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County-level determinants of local public services in Appalachia: a multivariate spatial autoregressive model approach

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Abstract We develop a multivariate spatial autoregressive model of local public expenditure determination based on the maximization of a strictly quasi-concave community utility function. The existence of spatial interdependence is tested for both the spatial error and spatial lag model. The full model is estimated by efficient GMM following Kelejian and Prucha (J Real Estate Finan Econ 17(1):99–121, 1998). The results indicate significant spillover effects among local governments with respect to spending on public services. The OLS estimates of the conventional (non-spatial) model and the corresponding maximum likelihood estimates of the spatial lag and the spatial error models are presented for comparison purposes. The GMM estimates are found to be more efficient.

JEL Classification C31 · O1 · R15 · R51

1 Introduction

Public–private sector interactions are common. For example, to create jobs, governments offer businesses incentives (Gabe and Bell 2004) and government tax, spending,

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and regulatory policies affect private location and investment decisions (Bartik 1991, 2003; Drabenstott 2005; Bell et al. 2005). Level and composition of public expenditures and revenues are determined by local economic, demographic, and political characteristics (Inman 1987; Duffy-Deno and Eberts 1991; Fisher and Navin 1992; Falch and Rattso 1997; Merrifield 2000).

Fiscal transfers from higher level governments to lagging places also influence local public expenditures.[1] The standard model assumes that local public expenditures differ across regions only because of differences in per capita income, population density, population, tax base, tax rates, demographic characteristics, labor market characteristics, and other socioeconomic and institutional factors, but theory and causal observation also suggest spatial dependence (Brueckner 2003; Lundberg 2006). Spatial spillovers occur because of policy interdependence or because of spatially autocorrelated shocks (Case et al. 1993).

The tax competition model accounts for spatial interdependence because local governments finance spending through taxing mobile capital. Therefore, their tax base depends on their own as well as other jurisdictions' tax rates, and strategic interactions result (Wildasin 1986; Wilson 1999; Brett and Pinkse 2000; Brueckner and Saavedra 2001; Revelli 2005; Hayashi and Boadway 2001; Fredriksson et al. 2004). Figlio et al. (1999) find that decentralized welfare benefit setting lead states to respond more sharply to decreases in neighbor's benefits than to increases (asymmetric response). In California, city land development restrictions raise land rent in its own and in neighboring jurisdictions. The positive externalities encourage strategic interaction in growth control decisions (policy interdependence) (Brueckner 1998).

Externality approach (spillover effect) models note that many public service expenditures also impact neighboring jurisdictions (Case et al. 1993; Murdoch et al. 1993; Ladd 1992; Revelli 2005). For example, Case et al. (1993) find that states' per capita expenditures are positively and significantly influenced by their neighbors' spending. Similarly, Kelejian and Robinson (1993) find that county police expenditures are positively and significantly influenced by neighboring counties' expenditures on police.

A third alternative is the "political agency—yardstick competition" model, which assumes that voters in one jurisdiction use the performance of other governments as a yardstick to evaluate their government. Thus, local governments do not want to deviate "too far" from other jurisdictions and mimic each other's behaviors. Besley and Case (1995) test this model and find that a state's tax changes are positively and significantly related to neighbors' tax changes.

The model developed in Sect. 4 incorporates expenditure spillovers into the conventional model. We hypothesize that county j's public spending also depends on its neighbors' spending. Neighbors are defined as counties that share common borders.

The remainder of this study is organized into seven sections. Section 2 describes the study area. A literature review of determinants of local public expenditures follows

[1] Drabenstott (2005, 2006), Glasmeier and Wood (2005), and Markusen and Glasmeier (2008) review how the US federal government supports lagging places. Dall'erba and Gallo (2008) document the role of the European Structural Funds as an instrument to support the development of the peripheral and less prosperous regions of the European Union.

in Sect. 3. Section 4 develops the econometric models and test statistics for spatial dependencies and to distinguish between spatial lag and spatial error dependencies. Model specifications and estimation issues are discussed in Sect. 5. The data used are presented in Sect. 6, followed by the empirical results in Sect. 7. The article ends with Sect. 8, conclusions and implications.

2 The study area

Appalachia covers some 200,000 square miles from New York State to Mississippi. It encompasses 418 counties, including 8 independent cities in Virginia, all of West Virginia and parts of twelve other states (Fig. 1). Historically, Appalachians suffer from high rates of unemployment and poverty, low per capita income, low educational

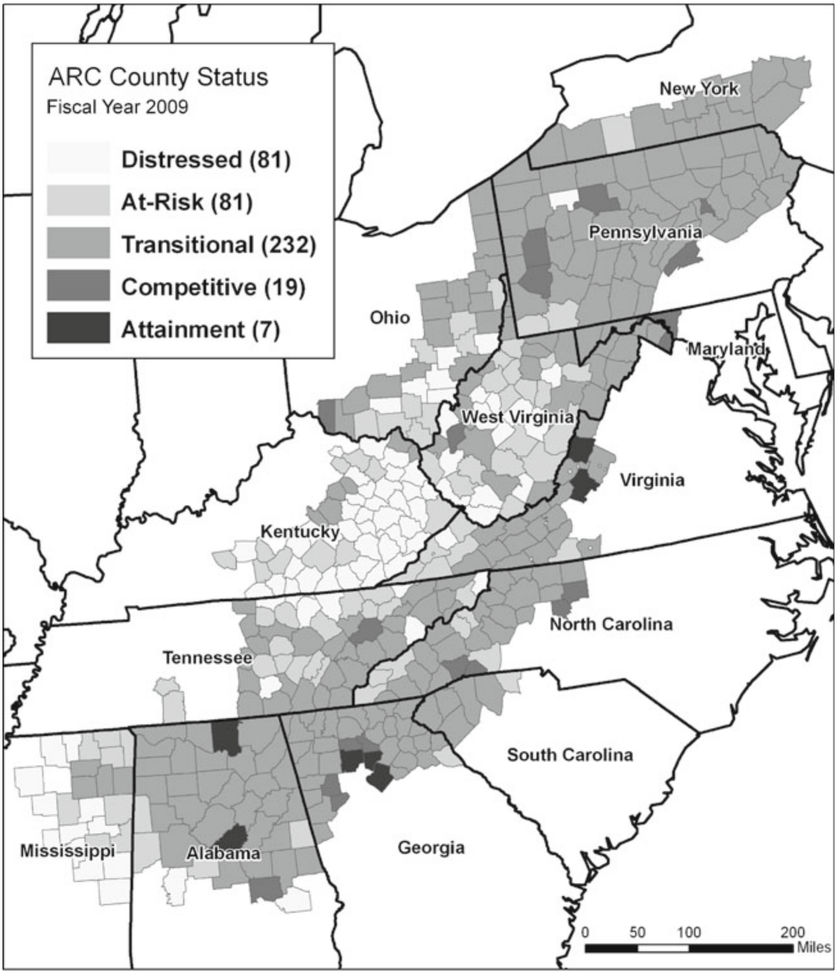

Fig. 1 Appalachian counties by their economic status, *Source*: based on Appalachian Regional Commission (2009)

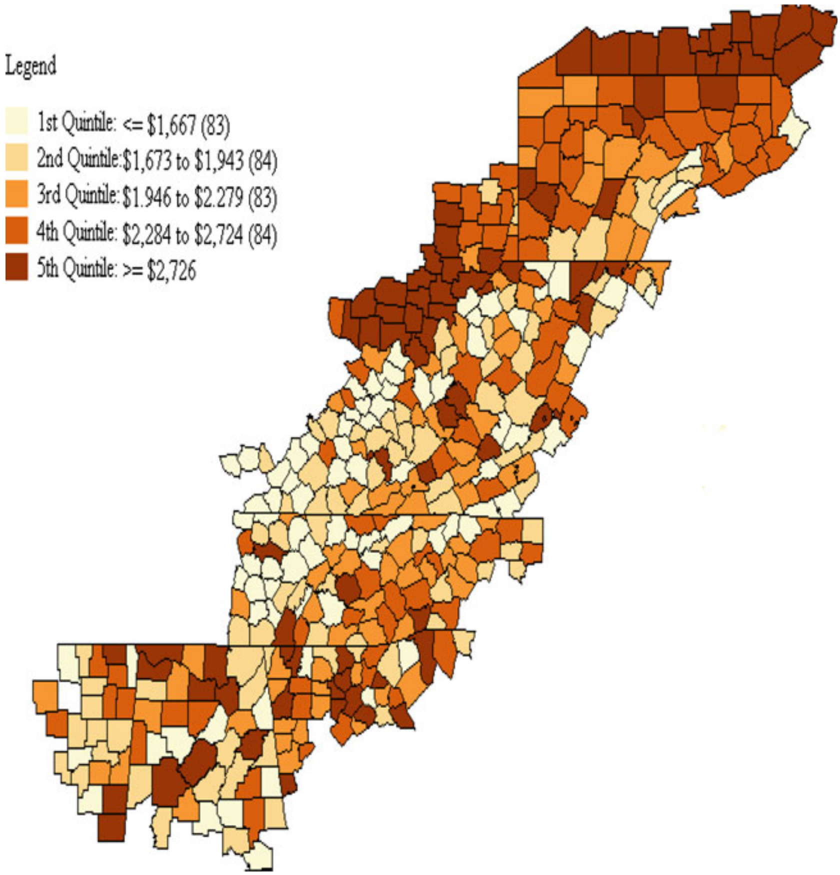

Fig. 2 Quintile map of total direct government expenditure per capita in Appalachia, in dollars, 2002

achievement, and significant isolation in the Appalachian Mountains (Appalachian Regional Commission 1998). Thus, the region remains a symbol of poverty in the midst of American prosperity. In the 1960s, when the Appalachian Regional Commission (ARC) was established (Pollard 2003), per capita income in Appalachia was about 77 percent of the US average in 1960, and 31.1 percent of its residents lived in poverty, compared to 22.1 percent of all Americans (Wood and Bischak 2000). Per capita income reached 81 percent and 84 percent of the national average in 1989 and 1999, respectively, but had not reached parity with the rest of the country by 2007.

Since its inception in 1965 until 2008, the ARC invested $12.19 billion (Appalachian Regional Commission 2008). Central Appalachia receives substantially higher per capita federal funding than northern or southern Appalachia (Bagi et al. 1999, 2002). By contrast, local public expenditures per capita are significantly lower in central Appalachia, the southwest parts of Appalachian Mississippi and Alabama, and West Virginia (northern Appalachia), where the majority of the distressed counties are clustered (see Fig. 2).

3 County-level determinants of local public services

Many cross-sectional studies are trying to explain regional variations in per capita local public expenditures (Hawley 1957; Brazer 1959; Hirsch 1959; Hansen 1965; Henderson 1968; Borcherding and Deacon 1972; Ohls and Wales 1972; Bergstrom and Goodman 1973; Bergstrom et al. 1982; Fisher and Navin 1992). Borcherding and Deacon (1972) estimate demand functions for eight public services, while Ohls and Wales (1972) estimate demand and cost functions for three broad categories of state and local public expenditures. Bergstrom and Goodman (1973) estimate the demand functions for three categories of municipal services. These studies use the median voter model. Bergstrom et al. (1982) estimate demand for local public goods without recourse to the median voter. By combining individuals' survey responses to questions about whether they want more or less of various public goods with observations of their incomes, tax rates, and actual spending in their home communities, they are able to estimate demand functions.

Several studies show that the income elasticity of local public expenditures is positive and significant, while the tax price elasticity is 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). Randolph et al. (1996), Canning and Pedroni (1999), and Fay (2000) find that spending on services such as transport and communications responds primarily to per capita income changes. Similarly, various studies show estimates of income elasticity greater than one for merit goods such as health, education, and housing (Leu 1986; Newhouse 1987; Gerdtham et al. 1992; Falch and Rattso 1997; Snyder and Yachovlev 2000; Hashmati 2001). Duffy-Deno and Eberts (1991) analyze the linkage between public infrastructure and regional development and conclude that per capita real personal income has a positive and statistically significant contemporaneous effect on local public investment.

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 expenditures (Painter and Bae 2001). Net migration changes population size, density, and composition and impacts public revenues as well as demand for public goods (Ahlin and Johansson 2001; Curie and Yelowitz 2000; Di Matteo and Di Matteo 1998; Fisher and Navin 1992; Hagemann and Nicoletti 1989; Heller et al. 1986; Henderson 1968; Marlow and Shiers 1999). Significant net out-migration can cause excess capacity. If out-migration also depresses property values and tax collections, the overall fiscal health of the community suffers (Charney 1993).

4 Methodology

4.1 Model formation

We use the median voter model to analyze the determinants of the demand for local public services or the expenditures for local public services (Borcherding and Deacon 1972; Bergstrom and Goodman 1973). This model assumes that utility-maximizing citizens elect officials by majority rule; the size of the public sector is the only issue to be decided. Citizens know the costs and benefits of government expenditures. Hence, the median voter supports candidates who offer the most beneficial combination of services and taxes. Aggregating over individuals, a community preference (utility) function can be generated.

Based on these assumptions, the model takes the form:

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

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

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

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

The community utility function (Eq. 1a) is strictly quasi-concave over local public services (G), community income tax rate (INCTAXR) and also depends on socio-economic, demographic, and amenity variables (**X**). The local government expenditure function (DGEX) (Eq. 1b) depends on G and other local government functions (GF). The local government revenue function (Eq. 1c) depends on the community income tax rate (INCTAXR), the tax base—personal income tax (PCTAX), property tax (PCPTAX), and intergovernmental grants (DFEG), and a vector of socioeconomic, demographic, and amenity variables (**X**). Finally, the government budget constraint, (Eq. 1d), requires local government to spend (DGEX) within their means (REV). Maximizing the utility function (Eq. 1a) with respect to G, GF, and INCTAXR, subject to Eqs. 1b–1d, gives the local public services demand function.

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

Substituting Eq. 2a into Eq. 1b yields the reduced form of the local public services demand function, which forms the basis for empirical analyses.

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

We use a multiplicative (log-linear) model, which implies a constant-elasticity form for the equilibrium conditions in Eq. 2b. A log-linear representation of this condition can be expressed as:

$$\begin{aligned}\mathrm{DGEX}_{it} &= (\mathrm{PCTAX}_{it})^{a} \times (\mathrm{PCPTAX}_{it})^{b} \times (\mathrm{DFEG}_{it})^{c} \times \prod_{k=1}^{K} (\mathbf{X}_{kit})^{x_k} \\ &\rightarrow \ln(\mathrm{DGEX}_{it}) = a \ln(\mathrm{PCTAX}_{it}) + b \ln(\mathrm{PCPTAX}_{it}) + c \ln(\mathrm{DFEG}_{it}) \\ &\quad + \sum_{k=1}^{K} x_k \ln(\mathbf{X}_{kit})\end{aligned} \tag{3a}$$

a, b, c and $x_k, k = 1, \ldots, K$ are exponents; K is the total number of variables included in vector **X**. The reduced form is also log-linear; hence, estimated coefficients represent elasticities. Duffy-Deno (1998) and MacKinnon et al. (1983) show that for models involving population and employment densities, a log-linear is more appropriate than a linear specification.

Equation 3b presents the empirical model that corresponds to Eq. 3a:

$$\begin{aligned} \text{DGEX02} = \beta_1 + \beta_2\text{POPD} + \beta_3\text{POP5\_17} + \beta_4\text{POP} > 65 + \beta_5\text{DFEG} \\ + \beta_6\text{PCTAX} + \beta_7\text{PCPTAX} + \beta_8\text{LTD} + \varepsilon \end{aligned} \tag{3b}$$

4.2 Spatial model

Data that include a spatial component may display dependence between observations at each point in time and parameter variations between locations (spatial heterogeneity) (Elhorst 2003). Spatial autocorrelation can result from policy interdependence, that is, spillover effects across jurisdictions. For example, commuters use public transportation, streets, recreation, and cultural facilities where they work, not only where the live. Similarly, environmental controls enhance the quality-of-life, and education and job training contribute to productivity gains, beyond the community implementing such programs.

Spatial dependence means that observations at one location also reflect values of observations at other locations (Anselin 1988, 2003). There are two possible sources of spatial autocorrelation—lag dependence, which reflects true spatial interaction of variables across spatial units, and error dependence because, for example, counties are political-administrative constructs that do not spatially coincide with the variable of interest. Spatial dependence may be modeled by spatially lagged dependent variables or spatial error autocorrelation. Spatial dependence in the dependent variable (substantive spatial dependence) means that employment growth in one county depends on employment growth in neighboring counties and model specification is motivated by theory (Anselin 2006a,b; Fingleton and López-Bazo 2006). Spatial dependence in the disturbance term implies that the values of the residuals in one county depend on the residuals in neighboring counties (nuisance spatial dependence). Spatial error specifications are motivated to deal with correlation problems that result from the cross-sectional, not from the spatial nature of the model (Anselin 2006a,b).

With spatial dependence, model estimation requires the identification of county's neighbors through an $N \times N$ spatial weights matrix, W. The diagonal elements are zero. The off-diagonal elements, $\boldsymbol{w}_{\mathbf{k},\mathbf{l}}$, represent neighbor relations between observations k and l. There is little guidance for choosing spatial weights (Anselin 2006a,b). A common method is to use geographic criteria, such as having a common boundary (contiguity) or points being within a critical distance band:[2]

$$w_{kl} = \left\{ \begin{array}{ll} 1 & \text{if } k \text{ and } l (k \neq l) \text{ have common boundary} \\ 0 & \text{otherwise} \end{array} \right\}, \quad \text{contiguity weights matrix, or}$$

$$w_{kl} = \left\{ \begin{array}{ll} 1 & \text{if } d_{kl} \leq \overline{d} \text{ where } \overline{d} \text{ is a threshold value} \\ 0 & \text{otherwise} \end{array} \right\}, \quad \text{distance-based weights matrix.}$$

[2] The most common choice of spatial weights in the empirical literature is the simple contiguity matrix, followed by distanced-based weights (Abreu et al. 2005).

We use row-normalized versions of these matrices. The cut-off distance ($\bar{d}$) is 18 miles, based on an average commuting time in Appalachia of 25 min one way, or roughly 18 miles (US Census Bureau 2005).

4.3 Diagnostics for spatial autocorrelation

Perhaps, the best-known test against spatial autocorrelation is the application of Moran's I statistic to regression residuals (Anselin 2003). Given a row-standardized spatial weight matrix, **W**, Moran's I on the OLS residuals of Eq. 3b is:[3]

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

where $\boldsymbol{e}$ are the OLS residuals. Moran's I statistic is powerful in detecting misspecifications, but less helpful in suggesting alternative specifications.

Two Lagrange Multiplier tests help us distinguish between the two forms of spatial dependence. The first test, LM-Lag and Robust LM-Lag, applies when the alternative is the spatial lag model.

$$\mathrm{LM}_{(\mathrm{Lag})} = \frac{\left(\frac{e'Wy}{(e'e)/N}\right)^2}{\frac{(WXb)'M(WXb)}{(e'e)/N} + T}$$

and

$$\text{Robust LM}_{(\mathrm{Lag})} = \frac{\left[\frac{e'Wy}{(e'e)/N} - \frac{e'We}{(e'e)/N}\right]^2}{\frac{(WXb)'M(WXb)}{(e'e)/N}},$$

$\mathrm{T} = tr\left(W'W + W^2\right)$, tr denotes the trace of $M = I - X\left(X'X\right)^{-1}X'$, and b is the OLS estimate of β in Eq. 3b. The second test, LM-Error and Robust LM-Error, uses to the spatial error model as the alternative:

$$\mathrm{LM}_{(\mathrm{Error})} = \frac{\left(\frac{e'We}{(e'e)/N}\right)^2}{T}$$

and

$$\text{Robust LM}_{(\mathrm{Error})} = \frac{\left[\frac{e'We}{(e'e)/N} - T\left(\frac{(WXb)'M(WXB)}{(e'e)/N} + T\right)^{-1}\frac{e'Wy}{(e'e)/N}\right]^2}{T\left[1 - T\left(\frac{(WXb)'M(WXb)}{(e'e)/N} + T\right)^{-1}\right]}.$$

[3] We used both contiguity and distance-based weights matrices, and the existence of spatial dependence in our data set is confirmed using either type. Since the strength and nature of the spatial dependencies are similar, we present our results only using the contiguity weights matrix.

Table 1 Diagnostics for spatial dependence

Test	MI/DF	Value	Prob
Moran's I (error)	0.208024	7.002496	0.0000000
Lagrange multiplier (lag)	1	21.857340	0.0000029
Robust LM (lag)	1	4.035716	0.0445468
Lagrange multiplier (error)	1	43.715800	0.0000000
Robust LM (error)	1	25.894170	0.0000004
Lagrange multiplier (SARMA)	2	47.751510	0.0000000

Both sets of test statistics have a χ^2 distribution with one degree of freedom. Robust versions of the statistics are considered only when the standard versions are significant.

5 Estimation methods

Moran's I (Table 1) indicates spatial autocorrelation.[4] Therefore, the Lagrange Multiplier test statistics from Sect. 4.3 are used. The ML-Lag and ML-Error are highly significant. We reject the null hypothesis of spatial independence and consider the robust forms of the test. The Robust ML-Error is more significant than the Robust ML-Lag ($p < 0.0000$ vs. $p < 0.0445$), indicating that the spatial error specification is more appropriate. Spatial error models can be estimated consistently by maximum likelihood provided the error terms are normally distributed (Case et al. 1993; Brueckner 1998, 2000; Baicker 2005; Saavedra 2000). However, the Jarque–Bera test statistic is highly significant ($p < 0.0000$); thus, we reject the null hypothesis of normally distributed error terms and MLE as an appropriate procedure.

Instrumental variables provide an alternative that does not require distributional assumptions on the error term (Kelejian and Robinson 1993; Kelejian and Prucha 1998; Lee 2003). We formulate a spatial model with autoregressive disturbances, incorporating both spatial dependencies. Estimation is by generalized spatial two-stage least squares (GS2SLS).

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

$\mathbf{u} = \lambda\mathbf{W}\mathbf{u} + \boldsymbol{\varepsilon} \cdot \mathbf{y}$ is an $(N \times 1)$ vector of direct local government expenditures per capita, $\mathbf{W}\mathbf{y}$ is the corresponding spatially lagged dependent variable for the weights matrix $\mathbf{W}$, $\mathbf{X}$ a $(N \times K)$ matrix of explanatory variables, ρ the spatial autoregressive parameter, and β a $(K \times 1)$ vector of parameters. The $(N \times 1)$ vector of error terms, $\mathbf{u}$, is assumed to follow a spatial autoregressive process; λ is the spatial autoregressive coefficient for the error lag $\mathbf{W}\mathbf{u}$, and $\boldsymbol{\varepsilon}$ is a $(N \times 1)$ vector of white noise errors. We use a row-standardized queen-based contiguity weights matrix $\mathbf{W}$.

Because $\mathbf{W}\mathbf{y}$ is correlated with the error term, OLS yields inconsistent estimates. The reduced form of the system in Eq. 4 is non-linear and cannot be estimated

[4] Inference for Moran's I is based on a random permutation procedure, which recalculates the statistic many times to generate a reference distribution. The obtained statistic is then compared to this reference distribution, and a pseudo significance level is computed.

consistently by OLS either:

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

Therefore, we use the efficient GMM method, following Kelejian and Prucha (1998) procedure. To define the GMM estimator, we rewrite Eq. 4 as follows:

$$\mathbf{y} = \mathbf{Z}\boldsymbol{\delta} + \mathbf{u} \tag{6}$$

with

$$\mathbf{u} = \lambda\mathbf{W}\mathbf{u} + \boldsymbol{\varepsilon} \quad \text{and} \quad \boldsymbol{\delta} = (\boldsymbol{\beta}', \boldsymbol{\rho}')'.$$

The GMM method identifies $\boldsymbol{\delta}$ by the moment condition of orthogonality between the set of instruments, $\mathbf{H}$, and the error term, $\mathbf{u}$**:**

$$E\left(\mathbf{H}'\mathbf{u}\right) = \mathbf{0}, \tag{7}$$

where $\mathbf{H}$ is a subset of the linearly independent columns of $\left(\mathbf{X}, \mathbf{WX}, \mathbf{W^2X}\right)$. We assume that the elements of $\mathbf{H}$ are uniformly bounded in absolute value. $\mathbf{H}$ is a full column rank non-stochastic instrument matrix (Kelejian and Prucha 1998). The GMM estimator is:

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

$\overline{\mathbf{Z}}_{(\hat{\lambda})} = \mathbf{P}_H(\mathbf{Z} - \hat{\lambda}\mathbf{WZ}), \mathbf{y}_{(\hat{\lambda})} = \mathbf{y} - \hat{\lambda}\mathbf{Wy}$ and $\mathbf{P}_{\mathrm{H}} = \mathbf{H}(\mathbf{H}'\mathbf{H})^{-1}\mathbf{H}'$. This is the result of the three-step GMM procedure. In the first step, the parameter vector ($\boldsymbol{\delta}$), consisting of betas and rho $[\beta', \rho']$, is estimated by 2SLS, using the instrument matrix $\mathbf{H}$. The disturbance term is computed using the estimates for the betas and rho (ρ) from step one. In the second step, this estimate of the disturbance term is used to estimate the autoregressive parameter lambda (λ). Third, a Cochran–Orcutt-transformation is performed, using the estimate for lambda (λ) from step two to account for the spatial autocorrelation in the disturbance. The GS2SLS estimators for the betas and rho (ρ) are obtained by estimating the transformed model, using $[\mathbf{X}, \mathbf{WX}, \mathbf{W^2X}]$ as the instrument matrix (Eq. 8) (Kelejian and Prucha 1998).

6 Data

We use cross-sectional data for Appalachian counties. Direct local government expenditures per capita are the dependent variable. Population data from the Bureau of the Census and estimates are used to calculate per capita local government expenditures (Table 2).

Direct federal government expenditures and grants per capita (DFEG), per capita local income tax (PCTAX), property tax per capita (PCPTAX), long-term debt (LTD),

Table 2 Descriptive statistics

Variables	Description	Mean	SD	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 of local gov'ts, 2002	11,728.4	71,189.1	0	1,368,142

population density (POPD), percent of the population between 5 and 17 (POP15_17), and percent of the population over 65 years old (POP $>$ 65) are included as conditioning variables; they are also from the US Bureau of the Census. Grants and income taxes measure the resources available to local governments. Population density is the ratio of county population to total county land area. It is included 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 influence of age composition on demand for local public services.

7 Results and analysis

Table 3 contains the results from the OLS, MLE, and Generalized Spatial Two-Stage Least Squares (GS2SLS) procedures. Values for the dependent variable are for 2002, and the values for the exogenous variables are for 2000. All variables are in logs, and all coefficients are interpreted as elasticities. The weights matrix is a queen-based contiguity spatial weights matrix.

Column 2 of Table 3 presents the OLS estimates of the conventional linear model ($\rho = 0$, $\lambda = 0$). We use it to compute test statistics for spatial dependence (Table 1).[5] Results for the spatial lag and spatial error models are in columns 3 and 4 of Table 3. The fit of the model improves when spatial effects are included. The measures of fit are the log likelihood, Akaike information criterion (AIC), and Schwarz criterion (SC). The log likelihood is 37.96 for OLS, 47.74 for spatial lag, and 57.20 for spatial error. The AIC and SC follow the same pattern.

[5] LM SARMA is a two-directional LM test relates to higher order alternative of a model with both spatial lag and spatial error terms. In addition to detecting the higher order alternative, since this test has a high power against one-directional alternatives, it tends to be significant when either the lag or the error model is the proper alternative, but not necessarily the higher order alternative (Anselin et al. 1996). Thus, the test is included for completeness only, since it is not that useful in practice.

Table 3 Regression results (dependent variable: direct local government expenditures 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)	−0.122 (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

Figures in brackets are standard errors. *, **, and *** denote statistical significance levels at 10, 5, and 1 percent, respectively

The likelihood ratio test compares the no-spatial-effect model to the unrestricted, spatial lag or spatial error, model. It has a χ^2 distribution with one degree of freedom. The 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 insignificance of the Breusch–Pagan test means that heteroskedasticity in the error terms is not a problem. As noted earlier, however, the errors are not normally distributed. Given the finite sample data, it is difficult to draw inferences based on the maximum likelihood estimators. Therefore, further discussion is based on GS2SLS coefficients only.

The results of the GS2SLS estimation of Eq. 6 are presented in column 5 of Table 3. When spatial lag and spatial error effects are modeled together, the spatial lag effect becomes negative and insignificant ($\rho = -0.113$), indicating that it captures the spatial error effect in the spatial lag model. The degree of correlation between levels of direct local public expenditures per capita between neighbors is measured by rho (ρ). The result, although statistically insignificant, indicates that an increase in one county's expenditure leads to a decrease in the expenditures of its neighbors. As noted above, spillover effects could decrease pressure on neighboring counties to provide such services and suggests that the "political agency—yardstick competition" model is not relevant for explaining spatial interactions between local governments in Appalachia during the study period. The spatial error effect, however, is positive and highly significant ($\lambda = 0.125$); it measures the degree of correlation between neighbors' errors. It could be that governments are being hit by spatially autocorrelated shocks because of similarities shared across Appalachia.

The results indicate a positive and significant effect of population density on the dependent variable, which suggests a lack of economies of scale. Maybe the threshold for exploiting economies of scale has not yet been reached. The elasticity is 0.10. The coefficients for the demographic variables (POP5_15) and (POP $>$ 65) have the expected signs (positive of POP5_15, negative for POP $>$ 65), but are insignificant (Marlow and Shiers 1999; Ahlin and Johansson 2001). Direct federal government expenditures and grants (DFEG) significantly affect the level of local public expenditures. The estimated coefficient for DFEG is 0.20. This is commonly referred to as "flypaper effect". The effect of the per capita income tax is found to be statistically significant with an elasticity of 0.44.

8 Conclusions and implications

We develop a spatial autoregressive disturbances model and investigate the impacts of spatial spillovers on the determination of local public spending at the county level in Appalachia. A non-spatial model of local public expenditure determination is estimated by OLS, and the spatial lag and the spatial error versions are estimated by maximum likelihood. Statistics to test for spatial lags and/or spatial errors in local public expenditure determination are based on the OLS estimates. Moran's I statistic indicates spatial dependence. We cannot consistently estimate the spatial autoregressive disturbances model by maximum likelihood because the error terms are not normally distributed. The GS2SLS estimator requires no distributional assumption on the error terms and is, therefore, more efficient under these conditions.

We find that counties in the study area are not engaged in strategic interaction in determining local public expenditures. The coefficient for the spatial lag–dependent variable is negative but insignificant, indicating that the "copy-cat" effect is not relevant. This result also indicates that the "political agency—yardstick competition" model is not relevant in explaining spatial interactions during the study period. The coefficient for the spatial error variable is, however, positive and highly significant. This shows the positive interdependence in local public expenditures through a spatial error process, which could simply be because county-level governments in Appalachia are affected by common trends.

Estimates for the conditioning variables conform to those in the literature, although most previous US research is at the state level. Thus, population density has a positive and significant effect on local public expenditures per capita. There is also a positive and strong "flypaper effect" and a positive and significant effect of per capita income taxes on per capita local public expenditures. The effects of the demographic variables and the long-term government debt variable, however, are insignificant.

The use of county-level data 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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