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Author: Sudiksha Joshi & Tesfa Gebremedhin

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

Sudiksha Joshi
West Virginia University
Morgantown, West Virginia, USA
sudiksha.joshi@mail.wvu.edu

Tesfa Gebremedhin
West Virginia University
Morgantown, West Virginia, USA
tgebrem@wvu.edu

Abstract

The Appalachian Region has neared parity with the national average in terms of poverty rate but Appalachian residents are still poorer than the non-Appalachian residents. The relationship between poverty and income inequality has continued to be region specific and understanding the relationship is important to evaluate how a development strategy would benefit the region. Cross sectional county level data from 1990 and 2000 are used to examine the relationship between poverty and income inequality in the region. Since spatial models fail to capture the spatial dependence of the variables across the region, a spatial regression approach is used in the study. The empirical results indicated an inverse relationship between poverty and income inequality in the Appalachian region.

Keywords: Poverty rate, Income inequality, Gini coefficient, Spatial Durbin Model

1.0 Introduction

Persistence of poverty and growing income inequality has continued to be challenging socioeconomic problems in the United States. The nation's poverty rate has declined since 1959 (22.4%), the first year for which poverty estimates are available, but 1973 (11.1%) was the year with the lowest poverty rate ever measured; the official poverty rate in 2000 was 11.3% but then in 2010 was 15.1%. Further, poverty rates in the United States have been relatively higher than the poverty rates in most of the other rich countries (Smeeding, 2006) with relatively higher percentage of children and elderly under poverty. In case of income inequality, 1968 was the year with the lowest income inequality recorded and it has continued to grow over the years. When President Lyndon B. Johnson declared War on Poverty in 1964, the Appalachian Region received a lot of attention as a geographically isolated and rural region that lagged behind in the social and economic development from the rest of the nation. The pattern of poverty in the Appalachian Region has since converged with the pattern of national poverty because of the various national and local policy programs to induce economic prosperity, curtail out-migration, and mitigate poverty (Lichter & Campbell, 2005). However, the region "still does not enjoy the same economic vitality and living conditions as the rest of the nation" because of the "region's isolation and its difficulty with diversifying its economy" (ARC, 2011, p. 1).

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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 suggest a positive relationship between poverty and income inequality (Allegrezza, Heinrich, & Jesuit, 2004; Persson & Tabellini, 1994) while others suggest an inverse relationship (Dollar & Kraay, 2002; Nijhawan & Dubas, 2006; Williamson, 1999). Bourguignon (2004) suggested that the 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, this paper is intended to explore the relationship between poverty and income inequality in the Appalachian Region in the spatial context. Understanding whether income inequality hinders or actually helps in poverty reduction in the Appalachian Region could provide valuable policy insights.

2.0 Literature Review

The Appalachian Region stretches from southern New York to northern Mississippi and includes 420 counties in 13 states (Figure 1). Isserman (1996) noted the popular image of the Appalachian Region to be "low income, high poverty, limited education, poor living standards, job deficits, high unemployment, outmigration, stagnation, and decline" (p. 20). However, this stereotypical image of the region changed as the region's economy which was "highly dependent on mining, forestry, agriculture, chemical, and heavy industries…now includes diverse manufacturing and professional and technical service industries, as well as several auto manufacturing plants and a vast network of suppliers" (ARC, 2011, p. 1). However, the region's poverty rates are still higher, labor force participation is lower and median family income is still below the national average. Therefore, it is important to understand the functioning of the region to get better insights for ways forward.

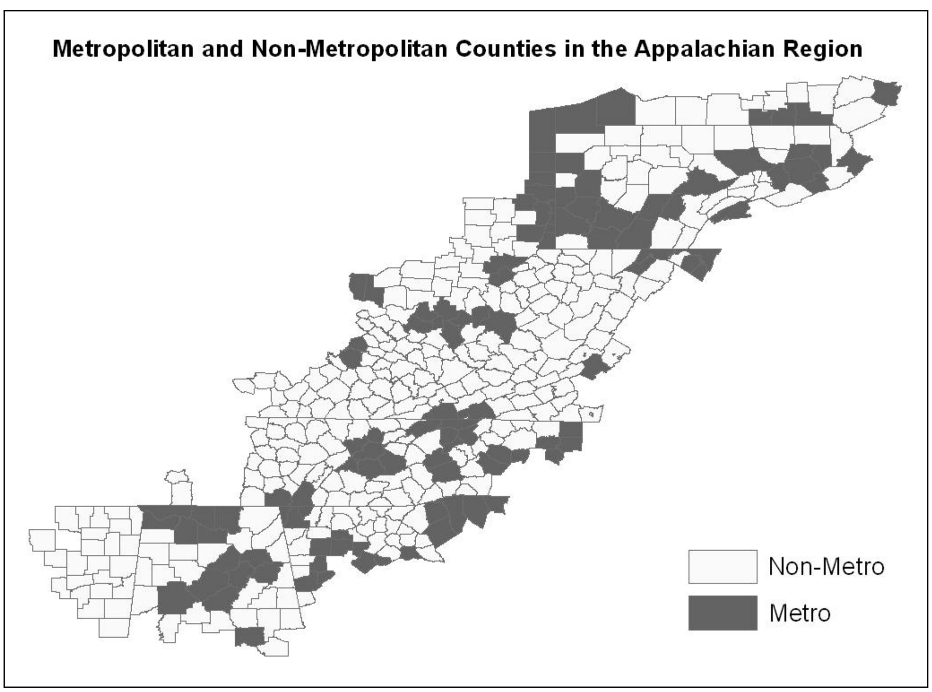

Figure 1. Metro and Non-Metro Counties in the Appalachian Region

Research on the relationship between poverty and income inequality have produced ambiguous results. Persson et al. (1994) presented a theoretical politico-economic equilibrium growth model to suggest that income inequality accentuates poverty and deters economic growth. The study suggested that distributional conflicts discourage human and capital accumulation and deter economic growth. Ravallion (1997) used household survey data from 23 developing countries to suggest that economic growth had only a small impact of reducing absolute poverty in countries with high income inequality. The study also suggested that poor countries were resilient in cases of economic contraction. Janvry and Sadoulet (2000) conducted a causal analysis of urban and rural poverty and income inequality in 12 Latin American countries for the 1970-1994 periods. The results of the study showed that economic growth reduced poverty but not income inequality. Bourguignon (2004) described any change in the poverty as a function of economic growth, income distribution and change in the distribution of income. The study suggested that economic growth and income distribution need to be considered simultaneously and the study also showed that both the income and distributional effects of poverty are positively dependent on the level of economic development and negatively dependent on the degree of income inequality. Nijhawan et al. (2006) 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 relationship between income inequality and poverty. The study found that income inequality may cause income growth and therefore reduce poverty. Addison (2007) found a positive relationship between poverty and income inequality in his cross-sectional empirical analysis of the West Virginia counties. These ambiguous findings on the relationship between poverty and income inequality warrant a region specific exploration of the relationship for the Appalachian Region. Studies have shown that initial income inequality matters in how a region responds to economic growth in alleviating poverty (Alisjahbana, Yusuf, Chotib, & Soeprobo, 2003; Bourguignon, 2004; Ravallion, 1997). Further, a spatial analysis to consider the added factor of spatial dependence is also warranted as suggested by LeSage and Fischer (2008) for the regional economic growth studies.

3.0 Empirical Model

A modified spatial simultaneous equations model is used in this study to understand the relationship between poverty and income inequality in the Appalachian Region. Gini coefficient is used as the measure of income inequality. Gini coefficient sorts the population from poorest to richest and plots the cumulative proportion of population on the horizontal axis and the cumulative proportion of income on the vertical axis. Gini coefficient of 0 signifies perfect equality and 1 signifies perfect inequality (Haughton & Khandker, 2009). Poverty and Income inequality are influenced by a set of socio-economic variables. The control variables used in 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 ($\text{POVCHNG}=\left(POV_{t+10}/POV_t\right)^{1/10}-1$) and the compounded annual rate of change in Gini coefficient ($\text{GINICHNG}=\left(GINI_{t+10}/GINI_t\right)^{1/10}-1$) 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 and unskilled workers than other sectors and thus are expected to reduce both poverty and income inequality. Since the 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 tend to influence each other and the observations might have spillover effects from the neighboring counties. The non-spatial, OLS regression model in case of spatial dependence in the observations might be biased and/or inconsistent. Therefore, the models were tested for possibility of spatial dependence. There are three basic forms of spatial econometric models: The spatial autoregressive model (SAR), the spatial error model (SEM) and the spatial Durbin model (SDM). SAR is used when spatial autocorrelation occurs in the dependent variable, SEM when spatial autocorrelation occurs in the error term, and SDM when the spatial autocorrelation occurs both in the dependent and independent variables. Lagrange multiplier tests and robust Lagrange multiplier tests were run to test for the type of spatial autocorrelation. The Lagrange multiplier test for POVCHNG spatial lag model 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. Both the basic and the robust Langrange multiplier tests for GINICHNG spatial lag model were not found to be significant. On the other hand, both the basic and the robust Lagrange multiplier tests for POVCHNG and GINICHNG spatial error models were found to be significant. The Lagrange multiplier tests indicated the presence of spatial error correlation in both the models suggesting the data generating process for both the models to be SEM. However, before continuing with SEM models, LeSage and Pace. (2009) suggest using the spatial Hausman test to test for specification errors resulting from the omitted variables that are correlated with the explanatory variables and have spatial dependence with the error term. The spatial Hausman test was significant for both the models (Table 2) suggesting that the true data generating process to be SDM. SDM 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.

Table 1. *Description and Summary Statistics of the Variables*

Variables	Variable Description	Mean	Std deviation
POVCHNG	Compounded annual rate of change in poverty rate between 1990 and 2000.	-0.01	0.01
GINICHNG	Compounded annual rate of change in gini coefficient rate between 1990 and 2000.	0.00	0.01
POV	Poverty rate, 1990	19.10	7.90
GINI	Gini Coefficient, 1990	0.43	0.03
LN_PERCAP	Natural log of per capita income, 1990	4.20	0.07
AGE65	% of population 65 years and over, 1990	14.33	2.65
HSCD	% of population with high school degree or above, 1990	61.17	10.20
FEMHH	% of households of single female as the head of the household with children 18 years or below, 1990	6.38	1.83
BLACK	% of black population, 1990	5.82	10.76
UNEMP	% of population unemployed, 1990	7.75	2.75
WELFARE	% of population receiving public assistance, 1990	10.35	4.41
AGRI	% of population 16 years or older employed in agriculture, forestry, fishing and hunting, 1990	2.00	1.60
CONSTR	% of population 16 years or older employed in construction, 1990	7.63	2.44
MANUF	% of population 16 years or older employed in manufacturing, 1990	26.50	11.33
METRO	dummy variable 1=metro counties and 0=non-metro counties	0.27	0.44

The study uses SDM for analysis as it would produce unbiased coefficient estimates even when the true data generating process is SAR or SEM. The general form of the SDM model is as follows (LeSage et al., 2009).

$$y = \rho W y + x(\beta + \gamma) + Wx(-\rho\beta) + \varepsilon$$

$$y = \rho W y + x\beta + Wx\psi + \varepsilon$$

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. Modified SDM, as suggested by Kahsai (2009), was used to account for the simultaneity in the dependent variables. A reduced form equation is estimated using OLS for each of the two models and the fitted values of the endogenous variables are then included as an independent variable in SDM.

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.

3.1 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).

4.0 Empirical Results and Analysis

The descriptive statistics (Table 3 and Figure 2) show a considerable decrease in the poverty rates in the 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.

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 means that the independent variables explained 37% and 48% of the models with POVCHNG and GINICHNG as the dependent variables, respectively. Interpretation of the results is based on the direct, indirect and total effects of the estimates (Tables 4 and 5) as suggested by LeSage et al. (2009). Estimates of direct effects in the study would include the direct and the feedback effects from its neighboring counties. On the other hand, estimates of indirect effects would include the spatial spillover effects. Total effects would indicate estimates of the combined direct and indirect effects.

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

4.1 Change in Poverty Rate (POVCHNG)

Change in the Gini coefficient (GINICHNG) had the largest direct effect on the change in the poverty rate (POVCHNG) meaning higher income inequality in a county Gini coefficient lowered the poverty rate in that county. The indirect and total effects of change in income inequality on POVCHNG were not significant. Poverty rate (POV) had a negative direct effect but a positive indirect effect on POVCHNG meaning that higher poverty rate of a county lowered the poverty rate in that county. However, higher poverty rates of the neighboring counties increased the poverty rate of that county. The total effect of poverty on change in poverty rate was not significant.

Table 4. *Effects Estimates of the Spatial Durbin Model for the Change in Poverty Rates from 1990 to 2000 in the Appalachian Region*

Variable	Direct effect	Asymptotic t stat	Indirect effect	Asymptotic t stat	Total effect	Asymptotic t stat
GINICHNG	-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
LN_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
CONSTRUCT	-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

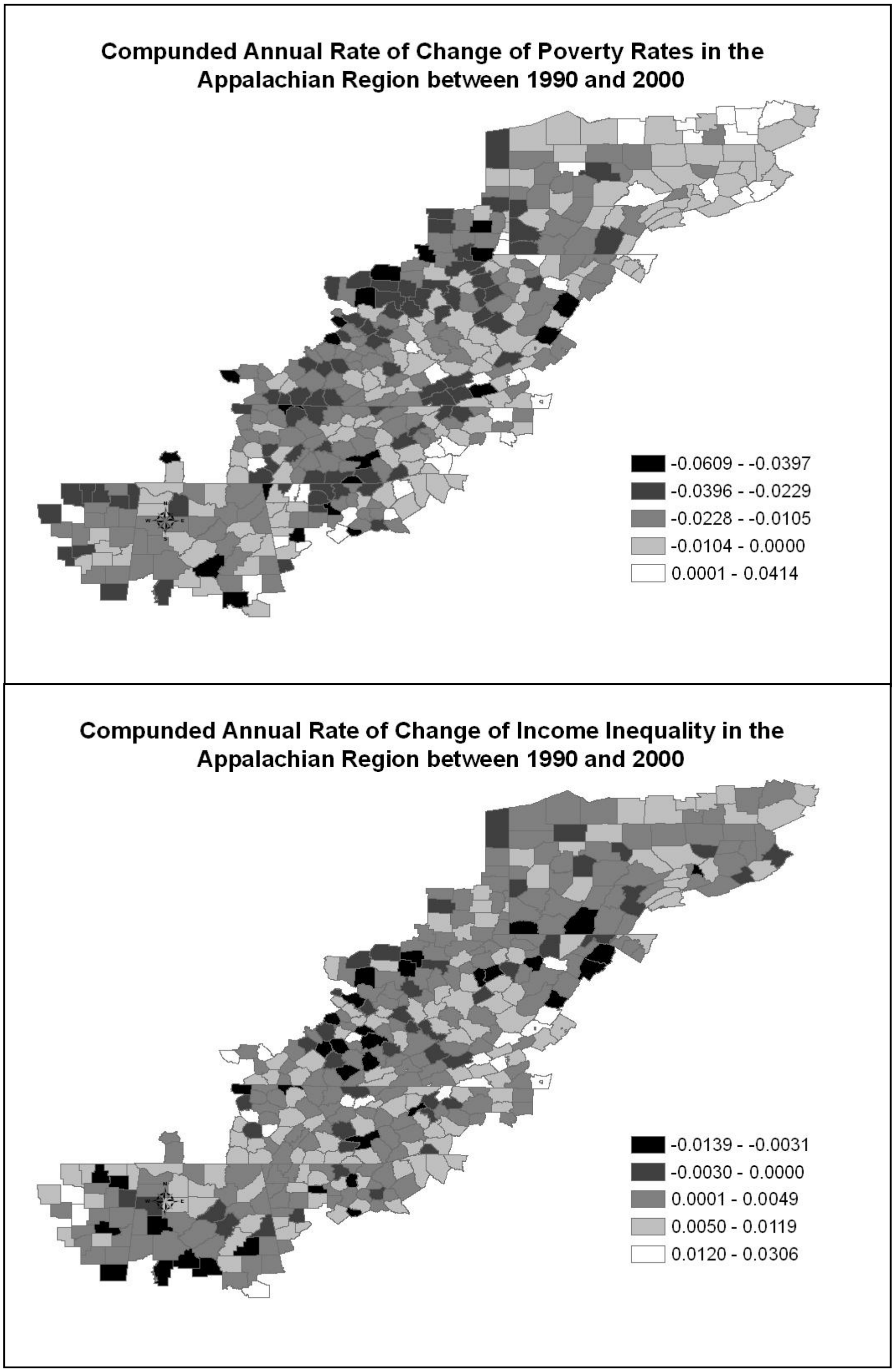

Figure 2. Maps on the Change in the Poverty Rate and Change in the Gini Coefficient in the Appalachian Region from 1990 to2000.

Table 5. *Effects Estimates of the Spatial Durbin Model for the Change in the Gini Coefficients from 1990 to 2000 in the Appalachian Region*

Variable	Direct effect	Asymptotic t stat	Indirect effect	Asymptotic t stat	Total effect	Asymptotic t stat
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 ***
LN_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 **
CONSTRUCT	-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.

Per capita income (LN_PERCAP) also had negative direct effect on the change in poverty rate (POVCHNG) which indicated a county with higher per capita income in 1990 had less poor people by 2000. Per capita income did not have significant indirect effect but it did have a negative total effect on POVCHNG meaning that an increase in the per capita income lowered the poverty rate. Population over 65 years of age had a negative direct effect but indirect and total effects were not significant. Population with higher education (HSCD) and female headed households (FEMHH) did not have any significant effect on POVCHNG. Counties with a high percentage of black population (BLACK) had positive direct effect but did not have indirect and total effect on POVCHNG. Population receiving public assistance (WELFARE) and unemployed population (UNEMP) had no significant direct effect but both had significant negative indirect effects on POVCHNG. This means that county with neighboring counties that had high percentage of population receiving public assistance and high unemployed population in 1990 led to lower poverty rates by 2000 in that county. The overall effects of WELFARE and UNEMP on POVCHNG were also negative and significant meaning that higher percentage of population with public assistance and unemployed in 1990 lowered the poverty rates in the Appalachian counties by 2000. The negative effects of WELFARE and UNEMP seem counterintuitive however; this indicates that these variables representing the relatively poor population might have gained the most from the changes between 1990 and 2000.

The direct effects of all the three variables representing population in employment sectors: agriculture (AGRI), construction (CONSTRUCT) and manufacturing (MANUF) were significant and negative meaning that a county with higher percentage of population employed in these sectors lowered the poverty rate of that county. Employment only in the construction sector showed a significant and positive indirect effect on POVCNHG meaning that the spillover effects of higher percentage of population employed in the construction sector resulted in increasing the poverty rate in the county. However, only the manufacturing sector had a significant and negative total effect meaning that the overall employment in the manufacturing sector helped in lowering the poverty rate in the Appalachian Region. There was no significant difference in the effect of metro counties on POVCHNG.

4.2 Change in Income Inequality (GINICHNG)

In case of the model with GINICHNG as the dependent variable, POVCHNG had the highest effect on GINICHNG. The direct effect and total effect of POVCHNG were significant and negative meaning that higher poverty rate was associated with lower income inequality. The direct and total effects of income inequality in 1990 (GINI) was also negative and significant. This suggested that a county with high income inequality in 1990 led to a lower income inequality by 2000. The overall effect of higher income inequality in 1990 was also associated with lower income inequality in 2000.

The direct effect of per capita income (LN_PERCAP) was not significant but the indirect and total effects were negative and significant indicating that higher per capita income led to lower income inequality. Population over the age of 65 (AGE65) did not have a significant effect on GINICHNG. Higher percentage of population with higher education (HSCD) was shown to have negative and significant direct and total effects on GINICHNG. The indirect effect indicated that counties with an educated population would lower the income inequality of a neighboring county. The total effect indicated that the highly educated population helped in lowering income inequality. Population with high percentage of female headed households did not have any significant effect on GINICHNG. Higher percentage of black population was shown to have positive and significant direct and total effects on GINICHNG. This suggested that high black population in a county led to higher income inequality in that county and the overall effect of high black population would cause an increase in the income inequality. As with the POVCHNG model, WELFARE and UNEMP had negative and significant direct and total effects on GINICHNG. This suggested that high percentage of population receiving public assistance and unemployed population in 1990 led to a low income inequality in 2000.

All the three employment sectors showed negative and significant direct effects on GINICHNG meaning that employment in all the three sectors: agriculture (AGRI), construction (CONSTRUCT) and manufacturing (MANUF) in a county helped to reduce the income inequality in the county. The indirect effect was not significant in any of the three sectors meaning that the spillover effects of any of the three sectors were significant in affecting the income inequality in the county. However, only the manufacturing sector had a significant and negative total effect meaning that overall employment in the manufacturing sector helped in lowering the income inequality in the Appalachian Region. There was no significant difference in the effect of metro counties on GINICHNG.

5.0 Conclusion and Discussion

This paper presented a spatial 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 designing development strategies. This study shows some interesting findings regarding the relationship between poverty and income inequality. During the period of 1990 and 2000, poverty rate in the region declined from 15.4% in to 13.6% nearing parity with the national average of 12.6%. Income inequality in the region on the other hand increased from 13.2% in 1990 to 13.7% in 2000. The figures and the modified Spatial Durbin Models suggest an inverse relationship between poverty and income inequality in the Appalachian Region.

The models also indicated some variables that showed significant effects on both poverty and income inequality and other variables that had significant effects on only one of the two dependent variables. Higher per capita income helped in lowering both poverty rate and income inequality in the region. Current measures of public assistance were also found to be effective in lowering both poverty and income inequality. Further, the unemployed population in 1990 was also shown to improve both the poverty and income inequality scenario of the Appalachian Region. The results suggest that the unemployed population benefitted from the concerted efforts put in place in order to create more job opportunities which helped in reducing the scenario of both poverty and income inequality in the region. The results of the study support the findings of Lichter et al. (2005) who noted that the poorest of the population and the poorest of the counties in the Appalachian Region showed the fastest decline in terms of poverty rates. Higher education and black population had significant overall effects in lowering the income inequality of the region. Employment in the manufacturing sector was shown to lower poverty rate but all the three sectors: agriculture, construction and manufacturing industries were found to help reduce income equality in the Appalachian Region.

The study suggests an inverse relationship between poverty and income inequality. Billings and Blee (2000) suggest that economic, political and cultural makeup of the region, which has sustained the Appalachians across generations, have to be addressed for the public policies to be successful. Future research is therefore warranted to include other variables that reflect political and cultural makeup of the region. Additional variables that reflect sub-regional differences and government expenditures, entrepreneurship and other institutional variables are also recommended for future research.

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7.0 References

Alisjahbana, A. S., Yusuf, A. A., Chotib, Yasin, M., & Soeprobo, T. B. (2003). *Understanding the Determinants and Consequences of Income Inequality in Indonesia*. East Asian Development Network

Addison, H. (2007). *Empirical Analysis of Poverty and Inequality in West Virginia*. The Selected Works of Hector Addison Available at: http://works.bepress.com/hector_addison/2

Allegrezza, S., Heinrich, G., & Jesuit, D. (2004). Poverty and income inequality in Luxembourg and the Grande Région in comparative perspective. *Socio-Economic Review, 2*(2), 263-283.

Appalachian Regional Commission. (2011). *Economic Overview of Appalachia-2011*. Appalachian Regional Commission.

Billings, D. B., & Blee, K. M. (2000). *The Road to Poverty: The Making of Wealth and Hardship in Appalachia*. Cambridge, UK: Cambridge University Press.

Bourguignon, F. (2004). *The Poverty-Growth-Inequality Triangle*. Paper presented at the International Economic Relations.

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

Dollar, D., & Kraay, A. (2002). Growth is Good for the Poor. *Journal of Economic Growth, 7*(3), 195-225.

Haughton, J., & Khandker, S. R. (2009). *Handbook on Poverty & Inequality*. Washington, DC: The World Development Bank.

Isserman, A. M. (1996). *Socioeconomic Review of Appalachia Then and Now: An Update of the "Realities of Deprivation" Reported to the President in 1964*: Appalachian Regional Commission.

Kahsai, M. S. (2009). *An analysis of amenity-led rural economic development in northeast region: A spatial simultaneous equations approach* Unpublished Dissertation, West Virginia University, Morgantown.

LeSage, J. P., & Fischer, M. M. (2008). Spatial Growth Regressions: Model Specification, Estimation and Interpretation *Spatial Economic Analysis, 3*(3), 275-304.

LeSage, J. P., & Pace, K. R. (2009). *Introduction to Spatial Econometrics*. 354: CRC Press.

Lichter, D. T., & Campbell, L. A. (2005). *Changing Patterns of Poverty and Spatial Inequality in Appalachia*: Population Reference Bureau and Appalachian Regional Commission.

Nijhawan, I. P., & 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., & Tabellini, G. (1994). Is Inequality Harmful for Growth? *The American Economic Review, 84*(3), 600-621.

Ravallion, M. (1997) Can high-inequality developing countries escape absolute poverty? *Policy Research Working Paper Series*: The World Bank

Smeeding, T. (2006). Poor People in Rich Nations: The United States in Comparative Perspective. *The Journal of Economic Perspectives, 20*(1), 69-90.

Smeeding, T. M. (1991). Cross-National Comparisons of Inequality and Poverty Position. In L. Osberg (Ed.), *Economic Inequality and Poverty: International Perspectives* (pp. 39-59). Armonk: M.E.Sharpe.

Suryadarma, D., Prama Artha, R., Suryahadi, A., & Sumarto, S. (2005). A Reassessment of Inequality and its Role in Poverty Reduction in Indonesia. *SSRN eLibrary*.

Williamson, J. G. (1999). Policy backlash: can the past inform the present? In P. Aghion & J. G. Williamson (Eds.), *Growth, Inequality, and Globalization* (pp. 169-200). Cambridge University Press.