County-Level Determinants of Local Public Services in Appalachia: A Multivariate Spatial Autoregressive Model Approach

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Abstract: A multivariate spatial autoregressive model of local public expenditure determination with autoregressive disturbance is developed and estimated in this paper. The empirical model is developed on the principles of utility maximization of a strictly quasi concave community utility function. The existence of spatial interdependence is tested using Moran's I statistic and Lagrange Multiplier test statistics for both the spatial error and spatial lag models. The full model is estimated by efficient GMM following Kelejian and Prucha's (1998) approach using county-level data from 418 Appalachian counties. The results indicate the existence of significant spillover effects among local governments with respect to spending in local public services. The OLS estimates of the conventional (non spatial) model of local public expenditure determination and the corresponding maximum likelihood estimates of the spatial lag and the spatial error models are also presented for comparison purposes. The GMM estimates are found to be more efficient.

Key Words: Appalachia, **s**patial, autoregressive, GMM, public services, spatial lag

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Introduction

The public sector interacts with the private sector and affects the economic well being of individuals in many ways. For example, in an effort to create jobs, spur income growth, and enhance economic opportunities of their citizens more generally, state and local governments often offer newly locating or expanding business firms substantial financial incentives (Gabe and Bell, 2004). The distribution of income, the overall price level, and the quality and quantity of public goods and services such as highways, education, health and other local public services are also affected by local government activities such as taxes, and other public expenditure. The level of public expenditure and tax revenue in turn are determined by the economic, demographic and political characteristics of the local economy.

The standard model in the literature assumes that the differences in local public expenditures across regions are generally explained by differences in county-level covariates such as per capita income, population density, tax base, tax rates, population size, age structure of the population, grants in-aid from higher levels of governments, labor market characteristics, and school-age population as well as other socio-economic and institutional factors.

Although most empirical studies in the local public finance literature assume that the level of public expenditure in a jurisdiction is not affected by the expenditures in neighboring jurisdictions, both economic theory and causal observations, however, suggest that expenditure spillovers are a widespread feature of many services provided by local governments.

In this paper, an empirical model that incorporates expenditure spillovers into the conventional model of local public spending determination is developed. The idea that county j's local public spending is dependent on its neighbors' spending on public services and this dependency is tested using county-level data from Appalachia. Neighbors are defined as those counties who share common geographic borders, although it is recognized that economic or demographic similarities could also define neighborliness.

A literature review on the determinants of local public expenditure and the econometric model is presented in the following section. A theoretical model of local public expenditure determination based upon the median-voter model of utility maximization is developed. The basic model is expanded to incorporate spatial spillover effects. Test statistics are developed to test the existence of spatial dependences as well as to discriminate between the spatial lag and the spatial error dependences. The specification of the empirical models and issues related to their estimation are also discussed in detail. Description of the data and its sources, the results, discussion, and the conclusion are also presented accordingly.

County-Level Determinants of Local Public Services

Many cross-sectional studies exist in the literature trying to explain regional variations in per capital local public expenditures (Hawley, 1957; Brazer, 1959; Hirsch, 1959; Hansen, 196; Henderson, 1968; Borcherding and Deacon, 1972; Ohls and Wales, 1972; Bergstrom and Goodman, 1973; Bergstrom, Rubinfeld and Shapiro, 1982; Fisher and Navin, 1992). Hawley (1957), Brazer (1959), Hirsch (1959), and Hansen (1965), for example, employed a one-equation multiple-regression model to express per capita local public expenditure as a function of selected explanatory variables using cross-sectional data. Henderson (1968) also used a multiple-regression analysis of per capita cross-sectional county data for the United States with two equations. Borcherding and Deacon (1972) estimated demand functions for eight specific public services: local education, higher education, highways, health and hospitals, police, fire, sewers and sanitation using cross-sectional data aggregated at state level. Using cross-sectional expenditure data for 1968, Ohls and Wales (1972) also estimated the demand and cost functions for three broad categories of state and local public expenditure: expenditures on highways per capita, education expenditures per school-age population and local service expenditures per capita (including fire, police, sanitation, health and hospitals, and local utility expenditure).

Similarly, Bergstrom and Goodman (1973) employed multiple-regression analysis to estimate the demand functions for three categories of municipal services: police, parks and recreation, and total municipal expenditure excluding education and welfare. These studies are based on the median voter theory where individual demand functions are inferred from cross-sectional studies in which actual public expenditure by local governments are regressed on indicators of economic and social composition of the jurisdiction's population. Bergstrom et al. (1982), however, devised and applied a method for estimating demand for local public goods, which does not require the median voter assumption. By combining individual's responses from survey data to questions about whether they want more or less of various public goods with observations of their incomes, tax rates, and of actual spending in their home communities to obtain estimates of demand functions.

The results from the various studies show that the income elasticity of local public expenditure is positive and significant whereas the estimates of tax price elasticity are negative and significant (Henderson, 1968; Borcherding and Deacon, 1972; Ohls and Wales, 1972; Bergstrom and Goodman, 1973; Bergstrom et al., 1982; Sanz and Velazquez, 2002; Painter and Bae, 2001). Studies by Randolph et al. (1996), Canning and Pedroni (1999) and Fay (2000) also found that spending on economic services such as those relating to transport and communications respond primarily and directly to per capita income changes. Similarly, wide varieties of studies show that estimates of income elasticity greater than one for merit goods such as health, education and housing (Lue, 1986; Newhouse, 1987; Gertham, Sogaard et al., 1992; Falch and Rattso, 1997; Snyder and Yachovlev, 2002; Hashmati, 2001). Duffy-Deno and Eberts (1991) analyzed the linkage between public infrastructure and regional development in a system of two equations and found that per capita real personal income has a positive and statistically significant contemporaneous effect on local public investment.

The findings from the study by Painter and Bae (2001) indicates that income per capita, total long-term debt, the unemployment rate, and the proportion of students of college age have a positive and statistically significant impact on state government expenditure. The results from this study and others (Randolph et al., 1996; Gertham et al., 1992; Falch and Rattso, 1997; Fay, 2000; Hashmati, 2001) also show that population density has negative coefficient. Population and its density play an important role in per capita spending on the purest or non-rival goods such as transportation and communications as well as merit goods and other economic services. A negative coefficient, thus, indicates the advantage of economies of scale in the provision of these public services. A small community must provide many public services such as education, hospitals, police protection, and sewage removal at relatively high per capita costs, which decline as its population increases. The reverse also holds true that large expenditures result in places with declining population (Bergstrom and Goodman, 1973). This is one of the significant problems that small rural communities face. Larger communities usually have better taxable capacity, which can provide a broader range of services that a small community cannot or need not provide (Henderson, 1968).

Since net migration changes the size and the density of population of a region, it has an impact on the demand of locally provided public goods and services as well as on the revenues that support the provision of these public goods and services. The mix of migrants or the mix of individuals who choose not to migrate may have profound consequences on the local public sector. A high-income in-migrant family, for example, may provide more tax revenue to the local economy than a low-income in-migrant family. The type and the quantity of public services they demand, however, are likely to be different. Similarly, growth in population of children that results from in-migrant families with children or women likely to have children creates increased pressure on to expand services. At the same time, excess capacity and maintenance costs of school buildings in the areas of out-migration will be created. The problems are exacerbated if out-migration is severe to impact property value and overall fiscal health of the community (Charney, 1993).

The population age structure is also a significant determinant of local public services and goods. An increase in the proportion of the old and the young in a community increase spending in health, housing and social security (Heller, Hemming and Kalvert, 1986; Hagmann and Nicolleti, 1989; Di Matteo and Di Matteo 1998; Curie and Yelowtz, 2000). An increase in the proportion of young people will also generate pressure for increases in public spending on education (Marlow and Shiers, 1999; Alhin and Johansson, 2001). Local public expenditure per capita is also positively related to grants in-aid from higher-level governments (Fisher and Navin, 1992; Henderson, 1968).

Spatial spillovers in public expenditure might be due to policy interdependence between local governments or it might simply be due to the fact that local governments are hit by a spatially auto-correlated shocks. Thus, local governments affect each other in their public spending decisions, and as Case, Rosen and Hines (1993) indicate, not accounting for such spillover effects would result in biased and inconsistent estimates of the parameters of the demand equation for local public services.

One way of explaining and testing the existence of spatial interactions among local governments is through the tax competition model. This model assumes that local governments finance public spending through a tax on mobile capital and since the level of tax base in a jurisdiction depends both on own and on other jurisdictions' tax rates, strategic interactions results (Wildasin, 1986). Local governments are, thus, concerned about how their tax rates and local public expenditure compare with those of their neighboring jurisdictions. The reason for this concern could be the fear of driving away taxpayers and attracting welfare recipient from other jurisdictions if benefits are generous. Local governments may react to the actions of their neighbors asymmetrically or complementarily. The study by Figlio et al. (1999) on a panel of United States, for example, found that decentralized welfare benefit setting exacerbates inter-state competition that might induce states to respond to changes in their neighbor' policies asymmetrically. In a study of California cities, Bruerckner (1998), however, found that a city government raises land rent both in its own and in neighboring cities by restricting the amount of developable land, thereby generating an externality and strategic interaction in growth control decisions (policy interdependence).

The other model that tries to explain and test the existence of spatial interactions among local governments is the externality or spill-over effect model. This model postulates that beneficial or harmful effect could spillover onto residents of neighboring jurisdiction from expenditures on local public service in a given jurisdiction. Using a model of spatially correlated random effect, Case et al. (1993), for example, found that states' per capita expenditures are positively and significantly influenced by their neighbors' spending and that omitting this spillover effect from the analysis would result in biased estimates of the effects of other covariates on state spending. Using United States county-level data, Kelejian and Robinson (1993) also found that police expenditures in a given county are positively and significantly influenced by neighboring counties' expenditure on police protection.

The third model that tries to explain and test the existence of spatial interactions among local governments is the "political agency – yardstick competition" model. This model postulates that imperfectly informed voters in a given jurisdiction use the performance of other governments as a yardstick to evaluate their own governments. Thus, local governments react to the actions of their neighbors in an effort not to get too far out of line with policies in other jurisdictions, resulting in local governments mimicking each other's behavior. Besley and Case (1995) found evidence of this "political agency – yardstick competition". They tested their yardstick competition hypothesis on United States' income taxes from 1960 to 1988 and found that geographic neighbors' tax changes have a positive and significant effect on a given state's tax change.

Methodology

Model Formation

Following the studies by Borcherding and Deacon (1972), and Bergstrom and Goodman (1973), the median voter model will be used to analyze the determinants of the demand for local public services or the expenditures for local public services. In this model it is assumed that utility-maximizing citizens elect government by majority rule and that the size of the public sector is the only issue to be decided. Citizens are assumed to be informed about the costs and benefits of government expenditures and hence the median voter chooses the level of spending by voting for candidates who offer him/her the most efficient set of public services and taxes. Aggregating over individual in a community, a utility function that represents community preferences can be generated.

Based on these assumptions, a theoretical model is developed to test the hypotheses of the determinants of public spending on local public services. The model is given by the following set of equations:

$$\mathbf{U = U(G, INCTAXR; X)} \tag{1a}$$

$$\mathbf{DGEX = DGEX(G, GF)} \tag{1b}$$

$$\mathbf{REV = REV(INCTAXR, PCTAX, PCPTAX, DFEG; X)} \tag{1c}$$

$$\mathbf{REV} = \mathbf{DGEX} \tag{1d}$$

Equation (1a) is the community utility function which is assumed to be strictly quasi-concave over local public services (G), community income tax rate (INCTAXR), and also may depend on socio-economic, demographic and amenity variables (**X**). Equation (1b) is local government expenditure function (DGEX), which depends on G and other local government functions (GF). Equation (1c) represents local government revenue function, which is assumed to depend upon the community income tax rate (INCTAXR), the tax base that includes personal income tax (PCTAX) and property tax (PCPTAX), intergovernmental grants (DFEG) and a vector of other socio-economic, demographic and amenity variables (**X**). Equation (1d) is local government budget constraint, which states that local government revenue (REV) should equal to local government expenditure (DGEX). Maximizing the utility function given in (1a) with respect to G, GF and INCTAXR subject to (1b)-(1d), gives a local public services demand function of the form (all other notations as defined before)

$$\mathbf{G} = \mathbf{G}\left(\mathbf{PCTAX}, \mathbf{PCPTAX}, \mathbf{DFEG}; \mathbf{X}\right) \tag{2a}$$

Substituting in (4.b) gives the reduced form of local public services expenditure demand function as follows:

$$\mathbf{DGEX} = \mathbf{DGEX}\left(\mathbf{PCTAX}, \mathbf{PCPTAX}, \mathbf{DFEG}; \mathbf{X}\right) \tag{2b}$$

Equation (2b) forms the basis for the empirical analysis. In order to reduce the effects of the large diversity found in the data used in empirical analysis, a multiplicative (log-linear) form of the model is used. Such specification also implies a constant-elasticity form for the equilibrium conditions given in (2b). A log-linear (i.e., log-log) representation of this equilibrium condition can thus be expressed as:

$$\mathbf{DGEX}_{it} = \left(\mathbf{PCTAX}_{it}\right)^{a} \times \left(\mathbf{PCPTAX}_{it}\right)^{b} \times \left(\mathbf{DFEG}_{it}\right)^{c} \times \prod_{k=1}^{K} \left(\mathbf{X}_{kit}\right)^{x_k}$$

$$\rightarrow \mathbf{ln}\left(\mathbf{DGEX}_{it}\right) = a\mathbf{ln}\left(\mathbf{PCTAX}_{it}\right) + b\mathbf{ln}\left(\mathbf{PCPTAX}_{it}\right) + c\mathbf{ln}\left(\mathbf{DFEG}_{it}\right) + \sum_{k=1}^{K} x_k \mathbf{ln}\left(\mathbf{X}_{kit}\right) \quad \textbf{(3a)}$$

Where a, b, c and x_k, $k = 1,...,K$ are exponents with K being the total number of variables included in vector **X**. The log-linear specification has an advantage of yielding a log-linear reduced form for estimation, where the estimated coefficients represent elasticities. Duffy-Deno (1998) and MacKinnon, White et al., 1983 also showed that, compared to a linear specification, a log-linear specification is more appropriate for models involving population and employment densities.

The empirical model that corresponds to equation (3a) can be expressed more compactly as follows:

$$\mathbf{y} = \mathbf{X\beta} + \mathbf{u} \quad (3b)$$

Where y is (Nx1) vector of the log of per capita local public expenditure, $\boldsymbol{X}$ is (NxK) matrix of explanatory variables in log, β is (Kx1) vector of parameters to be estimated, and u is an error term that is assumed to be identically and independently distributed across the observations. Equation (3b), however, may not be correctly specified due to the presence of spatial autocorrelation in local public expenditures because of policy interdependence among local governments. A possible reason for policy interdependence in local public expenditure is the existence of spillover effects across jurisdictions. Commuters, for example, use public transportation, roads, recreation and cultural facilities in their working communities. Air pollution controls and sewage treatment enhance the environmental quality of neighboring jurisdictions, and educational and job training expenditures may lead to productivity gain in workplaces outside the community.

The presence of spatial spillover demands the explicit modeling of the spatial interactions, by taking into account that local jurisdictions make their decisions simultaneously, and each local government takes its neighbors' behavior into account when setting its own policy. Thus, equation (3b) should be extended to accommodate this spatial interdependence as follows:

$$\mathbf{y} = \boldsymbol{\rho}\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \mathbf{u} \tag{3c}$$

where **y** is an (Nx1) vector of observations on the dependent variable, **Wy** is the corresponding spatial lagged dependent variable for weights matrix **W**, **X** is (Nx K) matrix of observations on the explanatory variables, **u** is an (n x 1) vector of error terms, ρ is the spatial autoregressive parameter and β is a (Kx1) vector of regression coefficients. The parameter ρ measures the degree of spatial dependence inherent in the data. As this model combines the standard regression model with a spatially lagged dependent variable, it is also called a mixed regressive-spatial autoregressive model (Anselin and Bera, 1998).

Equation (3b) may not also be correctly specified due to spatial autocorrelation in the error term. Thus, a second way to incorporate spatial autocorrelation in a regression model is to specify a spatial process for the disturbance term. The disturbance terms in a regression model can be considered to contain all ignored elements, and when spatial dependence is present in the disturbance term, the spatial effects are assumed to be a white noise, or perturbation, that is, a factor that needs to be removed (Anselin, 2001). For example, any spatially auto-correlated variable that has an influence on y and is omitted from the model will lead to a spatial dependence in the residual. Such spatial pattern in the residuals of the regression model may lead to the discovery of additional variables that should be included in the model. Local jurisdictions may also be subjected to shocks that affect their expenditure decisions, and are spatially auto-correlated – such as common shocks to income and tax base, that may result from central government regional policies or intermediate level of government fiscal policies. Spatial dependence in the disturbance term also violates the basic OLS estimation assumption of uncorrelated errors. Hence, when the spatial dependence is ignored, OLS estimates will be inefficient, though unbiased, the student t- and F-statistics for tests of significance will be biased, the R^2 measure will be misleading, which in turn lead to a wrong statistical interpretation of the regression mode (Anselin, Bera, Florax and Yoon, 1996). More efficient estimators can be obtained by taking advantage of the particular structure of the error covariance implied by the spatial process. The disturbance term is non-spherical where the off-diagonal elements of the associated covariance matrix express the structure of spatial dependence. The spatial dependence in the disturbance term, thus, can be expressed using matrix notation as:

$$\mathbf{y} = \mathbf{X}\beta + \mathbf{u} \tag{3d}$$

With $\mathbf{u} = \lambda \mathbf{W} \mathbf{u} + \boldsymbol{\varepsilon}$

Where $\mathbf{u}$ is assumed to follow a spatial autoregressive process, with λ as the spatial autoregressive coefficient for the error lag $\mathbf{Wu}$, and $\boldsymbol{\varepsilon}$ is (Nx1) vector of innovations or white noise error, and the other notations as defined before. Equation (3d) is the structural form of the SAR model which expresses global spatial effects. The corresponding reduced form of the model can be specified as:

$$\mathbf{y} = \mathbf{X}\beta + \left(\mathbf{I} - \lambda\mathbf{W}\right)^{-1} \boldsymbol{\varepsilon} \tag{3e}$$

With the corresponding error covariance matrix given as

$$E(\mathbf{uu'}) = \sigma^2 (\mathbf{I} - \lambda \mathbf{W})^{-1} (\mathbf{I} - \lambda \mathbf{W'})^{-1} = \sigma^2 (\mathbf{I} - \lambda \mathbf{W})' (\mathbf{I} - \lambda \mathbf{W})^{-1} \qquad (3f)$$

The structure in equation (3f) shows that the spatial error process leads to a non-zero error covariance between every pair of observation, but decreasing in magnitude with the order of contiguity. Note also that hetroskedasticity is induced in **u**, irrespective of the hetroskedasticity of $\boldsymbol{\varepsilon}$, because the inverse matrices in equation (3f) yields non-constant diagonal element in the error covariance matrix.

Diagnostics for Spatial Autocorrelation

When there are no strong a priori theoretical reasons to believe that interdependences between spatial units arises either due to the spatial lags of the dependent variables or due to spatially autoregressive error terms, the standard approach is to model the system with both effects included (Anselin, 2003). There are, however, a number of diagnostic tests that can be applied to discriminate between the two forms of the spatial dependence described by equations (3c) and (3d). The most widely used diagnostic test for spatial dependence in a regression model is an application of the Moran's I statistic to the residuals of an OLS regression. Given a row-standardized spatial weight matrix **W** Moran's I on the OLS residuals of equation (3a) is given by:

$$I_{(e)} = \frac{e''We}{e'e}$$

Where ***e*** are the OLS residuals. Although Moran's I statistic has great power in detecting misspecifications in the model (and not only spatial autocorrelation), it is less helpful in suggesting which alternative specification should be used. To this end, two sets of Lagrange Multiplier test statistics are used.

The first set, LM-Lag and Robust LM-Lag, pertain to the spatial lag model as the alternative. These are given as follows:

$$LM_{(Lag)} = \frac{\left(\dfrac{e'Wy}{(e'e)/N}\right)^2}{\dfrac{(WXb)' M (WXb)}{(e'e)/N} + tr\left(W'W + W^2\right)}$$

$$RLM_{(Lag)} = \frac{\left[\dfrac{e'Wy}{(e'e)/N} - \dfrac{e'We}{(e'e)/N}\right]^2}{\dfrac{(WXb)' M (WXb)}{(e'e)/N} + tr}$$

Where *tr* is the matrix trace operator, $M = I - X\left(X'X\right)^{-1} X'$ and b is the OLS estimate of β in equation (3a).

The second set, LM-Error and Robust LM-Error), refer to the spatial error model as the alternative. These are given by:

$$LM_{(Lag)} = \frac{\left(\dfrac{e'We}{(e'e)/N}\right)^2}{tr\left(W'W + W^2\right)}$$

$$RLM_{(err)} = \frac{\left[\dfrac{e'We}{(e'e)/N} - tr\left(\dfrac{(WXb)' M (WXB)}{(e'e)/N} + tr\right)^{-1} \dfrac{e'Wy}{(e'e)/N}\right]^2}{tr - tr^2\left(\dfrac{(WXb)' M (WXB)}{(e'e)/N} + tr\right)^{-1}}$$

Both sets of Lagrange Multiplier test statistics are distributed as χ^2 with one degree of freedom. Note that the robust versions of the statistics are considered only when the standard versions (LM-Lag or LM-Error) are significant. A rejection of the null hypothesis by LM-Lag and LM-Error test statistics, thus, requires the consideration of the robust versions of the statistics.

Estimation Methods

The existence of spatial dependence in the data set is tested by Moran's I test statistic and its high significance shows an indication that spatial autocorrelation exists in the data set. Although Moran's I statistic is powerful in detecting spatial misspecifications in the data set, it could not, however, discriminate the form of the spatial dependence. The Lagrange Multiplier test statistics is done to discriminate between the spatial lag and the spatial error dependences. Since the ML-Lag and ML-Error are highly significant which lead to the rejection of the null hypothesis of absence of spatial dependence, the robust forms of the statistics has to be considered. RML-Error is more significant than RML-Lag ($p<0.0000$ compared to $p<0.0445$). From this result it can be inferred that the spatial error specification of the model is more appropriate. Such models can be estimated consistently by maximum likelihood estimator provided that the error terms are normally distributed. A number of studies have used this method (see Case et al., 1993; Brueckner, 1998, 2000; Baicker, 2005; Saavedra, 2000). In this study, however, the normally distributed error term assumption upon which the maximum likelihood estimation is based is not fulfilled. The Jarque-Bera test statistic is highly significant ($p<0.0000$) which lead to reject the null hypotheses of normally distributed error term. Besides, maximum likelihood estimation is computationally expensive and is subjected to the identification problem as a result of the need to estimate the too many parameters of the n x n disturbance covariance matrix from only cross-sectional data. Thus, maximum likelihood estimation may not give consistent and unbiased estimates of parameters of the model.

A better alternative is the use of instrumental variables, as suggested by Kelejian and Robinson (1993), Kelejian and Prucha (1998) and Lee (2003). This approach is computationally easier to implement and it does not require distributional assumptions on the error term. Thus, the model is also estimated by generalized spatial two-stage least squares (GS2SLS) as a better alternative. To this end, the model is specified as a spatial autoregressive model with autoregressive disturbances by incorporating both dependences. Thus, by combining equations (3c) and (3d), the empirical model for a cross-section of counties of Appalachia is expressed as:

$$\mathbf{y} = \rho \mathbf{W}\mathbf{y} + \mathbf{X}\beta + \mathbf{u} \tag{4}$$

With $\mathbf{u} = \lambda \mathbf{W} \mathbf{u} + \boldsymbol{\varepsilon}$

where **y** is an (418x1) vector of direct local government expenditure per capita, **Wy** is the corresponding spatial lagged dependent variable for weights matrix **W**, **X** is (418x K) matrix of observations on the explanatory variables, ρ is the spatial autoregressive parameter, β is a (Kx1) vector of regression coefficients, **u** is an (418x1) vector of error terms, that is assumed to follow a spatial autoregressive process, with λ as the spatial autoregressive coefficient for the error lag **Wu**, and $\boldsymbol{\varepsilon}$ is (418x1) vector of innovations or white noise error. A row standardized queen-based contiguity weights matrix **W** is used.

Since the right-hand side spatial lag dependent variable (**Wy**) is correlated with the error term, Ordinary Least Squares (OLS) cannot give consistent estimates of the parameters of equation (4) as it stands. The reduced form of the system in (4) is non-linear in parameters and can be given by:

$$y = \left(I_n - \rho W\right)^{-1} X\beta + \left(I_n - \rho W\right)^{-1}\left(I_n - \lambda W\right)^{-1} \varepsilon \tag{5}$$

Equation (5) cannot be estimated consistently by OLS either.

Thus, the parameters of the model given in (4) are estimated using efficient GMM method by following Kelejian and Prucha's (1998) procedure. In order to define the GMM estimator, equation (4) is first rewritten as follows:

$$\mathbf{y} = \mathbf{Z}\boldsymbol{\delta} + \mathbf{u} \qquad (6)$$

With

$$\mathbf{u} = \lambda \mathbf{W} \mathbf{u} + \boldsymbol{\varepsilon}$$

where $\mathbf{Z} = (\mathbf{X}, \mathbf{W}\mathbf{y})$ and $\boldsymbol{\delta} = (\boldsymbol{\beta}', \boldsymbol{\rho}')'$.The GMM method identifies $\boldsymbol{\delta}$ by a moment condition which is the orthogonality between the set of instruments **H** and the error term **u** given by:

$$E(\mathbf{H}'\mathbf{u}) = \mathbf{0} \qquad (7)$$

where **H** is defined as a subset of the linearly independent columns of $(\mathbf{X}, \mathbf{WX}, \mathbf{W^2X})$. It is assumed that the elements of **H** are uniformly bounded in absolute value. Besides, **H** is full column rank non-stochastic instrument matrix (see Kelejian and Prucha (1999) for the description of its prosperities). The GMM estimator is given by:

$$\hat{\boldsymbol{\delta}} = \left(\overline{\mathbf{Z}}_{(\hat{\lambda})}{}'\overline{\mathbf{Z}}_{(\hat{\lambda})}\right)^{-1} \overline{\mathbf{Z}}_{(\hat{\lambda})}{}'\mathbf{y}_{(\hat{\lambda})} \qquad (8)$$

where $\overline{\mathbf{Z}}_{(\hat{\lambda})} = \mathbf{P}_H\left(\mathbf{Z} - \hat{\lambda}\mathbf{WZ}\right), \mathbf{y}_{(\hat{\lambda})} = \mathbf{y} - \hat{\lambda}\mathbf{Wy}$ and $\mathbf{P}_{\mathrm{H}} = \mathbf{H}(\mathbf{H}'\mathbf{H})^{-1}\mathbf{H}'$. This is the result of the third step in the three step generalized moment procedure suggested by Kelejian and Prucha. In the first step, the parameter vector $(\boldsymbol{\delta})$ consisting of betas and rho $[\beta', \rho']$ is estimated by two stage least squares (2SLS) using the instrument matrix **H** that consists of a subset of $\mathbf{X}, \mathbf{WX}, \mathbf{W^2X}$, where **X** is the matrix that includes all control variables in the model, and **W** is a weight matrix. The disturbance term in the model is computed by using the estimates for betas and rho (ρ) from the first step. In the second step, this estimate of the disturbance term is used to estimate the autoregressive parameter lambda (λ) using Kelejian and Prucha's generalized moments procedure. In the third step, a Cochran-Orcutt-type transformation is done by using the estimate for lambda (λ) from the second step to account for the spatial autocorrelation in the disturbance. The GS2SLS estimators for betas and rho (ρ) are then obtained by estimating the transformed model using $\left[\mathbf{X}, \mathbf{WX}, \mathbf{W}^2\mathbf{X}\right]$ as the instrument matrix as given in equation (8).

Data Types and Sources

The model is estimated using cross-sectional data for Appalachian counties. Descriptive statistics of the variables of the model is given in Table 1**.** The dependent variable is direct local government expenditure per capita. The data for the direct local government expenditure comes from U.S. Bureau of Census. Population data from Bureau of the Census and estimates are used to calculate the per capita local government expenditures.

Table 1: Descriptive Statistics

Variables	Description	Mean	Std Dev	Minimum	Maximum
DGEX02	Direct Local Gov. Expenditure per Capita, 2002	7.84232	0.4929	6.6399	12.54322
WDGEX02	Spatial Lag of DGEX02	7.84624	0.2193	7.3985	8.96555
POPD	Population Density, per Square mile,2000	4.28811	0.9115	1.846	7.74918
POP5_15	Percent of Population of School Age,2000	2.92443	0.12	2.1748	3.22287
POP>65	Percent of Elderly population,2000	2.64571	0.2027	1.5476	3.20275
DFEG	Per capita Grants from Higher Gov'ts,2002	7.98688	0.3758	6.9829	10.1766
PCTAC	Per Capita Personal Income Tax,2000	5.91452	0.5299	4.5074	7.42253
PCPTAX	Per Capita Property Tax,2000	5.5236	0.616	3.912	7.36265
LTD	Long-term Debt by Local Gov'ts,2002	11728.4	71189.1	0	1368142

Direct federal government expenditure and grants per capita (DFEG), per capital local income tax (PCTAX), property tax per capita (PCPTAX), long-term debt (LTD), population density (POPD), percent of population between 5 and 17 years old

(POP15_17), and percent of population above 65 years old (POP_65) are included in the model as the conditioning variables. All these variables are obtained from U.S. Bureau of the Census. Grants and income taxes variables are measures of the resources available to local governments. Population density is measured as the ratio of county population to total county land area in square miles. It is included in the model in order to capture the possibility of potential congestion effects or economies of scale in the provision of local public services. The demographic variables, POP5_17 and POP_65, are included to account for the impacts of variation in age structures on the demand for local public services in the county.

Empirical Results and Analysis

Table 2 presents the results from OLS, Maximum Likelihood, and Generalized Spatial Two-Stage Least Squares (GS2SLS) estimation of (3b), (3c), (3d) and (6), respectively. Direct local government expenditure per capita of Appalachian counties for 2002 is used as the dependent variable. The exogenous variables of the models are for 2000. Since all the variables are measured in logs, the coefficients are interpreted as elasticites. The weights matrix used is queen-based contiguity spatial weights matrix.

Column 2 of Table 2 presents the OLS estimation of the restricted model (rho=0 and lambda = 0) or the conventional linear model of local public services determination. This model is used to compute the test statistics for spatial dependence which are summarized in Table 3 **(see also Maps 1 & 2 in appendix)**. The results for the spatial lag and for the spatial error model are given in column 3 and column 4 of Table 2, respectively. The fit of the model is increased when spatial effects are included. The proper measures of fit are the Log-Likelihood, Akaike Information Criterion (AIC), and

TABLE 2: Regression Results (Dependent Variable: Direct Local Government Expenditure Per Capita)

	Non Spatial Model OLS Est.	Spatial Lag Model LM Estimation	Spatial Error Model LM Estimation	Spatial Lag with Spatial Error Model GS2SLS Estimation
RHO (ρ)	-	0.265*** (0.058)	-	-0.113 (0.174)
LAMBDA(λ)	-	-	0.410*** (0.061)	0.125*** (0.008)
CONSTANT	2.992*** (0.508)	1.456** (0.592)	3.210*** (0.522)	5.195*** (1.650)
POPD	0.013 (0.015)	0.013 (0.015)	0.016 (0.016)	0.099*** (0.030)
POP5_17	0.399*** (0.112)	0.346*** (0.108)	0.305** (0.120)	0.030 (0.221)
POP_65	0.104* (0.062)	0.079 (0.060)	0.080 (0.063)	-0.076 (0.123)
DFEG	0.108*** (0.031)	0.117*** (0.030)	0.107*** (0.030)	0.197*** (0.060)
PCTAX	0.257*** (0.054)	0.261*** (0.052)	0.300*** (0.061)	0.445*** (0.107)
PCPTAX	0.065 (0.043)	0.018 (0.042)	0.041 (0.053)	-0122 (0.086)
LTD	-8.27e-008 (1.57e-007)	-9.76e-008 (1.51e-007)	-1.422e-007 (1.45e-007)	0.35e-006 (0.305e-006)
Jarque-Bera	19.35 *p=0.000*	-	-	-
Breusch-Pagan	8.78 *p=0.27*	10.88 *p=0.14*	16.02 *p=0.02*	-
Log Likelihood	37.96	47.74	57.20	-
Akaike inf. criterion	-59.91	-77.48	-98.40	-
Schwarz criterion	-27.63	-41.17	-66.12	-
Likelihood Ratio	-	19.57 *p=0.000*	38.49 *p=0.000*	-
Observations	418	418	418	418

Note: figures in brackets are standard errors. * denotes significance at 10%, ** is significant at 5%, and *** is significant at 1%.

TABLE 3: DIAGNOSTICS FOR SPATIAL DEPENDENCE

FOR WEIGHT MATRIX : **Appalachia.GAL** (row-standardized weights)

TEST	**MI/DF**	**VALUE**	**PROB**
Moran's I (error)	0.208024	7.0024957	0.0000000
Lagrange Multiplier (lag)	1	21.8573414	0.0000029
Robust LM (lag)	1	4.0357158	0.0445468
Lagrange Multiplier (error)	1	43.7157959	0.0000000
Robust LM (error)	1	25.8941704	0.0000004
Lagrange Multiplier (SARMA)	2	47.7515118	0.0000000

Schwarz Criterion (SC). Compared to that of the OLS (37.96), the Log-Likelihood has increased to 47.74 (for spatial lag) and to 57.20 (for spatial error). Both the AIC and SC in both the spatial lag and the spatial error models have decreased in similar pattern compared to the OLS, compensating the improved fit for the added variable. The fact that spatial effects really matter in the specification of a model for the determination of local public spending is further confirmed by the result of the Likelihood Ratio (LR) test. The LR test compares the null model (the restricted or no spatial effect) to the alternative (the unrestricted, either the spatial lag or the spatial error) model. It is distributed as χ^2 with one degree of freedom. The significant values of 19.57 and 38.49 confirm the strong significance of the autoregressive coefficient for the spatial lag and the spatial error models, respectively.

The insignificant values of the Breusch-Pagan test for heteroskedasticty in the error terms of the models also suggest that heteroskedasticty is not a problem. The error terms, however, are not normally distributed as confirmed by the Jarque-Bera test statistic. Given the finite sample data, it is hard to make inferences based on the maximum likelihood estimators. Thus, discussion is based only on GS2SLS coefficients.

The results of the GS2SLS estimation of the full model (6) are presented in column 5 of Table 2. When both the spatial effects (spatial lag and spatial error) are included together in the full model, the spatial lag effect becomes negative and insignificant (rho = -0.113) indicating that it just captures spuriously the spatial error effect in the spatial lag model. The degree of correlation in the level of direct local public expenditure per capita between neighboring counties is measured by rho (p). This copy-cat effect indicates that, although insignificantly, an increase in county j's neighbors expenditure leads to a decrease in county j's expenditures. This could be because of the positive spillover effects of public services. Commuters, for example, use public transportation, roads, recreation and cultural facilities in their working communities. Air pollution controls and sewage treatment enhance the environmental quality of neighboring jurisdictions, and educational and job training expenditures may lead to productivity gain in workplaces outside the community. The existence of such positive spillover effects in neighboring counties reduces the need to invest in similar public services. This result also indicates that the "political agency – yardstick competition" model is not relevant in explaining the spatial interactions among local governments in Appalachia during the study period. The spatial error effect, however, is still positive and highly significant (lambda = 0.125). This spatial effect measures the degree of correlation between neighbors' errors. This could simply be due to the fact that local governments are hit by spatially auto-correlated shocks because of the geographic similarities of counties in Appalachia.

The empirical results indicate a positive and significant effect of population density on local public expenditure per capita, indicating that per capita local public expenditure increases with population density (absence of economies of scale in the provision of local public services). This could be because of the fact that the threshold to exploit economies of scale in the provision of local public services has not yet reached. The elasticity is about 0.10. The coefficients for the demographic variables (POP5_17) and (POP_65) are insignificant although they have the expected signs. Normally, the proportion of school-age population is expected to increase local public expenditures whereas the proportion of the elderly is expected to decrease it.

Direct federal government expenditure and grants (DFEG) has a statistically significant effect on the level of local public expenditures. The estimated coefficient for DFEG is 0.20. This is what is commonly called as ‘flypaper effect’ in the literature. The effect of per capita income tax is found to be statistically significant. The elasticity is about 0.44. Long-term debt and per capita property tax, however, are not significant.

Conclusions and Implications

To investigate the impacts of spatial spillover effects in the determination of local public spending, a spatial autoregressive model with spatial autoregressive disturbance is developed. The model is estimated by Generalized Spatial Two-Stage Least Squares (GS2SLS) estimator using county-level data from Appalachia for the 2002 fiscal year. The conventional (non spatial) model of local public expenditure determination is also estimated by Ordinary Least Squares estimator and the spatial lag as well as the spatial error models by Maximum-Likelihood estimator.

On the basis of the OLS estimates, test statistics are developed in order to test the existence of spatial lag or spatial error dependences in local public expenditure determination. Moran’s I test statistic indicates the existence of spatial dependence in our data set. The Lagrange Multiplier (LM) test statistics further indicate that the spatial error model is more appropriate than Moran’s I test statistic. Given the finite date set, it is hard to consistently estimate this model by maximum likelihood estimator because the basic assumption upon which the maximum likelihood estimation is based, normally distributed error terms, is not fulfilled as indicated by the Jarque-Bera test statistic. Since the GS2SLS estimator does not require a normal distribution on the error terms, it is more efficient under this circumstance. Thus, analysis is based on the GS2SLS coefficients.

It is found that counties in the study area are not engaged in strategic interaction in the determination of local public expenditures. The coefficient for the spatial lag dependent variable is negative but insignificant, indicating the ‘copy-cat’ effect is not important. This result also indicates that the “political agency – yardstick competition” model is not relevant in explaining the spatial interactions among local governments in Appalachia during the study period. The coefficient for the spatial error variable is, however, positive and highly significant. This show the positive interdependences in local public expenditures through spatial error process, which could simply be because the local governments at the county-level in Appalachia are hit by a common shock.

Coefficient estimates for the conditioning variables are similar to those found in the literature. According to the empirical results, population density has positive and significant effect on local public expenditure per capita. It is also found a positive and strong ‘flypaper effect’ and a positive and significant effect of per capita income taxes on per capita local public expenditure. The effects of the demographic variables and the long-term government debt variable, however, are found to be insignificant.

The results are generally consistent with the findings of previous literature, although most U.S. studies are done at the state level. The application of county-level data to test the expenditure spillover effects in the determination of local public expenditure is one of the contributions of this study. Knowledge of how governments at the county-level behave with respect to the provision of local public services is vital for fiscal sustainability. It is also essential to pool resources in order to finance the provision of local public services with significant spillover effects.

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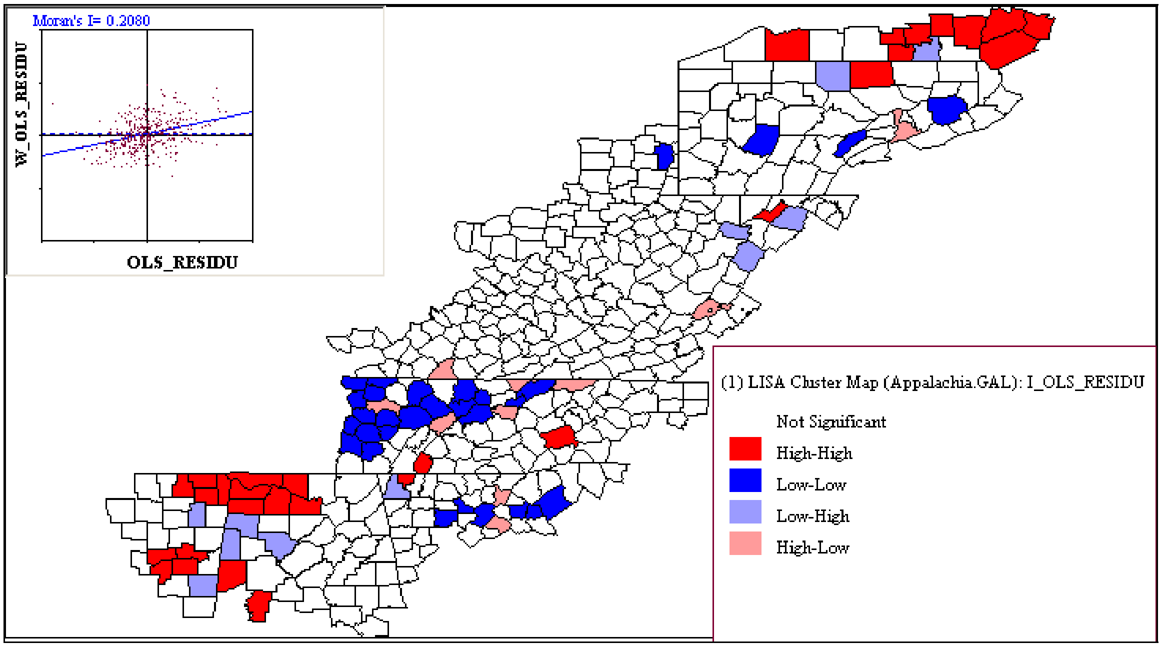
Map 1: Global Spatial Autocorrelation and Local Indicator of Spatial Autocorrelation: Residual



Map 2: Global Spatial Autocorrelation and Local Indicator of Spatial Autocorrelation: Spatial Lag Dependent Variable