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A Spatial Analysis of Supplemental Nutrition Assistance Program in the Appalachian Region

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Abstract

Supplemental Nutrition Assistance Program (SNAP) helps low income people and households buy food for proper health. This study seeks to examine the effects of changes in economic conditions and welfare on SNAP participation in the Appalachian region. Using county level data, the Spatial Durbin (SDM) Model was used to examine the effect of economic conditions, demographic attributes and institutional factors on SNAP participation. Empirical results from the marginal effects indicate that poverty had the greatest influence on SNAP participation. Findings from this study could be helpful in improving welfare programs in this region.

Keywords: Supplemental Nutrition Assistance Program, Spatial Durbin Model, Appalachia

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Introduction

The poverty rate in the United States (U.S.) has been increasing since the 1970's, particularly during recessions. The 2009 poverty rate of 14.3 percent was substantially higher than the 11.1 percent level reported in 1973, showing that a significant portion of families and children in the U.S. live in poverty today, and that the portion is more than three and a half decades ago. The U.S. government has an obligation in implementing appropriate welfare and effective food assistance programs to its people (USDA 2010).

The Supplemental Nutrition Assistance Program (SNAP), formerly known as the Food Stamp Program, is a federal assistance program that provides assistance to low and no-income people and families living in the U.S. It is the largest food assistance program and the cornerstone of the federal government's efforts to alleviate hunger and food insecurity among low income households. The federal government and states share authority over the assistance program. The federal government sets the program's income eligibility limits and benefit levels, both of which are uniform across most states. It also pays the full costs of benefits, all administrative costs at the national level, and half of the administrative costs at the state level. The states administer the program, pay the other half of administrative costs and choose policy options that affect eligibility in their state (Finegold 2008). The SNAP is an integral component of the social safety net in the U.S. and accounts for a total of $53.6 billion in fiscal year 2009 compared to $17.1 billion in fiscal year 2000 (USDA 2010).

Past studies on SNAP participation attributed its dynamics to a region's economic conditions along with changes in welfare reform. They indicated that SNAP participation is positively correlated with unemployment and poverty (Kornfeld and Wilde 2002). Recent trends show that SNAP participation has grown from 17.2 million in 2000 to 35.8 million people in 2009 (USDA 2010). Given these trends, it is important to analyze what has caused SNAP participation to undergo changes since 2000. The most recent recession which started in December 2007 and lasted 18 months indicated a jump in individual monthly participation in SNAP (NBER 2008; NBER 2010).

Past studies have focused on these dynamics at the national level, with little research done at the regional level. In general, there is lack of adequate information about the factors affecting SNAP participation which need to be addressed in a wider perspective within a policy context. In addition, little has been done with regards to spatial analysis of SNAP participation. With the exception of Goetz, Rapusingha et al. (2004), early work on the SNAP program ignored the fact that latent variables can vary over geographical regions, thereby creating spatial interdependence on counties (Lacombe 2004). This paper examines the influence of economic activity, administrative and institutional policies, transaction costs, demographic factors, and welfare policy on SNAP program participation. This paper attempts to answer the following questions: (1) What results do we obtain when we run an OLS model and how do they change when we employ spatial econometric techniques? (2) Which spatial model do we employ for making inferences? This paper attempts to answer these questions using secondary data together with spatial models.
At the macroeconomic level, individual income and employment opportunities are expected to influence households' decisions to participate in the SNAP program. For example, the recent economic downturn between 2008 and 2009 caused a rise in unemployment levels, perhaps

increasing SNAP participation by eligible households. Conversely, policies aimed at promoting employment may lower SNAP participation, while a reduction in transaction costs may cause an increase in participation. Measures to increase awareness among low income households are also likely to increase SNAP participation rates. By analyzing these trends, we can examine how the economy has affected low income households in the Appalachian region. The results from the empirical analysis will assist in drawing appropriate policy implications for improving the program to reach the desired goals. Research findings are anticipated to guide future development of welfare and SNAP policy measures, and aid policy makers to develop appropriate programs. This study is unique in the sense that the results calculate the marginal effects estimated in many spatial econometric models. These effects estimates differ from the standard regression interpretation of coefficient estimates. Models that contain spatial lags of the dependent variable must account for the fact that changes to an explanatory variable in all regions can occur through changes in its own dependent variable. The paper is also unique in the sense that it is the primary study to cover the Appalachian region with regard to SNAP participation.

The paper is organized as follows: Section 2 provides an overview of past literature and explains the factors that affect SNAP participation. Section 3 covers the methodology where the spatial models are developed. Section 4 presents the empirical results and analysis. Section 5 presents the conclusions and limitations of the study.

Literature Review

There are eight factors that affect SNAP participation dynamics: participation trends, poverty and unemployment, administrative measures, demographic factors, institutional factors, theoretical explanations, empirical models applied and other welfare changes. The role and effectiveness of SNAP can be better understood by observing participation patterns and trends. Participation patterns look at those individuals who have enrolled in the program and received benefits. Lately, policymakers have been concerned with individuals who meet eligibility requirements but do not receive benefits. According to USDA (2010) there were 33.7 million SNAP participants in 2009 compared to the 25.7 million reported in 2005. On a monthly basis, 26 out of the 39 million eligible individuals participated for the SNAP program in 2007, which was one percent lower than the total reported in 2006. Participation trends varied among individuals and households. The number of participating individuals has been rising steadily since 2001, while household participation has been non-uniform. This relationship is illustrated in Figure 1.

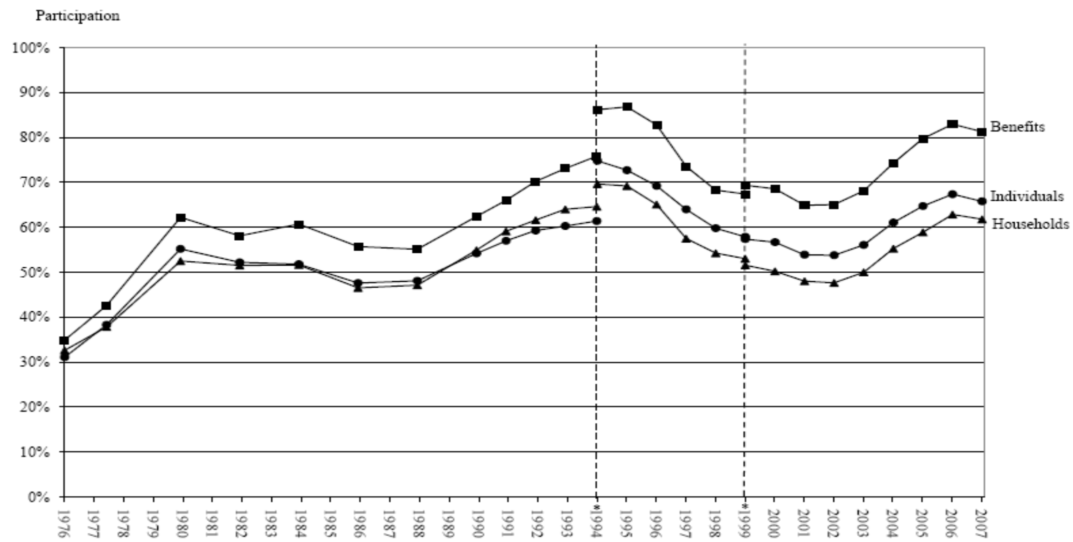

Figure 1. Trends in SNAP participation rates (1976-2007)[1]

Source. Wolkwitz, 2008. SNAP Program Operations data, SNAP QC data, and March CPS data. There are breaks in the time series in 1994 and 1999 due to revisions in the methodology for determining eligibility.

Unemployment levels and SNAP participation have followed parallel patterns over the last two decades. They rise and fall together over the same periods as shown in Figure 2. However, this is not always the case. Some deviation between the two has been observed, suggesting that SNAP participation is not only affected solely by economic factors but also by non-economic ones. This can be shown in Figure 2 where the two patterns were different, with SNAP participation declining as unemployment peaked as observed in the early 1980's or mid 1990's (Wilde, Cook et al. 2000).

A study by Kabbani and Wilde (2003) also attempted to explain the fact that administrative measures may have a significant effect on SNAP participation dynamics. The federal government requires that states recertify participants at least once a year. States vary recertification periods in a bid to lower error rates by keeping up-to-date information on users. Varying the recertification periods has an influence on SNAP participation. Past studies found that using shorter recertification periods lowered SNAP participation either because ineligible participants were unable to participate or eligible participants failing to participate in the program (Currie and Grogger 2001; Kornfeld and Wilde 2002; Kabbani and Wilde 2003).

[1]There are breaks in the time series in 1994 and 1999due to revisions in the methodology for determining eligibility.

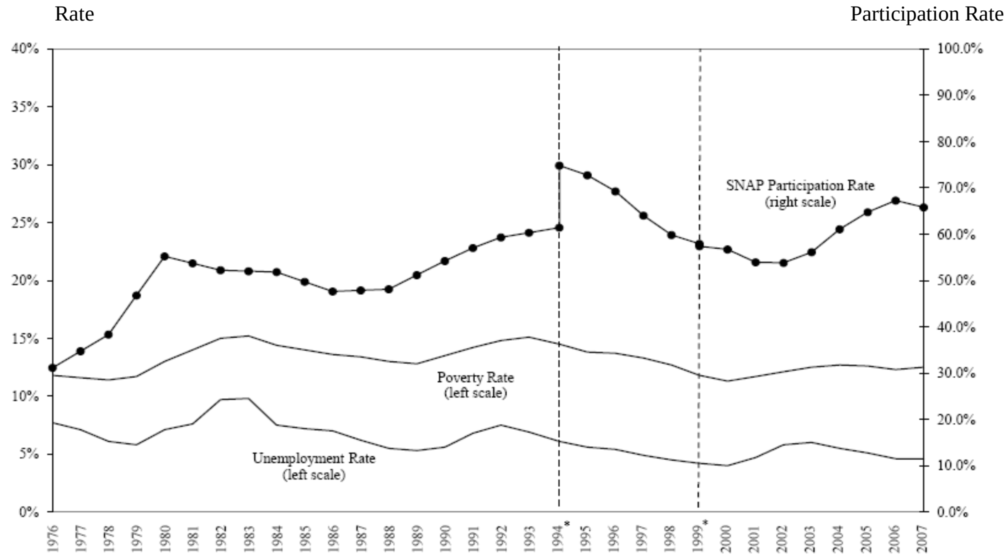

Figure 2. Trends in SNAP participation rates, Poverty Rates, and Unemployment Rate (1976- 2007)[2]

Sources. Wolkwitz, 2008. Participation rates from SNAP Program Operations data, SNAP QC data, and March CPS data for the years shown. Poverty rates from U.S. Bureau of the Census, Poverty in the United States. Unemployment rates from Department of Labor, Bureau of Labor Statistics.

A state based study by Finegold (2008) elaborates on the issue of recertification periods. Participants are required to report changes in income and employment within recertification periods. With different reporting requirements, states that had lenient requirements had higher participation rates compared to those that had stricter rules. The same study found that states that had face to face interviews with individuals had lower participation rates. This task proved onerous because participants had to schedule the interviews during hours in which they were supposed to be working. The realization of this has led to the adoption of interviews by telephones in a bid to ease the reporting process (Finegold 2008).

Hanratty (2006) reported that demographic factors can cause changes in SNAP participation. His study showed that participation is highly correlated with a person's age, parental race, educational attainment, and disability status. Kim (1997) argued that individuals who are older, male, have higher income, higher education, fewer children, and fewer jobs are less likely to participate in SNAP.

Welfare reform may have indirectly reduced the rate of SNAP participation by reducing the number of people receiving welfare (McConnell 2001). Most people receiving welfare were almost automatically eligible to benefit from SNAP. The Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA) changed welfare and altered eligibility requirements for the poor. Welfare reform seeks to move people from welfare to work by

[2]There are breaks in the time series in 1994 and 1999due to revisions in the methodology for determining eligibility.

imposing time limits on receiving benefits and penalizing states that have too few welfare recipients at jobs. The legislation reduced SNAP (food stamps at the time) participants by limiting able bodied adults without dependents (ABAWD) to face a 3-month limit on receiving food stamps unless they were working. The program made it more difficult for single mothers to receive cash welfare, and may have had the largely unintended consequence of making it more difficult for them to access food stamps. Non-citizens could not receive food stamps until they became citizens or worked for ten years or more (Wilde 2001). However, the 2002 Farm Bill made many legal immigrants eligible for benefits of the SNAP program by allowing those residing in the US for at least 5 years and those less than 18 years old eligible to receive benefits (FRAC 2004). These issues show how the influences of institutional factors affect the success of the program.

Other factors such as lack of information and high psychological costs or stigma can cause SNAP participation to decline. McConnell (2001) suggested that the stigma of getting food stamps in rural areas is lower compared to that in urban areas. According to their study, SNAP participation in urban areas dropped from 72 percent to 63 percent while rising from 71 percent to 73 percent in rural areas between 1996 and 1998, a period that witnessed a strong economy. The Electronic Benefit Transfer (EBT) system helps to encourage participation by reducing stigma in the use of food stamps, but EBT may make it harder for people unfamiliar with debit card to get benefits (Currie and Grogger 2001; Kabbani and Wilde 2003). This system was introduced to lower administrative costs and deter fraud. Even so, recipients of the EBT card perceived less stigma in using it in comparison to the more visible coupons. On the downside, the card can only be used in certain stores which have EBT conversion technology.

Clarke, Levedahl et al. (2004) argue that the variations of Temporary Assistance for Needy Families (TANF), formerly Aid to Families with Dependent Children (AFDC) caseloads are important in explaining the movements of SNAP participation caseloads. Households made up entirely of AFDC/TANF recipients are automatically eligible for food stamps (Currie and Grogger 2001). Caseload levels in the two programs are indirectly linked through their implementation at the state level. Any shared approach would imply that states' practices in one program might affect implementation of both programs (US GAO 1999). Therefore, caseloads track the general pattern of per capita SNAP participants fairly well. Fluctuations in per capita SNAP participants are consistently tracked by concomitant rise and drop predicted by per capita AFDC/TANF caseloads (Clarke, Levedahl et al. 2004). This may raise the issues of simultaneity but studies get around this problem by employing proxies (Currie and Grogger 2001).

There is a growing literature concerning the factors associated with SNAP participation. Economists and researchers have attempted to examine the factors and causes for changes in participation, and found that trends varied over the years due to various reasons such as unemployment, income, poverty, recertification periods and so on.
Figlio, Gunderson et al. (2000) found that unemployment rate was statistically significant and had countercyclical impact movement of SNAP participation. They also reported that nearly six percent of the food stamp caseload declines were observed in states that implemented Electronic Benefit Transfers (EBT). Some researchers attributed the current rise in SNAP participation to increasing poverty levels (Smeeding 2009). Other studies by Currie and Grogger (2001), Kornfeld and Wilde (2002) and Kabbani and Wilde (2003) attempted to investigate the role of

recertification periods in SNAP participation. The studies above employed econometric models for empirical analysis. Clarke, Levedahl et al. (2004) employed time series analysis of the SNAP program and found that poor economic conditions increased caseloads.

Goetz, Rapusingha et al. (2004) used spatial econometric methods to investigate factors affecting SNAP participation dynamics in U.S. counties and states. Using the Spatial Error Model (SEM), they found that individual and community level factors affected SNAP participation. They also found that controlling spatial dependence bias in such studies was important. This study builds on that conducted by Goetz, Rapusingha et al. (2004) where the focus is on the Appalachian region using a different spatial model.

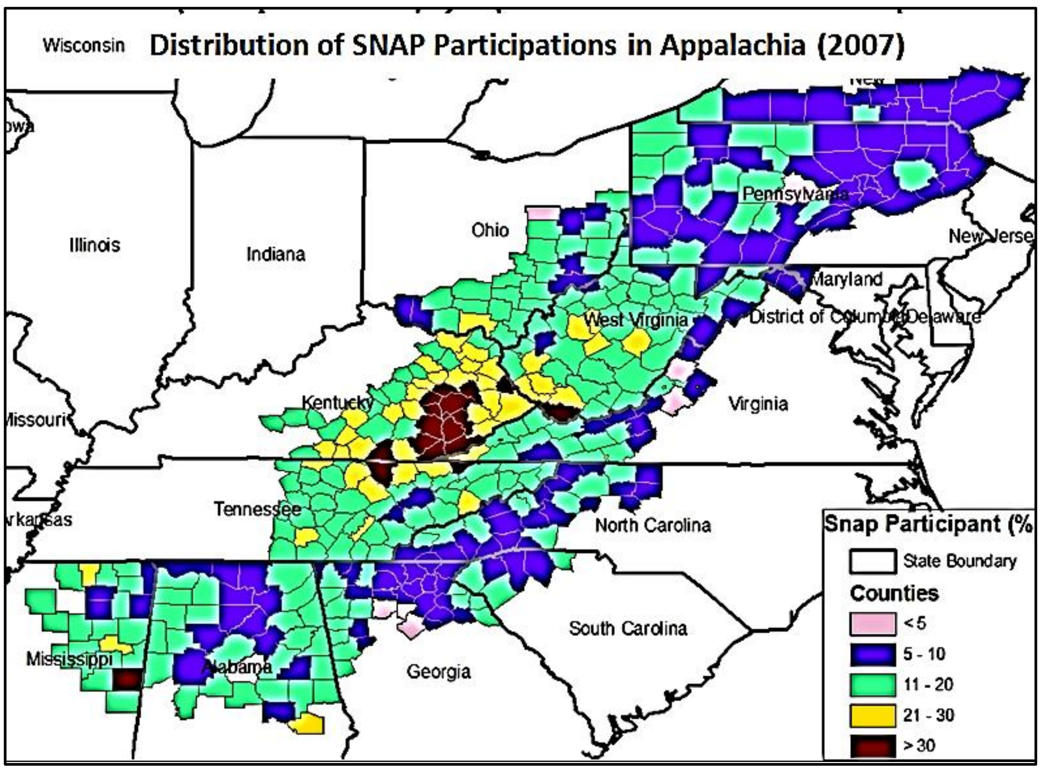

Figure 3. SNAP Participants Distribution in Appalachian Counties (2007)

Methodology

LeSage (1997) found that practitioners engaged in statistical work with regional data samples should try considering spatial configuration in their work. It has also been realized that geographical factors play an important role in determining the effects of public policy (Lacombe 2004). Spatial autocorrelation in SNAP studies can occur in many contexts, but this study aims to address the common issues that lead to the suspicion that variables are measured with errors.

It is known that poverty occurs in clusters, especially where inner cities are located. Also, state level policies may cause clustering to occur in SNAP caseloads (Goetz, Rupasingha et al. 2004). Not surprisingly, participation is clustered in a spatial sense in the Appalachian region as shown in Figure 3. The diagram shows "pockets" of high participation numbers located around the south eastern part of Kentucky.

Populations possessing unobservable characteristics such as culture and attitude are likely to cluster around certain areas in communities. These groups may possess attitudes towards government assistance programs that may be uniform within certain geographical areas. Studies wishing to account for unobservable qualities require the use of proxies to capture these unobservable characteristics. To make the proxies operational, a set of geographic boundaries must be assumed where clustering of the behaviors occur. However, these boundaries may not be the same boundaries used by data collectors. These two problems, unobservability and boundaries, make it virtually certain that SNAP variables will be measured with error, with the result that the regression error terms will be autocorrelated. Overall, ignoring the spatial configuration of sample observations in regression analysis is known to contribute to spatial autocorrelation (Dubin 1998). Overlooking this information may produce inferences that are qualitatively and quantitatively different from models that contain these relations due to the biasedness and inconsistency of OLS estimates.

The spatial model proposed in this study includes three specifications. The first is the Spatial Error Model (SEM), the second is the Spatial Autoregressive Model (SAR) and the third is the Spatial Durbin Model (SDM). The models are useful for analyzing the effects of all the independent factors responsible for changes in SNAP participation over time *t* and space. These models are employed to capture the level of interdependence among regions in the independent variables (LeSage 1997). The study is built on past models developed by Goetz, Rapusingha et al. (2004), Figlio, Gunderson et al. (2000), Currie and Grogger (2001), Kornfeld and Wilde (2002), Kabbani and Wilde (2003) and Clarke, Levedahl et al. (2004). The model is unique because it addresses the issue of marginal effects in SNAP participation within the Appalachian region. The models focus on four major groups of independent variables representing: economic conditions, business cycle, welfare policy changes, demographic variables, and institutional factors.

SNAP participation rate is assumed to be a function of economic and business cycle conditions, changes in welfare reforms, demographic and household attributes, and institutional factors. The available data is a panel dataset which is more informative, provides more variability, has less collinearity among the variables, results in more degrees of freedom, and gives more efficient estimates (Baltagi 1995). This approach controls for individual unobserved heterogeneity which is not easily detectable in cross-section or time-series data. The general form of this model is expressed as follows:

$$(1) \quad SNAP = f\,(UNEM, EMPGR, POVRTY, NLINC, RECERT, ERRT, IMMIG)$$

where: *SNAP* is SNAP participation rate, *UNEM* is unemployment per capita, *EMPGR* employment growth rate is the rate of change of employment, *POVRTY* poverty per capita, *NLINC* non labor income as a fraction of total income, *RECERT* recertification interval, *ERRT* the state error rate, and *IMMIG* the immigrant population per capita (as shown in Table 1).

Table 1. Data Types and Sources

Variable	Description	Source
SNAP	Supplemental Nutrition Analysis Caseloads	U.S. Census Bureau
UNEMP	Unemployment rate	Bureau of Labor Statistics
EMPGR	Employment growth rate	Bureau of Labor Statistics
POVRTY	Poverty rate	U.S. Census Bureau
NLINC	Non labor sources of income	Bureau of Economic Analysis
RECERT	Recertification interval[3]	United States Department of Agriculture
ERRT	State SNAP Participation error rate	United States Government Accountability Office
IMMIG	Percentage of immigrants population	U.S. Census Bureau

Given the geographic nature of the data, it is reasonable to suspect that spatial autocorrelation may be an issue. Spatial autocorrelation is formally defined as follows (Anselin and Bera 1998):

$$(2) \quad \mathrm{cov}(y_i, y_j) = E(y_i, y_j) - E(y_i)E(y_j) \neq 0 \; for \; i \neq j$$

where y_i and y_j are observations on a random variable at locations i and j in space. The subscripts i and j can refer to any geographic designation and the equation implies non-independence of the random variable across space. Spatial autocorrelation can pose problems when using standard econometric techniques, such as OLS.

The Spatial Error Model (SEM) is used to account for the possibility of residual spatial autocorrelation as justified by Anselin and Bera (1998) and implied in their model as the most relevant for applied empirical work on cross sectional data. The SEM model can be expressed as follows:

$$(3) \quad Y_{it} = \beta X'_{it} + u_{it} \qquad i = 1,.....N; \; t = 1,....T$$

$$(4) \quad u_{it} = \lambda \mathrm{W} \mu_i + \varepsilon_{it}$$

$$(5) \quad \varepsilon_{it} = N(0, \sigma^2 I_n)$$

where Y is the dependent variable (SNAP participation rate), ε is the error term, X is the vector of independent variables, λ is the spatial error parameter to be estimated which measures the degree of spatial error independence across neighboring counties. W is a 417 X 417 first order contiguity weight matrix. It is used to incorporate the spatial configuration information about the

[3]The federal government requires households be recertified for SNAP eligibility at least once a year, or at least every two years if they contain an elderly person. Recertification describes the process where households are required to prove eligibility in receiving SNAP benefits by periodically reporting their levels of incomes and assets. Based on reported figures and state requirements, SNAP officials decide whether or not to issue benefits to the households. This exercise enables states to keep up to date information on participants and households, so as to issue benefits to intended people and reduce errors. States believed that they could reduce their risk of errors by imposing shorter recertification periods, especially for households whose incomes were likely to fluctuate (Kabbani and Wilde, 2003).

points in space at which our data observations gathered, and is therefore a convenient way to summarize the spatial configuration of the Appalachian counties. The subscript i denotes the cross-section dimension and t denotes the time-series dimension. In this model i represents counties and t represents years.
We also employed the Spatial Autoregressive Model (SAR) which is specified as:

$$(6) \qquad Y_{it} = \rho WY_{it} + \beta X'_{it} + \varepsilon_{it} \qquad i = 1,.....N; \; t = 1,....T$$

where ρ is the spatial autoregressive coefficient for the SAR model, ε is the vector of error terms and the other notation is as indicated before (Anselin 1999). Finally, the Spatial Durbin Model (SDM) is specified as:

$$(7) \qquad \rho WY_{it} + \beta X'_{it} + \mathrm{W}X'_{it}\theta + \varepsilon_{it} \qquad i = 1,.....N; \; t = 1,....T$$

$$(8) \qquad Y_{it} = (I_n - \rho W)^{-1}(\beta X'_{it} + \mathrm{W}X'_{it}\theta + \varepsilon_{it})$$

$$(9) \qquad \varepsilon_{it} \sim N(0, \sigma^2 I_n)$$

We can further simplify the equation (8) or the Data Generating Process (DGP) such that

$$(10) \qquad Y_{it} = P^{-1}\left[(\beta X'_{it} + \mathrm{W}X'_{it}\theta + \varepsilon_{it})\right]$$

where P^{-1} is a 417 X 417 matrix. Assuming that the β's do not vary over time, the matrix of the marginal effects changes in the X_r variable at time t is given by $(I_n - \rho W)^{-1}(I_n\beta_r + W\theta_r)$. The diagonal elements of this matrix are the effects on region i from changing X_r in the region at time t plus feedback effects. In the presence of spatial dependence, these "own derivatives" account for higher-order neighbor effects. This follows from the fact that: $(I_n - \rho W)^{-1} = (I_n + \rho W + \rho^2 W^2 + \rho^3 W^3 ... + \rho^\infty W^\infty)$ which are the direct plus feedback effects. The infinite series expansion shows that if a region is influenced by its neighbors, and those neighbors are influenced by their neighbors, then every region is influenced by higher order neighbors. Similarly, the off-diagonals of this matrix represent the indirect effects (LeSage and Pace 2009).

The data for the 417 Appalachian counties used for empirical analysis was collected from various sources for the period between 2000 and 2007. Data on the number of SNAP participants was collected from the data sets contained in the Economic Research Service under the United States Department of Agriculture. Poverty rates and immigrant population data was obtained from the U.S. Census Bureau. Data on employment and unemployment are obtained from the Bureau of Labor Statistics. The Bureau of Economic Analysis (BEA) provided data on non-labor sources of income while the Government Accountability Office (US GAO) provided data on error rates. Table 1 provides a description of variables and sources.

The dependent variable used in the empirical analysis is the SNAP participation rate. SNAP participation rate is the ratio of people who participate in the program divided by the total county population. It is a measure that has been used in previous studies to see how well the program is reaching its target population (Castner and Schirm 2004). Not all of those who are eligible participate in the program; some choose not to participate while others are unaware that they are eligible (Finegold 2008). The SNAP participation rate may rise or drop depending on economic conditions or institutional factors which affect eligibility rules. Relaxing these regulations affects the participation rate by expanding or shrinking the number of people eligible for benefits. Past studies have used estimates of participation rates to assess the programs performance (Castner and Schirm 2004; Cunnyngham and Castner 2009).This paper assumes that participation rates change due to a number of reasons, hence its use as a dependent variable. SNAP participation rate is specifically affected by eight factors: participation trends, poverty and unemployment, administrative measures, demographic factors, institutional factors, theoretical explanations, empirical models applied and other welfare changes.

Like other studies, Figlio, Gunderson et al. (2000) concluded that macroeconomic conditions had a significant effect on a person's decision whether or not to be a SNAP participant. For this reason, we included unemployment rate (UNEMP) and employment growth rates (EMPGR) in the model in order to capture the effects of business cycle conditions on SNAP caseloads. The model also included poverty (POVRTY) and non-labor income (NLINC) variables to capture the effects of the individual's economic condition.

High transaction costs are likely to reduce SNAP participation rate. This effect can be captured by the use of a variable that includes the individual states' recertification rates (RECERT), which also acts as a variable measuring the state-level policy differences. SNAP participants do not receive supplemental nutrition assistance continuously; they are eligible only for a certain period. They need to reapply to receive continued assistance when their certification period expires. Mostly, reapplying for the assistance involves face-to-face interviews. We assume that higher recertification rates add expenses to the SNAP participants because they have to make repeated trips to agency offices to prove that they are eligible to receive benefits (Kabbani and Wilde 2003). These repeated trips tend to lower participation rates. The variable is also used to capture the effects of the stigma associated with SNAP participation. The state error rate (ERRT) is also useful in explaining the caseload dynamics. Error rates are used to report state's overpayment and underpayment, and vary across states. The percentage of immigrants in each county is the variable used to capture the effect of demographics in our model. This variable is expected to capture the households' participation decision in being a SNAP participant. Since individual county level recertification intervals were not available, we divided the states' recertification intervals with each county's SNAP participants to capture the magnitude of the interval at the county level. The same procedure was conducted for the state error rates. Finally, we employed a log-linear model where all the variables we used were natural logs for all the variables except the employment growth rate and non-labor income because some values had zeros.

Results and Analysis

To estimate the results, MATLAB 9.1 is used together with the Spatial Econometric Toolbox developed by James LeSage. The results obtained from the SEM and SAR models are estimated using maximum likelihood techniques. However, model specification needs to be carried out to enable us to select one of the models for inference. To do the estimation, as shown in Table 4 (see Appendix), the Panel Lagrange Multiplier (LM) test for specification was employed (Elhorst 2010). According to the test, the SAR model had a Lagrange Multiplier value of 905.80 while the SEM had a value of 1073.32. These results obtained through the classical approach were confirmed by the powerful robust test which found that the SEM model was preferred because the SAR tests were not significant. The results of the Likelihood ratio tests point to the SEM model as the preferred one of the two. This outcome requires reporting the SEM estimates of the model.

Theory indicates that the OLS and SEM estimates should be the same, if the true Data Generating Process (DGP) is OLS, SEM or any other error model (LeSage and Pace 2009). However, our results reported in Table 2 show otherwise. Although estimates exert similar signage and significance, the point estimates differ in magnitude. The OLS estimates of most variables tend to underestimate the coefficients of the SEM, where the largest differences in variables are observed in the immigration and poverty variables. Discrepancies in these two variables are 0.57 and 0.31 percentage points, respectively. With the exception of the error rate and non-labor income variables, all coefficients in the OLS are an underestimate of the SEM

Table 2. Empirical Results of Spatial Econometric Model Estimation

Variables	**SEM Model** *(spatial and time period fixed effects)*	**Fixed Effect Model** *(spatial and time period fixed effects)*
log_unemp	0.5299***	0.2235***
	(26.2300)	(16.5661)
empgr	0.0029*	0.0007*
	(3.0925)	(1.7913)
log_povrty	1.2387***	0.9258***
	(54.4005)	(14.6276)
log_errt	-0.1105***	-0.0752***
	(-7.7467)	(-11.3319)
nlinc	0.0102***	0.0261***
	(6.5636)	(7.3079)
log_immig	-0.025***	-0.5921***
	(-4.5546)	(-10.4690)
log_recert	0.1921***	0.1767***
	(7.1150)	(8.1159)
spat.aut.	0.4320***	
	(18.9203)	
R^2	0.8419	0.9801
Log-Likelihood	181.5067	3696.107

Note. ***, ** and * denotes level statistical significance at 1%, 5% and 10%, respectively. Number in brackets represents t-stat.

coefficients. Nevertheless, the spatial error correlation parameter, $\boldsymbol{\rho}$, is significant at the 99% confidence level and displays a moderate level of spatial error correlation, with a value of 0.4320. Also of note is that the overall fit of the SEM model is very good with approximately 84.19% of the variation in the dependent variable explained by the set of independent variables.

This mismatch in values of estimates could be attributed to the omission of variables that are spatially dependent. The DGP associated with spatially omitted variables matches the SDM

DGP. Using this model shrinks the bias relative to OLS estimates, which provides a good econometric motivation for its use in this analysis (LeSage and Pace 2009). This also adds to the richness of our results because we cater for spatial dependence in the dependent variable and error terms, thereby avoiding bias in estimates of coefficients. Consequently, we estimated SDM with spatial and time fixed effects to control for place-and-time-specific variations resulting from additional variable omission not captured in traditional panel-data analysis. Ignoring these effects in our study may lead to biased estimates (Elhorst and Fréret 2009).

Table 3 shows the direct, indirect and total effects estimates of the SDM. The second column presents the direct effect estimates which relay the impacts of the variables on their own-county's SNAP participation rate plus feedback effects. The indirect effect estimates presented in the third column reflect the effects of the variables on SNAP participation rate in neighboring counties. The sum of the direct and indirect effects give the total effects estimates. These estimates reflect the variable's effect on its own-county plus the (average) cumulative sum of impacts on all other counties as well (Kirby and LeSage 2009).

Table 3. Empirical Results of Spatial Durbin Model with Spatial and Time Fixed Effects

Variables	Direct	Indirect	Total
log_unemp	0.5247***	-0.1298*	0.3948***
	(25.4974)	(-2.2092)	(6.1832)
empgr	0.0019**	-0.0067**	-0.0047
	(1.9038)	(-1.8671)	(-1.1607)
log_povrty	1.3611***	0.3167***	1.6777***
	(31.5060)	(3.9325)	(21.1792)
log_errt	-0.1007***	0.2204***	0.1197***
	(-6.7430)	(5.7666)	(2.9125)
nlinc	0.0102***	-0.0137***	-0.0035
	(5.6250)	(-4.1499)	(-1.1398)
log_immig	-0.1768***	0.0886	-0.0881
	(-4.4393)	(1.2636)	(-1.3585)
log_recert	0.2528***	-0.3597***	-0.1070*
	(7.5904)	(-6.8254)	(-2.3748)
W*dep.var.	0.3280***		
	(13.2273)		
R^2	0.8480		
Log-Likelihood	273.1215		

Note. ***, ** and * denotes level statistical significance at 1%, 5% and 10%, respectively. Number in brackets represents t-stat.

The degree of spatial dependence is 0.33 and statistically significant indicating a level of spatial autocorrelation in the regression relationship. The direct and indirect effects estimates of the unemployment variable are significant at the 1% and 10% levels of significance respectively. A 10% point increase in unemployment rate increases the SNAP participation rate by 5.25% within the county whereas the indirect effects cause a 1.29% decrease. The total effect is a 3.90% increase in SNAP participation rate in the Appalachian region. The direct and indirect effects of the employment growth rate are significant at the 5% level of significance. A one unit increase in the employment growth rate increases SNAP participation by 0.19% due to direct effects but the indirect effects reduces it by 0.67%. The covariate for the total effect is not significant hence implying that the employment growth rate exhibits no effect on SNAP participation in the Appalachian region.

The poverty variable exerts the greatest influence on the SNAP participation rate in Appalachia based on the characteristics and magnitudes of the marginal effects. A 10% increase in poverty rate exerts a 13.6% increase in participation due to the direct effects and a 3.17% increase due to the indirect effects. The total effect on participation due to the 10% increase in poverty rate is a 16.77% rise in participation rate. The direct effect estimates for the error rate reveals that a 10% increase in the error rate reduces SNAP participation by 1.01%, whereas the indirect effects impart a 2.20% increase in participation rate. The overall effect for the error rate on the county is an increase of 1.16% in participation rate. This came as no surprise, as higher error rates could signify an increase in participation rates. The direct and indirect effects estimates for the non-labor income falls within the 99% confidence level but that of the total effect is not significant. The impact of a one unit increase in the direct effect increases SNAP participation by 1% whereas the indirect effects exerted a 1.30% decrease in participation. The total effects did not impact participation rates in the region. Only the direct effects of the immigrant numbers affected SNAP participation in the region, where a 10% increase in the immigrant numbers causes a 1.70% decrease in SNAP participation in the county. Finally, increasing the recertification intervals by 10% causes SNAP participation to rise by 2.53% due to the direct effects but the indirect effects cause a reduction of 3.60. The overall effect decreases SNAP participation in the Appalachian region by 1.07%. The overall fit of the SDM is good, with approximately 84.8% of the variation in the dependent variable being explained by the variation within the set of independent variables.

Concluding Summary

This study employs county level data to capture variation in SNAP participation rates in the Appalachian region. The Spatial Durbin Model is employed to examine the effects between economic and business cycle conditions, changes in welfare reforms, demographic and household attributes, and institutional factors upon SNAP participation rates. The results from the marginal effects estimates presented new findings on how participation rates in counties are affected by factors within their counties. They also shed light on how factors in neighboring counties affect their participation. All the covariates of the direct effects yielded an influence in participation rate in the Appalachian region. They also suggested that poverty exerted the greatest influence on SNAP participation in Appalachia. The results from the indirect effects estimates produced similar results in terms of significance, except for the demographic factor which indicated that immigration numbers did not influence SNAP participation in the region. The total effects produced mixed results. The economic variables namely unemployment and poverty exerted a positive influence on SNAP participation, while the institutional factors namely error rate and recertification interval produced negative effects. Surprisingly, the employment growth rate showed no effect on SNAP participation rates in the region. One possible explanation for this could be that the jobs created might not match the skills of the SNAP participants. It is also possible that jobs might not pay enough for those employed to still be eligible for SNAP participation. The total effects also relayed that longer recertification intervals were found to reduce participation in the region. This result differs with Kabbani and

Wilde (2003) who found that shorter recertification intervals reduced participation. The reason for this could not be immediately inferred because different states were in the process of adopting new techniques for recertification. Most of the Appalachian counties were conducting recertification through telephone interviews thereby reducing the burden of participants to go to state agencies to recertify (Finegold 2008). Although the impact was present in the direct and indirect effects, the demographic factors showed no impact on SNAP participation in the total effects estimates. These results could give an insight to the progress of the 2002 Farm Bill, which sought to ease regulations regarding immigrants' eligibility for SNAP programs. Then again, the Bill was introduced during the study period and as such it would not be suitable to assess its' progress at this time.

The findings from this study could be helpful in designing welfare programs in this region. The SNAP program helps low income individuals and families to obtain a more nutritious diet by supplementing their income with SNAP benefits. However, not all eligible individuals participate because of various challenges they face in obtaining benefits. Policy makers need to be concerned about the situation because they want all affected individuals to participate in the program and receive benefits. This study looked at factors that induce individuals to participate in the program. Understanding these factors can give policy makers a better ability to forecast demands on federal and state funds during periods of economic downturns. They can concentrate on formulating policies that encourage participation or save costs incurred in running the program. As an example, if high unemployment rate increases participation numbers, the government can introduce policies that create more jobs, or those that provide education and training. This can reduce unemployment rates, lower poverty numbers and reduce the number of SNAP participants, thereby making government spending more cost effective. Finally, the analysis of such studies can help in measuring and comparing the effectiveness and impacts of alternative programs.

This study analyses various factors affecting SNAP participation rates in the Appalachian region using spatial analysis. However, there are limitations in this study that should be improved in future work. The first limitation is related to data sets. Some of the data sets for the study area were only available for the period 2000 to 2007, precluding conducting the analysis for extended time period. Some data were not easily accessible at the county level. For example, policy variables for the error rate and recertification interval are collected at the state level and we had to manipulate the state variable to represent the county effect which affected the accuracy of the results. Future work in this area would involve assessing the relationship between the SNAP program and the overall health of the participants. It would also be interesting to carry out an analysis of the program where the effect of welfare programs such as TANF/AFDC or ABAWD were taken into consideration.

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Appendix

Table 4. Model Specification: Lagrange Multiplier Test

LM Lag Test for Omitted Spatial Autoregressive Model (SAR)	
LM value	905.8021
Marginal Probability	0.0000
Chi(1) .01 value	6.6400
LM Error Test for Omitted Spatial Error Model (SEM)	
LM value	1073.3237
Marginal Probability	0.0000
Chi(1) .01 value	6.6400
Robust LM Spatial Autoregressive Model (SAR)	
LM value	104.2275
Marginal Probability	0.0000
Chi(1) .01 value	6.6400
Robust LM Spatial Error Model (SEM)	
LM value	271.7491
Marginal Probability	0.0000
Chi(1) .01 value	6.6400