7 BLACK+\beta_8 UNEMP+\beta_9 WELFARE+\beta_{10} AGRI\\&+\beta_{11} CONSTR+\beta_{12} MANUF+\beta_{13} METRO+\varepsilon\end{aligned}$$

The descriptions and summary statistics of the variables are presented in Table 1. The signs for the relationship between other socio-demographic variables and the two dependent variables, change in poverty rate and income inequality are assumed to be similar in nature. A negative value of the compounded annual rate of changes in poverty rate and gini coefficient means low poverty rate and low income inequality, respectively. Both of the variables are expected to be negatively associated with higher per capita income (LN_PERCAP) meaning that counties with higher per capita income tend to be less poor and have lower income inequality. Elderly populations (AGE65) tend to have a high incidence of poverty and also high income inequality while populations with higher education (HSCD) tend to be less poor and perhaps have less income inequality. Single parents and especially single female headed households with children (FEMHH) tend to be more prone to poverty, and the same is the case for black communities (BLACK). Counties with high unemployment (UNEMP) rate tend to be poor and with high percentage of population on public assistance (WELFARE). People in the metro counties tend to have lower poverty rates than their rural counterparts.

The variables related to the different sectors of the employment, agriculture (AGRI), construction (CONSTR) and manufacturing (MANUF), tend to pay higher wages to semi-skilled



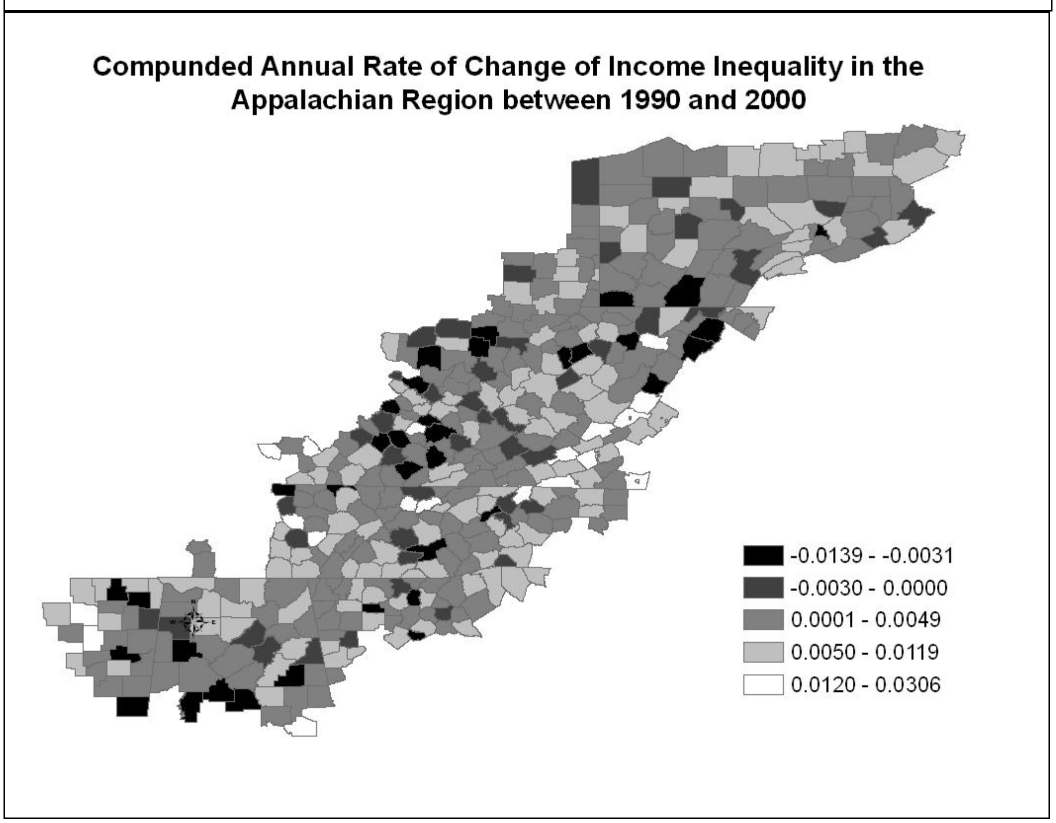


Figure 2. Maps on the Change in the Poverty Rate and Change in the Gini Coefficient in the Appalachian Region from 1990 to2000.

Table 1. Description and Summary Statistics of the Variables

Variables	Variable Description	Mean	Std deviation
POVCHNG	Compounded annual rate of change in poverty rate	-0.01	0.01
GINICHNG	Compounded annual rate of change in gini coefficient rate	0.00	0.01
POV	Poverty rate	19.10	7.90
GINI	Gini Coefficient	0.43	0.03
FIT_POVCHNG	Fitted values of change in poverty rate	-0.01	0.01
FIT_GINICHNG	Fitted values of change in Gini coefficient	0.00	0.00
LN_PERCAP	Natural log of per capita income	4.20	0.07
AGE65	% of population 65 years and over	14.33	2.65
HSCD	% of population with a high school degree or above	61.17	10.20
FEMHH	% of households of single female as the head of the household with children 18 years or below	6.38	1.83
BLACK	% of black population	5.82	10.76
UNEMP	% of population unemployed	7.75	2.75
WELFARE	% of population receiving public assistance	10.35	4.41
AGRI	% of population 16 years or older employed in agriculture, forestry, fishing and hunting	2.00	1.60
CONSTR	% of population 16 years or older employed in construction	7.63	2.44
MANUF	% of population 16 years or older employed in manufacturing	26.50	11.33
METRO	dummy variable 1=metro counties and 0=non-metro counties	0.27	0.44

and unskilled workers than other sectors and thus are expected to reduce both poverty and income inequality. Since poverty rate and income inequality tend to affect each other and estimating the two equations independently might cause bias, the two equations are therefore estimated simultaneously. Since the study uses county-level data, the counties influence each other and the observations might have spillover effects from the neighboring counties. The non-spatial regression model in case of spatial dependence in the observations might be biased and/or inefficient. Therefore, the models were tested for possibility of spatial dependence. The Lagrange multiplier test for spatial lag model for POVCHNG was found to be significant as shown in Table 2. However, the robust test for the spatial lag model was not found to be significant. The spatial lag model for GINICHNG either was not found to be significant. The spatial error model for both of the equations was found to be significant.

Table 2. Spatial Dependence Test Results

Tests	POVCHNG	GINICHNG
LM lag test	10.17***	1.26
Robust LM lag test	0.03	0.79
LM error test	13.29***	3.53*
Robust LM error test	3.16*	3.53*
Spatial Hausman test	30.27***	46.83***

Note: *** significant at 99%, ** significant at 95% and * significant at 90% confidence level.

The models were also tested for omitted variable bias using the spatial Hausman test, which was also significant for both the models (Table 2). The results indicated that spatial error model (SEM) would result in specification errors due to omitted variables and spatial dependence in the error terms (LeSage and Pace, 2009). Therefore, the Spatial Durbin Model (SDM) is used to estimate the equations. The Spatial Durbin Model takes into account neighboring counties dependent and explanatory variables by adding spatial lags for the dependent and independent variables. The model is expected to capture the direct and indirect effects of each of the different variables that explain change in the poverty rate and change in the income inequality (Gini coefficient) in the Appalachian Region. The general form of the models would then be as follows (LeSage & Pace, 2009):

$$y = \rho Wy + x \quad \beta + \gamma \quad + Wx \quad - \rho\beta \quad + \varepsilon$$
$$y = \rho Wy + x\beta + Wx\psi + \varepsilon$$

Where, y is the dependent variable, X is a vector of independent variables, W is the contiguity weight matrix, and ρ is the spatial error parameter. Since current MATLAB codes do not support solving the spatial simultaneous equations, the paper uses the technique of instrumenting the dependent variables. First, a reduced form equation for each of the two models is estimated using OLS and the fitted values of the endogenous variables are included as another independent variable in the Spatial Durbin Model.

Data and Sources

The county-level data for the Appalachian Region were collected from secondary sources for the year 1990 and 2000. The data on poverty rates, per capita income, education, single female headed households, race, population receiving public assistance, employed population according to industry and metropolitan counties were obtained from US Census Bureau and the Appalachian Regional Commission. The calculated Gini coefficients were obtained from the Arizona State University GeoDA Center. The unemployment data were obtained from the US Bureau of Labor Statistics. The county level shape file for the region was also extracted from the US Census Bureau (TIGER/Line).

Empirical Results and Analysis

The descriptive statistics in Table 3 and Figure 2 show a considerable decrease in the poverty rates in majority of the counties in the Appalachian Region between 1990 and 2000. However, the statistics show a relative increase in the Gini coefficients in the majority of counties in the Appalachian Region between 1990 and 2000.

Table 3. Descriptive Statistics of the Poverty rates and GINI Coefficients in the Appalachian Region in 1990 and 2000.

Description	Poverty Rate		GINI Coefficient	
	1990	2000	1990	2000
Mean	19	16	0.4329	0.4484
Median	17	15	0.4302	0.4457
Maximum	52	45	0.5574	0.5859
Minimum	19	16	0.4329	0.4484

The regression run for both the models were significant with R^2s of 0.37 and 0.48 for change in poverty rate and change in Gini coefficient, respectively. This meant that the independent variables explained 37 percent and 48 percent of the models with POVCHNG and GINICHNG as the dependent variables, respectively. The coefficient estimates of the Spatial Durbin Model as shown in Table 4, are not very intuitive except for the signs of the variables. Therefore, the interpretation of the results focuses on the direct and indirect effects of the estimates as depicted in Table 5 and Table 6.

Change in Poverty Rate (POVCHNG)

Of the 13 variables, 11 were significant in explaining the change in poverty rate between 1990 and 2000. All the variables had the expected sign except AGE65, FEMHH, WELFARE and UNEMP. Counties with higher percentages of people representing these variables were assumed to result in higher poverty rates. However, the results may suggest that since these variables tended to represent the relatively poor population, they may have gained the most from the changes between 1990 and 2000 or at least may not have been worse off in 2000 than they were in 1990. Change in the Gini coefficient (FIT_CHNG) had the largest negative impact which means that a one unit (1%) increase in the compounded annual rate of change in the Gini coefficient in a county decreases the poverty rate in the county by 0.55 units (0.55%). Per capita income (LN_PERCAPITA) and the education level (HSCD) of population of the county were negatively associated with POVCHNG, which indicated that counties with higher per capita income and higher level of education in 1990 showed a reduction in their poverty rates in 2000. Counties with a high percentage of black population (BLACK) showed to exacerbate the higher poverty condition of the counties. Counties with a higher population engaged in any of the three sectors, agriculture (AGRI), construction (CONSTRUCT) and manufacture (MANUF), were shown to improve the poverty condition of the counties. Also as indicated in previous literature, metro counties showed more improvement in terms of lowering the poverty rate than the non-metro counties.

In addition, 5 of the 13 weighted variables were also significant indicating the presence of spillover effects. Poverty rate of the neighboring counties in 1990 (W_POV) had a positive effect on POVCHNG, which meant that a county with neighboring counties with high poverty rates tended to also have higher poverty rates than a county with neighboring counties with low poverty rates. The spatially weighted variables, W_BLACK, W_WELFARE and W_UNEMP, were negatively correlated with POVCHNG, which meant that neighboring county with high black population, receiving public assistance and unemployed in 1990 resulted in an improved condition in terms of the change in the poverty rates. The results further strengthen the argument that the relatively poor population either gained the most or were not worse off between 1990 and 2000. Finally, W_CONSTRUCT was positively associated with POVCHNG, which meant that a county with a high percentage of population engaged in the construction sector in neighboring counties tended to have higher poverty rates.

The direct effect of GINICHNG on POVCHNG was significant and the indirect effect was not significant, which indicated that there were no spillover effects of the change in income inequality in the neighboring counties in determining the change in the poverty rate of the given county. Both the direct and indirect effects of POV were significant; however the direct effect of POV on POVCHNG was negative while the indirect effect of POV on POVCHNG was positive. This also indicated the same result as mentioned above that while counties with high poverty rates in 1990 showed the most improvement in terms of the poverty rates, the high poverty rates of the neighboring counties hurt the economic growth potential of the county. The direct and indirect effects of per capita income (LN_PERCAPITA) indicated that higher per capita income of the counties themselves and their neighboring counties in 1990 helped in lowering the poverty rates of the counties in 2000. Other interesting outcome was that counties with a higher percentage of population employed in the construction sector (CONSTRUCT) helped the counties themselves but hurt the neighboring counties.

Change in Income Inequality (GINICHNG)

In case of the model with GINICHNG as the dependent variable, 10 out of 13 variables were significant. Unlike the previous model only WELFARE and UNEMP had signs that were not expected. The data on the percentage of people receiving public assistance showed that there was an average of 7 percentage reduction in the people receiving public assistance. Also, there was an average of 2 percentage reduction in the unemployment population. These figures suggest that the higher percentage of population receiving public assistance and those unemployed fared better in 2000 contributing to lower income inequality in 2000. The negative association of GINI on GINICHNG also indicates a similar explanation, meaning that counties with higher income inequality in 1990 actually faced an improved scenario in 2000. The highest positive effect on the change in poverty rate is change in the poverty rate, a one unit (1%) increase in the compounded annual rate of change in the poverty rate in a county decreases the Gini coefficient in the county by 0.49 units (0.49%). Per capita income (LN_PERCAPITA) of the county was not significant. However, high percentage of population with higher education (HSCD) still helped in lowering the income inequality of the county. High percentage of black population (BLACK) still tended to be associated with higher income inequality. As with the previous model, higher percentage of population employed in any of the three sectors, AGRI, CONSTRUCT and MANUF, helped in reducing the income inequality of the county. Metro counties also tended to have lower income inequality than the non-metro counties. Unlike the previous model, only 2 of the 13 weighted variables were significant indicating the presence of spillover effects in the model. Neighboring counties with high income inequality (W_GINI) hurt the improvement prospects while neighboring counties with high per capita income (W_PERCAPITA) actually helped the improvement prospects of a county. The indirect effect of LN_PERCAPITA on GINICHNG indicated that a 1 percentage increase in the per capita income of the neighboring counties reduces the income inequality of a county by 0.002 units. The result suggested that even though higher per capita income of the county had no significant effect on improving the income inequality condition of the county, per capita income still had an indirect effect. Higher per capita income of the neighboring counties could suggest a higher employment opportunity for the county in those neighboring counties to improve the income inequality condition of the county itself.

Conclusions

This paper presented a spatial simultaneous equations approach for evaluating the relationship between poverty and income inequality in the Appalachian Region. The Appalachian Region is regarded as a geographically isolated area, mired in poverty and income inequality. Even though the region has made great strides in development over the past decades, the region still lags behind other areas of the nation. Understanding the relationship between economic growth and its effect on poverty and income inequality is crucial in developing development strategies. Both the spatial analysis and Gini coefficients show an inverse relationship between poverty and income inequality, as also indicated by Nijhawan et al. (2006). This suggests that a policy geared towards reducing both poverty rate and income inequality at the same time may not be effective in the Appalachian Region. The study supported previous findings that higher per capita income,

Table 4. Spatial Durbin Model Coefficient Estimates of the models for the Change in Poverty Rates and Change in the Gini Coefficients from 1990 to 2000 in the Appalachian Region.

	POVCHNG			GINICHNG		
	Coefficient	Asymptotic t stat		Coefficient	Asymptotic t stat	
CONSTANT	0.6144	0.1867	***	0.3005	0.1039	***
FIT_POVCHNG	--------	--------		-0.4986	0.0708	***
FIT_GINICHNG	-0.5536	0.3017	**	--------	--------	
POV	-0.0017	0.0003	***	--------	--------	
GINI	--------	--------		-0.1660	0.0110	***
LN_PERCAP	-0.0534	0.0093	***	-0.0042	0.0041	
AGE65	-0.0006	0.0003	**	0.0001	0.0001	
HSCD	-0.0003	0.0002	*	-0.0003	0.0001	***
FEMHH	-0.0005	0.0008		0.0001	0.0003	
BLACK	0.0005	0.0002	***	0.0002	0.0001	***
WELFARE	-0.0005	0.0004	*	-0.0007	0.0002	***
UEMP	-0.0002	0.0004		-0.0005	0.0001	***
AGRI	-0.0009	0.0006	**	-0.0009	0.0002	***
CONSTR	-0.0018	0.0003	***	-0.0010	0.0001	***
MANUF	-0.0004	0.0001	***	-0.0002	0.0000	***
METRO	-0.0022	0.0017	*	-0.0025	0.0006	***
W-FIT_POVCHNG	0.0090	0.6471		-0.0651	0.1613	
W-FIT_GINICHNG	--------	--------		--------	--------	
W- POV	0.0014	0.0006	**	--------	--------	
W- GINI	--------	--------		0.0422	0.0274	**
W-PERCAP	-0.0052	0.0192		-0.0172	0.0090	**
W-AGE65	0.0002	0.0005		0.0002	0.0002	
W-EDUC	0.0002	0.0003		0.0000	0.0001	
W-FEMHH	0.0012	0.0016		-0.0006	0.0005	
W-BLACK	-0.0004	0.0002		-0.0001	0.0001	
W-WELFARE	-0.0019	0.0009		-0.0003	0.0004	
W-UNEMP	-0.0014	0.0006		0.0000	0.0003	
W-AGRI	0.0003	0.0010		0.0002	0.0004	
W-CONSTR	0.0014	0.0007		-0.0003	0.0003	
W-MANUF	0.0001	0.0002		0.0001	0.0001	
W-METRO	-0.0001	0.0038		0.0012	0.0012	
RHO	0.1798	0.0761	*	0.1076	0.0806	*
No. of obs	420			No. of obs	420	
R^2	0.3730			R^2	0.4789	
$Sigma^2$	0.0001			$Sigma^2$	0.0000	

Table 5. Direct, Indirect and Total Effects of the Spatial Durbin Model for the Change in Poverty Rates from 1990 to 2000 in the Appalachian Region.

Variable	Direct effect	Asymptotic		Indirect	Asymptotic		Total	Asymptotic	
FIT_GINICHN	-0.5570	-1.8470	*	-0.1149	-0.1478		-0.6719	-0.8062	
POV	-0.0016	-5.7395	***	0.0013	1.7370	*	-0.0004	-0.4898	
PERCAP	-0.0539	-5.8496	***	-0.0182	-0.7731		-0.0720	-2.9145	**
AGE65	-0.0006	-1.8822	*	0.0001	0.2016		-0.0004	-0.6934	
HSCD	-0.0003	-1.4013		0.0002	0.7596		0.0000	-0.1426	
FEMHH	-0.0005	-0.5490		0.0013	0.6613		0.0008	0.4108	
BLACK	0.0005	2.9105	***	-0.0004	-1.5438		0.0001	0.2835	
WELFARE	-0.0006	-1.4595		-0.0024	-2.1299	**	-0.0030	-2.4977	**
UNEMP	-0.0002	-0.5998		-0.0017	-2.3324	**	-0.0020	-2.7716	**
AGRI	-0.0009	-1.6093	*	0.0001	0.1000		-0.0008	-0.8809	
CONSTR	-0.0017	-5.0903	***	0.0013	1.6570	*	-0.0005	-0.6768	
MANUF	-0.0004	-3.2492	***	0.0001	0.2611		-0.0003	-1.6384	*
METRO	-0.0022	-1.2766		-0.0006	-0.1365		-0.0028	-0.6097	

Table 6. Direct, Indirect and Total Effects of the Spatial Durbin Model for the Change in the Gini Coefficients from 1990 to 2000 in the Appalachian Region.

Variable	Direct effect	Asymptotic		Indirect	Asymptotic		Total	Asymptotic	
FIT_POVCHNG	-0.5011	-7.0978	***	-0.1356	-0.7270		-0.6368	-3.2567	***
GINI	-0.1658	-15.0613	***	0.0258	0.7804		-0.1400	-4.1000	***
PERCAP	-0.0045	-1.0971		-0.0196	-1.9337	**	-0.0241	-2.2491	**
AGE65	0.0001	0.5948		0.0002	0.9721		0.0002	1.2790	
HSCD	-0.0003	-5.1242	***	0.0000	0.1016		-0.0003	-3.6221	***
FEMHH	0.0001	0.3026		-0.0006	-1.0695		-0.0006	-0.9365	
BLACK	0.0002	4.4521	***	0.0000	-0.3719		0.0002	2.1596	**
WELFARE	-0.0007	-4.3445	***	-0.0005	-1.0308		-0.0012	-2.5186	***
UNEMP	-0.0005	-3.3434	***	0.0000	-0.0346		-0.0005	-1.6637	*
AGRI	-0.0009	-4.1313	***	0.0001	0.2313		-0.0008	-2.0270	**
CONSTR	-0.0010	-7.4946	***	-0.0004	-1.2638		-0.0015	-4.1050	***
MANUF	-0.0002	-6.6036	***	0.0000	0.4842		-0.0002	-2.8063	***
METRO	-0.0025	-4.3139	***	0.0010	0.7605		-0.0016	-1.2174	

Note: *** significant at 99%, ** significant at 95% and * significant at 90% confidence level.

education, reduced poverty. Agriculture, construction and manufacturing industries were found to help reduce poverty. The results also suggest that income inequality in the Appalachian Region may actually contribute to its economic growth and to the poverty reduction in the Region. However, a percentage of black population was found to be hindering poverty reduction and lowering income inequality.

Therefore, special programs on providing economic opportunities to the black community in the counties could help in the economic growth and in reducing both poverty and income inequality of the Region. Results also suggest for policies to encourage people to go for higher education and to develop agriculture, construction and/or the manufacturing industries in the Region. Future research should include other variables that reflect government expenditures, entrepreneurship and other institutional variables. The study could also be enhanced from the addition of a model on economic growth to get an understanding of how the three factors interact with each other.

References

Allegrezza,S., Heinrich, G., and Jesuit, D. 2004. Poverty and income inequality in Luxembourg and the Grande Région in comparative perspective. Socio - Economic Review: Twenty years of research on income inequality, poverty, 2(2):263.

Bourguignon, F. 2004. The Poverty-Growth-Inequality Triangle. Paper presented at the Indian Council for Research on International Economic Relations, New Delhi, February 4.

Brauer, C.M. 1982. Kennedy, Johnson, and the War on Poverty. The Journal of American History 69 (1982):98-119.

Isserman, A.M. 1996. Appalachia Then and Now: An Update of "The Realities of Deprivation" Reported to the President in 1964, Appalachian Regional Commission, Washington, DC.

Janvry, Alain de, and Sadoulet, E. 2000. Growth, Poverty and Inequality in Latin America: A Casual Analysis, 1970-94. Review of Income & Wealth 46(3):267-287.

Kray, A. 2002. Growth is Good for the Poor. Journal of Economic Growth, 7:193-225.

LeSage, J. and Pace, K.R. 2009. Introduction to Spatial Econometrics. Chapman & Hall/CRC, Taylor & Francis Group, Boca Raton, Fl, 354p.

Mannion, E. and Billings, D.B. 2006. Poverty and Income Inequality in Appalachia. In Kandel, W.A. & Brown, D.L. (Eds.), Population change and rural society, 357-379. New York: Springer.

Nijhawan, I.P. and Dubas, K. 2006. A Reassessment of the Relationship Between Income Inequality and Poverty. Journal of Economics and Economic Education Research, 7(2):103-115.

Persson, T. and Tabellini, G. 1994. Is Inequality Harmful for Growth? The American Economic Review, 84(3):600-621.

Pollard, K.M. 2003. Appalachia at the Millennium: An Overview of Results from the Census 2000. Washington, D.C: Population Reference Bureau and Appalachian Regional Commission.

Ravallion, M. 1997. Can High-inequality Developing Countries Escape Absolute Poverty? Economics Letters, 56: 51-57.

Smeeding, T. 2006. Poor People in Rich Nations: The United States in Comparative Perspective. Journal of Economic Perspectives 20:69-A2.

Suryadarma, D., Artha, R.P., Suryahadi, A., and Sumarto, S. 2005. A Reassessment of Inequality and Its Role in Poverty Reduction in Indonesia. SMERU Working Paper January 2005, SMERU Research Institute, Jakarta.