doi:10.1111/j.1435-5957.2011.00388.x

Employment, income, migration and public services: A simultaneous spatial panel data model of regional growth*

Gebremeskel H. Gebremariam[1], Tesfa G. Gebremedhin[2], Peter V. Schaeffer[2], Tim T. Phipps[2], Randall W. Jackson[3]

[1] Department of Economics, Virginia Tech, Blacksburg, VA 24061, USA (e-mail: gebre@vt.edu)
[2] Division of Resource Management, Davis College, West Virginia University, P.O. Box 6108, Morgantown, WV 26506-6108, USA (e-mail: tgebrem@wvu.edu, pschaef@wvu.edu, tim.phipps@mail.wvu.edu)
[3] Regional Research Institute, West Virginia University, P. O. Box 6825, Morgantown, WV26506-6825, USA (e-mail: randall.jackson@mail.wvu.edu)

Received: 11 November 2008 / Accepted: 6 June 2011

Abstract. We estimate a regional spatial panel simultaneous-equations growth model, using a five-step new estimation strategy that generalizes an approach outlined in Kelejian and Prucha. The study region consists of the 418 Appalachian counties 1980–2000. Estimates show feedback simultaneities among the endogenous variables, conditional convergence with respect to the respective endogenous variables, and spatial autoregressive lag and spatial cross-regressive lag effects with respect to the endogenous variables. A key policy conclusion is that sector-specific programs should be integrated and harmonized and that regionally differentiated development policies may yield greater returns than treating all locations the same.

JEL classification: C13, C31, C33, R11, R12, R23, R58

Key words: Simultaneous spatial panel data model, regional growth variation, spatial autoregressive and cross-regressive lags, FGS3SLS

1 Introduction

The regional economic growth literature has investigated the neoclassical convergence hypothesis that over time per capita income in poorer regions tends to catch up with that in richer regions because of factor mobility. Studies by Barro and Sala-i-Martin (1992) and Barro (2004) for US states, Japanese prefectures and European countries, and by Persson (1997) and Aronsson et al. (2001) for Swedish counties, found evidence of income convergence. Similar studies

* This research was supported by USDA Hatch funds appropriated to the West Virginia Agricultural and Forestry Experiment Station, Davis College of Agriculture, Natural Resources and Design, West Virginia University. We gratefully acknowledge the comments and suggestions of this journal's anonymous referees, which have resulted in significant improvements. The usual caveat applies.

by Arbia et al. (2005) of 92 Italian provinces (1970–2000), Ertur et al. (2006) of 138 European regions (1980−1995), and Rappaport (1999) of US counties (1970−1990), also found convergence. By contrast, Glaeser et al. (1995) did not discover significant evidence of income convergence between US cities. Higgins et al. (2006) and Young et al. (2007) studied per capita income net of government transfers in US counties in all fifty states from 1970 to 1998 and found a speed of convergence between 6 to 8 per cent, significantly above the approximately 2 per cent typically reported. Higgins et al. (2006) also found a much faster speed of convergence in counties in southern than in northeastern states.

The development of geographic information systems (GIS) has spurred new ways of thinking about the role of space or geography. Regional disparities have received renewed emphasis in the endogenous growth theory and new economic geography (NEG) literatures (Romer 1986, 1990; Lucas 1988; Krugman 1991a) which seek to explain the location of firms, agglomerative processes, and the uneven spatial division of economic activities between regions. Krugman's (1991a) seminal work has stimulated much additional research (e.g., Krugman and Venables 1995; Fujita et al. 1999; Martin and Ottaviano 1999, 2001; Fujita and Thisse 2002, 2003, 2006; Baldwin and Martin 2004; Fujita and Mori 2005). Two main insights of the NEG literature on the relationship between infrastructure, economic growth, and agglomeration have recently evolved. First, there is a trade-off between growth and regional equality because both agglomeration and growth are fostered by improved infrastructure in rich (core) regions, but hampered by improved infrastructure in poor (remote) regions. Second, improved transport and communication infrastructure between core and peripheral regions fosters not only growth but also agglomeration. Therefore, better interregional connections may lead to firm relocation and less employment in peripheral areas. As long as the growth effect is strong enough, increased agglomeration does not have to lead to the impoverishment of remote areas, however (Fujita and Thisse 2003).The emphasis of NEG theories on the uneven spatial distribution of economic activities and growth renewed interest in social interaction among economic agents and spatial spillovers (Anselin 2003).When decisions and transactions of one set of agents depend on behaviours of a set of neighbouring agents, then spatial or spatiotemporal dependence can result.

This paper examines regional growth processes in Appalachia in a spatial growth equilibrium framework. Particularly, it investigates the strengths and directions of the causality in the interdependence among employment growth, migration behaviour, median household income and local public services in 418 Appalachian counties during the period 1980 to 2000.This period is of particular interest because in spite of strong growth during the 1990s in the United States, Appalachian counties suffered from high unemployment, a shrinking economic base, low human capital formation, and out-migration (Pollard 2003; Black and Sanders 2004), continuing a long trend. Per capita market income was 77 per cent of the US average in 1960 and 31.1 per cent of the region's residents lived in poverty, compared to 22.1 per cent of all Americans (Wood and Bishak 2000). The gap has narrowed since then and per capita income reached 84 per cent of US income in 1999. Similarly, the poverty rate had dropped to 13.6 per cent by 1999, but remained above the 12.4 per cent for the US (Pollard 2003).

Educational attainment in Appalachia is also lower. In 2000 the proportions of residents of age 25 and older with a high school diploma or with at least a bachelor's degree, respectively, were 77 and 18 per cent, compared to 81 and 25 per cent for the US. The region was a destination for low-income populations with relatively little education and low-occupational status, while those with higher incomes, more education and higher job status moved out during the second half of the 1990s (Obermiller and Howe 2004). The availability as well as the quality of jobs, measured by average wage, was about 10 per cent lower than in the United States (Foster 2003). Forty-two per cent of Appalachia's population of about 23 million is rural, compared to 20 per cent for the nation as a whole. Because of Appalachia's mountainous topography and comparatively poor infrastructure, many communities are considered remote. To remedy the poor state of infrastructure in the region, in 1965 Congress established the Appalachian Regional Commission (ARC), a regional economic development agency. However, in spite of several decades of federal investments through ARC, Appalachia remains a distinct part of America and a symbol of poverty in the midst of prosperity (Pollard 2003).

The remainder of this paper is organized as follows. Section 2 deals with model develop, and Section 3 examines econometric and estimation issues. In Section 4, we present and analyse the empirical results. The article finishes with conclusions and policy implications in Section 5.

2 Model development

2.1 Previous empirical growth models

Studies in the 'do jobs follow people or do people follow jobs' literature have resulted in models that reflect the interdependence between households' and firms' location choices (Steinnes and Fisher 1974). To account for household-firm interdependency, Carlino and Mills (1987) constructed a simultaneous system model with two partial location equations and estimated it for counties in the contiguous United States. Of particular interest is their finding that in the 1970s family income had a strong impact on the growth of population and employment densities. Deller et al. (2001) extended the original Carlino-Mills model to three equations (jobs-people-income) to trace job quality and the role of income in non-metropolitan counties during the period 1985 to 1995. Their results indicate that initial conditions co-determine the outcome and that counties with larger initial populations tended to have higher employment growth. However, counties that had higher levels of population, employment, and per capita income in 1985 tended to have lower rates of overall growth, as predicted by the neoclassical model.

In other research, Clark and Murphy (1996) and MacDonald (1992) modelled interactions between employment growth and human migration; Duffy-Deno and Eberts (1991) looked at per capita personal income and public expenditures; and Greenwood et al. (1986) and Lewis et al. (2002) at net migration, employment growth and average *per capita* income. Clark's and Murphy's (1996) expansion of the Carlino-Mills model, by including amenity measures (beyond climate/temperature), neighbourhood poverty, and fiscal variables, using county data from 1981 to 1989, has been particularly influential. Like Carlino and Mills (1987), they found simultaneity between employment density and population density.

Boarnet (1994) integrated potential variables and spatial econometrics in a two-equation model of population and employment growth, using data of New Jersey municipalities. He adjusted for the difference between place of residence and place of work at the community level by adding spatial lags to the endogenous variables of the Carlino-Mills model. Because municipalities are not self-contained markets, he used a spatial cross-regressive lag model, where the right-hand side of each equation contains the spatial lag of the endogenous variable from the other equation, creating spatial links across equations. Community population change depends on the change in total employment within commuting distance, and community employment change depends on population change within commuting distance of the given community.

Henry et al. (1997) extended Boarnet's (1994) model and used it to analyse population and employment changes in rural areas. Their version of the model contains interaction terms between urban growth rates and the spatial lag variables as regressors. These linkages enabled them to examine how urban growth affects population and employment change in rural hinterlands. Parameter estimates on the interaction variables show whether urban growth had a spread or a backwash effect in proximate rural communities. Using data for southern functional economic areas, Henry et al. (1997) found a mix of spillover and backwash effects. Henry et al. (1999) used the same approach for empirically comparing Denmark, France, and the United

States to evaluate the effect of country differences in local socio-economic conditions on the linkage between urban growth and rural change. Their results indicate that rural population and employment changes in the three countries are sensitive to the performance of nearby urban cores/fringes. The general trends that emerge are those of urban spread to rural places with average or large labour markets and populations.

Henry et al. (2001) estimated the Carlino and Mills (1987), Boarnet (1994), and Henry et al. (1997) models for six French regions and compared the results for several related spatial econometric models for simultaneous equation systems defined in the taxonomy developed in Rey and Boarnet (2004). Their findings indicate that adding spatial cross-regressive terms to the Carlino-Mills model provides a correction that results in empirical results consistent with theory in the Carlino-Mills and Boarnet models. By comparing the strengths and directions of the effects of population on employment, and vice versa, they showed that people follow jobs in rural France. Their results also suggested a general tendency of local spread effects masking both urban backwash and spread effects, depending on the pattern of urban growth between core and fringe.

However, further analysis of the results from such simultaneous growth models shows that many exogenous variables have been unimportant, unstable, or statistically insignificant. Simultaneity bias could be one of the reasons for this because, for example, most models treat government as exogenous while research shows that local government actions are endogenous to employment and population changes (Duffy-Deno and Eberts 1991; Fay 2000; Hashmati 2001; Painter and Bae 2001). Another possible cause could be the use of net population changes, which involves a substantial loss of information (Greenwood 1975).Unless relevant characteristics of in-migrants, out-migrants, and 'natural growth' are very similar, the use of net-migration introduces specification errors into the model. In Appalachia, in-migrants and out-migrants are markedly different, as mentioned above. Finally, local governments affect the economy through taxation and spending, and are being affected by it. Models that treat the government as exogenous do therefore not adequately capture this sector.

To address such shortcomings, Section 2.2 develops a spatial panel simultaneous-equations model of interdependences among the growth rates of private non-farm employment, gross in-migration, gross out-migration, median household income, and local public expenditures per capita (at the county level) in a growth equilibrium framework. First, the model spells out the 'feed-back simultaneities' among the five endogenous variables conditional on a set of regional socio-economic variables. The rationale is that estimating the coefficients of each equation without considering feed-back would lead to biased, inconsistent, and inefficient estimates.

Second, the model incorporates spatial spillover effects (spatial autoregressive and spatial cross-regressive lag simultaneities). When the underlying data generating process includes a spatial dimension, ignoring the effect would yield inconsistent, inefficient and biased regression estimates (Anselin 1988, 2003).The inclusion of spatial spillover effects is also important from a policy perspective because they explain to what extent each dependent variable in one county depends on the characteristics of its neighbours (spatial correlation). Information about such cross-border effects can improve the design of policies.

Third, the two-period spatial simultaneous panel data model builds on Baltagi's (2008) one-way error component model. Panel data generally contain more variation and have less collinearity among variables. The greater degree of freedom that results from the use of panel data increases estimation efficiency, which permits the specification of complicated behavioural relationships that could not be addressed using either cross-sectional or time-series data alone (Elhorst 2003). Thus, the use of a spatial panel data model yields improvement in hypothesis testing and subsequent inferences about interdependences among the model's core variables. Table A1 provides a list of the data used in the study and their sources, and Table A2 the summary statistics.

2.2 The spatial growth model

Interdependencies between population, employment, and income arise because households and firms are both mobile. Households locate to maximize utility while firms locate to maximize profits. Thus, households migrate to capture higher wages or incomes and firms migrate to be near growing consumer markets. However, household location decisions are also influenced by factors such as local public goods and services, social and natural amenities, demographic factors, and the region's location. Similarly, location decisions of firms are expected to be influenced not only by population and income (i.e., consumer markets characteristics), but also by the local business climate, wage rates, tax rates, public services, and access to supply markets. Financial incentives to invest and create jobs also play a role. The median-voter model of local fiscal behaviour predicts that local public expenditures approximate the choices of the utility-maximizing median voter and depend on revenue sources such as property and income taxes and factors that determine consumer preferences.

Regional factors affecting household, firm and local government decisions frequently lack independence and exhibit spatial autocorrelation or spatial dependence, which refers to the correlation of the dependent variable or error term at one location with observations on the dependent variable or error term at other locations (Anselin 1988, 2003).

Based on the assumption outlined above, we develop a spatial simultaneous equations model of employment growth, migration behaviour, household median income and local public expenditures to test the following hypotheses:

Hypothesis 1. *Employment growth, migration behaviour, median household income growth, and local public expenditures per capita growth rates are interdependent and are jointly determined by county-level variables.*

Hypothesis 2. *Employment growth, migration behaviour, median household income growth and local public expenditures per capita growth rates in a county depend on initial conditions in that county.*

Hypothesis 3. *Employment growth, migration behaviour, median household income growth and local public expenditures per capita growth rates in a county are conditional on the same variables in neighbouring counties.*

Following Carlino and Mills (1987) and building upon and extending Boarnet (1994), a model incorporating own-county and neighbouring counties effects is specified as follows:

$$\mathbf{y}_{rt}^{*} = f_r(\mathbf{Y}_{rt}^{*}\mathbf{C}, (\mathbf{I}_T \otimes \mathbf{W})\,\mathbf{Y}_{rt}^{*} \,|\mathbf{X}_{rt-1}),\ r = 1, \ldots, 5$$
$$\text{with } \mathbf{Y}_{rt}^{*} = \begin{bmatrix} \mathbf{y}_{1t}^{*} \\ \mathbf{y}_{2t}^{*} \\ \vdots \\ \mathbf{y}_{5t}^{*} \end{bmatrix} = [\mathbf{EMP}_t^{*}\ \mathbf{INM}_t^{*}\ \mathbf{OTM}_t^{*}\ \mathbf{MHY}_t^{*}\ \mathbf{GEX}_t^{*}], \tag{1}$$

where $\mathbf{EMP}_t^{*}$, $\mathbf{INM}_t^{*}$, $\mathbf{OTM}_t^{*}$, $\mathbf{MHY}_t^{*}$, and $\mathbf{GEX}_t^{*}$ are vectors of dimension NT × 1 of the equilibrium levels of private non-farm employment, gross in-migration, gross out-migration, median household income, and per capita local public expenditures, respectively; t indexes time. N is the number of unique cross-sectional units, while T is the number of time periods. **C** is a (5 × 5) square matrix with zero elements on the diagonal and 1 everywhere off the diagonal. **I** is an identity matrix of dimension T and, **W** is an $N \times N$ spatial weights matrix that can be represented by $\mathbf{W} = \{w_{ij}\}_{i=1,j=1}^{N}$. Each element w_{ij} in **W** represents a measure of proximity between observation (location) i and observation (location) j. According to the adjacency criteria, we set w_{ij} equals to $1/c_i$, where c_i is the number of nonzero elements in row *i* if *i* and *j* are adjacent, and zero otherwise. The resulting matrix, **W**, is a row standardized spatial weights matrix with zero diagonal values. Therefore, $(\mathbf{I}_T \otimes \mathbf{W})\mathbf{Y}_{rt}^{*}$ represent the equilibrium values of neighbouring counties' effects; ⊗ denotes the Kronecker product. The matrices of additional exogenous variables included in the spatial simultaneous equations system are given by X_{rt-1}. Descriptions of these variables are provided in Appendix 2. Note that equilibrium levels of private non-farm employment, gross in-migration, gross out-migration, median household income, and per capita local public expenditures are assumed to be functions of the equilibrium values of the respective right-hand included endogenous variables and their spatial lags, and the values of the vectors of the additional exogenous variables.

Based on theoretical and statistical considerations, a multiplicative functional form of the model was adopted. Duffy-Deno (1998) and MacKinnon et al. (1983) also show that, compared to a linear specification, a log-linear specification is more appropriate for models involving population and employment densities. The literature (Mills and Price 1984; Carlino and Mills 1987; Duffy 1994; Boarnet 1994; Henry et al. 1997, 1999; Barkley et al. 1998; Duffy-Deno 1998; Aronsson et al. 2001; Deller et al. 2001; Edmiston 2004; Hamalainen and Bockerman 2004), suggests that employment, population, and median household income likely adjust to their equilibrium levels with a substantial lag (i.e., initial conditions). Therefore, a distributed lag adjustment is introduced and the corresponding partial-adjustment process yielded the following specification of the empirical model:

$$\begin{aligned} &\mathbf{Y} = \mathbf{YB} + \mathbf{X\Gamma} + (\mathbf{I}_T \otimes \mathbf{W})\mathbf{Y\Lambda} + \mathbf{U} \\ &\mathbf{U} = \rho(\mathbf{I}_T \otimes \mathbf{W}) + \boldsymbol{\varepsilon} \\ &\boldsymbol{\varepsilon} = \mathbf{Z}_\mu \boldsymbol{\mu} + \boldsymbol{\omega} \end{aligned} \tag{2}$$

with

$\mathbf{Y} = (\mathbf{y}_1, \ldots, \mathbf{y}_5) =$ (**EMPR**, **INMR**, **OTMR**, **MHYR**,**GEXR**)
$\mathbf{X} = (\mathbf{x}_1, \ldots, \mathbf{x}_k) \quad \mathbf{U} = (\mathbf{u}_1, \ldots, \mathbf{u}_5)$
$\mathbf{Z}_\mu = (\iota_T \otimes \mathbf{I}_N)$, $\boldsymbol{\mu}_r' = (\mu_{1r}, \mu_{2r}, \ldots, \mu_{Nr})$, and $\boldsymbol{\omega}_r' = (\omega_{11r}, \ldots, \omega_{1Nr}, \ldots, \omega_{T1r}, \ldots, \omega_{TNr})$

where $\mathbf{y}_r$ is the NT by 1 vector of cross sectional observations on the dependent variable in *r*th equation,[1] $\mathbf{x}_l$ is an NT × 1 vector of cross sectional observations on the *l*th predetermined or exogenous variable, *K* is the total number of exogenous and predetermined variables, and **B**, **Γ**, and **Λ** are correspondingly defined parameter matrices of dimension (5 × 5), (*K* × 5) and (5 × 5), respectively. **B** is a square matrix with zeros on the diagonal, and non-zero elements on the off-diagonals. The spatial interactions in the system are determined by the nature of **Λ**. Specifying **Λ** as a non-diagonal matrix allows the *r*th endogenous variable to depend on its spatial lag as well as on the spatial lags of the other endogenous variables. However, if there are theoretical reasons for the *r*th endogenous variable to depend either only on the spatial lags in the other endogenous variables or only on its own spatial lag, then **Λ** should be specified as a diagonal or identity matrix, respectively. $\mathbf{u}_r$ is an NT × 1 vector of error terms in the *r*th equation, ρ_r is the spatial autoregressive parameter which does not change over time, ε_r is an NT × 1 vector of

[1] **EMPR, INMR, OTMR, MHYR**, and **GEXR** represent the log difference between the end and beginning period values of private non-farm employment, gross in-migration, gross out-migration, median household income, and local government expenditures per capita, respectively. Hence, they represent the growth rates of the respective variables.

innovations in the rth equation, ι_T is a vector of ones of dimension T, $\mathbf{I}_N$ and $\mathbf{I}_T$ are identity matrices of dimension N and T, respectively. $\mathbf{Z}_\mu$ is the selector matrix for the random vector of individual effects $\boldsymbol{\mu}$.

Following Baltagi (2008) and as proposed by Baltagi et al. (2006), Kapoor et al. (2007) and Mutl and Pfaffermayr (2010), we utilized a one-way error component model for the disturbances and the disturbances in the rth equation are given by:

$$\mathbf{u}_r = \rho_r(\mathbf{I}_T \otimes \mathbf{W})\mathbf{u}_r + (\boldsymbol{\iota}_T \otimes \mathbf{I}_N)\boldsymbol{\mu}_r + \boldsymbol{\omega}_r, r = 1, \ldots, 5 \tag{3}$$

The vector of individual effects $\boldsymbol{\mu}_r$ is assumed to be independent and identically distributed (i.i.d.) $\left(0, \sigma_\mu^2 \mathbf{I}_N\right)$, and the (NT × 1) vector of idiosyncratic errors $\boldsymbol{\omega}_r$ is assumed to be i.i.d. $\left(0, \sigma_\varpi^2 \mathbf{I}_{NT}\right)$. In addition, $\boldsymbol{\mu}_r$ and $\boldsymbol{\omega}_r$ are assumed to be independent of each other. Hence, the innovations $\boldsymbol{\varepsilon}_{t,r}$ are auto-correlated over time but not spatially correlated across units.[2]Analogous to the classical simultaneous equation model, the specification of the model, however, allows for innovations that correspond to the same cross-sectional unit to be correlated across equations. Hence the vectors of disturbances are spatially correlated across units and across equations as given in (3). As a result, the covariance matrix between equations r and j is given by:

$$\boldsymbol{\Omega}_{rj} = E\left(\mathbf{u}_r \mathbf{u}_j'\right) = \boldsymbol{\sigma}_{\mu_{rj}}^2 (J_T \otimes \mathbf{I}_N) + \boldsymbol{\sigma}_{\omega_{rj}}^2 (\mathbf{I}_T \otimes \mathbf{I}_N), \tag{4}$$

where $\mathbf{J}_T$ is a matrix of 1s of dimension T. Similarly, the variance-covariance matrix of the innovations for the set of the five structural equations is given by

$$\boldsymbol{\Omega}_{\boldsymbol{\varepsilon}} = E(\boldsymbol{\varepsilon\varepsilon}') = \boldsymbol{\Sigma}_\mu \otimes (\mathbf{J}_T \otimes \mathbf{I}_N) + \boldsymbol{\Sigma}_\omega \otimes (\mathbf{I}_T \otimes \mathbf{I}_N) \tag{5}$$

$\boldsymbol{\Sigma}_\mu = \left[\boldsymbol{\sigma}_{\mu_{rj}}^2\right]$ and $\boldsymbol{\Sigma}_\omega = \left[\boldsymbol{\sigma}_{\omega_{rj}}^2\right]$ are 5 × 5 matrices. Alternatively, by replacing $\mathbf{J}_T$ with $T\bar{\mathbf{J}}_T$ and $\mathbf{I}_T$ with $\mathbf{E}_T + \bar{\mathbf{J}}_T$, where $\mathbf{E}_T$ is defined as $\left(\mathbf{I}_T - \bar{\mathbf{J}}_T\right)$, the variance-covariance matrix in (5) can be written as:

$$\begin{aligned} \boldsymbol{\Omega}_{\boldsymbol{\varepsilon}} &= E(\boldsymbol{\varepsilon\varepsilon}') = \left(T\boldsymbol{\Sigma}_\mu + \boldsymbol{\Sigma}_\omega\right) \otimes \left(\bar{\mathbf{J}} \otimes \mathbf{I}_N\right) + \boldsymbol{\Sigma}_\omega \otimes (\mathbf{E}_T \otimes \mathbf{I}_N) \\ &= \boldsymbol{\Sigma}_1 \otimes \mathbf{P} + \boldsymbol{\Sigma}_\omega \otimes \mathbf{H} \end{aligned} \tag{6}$$

$\boldsymbol{\Sigma}_1 = T\boldsymbol{\Sigma}_\mu + \boldsymbol{\Sigma}_\omega$, $\mathbf{P}$ is the matrix that averages the observations across time for each individual, and $\mathbf{H}$ is the matrix that obtains the deviations from individual means. The matrices $\mathbf{P}$ and $\mathbf{H}$ are the standard transformation matrices utilized in the error component literature, but adjusted for the different stacking of the data. Unlike in the classical error component literature, we group data first by time (t = 1, . . . ,T) and then by individual units (i =1, . . . , N). $\mathbf{P}$ and $\mathbf{H}$ are symmetric, idempotent, and mutually orthogonal. Thus,

$$\begin{bmatrix} \mathbf{P} = \mathbf{Z}_\mu\left(\mathbf{Z}_\mu'\mathbf{Z}_\mu\right)\mathbf{Z}_\mu' = \bar{\mathbf{J}}_T \otimes \mathbf{I}_N, \text{ where } \bar{\mathbf{J}}_T = \mathbf{J}_T / T \\ \mathbf{H} = \mathbf{I}_{NT} - \mathbf{P} = \left(\mathbf{I}_T - \dfrac{\mathbf{J}_T}{T}\right) \otimes \mathbf{I}_N \end{bmatrix}.$$

[2] In introducing spatial error autocorrelation into our one-way error component model, we followed the approach suggested by Kapoor et al. (2007) where the error (disturbance) vector ($\mathbf{u}$) is first subjected to spatial autocorrelation process (SAR): $\boldsymbol{\mu}_r = \rho_r(\mathbf{I}_T \otimes \mathbf{W})\boldsymbol{\mu}_r$, $r = 1, \ldots, 5$.Then the error components are introduced to the innovation vector $\boldsymbol{\varepsilon}_r$ as: $\boldsymbol{\varepsilon}_r = (\boldsymbol{\iota}_T \otimes \mathbf{I}_N)\boldsymbol{\mu}_r + \boldsymbol{\omega}_r$, $r = 1, \ldots, 5$. This formulation assumes that spatial error process applies to both the individual and the remainder error components. Spillovers are both time-invariant (permanent) and time variant (transitory) shocks in nature. The alternative formulation as suggested by Anselin (1988), and Baltagi et al. (2003) assumes that spatial correlation occurs only in the remainder error tem, whereas no spatial correlation takes place in the individual effect. Spillovers are inherently time-varying or transitory in nature. This approach consists of the specification of a SAR process for the error component $\boldsymbol{\omega}_r$ in each cross-section: $\boldsymbol{\omega}_r = \rho_r(\mathbf{I}_T \otimes \mathbf{W})\boldsymbol{\omega}_r$, $r = 1, \ldots, 5$.

The variance-covariance matrix of the disturbances can be written as

$$\begin{aligned} E(\mathbf{UU'}) = \mathbf{\Omega_U} &= \left[\mathbf{I}_T \otimes (\mathbf{I}_N - \rho\mathbf{W})^{-1}\right]\mathbf{\Omega_\varepsilon}\left[\mathbf{I}_T \otimes (\mathbf{I}_N - \rho\mathbf{W'})^{-1}\right] \\ = \mathbf{\Omega_\varepsilon} &= \left[\mathbf{I}_T \otimes (\mathbf{I}_N - \rho\mathbf{W})^{-1}\right]\left[\mathbf{I}_T \otimes (\mathbf{I}_N - \rho\mathbf{W'})^{-1}\right] \quad . \\ = \mathbf{\Omega_\varepsilon} &= \left[\mathbf{I}_T \otimes (\mathbf{I}_N - \rho\mathbf{W})^{-1}(\mathbf{I}_N - \rho\mathbf{W'})^{-1}\right] \end{aligned} \tag{7}$$

If the values of ρ, $\mathbf{\Sigma}_\mu$, and $\mathbf{\Sigma}_\omega$ are known, the efficient estimation procedure requires the transformation of the model by the square root of $\mathbf{\Omega}_\mathrm{U}$ given by:

$$\mathbf{\Omega_U}^{-1/2} = \mathbf{\Omega}_\varepsilon^{-1/2}(\mathbf{I}_{NT} - \rho(\mathbf{I}_T \otimes \mathbf{W})). \tag{8}$$

This transformation involves, first, the application of the spatial counterpart of the Cochrane-Orcutt transformation ($\mathbf{I}_{NT} - \rho(\mathbf{I}_T \otimes \mathbf{W})$) that eliminates the spatial correlation from the disturbances, and then the panel transformation $\mathbf{\Omega}_\varepsilon^{-1/2}$ to take account of the variance-covariance structure of the innovations induced by the random effects.

A Moran's *I* test statistic, as suggested by Anselin and Kelejian (1997) for models with endogenous regressors, and its more general version (Kelejian and Prucha 2001), confirmed the existence of spatial autocorrelation in the errors in all equations. The test results are given in Table 1.

3 Estimation issues

To control for unobserved heterogeneity and investigate inter-temporal changes, a panel model for two time periods is estimated. The degrees of freedom and efficiency increase with the use of panel data because they provide more information, more variables, and collinearity is less likely. The empirical application utilizes a one-way error component model following Baltagi (2008) and as proposed by Baltagi et al. (2006), Kapoor et al. (2007) and Mutl and Pfaffermayr (2010).

The system of equations in (2) constitutes a model with feedback simultaneity, spatial autoregressive lag simultaneity, and spatial cross-regressive lag simultaneity with spatially autoregressive disturbances. This creates a number of complications of which the question of whether or not each equation is identified and the choice of the estimator and instruments are particularly important. Concerning identification, in a linear simultaneous equations model, the necessary but not sufficient order condition is that the number of dependent variables on the right hand side of an equation must be less than or equal to the number of predetermined variables (both exogenous and lagged dependent) appearing in the model but not in that equation. In a spatial model, Kelejian and Prucha (2004, p. 40) conjecture that for the purposes of the order condition for identification "the spatially lagged dependent variables can be treated as if they are predetermined, since their conditional means will in general differ from the exogenous variables appearing in the original system". Thus, for a spatial simultaneous equations model, the order condition is that the number of dependent variables appearing on the right hand side of an equation must be less or equal to the number of predetermined (i.e., exogenous plus lagged dependent plus spatially lagged dependent) variables appearing in the model but not in that equation. Even without using the Kelejian and Prucha conjecture, the order condition of the system in (2) is fulfilled because the number of right-hand-side included dependent variables in each equation is 4, less than the number of exogenous variables excluded from the respective equations, which are 14, 18, 18, 16, and 17. Second, where there are more instruments than

Table 1. Feasible Generalized Spatial Three-Stage Least Squares(FGS3SLS) Estimation Results

	EMPR Equation		INMR Equation		OTMR Equation		MHYR Equation		GEXR Equation	
Variable	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
Constant	–0.7211	–1.4514	–0.3951	–1.6652	1.9110	7.3054	5.2007	6.7117	1.2586	5.1725
EMPR			1.1016	23.1230	0.5377	19.0894	0.1310	4.5632	–0.0031	–0.1148
INMR	0.0641	4.0017			–0.0264	–2.0152	0.0169	1.4344	–0.0594	–4.9518
OTMR	0.3717	8.6826	–0.5873	–13.8519			0.2131	6.1175	0.0613	2.2006
MHYR	0.2127	5.6273	–0.5129	–8.3058	–0.3917	–11.2243			–0.2373	–7.6835
GEXR	0.2897	6.4475	–0.5322	–8.6811	–0.3497	–9.1948	–0.3711	–10.1317		
($\mathbf{I} \otimes \mathbf{W}$) EMPR	–0.6500	–8.6300	0.3043	2.4562	0.2703	3.4283	–0.0058	–0.0818	–0.0441	–0.6429
($\mathbf{I} \otimes \mathbf{W}$) INMR	–0.0411	–0.7687	0.0225	0.3250	0.0010	0.0245	–0.0434	–1.3105	0.0554	1.6872
($\mathbf{I} \otimes \mathbf{W}$) OTMR	0.4872	4.9039	0.1952	1.4483	0.0469	0.5525	0.0909	1.3352	–0.0792	–1.1835
($\mathbf{I} \otimes \mathbf{W}$) MHYR	–0.1368	–1.3878	–0.0576	–0.4397	–0.2318	–2.6638	0.2394	3.5123	0.0527	0.9063
($\mathbf{I} \otimes \mathbf{W}$) GEXR	0.1875	1.8502	0.2020	1.1995	0.2256	2.2746	0.1866	2.4472	0.4216	5.5303
AREA			–0.0369	–1.5766	–0.0041	–0.2604				
POPs			0.5519	20.3534	0.2187	18.4429	–0.1567	–1.0471	0.0098	0.9167
POPd							0.0064	0.8912		
POP5_17									0.1267	2.7955
POP25_44	0.2694	3.8239								
FHHF	–0.0992	–4.1690					–0.0236	–1.0391		
POPHD							0.3128	7.5692		
POPCD	0.1754	7.9801								
OWHU	0.0578	0.5831			–0.0929	–1.6064				
MCRH			0.1141	8.1934						
UNEMP			–0.3036	–9.3346	–0.1679	–8.1801	–0.0026	–0.1692		
MANU	0.0032	5.4736					0.0023	5.1125		
WHRT	0.0181	7.3968					–0.0007	–0.3755		

Table 1. Continued

	EMPR Equation		INMR Equation		OTMR Equation		MHYR Equation		GEXR Equation	
Variable	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
SCRM									0.0410	0.4946
DFEG									0.0529	3.9894
PCTAX									0.0486	4.6624
PCPTAX	–0.0051	–0.6112								
PCTD									–0.0001	–4.6535
LTD									0.0017	4.8203
SCIX							–0.0099	–1.3853		
NAIX	0.0169	3.0763	0.0192	2.3163	0.0084	1.7953				
HWD	0.1808	6.5349								
ESBd	–0.1162	–4.7651								
EXTAX			0.0768	3.1002	0.0226	1.4816				
EMPt-1	–0.0873	–9.2827								
INMt-1			–0.6774	–23.8148						
OTMt-1					–0.2836	–22.4302				
MHYt-1							–0.5228	–18.9127		
GEXt-1									–0.2771	–13.3590
RHO	0.5713		0.0398		0.3429		0.0006		–0.3976	
SIGV	0.0603		0.0866		0.0396		0.0534		0.1236	
SIG1	0.063		0.0776		0.0465		0.0448		0.1028	
$NR^2 \sim \chi^2_{(38,42,42,40,41)}$ [a]	48.2655	0.8152[b]	20.5561	0.9937[b]	29.9805	0.8498[b]	44.1519	0.8740[b]	57.2199	0.2553[b]
Moran I	0.2895	4.5932[c]	0.061	2.1414[c]	0.1534	3.1612[c]	–0.0029	–0.0695[c]	–0.1176	–3.1981[c]
Eta (η)	0.0873		0.6774		0.2836		0.5228		0.2771	
N	836		836		836		836		836	

Notes: A coefficient is considered as statistically significant at 10 per cent, 5 per cent and 1 per cent levels, if 1.65 ≤ |t-stat.| ≤ 1.98, 1.98 < |t-stat.| ≤ 2.58, and |t-stat.| > 2.58, respectively.
[a] 58, 39, 39,56, 51 represent the degree of freedoms which are equal to the over-identifying restrictions in the EMPR, INMR, OTMR, MHYR, GEXR equations, respectively; [b] p-values;
[c] Z-values for Moran *I*.

needed to identify an equation, a test statistic is computed following Hausman (1983),[3] to investigate whether the additional instruments are valid in the sense that they are uncorrelated with the error term. That is $E(\mathbf{Q}'\mathbf{u}_r) = 0$, where E is the expectation operator and $\mathbf{Q}$ is an instrument matrix as defined below. This condition ensures that the instrument $\mathbf{Q}$ identifies the regression parameters $[\alpha', \beta', \lambda', \gamma']$ of Equation (2). α' is a vector of slope coefficients and β', λ', γ' are vectors of coefficients on the right–hand side dependent variables, the spatial lag variables and the predetermined variables, respectively. All equations are appropriately identified because the hypothesis of orthogonality for each equation cannot be rejected even at p = 0.02 as indicated by the NR_u^2 test statistics given in Table 1.

As to the choice of estimator, we use the method of moments approach (Kelejian and Prucha 1998, 1999) rather than maximum likelihood because the latter would involve significant computational complexity. Incidentally, conventional three-stage least squares estimation to handle the feedback simultaneity would be inappropriate in this context, given the spatial autoregressive lag and spatial cross-regressive lag simultaneities terms. The spatial generalized methods of moments approach followed by Rey and Boarnet (2004) in a Monte Carlo analysis of alternative approaches to modelling spatial simultaneity is also inappropriate because the model includes spatially autoregressive disturbances.

The time dimension in the panel data made the estimation more complex.[4] Therefore, we developed a new estimation strategy by adapting the generalized spatial three-stage least squares (GS3SLS) approach outlined by Kelejian and Prucha (2004) into a panel data setting. This new procedure is performed in a five-step routine as shown in Appendix 1.

4 Results and discussion

The FGS3SLS parameter estimation results, which indicate the existence of strong feedback simultaneities among the dependent variables of the spatial simultaneous equations system are shown in Table 1. For instance, they show strong positive interdependence between growth rate of employment (**EMPR**) and in-migration growth rate (**INMR**), which implies that counties with high in-migration growth rates are favourable for employment growth and that growth in employment further leads to increases in the growth of in-migration[5] into these counties. The positive effect of the employment growth rate is greater than the effect of in-migration growth on employment growth, as indicated by the values of the coefficients on the respective variables. This is consistent with the Todaro-thesis of rural-to-urban migration: one job opening attracts more than one migrant.

The results also show strong positive feedback simultaneity between **EMPR** and median household income growth rate (**MHYR**),which suggests that during the study period a county's

[3] This test statistic is obtained as NR_u^2, where N is the sample size and R_u^2 is the usual R-squared of the regression of residuals from the second-stage estimation on all included and excluded instruments. In other words, simply estimate Equation (2) by feasible generalized spatial two-stage least squares (GS2SLS) or any efficient limited-information estimator and obtain the resulting residuals, $\hat{u}_r$. Then, regress these on all instruments and calculate NR_u^2. The statistic has a limiting chi-squared distribution with degree of freedom equal to the number of over-identifying restrictions, under the assumed specification of the model.

[4] Since the time dimension of the panel in this study is small (T = 2), we could not apply a spatially corrected version of the system GMM estimator which was developed by Arellano and Bond (1991) and Blundell and Bond (1998). Moment conditions upon which the GMM estimator is based are valid only for panels with time dimension greater or equal to three (T≥3). To our knowledge, a system GMM estimator for a dynamic spatial panel setting which corrects for spatial error correlation is not currently available. Upon the availability of data from the 2010 census, the time dimension of our panel will increase to three and this will give us the opportunity to develop a spatially corrected system GMM estimator for a dynamic panel setting which also corrects for spatial error correlation in our future research.

[5] In this paper, in-migration and out-migration always refer to gross in-migration and gross out-migration, respectively.

employment growth rate was positively and significantly affected by the **MHYR**. Increases in median household income tend to increase regional wealth and thus consumer demand for goods and services; the latter encourages business growth and firm formation that create jobs. In addition, increases in median household income could lead to greater household savings and capital formation and improve funding for new jobs, which increases labour and entrepreneurial incomes. The enhanced incomes feed back into the **MHYR** equation and further stimulate growth in median household income, as shown by the positive and highly significant coefficient estimate on the **EMPR** in the **MHYR** equation. This interdependence is consistent with economic theory and prior empirical research (Armington and Acs 2002).

The results in Table 1 also suggest a strong negative interdependence between **INMR** and the growth rate of local public expenditures (**GEXR**). This result supports previous research in both the Tiebout (1956) and non-Tiebout tradition. Local government expenditures that are financed through higher taxes, particularly property taxes, tend to deter in-migration and encourage out-migration. Property taxes have their deterrent effects on in-migration through changes in employment (**EMPR**). Prior research(e.g., Mead 1982; Schachter and Althaus 1989) obtained similar results. The implication of this finding is that poorer communities in Appalachia that levy higher taxes to finance local public services may reach a certain level where they are no longer able to attract or even retain residents. If this occurs, the per capita tax increase needed to maintain local public services for the remaining population, drives even more people away, resulting in a vicious cycle of decline.

The growth rate of direct local government expenditures has a strong negative impact on median household income. This result is not ‘obvious’ because government expenditures’ effects depend on their type. Expenditures on education, health care, fire protection, or crime prevention should increase labour productivity and income. On the other hand, expenditures on unemployment insurance and social services, in general, may act as disincentives to work and not increase labour productivity and income. Traditionally, Appalachia has received higher than average payments from federal assistance programmes such as Food Stamps, Social Security Disability Insurance (SSDI), Temporary Assistance for Needy Families (TANF), and Supplemental Security Income (SSI) (Black and Sanders 2004). Income from social security makes up a larger portion of income in Appalachia than in the United States (Thorne et al. 2004). These two facts suggest that increases in the rate of growth of local government expenditures tend to reduce the rate of growth of median household income by encouraging welfare induced in-migrations, and creating disincentives to work. The result in this study is consistent with the findings of Dye (1980), Helms (1985), and Jones (1990), which showed that government expenditures on welfare programmes have negative and statistically significant impacts on per capita personal income growth rates.

The results also show strong spatial autoregressive lag and spatial cross-regressive lag simultaneities. The results show a negative and significant parameter estimate on the spatial autoregressive lag variable (($\mathbf{I} \otimes \mathbf{W}$) **EMPR**). This coefficient represents the spatial autoregressive simultaneity and indicates that the employment growth rate in one county tends to spillover to neighbouring counties and has negative effects on their rate of employment growth. There are strong and positive spatial autoregressive lag effects with respect to **GEXR**, as indicated by the statistically significant, at the 1 per cent level, coefficient on ($\mathbf{I} \otimes \mathbf{W}$) **GEXR** in the **GEXR** equation. Thus, the growth rate of direct local government expenditures in one county is positively associated with the growth rates of those expenditures in neighbouring counties. Such interdependencies could arise because: (*i*) 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 interaction results; (*ii*) beneficial or harmful effects from a county’s expenditures on local public services spill over onto residents of neighbouring counties; and (*iii*) imperfectly informed voters in a county use the performance of other governments as a yardstick to evaluate their own governments, so that local governments react to actions of their neighbours by mimicking each others' behaviour. The result supports findings in Case et al. (1993), Kelejian and Robinson (1993), Besley and Case (1995), Solé-Ollé (2003), Allers and Elhorst (2005), Wu and Hendrick (2009) and Elhorst and Fréret (2009) that show significant effects of tax mimicking and yardstick competitions among local governments.

The above results are important for policy as they indicate that each dependent variable in a county has spillover effects on the respective variable of its neighbours. From a theoretical perspective the significant spatial autoregressive and spatial cross-regressive lags effects indicate that a given dependent variable, say **EMPR**, depends on characteristics of the county and on those of its neighbours. Hence, empirical studies involving employment growth rates, and the growth rates of in-migration, out-migration, median household income, and local government expenditures should include tests for spatial effects.

Estimates for ρ_1, ρ_2 and ρ_3 are positive; ρ_4, while also positive, is very close to zero. Thus, random shocks with respect to employment growth, in-migration, and out-migration affect not only the county where the shocks originate and its neighbours, but create positive shock waves across Appalachia. Similarly, the negative parameter estimate for ρ_5 indicates that random shocks into the system with respect to the growth rate of local government expenditures affect the county where they originate, its neighbours, and create negative shock waves across Appalachia.[6]

We include the percentage of the population 25 to 44 years of age (POP25_44) to control for agglomeration effects. The estimates on this variable show positive and significant total (direct + indirect) effects on **EMPR** (see Appendix 3 for details on the interpretation of the coefficients). This result is consistent with that of Acs and Armington (2004a) who find that a growing population increases the demand for consumer goods and services, as well as the pool of potential entrepreneurs. From a policy perspective this indicates that counties with a high population concentration are benefiting from agglomerative and spillover effects, in line with Krugman's (1991a, 1991b) argument on regional spillover effects. The initial human capital endowment, measured by the percentage of adults older than 25 years who have a college degree (POPCD), also has a positive and statistically significant effect on employment growth. Well educated individuals are assumed to have more access to research and development facilities, and perhaps also better insights into business conditions and, therefore, more realistic ideas about the needs of the market. Christensen (2000) also contends that knowledge of how to transform innovative ideas into marketable products is positively related to education. Thus, the more highly educated the individuals the more likely they are to establish a business and be successful when they do. This result is consistent with the findings by Acs and Armington (2004b) that agglomerative effects that contribute to new firm formation could come from supply factors related to the quality of local labour market and business climate. One possible implication of these findings is that regions or counties with different levels of human capital endowment and different propensities of knowledge to spill over, tend to have different rates of new firm formation, survival, and growth.

The proportion of the school-age population, POP5-17, has a positive and statistically significant effect on the local government expenditures growth rate. An increase of this segment of the population tends to increase local spending on education, as reported in the empirical studies of Marlow and Shiers (1999) and Ahlin and Johansson (2001). Appalachian counties with higher proportions of adult residents with at least a high school diploma, POPHD, at the

[6] Apart from its topography (mainly rugged mountains) and resulting geographic isolation from the rest of America, Appalachia experienced a coal boom in the 1970s and a subsequent prolonged and deep coal bust in the 1980s and 1990s. The price of coal increased tremendously during the 1970s as a result of increases in the price of oil caused by the OPEC oil embargo. However, the price of coal started to decline precipitously with a subsequent drastic decline in the coal industry, as oil prices fell and competition from open-pit mines in the US West increased in the 1980s. This coal bust shocks increased the cost of providing local public services.

beginning of the period show stronger growth in **MHYR**, than counties with low initial POPHDs. This is consistent with studies of Romer (1986), Lucas (1993), Krugman (1991a), Rauch (1993), Glaeser et al. (1995), Duffy-Deno and Eberts (1991), and Simon and Nardinelli (2002), who found that per capita income growth is positively related to human capital endowments.

The county unemployment rate, UNEMP, is included in the vector of exogenous variables as a measure of local economic distress. We found that a high county unemployment rate is associated with a low in-migration growth rate, consistent with theory that suggests that job seekers tend to move from high-unemployment to low-unemployment regions. A number of prior empirical studies support this proposition, including those by Carlino and Mills (1987), Herzog et al. (1993), Hunt (1993), Gabriel et al. (1995) and Hamalainen and Bockerman (2004).

The coefficient estimates on direct federal expenditures and grants per capita (DFEG), per capita income tax per capita (PCTAX), and long-term debt per capita (LTD) in the **GEXR** equation are positive and statistically significant at the 1 per cent level. Since DFEG is a component of local government revenue, it is expected to have positive effects on the growth rate of direct local government expenditures per capita. The results are consistent with this expectation and empirical findings of Henderson (1968) and Fisher and Navin (1992) that local public expenditures per capita are positively related to per capita grants in-aid from higher level governments. Similarly, since PCTAX is also one of the components of local government revenue, increases in PCTAX provide local government with more money to spend on local public services.

Highway density (HWD) is included in the **EMPR** equation to measure the influence of accessibility on business and employment growth. The positive and statistically significant coefficient on HWD shows a positive association between the concentration of roads and employment growth. Thus, during the study period, Appalachian counties with higher road densities tended to have greater employment growth than other counties, a finding that is consistent with theory and empirical findings (e.g., Carlino and Mills 1987).

The results (Table 1) indicate the existence of significant conditional convergence in the growth rates of employment, in-migration, out-migration, median household income, and local government expenditures during the study period. The negative and statistically significant parameter estimates on the respective initial condition variables EMPt-1, INMt-1, OTMt-1, MHYt-1, and GEXt-1 indicate conditional convergence. That is, counties with low initial levels of employment, in-migration, out-migration, median household income, and local government expenditures tended to experience higher growth rates in these variables towards their respective steady-state values than counties with high initial levels, conditional on the other explanatory variables in the model. This result is consistent with findings of a rural renaissance by Deller et al.(2001) and Lundberg (2003). The speeds of adjustment, η_{em}, η_{in}, η_{ot}, η_{mh}, and η_{ge}, are 0.0873, 0.6774, 0.2836, 0.5228, and 0.2771, respectively, indicating that 8.73, 67.74, 28.36, 52.28, and 27.71 per cent of the equilibrium rates of growth in employment, in-migration, out-migration, median household income, and local government expenditures were realized every ten years between 1980 and 2000.

5 Conclusions and policy implications

This research found significant feedback simultaneities among the growth rates of employment, in-migration, out-migration, median household income, and direct local government expenditures per capita in Appalachian counties during the study period. This finding indicates that sector specific policies that are integrated and harmonized achieve desired objectives more efficiently because they considered both the direct and indirect impacts of a policy.

This study also shows the existence of spatial autoregressive lag and cross-regressive lag simultaneities with respect to the growth rates of the endogenous variables. The existence of these spatial lag effects indicates that the per capita growth rates of employment, in-migration, out-migration, median household income, and direct local government expenditures in a county depend on the characteristics of that county and also on those of its neighbours. This finding illustrates the need for testing for spatial effects in empirical research using similar endogenous variables as those used in this study.

The cross-county interdependences among the model's endogenous variables indicate the desirability of economic development policy co-ordination at the supra-county level. A policy region could consist of counties with similar socio-economic conditions or of the whole Appalachia region, depending on the policy. Poverty reduction policies, for example, may be co-ordinated among counties in Central Appalachia, where there is a higher concentration of poverty than in the other sub-regions. The multicounty local development districts (LDD) which were established to co-ordinate and administer programmes funded by the Appalachian Regional Commission, might be able to provide administrative and organizational support for such co-operative efforts. There are 73 LDDs in Appalachia with an average population size of 340,000 and an area made up of six counties. The role of the LDDs includes supporting a network of multicounty planning organizations, mostly for infrastructure planning. They therefore already have the experience and track record of working with different counties and other local governments.

The results show that neighbouring counties can either be competitors or mutually strengthen each other, depending on specific circumstances, but fear of competition, and a lack of a history of cross-county co-operation may require state government co-ordination to achieve regional co-operation, and states may first need to create frameworks to make such co-operation possible. The role of the state is particularly important because the results also indicate the presence of agglomeration economies which, combined with the economic weakness of counties with small and dispersed communities, suggests that concentrating public development investments in centres will yield a greater return than treating all locations equally. For example, we found a positive interdependence between the growth rates of employment and median household income, which implies that local government actions that promote employment growth can have significant effects on poverty reduction.

References

Acs ZJ, Armington C (2004a) The impact of geographic differences in human capital on service firm formation rates. *Journal of Urban Economics* 56: 244–278

Acs ZJ, Armington C (2004b) New firm survival and human capital. URL: http://ideas.repec.org/p/esi/egpdis/2004-14.html

Ahlin A, Johansson E (2001) Individual demand for local public schooling: Evidence from Swedish survey data. *International Tax and Public Finance* 8: 331–351

Allers MA, Elhorst JP (2005) Tax mimicking and yardstick competition among local governments in the Netherlands. *International Tax and Public Finance* 12: 493–513

Anselin L (2003) Spatial externalities, spatial multipliers and spatial econometrics. *International Regional Science Review* 26: 153–166

Anselin L (1988) *Spatial econometrics: Methods, and models*. Kluwer Academic, Dordrecht

Anselin, L, Kelejian HH (1997) Testing for spatial error autocorrelation in the presence of endogenous regressors. *International Regional Science Review* 20: 153–182

Anselin L, LeGallo J (2006) Interpolation of air quality measures in hedonic house price models: Spatial aspect. *Spatial Economic Analysis* 1: 31–52

Arbia G, Basile R, Piras G (2005) Using panel data in modelling regional growth and convergence. URL: http://www.isae.it/Working_Papers/WP_55_2005_Arbia_Piras_Basile.pdf

Arellano M, Bond S (1991) Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies* 58: 277–297

Armington C, Acs ZJ (2002) The determinants of regional variation in new firm formation. *Regional Studies* 36: 33–45

Aronsson T, Lundberg J, Wikstrom M (2001) Regional income growth and net migration in Sweden 1970–1995. *Regional Studies* 35: 823–830

Baldwin R, Martin P (2004) Agglomeration and regional growth. In: Henderson JV, Thisse JF (eds) *Handbook of urban and regional economics*, Vol. 4. North-Holland, New York

Baltagi BH (2008) *Econometric analysis of panel data* (4th edn). John Wiley and Sons, Chichester

Baltagi BH, Egger P, Pfaffermayr M (2006) A generalized spatial panel data model with random effects. URL: http://www.econ.cam.ac.uk/panel2006/papers/Baltagipaper11.pdf

Baltagi BH, Song SH, Koh W (2003) Testing panel data regression models with spatial error correlation. *Journal of Econometrics* 117: 123–150

Barkley DL, Henry MS, Bao S (1998) The role of local school quality and rural employment and population growth. *Review of Regional Studies* 28: 81–102

Barro RJ (2004) *Economic growth*, (2nd edn). MIT Press, Cambridge MA

Barro RJ, Sala-i-Martin X (1992) Convergence. *Journal of Political Economy* 100: 223–251

Besley T, Case AC (1995) Incumbent behaviour: Vote-seeking, tax-Setting and yardstick competition. *American Economic Review* 85: 25–45

Black DA, Sanders SG (2004) Labour market performance, poverty, and income inequality in Appalachia. URL: http://www.arc.gov/images/reports/labourmkt/labourmkt.pdf

Blundell R, Bond S (1998) Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics* 87: 115–143

Boarnet MG (1994) An empirical model of intra-metropolitan population and employment growth. *Papers in Regional Science* 73: 135–153

Bowman MJ, Myers RG (1967) Schooling experience, and gains and losses in human capital through migration. *Journal of the American Statistical Association* 62: 875–898

Carlino OG, Mills ES (1987) The determinants of county growth. *Journal of Regional Science* 27: 39–54

Case AC, Rosen HS, Hines JR (1993) Budget spillovers and fiscal policy interdependence. *Journal of Public Economics* 52: 285–307

Christensen G (2000) *Entrepreneurship education: Involving youth in community development*. Nebraska Department of Education, Marketing and Entrepreneurship Education, Lincoln, NE

Clark D, Murphy CA (1996) Countywide employment and population growth: An analysis of the 1980s. *Journal of Regional Science* 36: 235–256

Debarsy N, Ertur C, LeSage JP (2010) Interpreting dynamic space-time panel data models. URL: http://193.49.79.89/leo/images/espace_commun/seminaires/semmar2010/WP_65.pdf

Deller SC, Tsai T-H, Marcouiller DW, English DBK (2001) The role of amenities and quality of life in rural economic growth. *American Journal of Agricultural Economics* 83: 352–365

Duffy NE (1994) The determinants of state manufacturing growth rates: A two-digit-level analysis. *Journal of Regional Science* 34: 137–162

Duffy-Deno KT (1998) The effect of federal wilderness on county growth in the inter-mountain Western United States. *Journal of Regional Sciences* 38: 109–136

Duffy-Deno KT, Eberts RW (1991) Public infrastructure and regional economic development: A simultaneous equations approach. *Journal of Urban Economics* 30: 329–343

Dye T (1980) Taxing, spending and economic growth in the American states. *Journal of Politics* 42: 1085–1107

Edmiston, KD (2004) The net effect of large plant locations and expansions on country employment. *Journal of Regional Science* 44: 289–319

Elhorst JP (2003) Specification and estimation of spatial panel data models. *International Regional Science Review* 26: 244–268

Elhorst JP, Fréret S (2009) Evidence of political yardstick competition in France using a two-regime spatial durbin model with fixed effects. *Journal of Regional Science* 49: 931–951

Ertur C, Le Gallo J, Baumont C (2006) The European regional convergence process 1980–1995: Do spatial regimes and spatial dependence matter? *International Regional Science Review* 29: 3–34

Fay M (2000) Financing the future: Infrastructure needs in Latin America 2000–05. Finance, Private Sector Development, and Infrastructure Sector Unit, Latin America and the Caribbean Region, World Bank, Washington, DC

Fisher RC, Navin JC (1992) State-local fiscal behaviour: An analysis interjurisdictional differences 1962–1987. *Public Finance Quarterly* 20: 433–449

Foster L (2003) The Appalachian economy, establishment and employment dynamics 1982–1997: Evidence from the longitudinal business database. URL: http://www.arc.gov/images/reports/service/service_sector.pdf

Fujita M, Krugman P, Venables A (1999) *The spatial economy: Cities, regions, and international trade*. Cambridge MIT Press, Cambridge, MA

Fujita M, Mori T (2005) Frontiers of new economic geography. *Papers in Regional Science* 84: 377–405

Fujita, M, Thisse JF (2002) *Economics of agglomeration*, Cambridge University Press, Cambridge

Fujita M, Thisse JF (2003) Does geographic agglomeration foster economic growth? And who gains and who loses from it? *Japan Economic Review* 54: 121–145

Fujita M, Thisse JF (2006) Globalization and the evolution of the supply chain: Who gains and who loses? *International Economic Review* 47: 811–836

Gabriel S, Mattey J, Wascher W (1995) The demise of California reconsidered: Interstate migration over the economic cycle. *Federal Reserve Bank of San Francisco Economic Review* 2: 30–45

Glaeser EL, Scheinkman JA, Shleifer A (1995) Economic growth in a cross-section of cities. *Journal of Monetary Economics* 36: 117–143

Greenwood MJ (1975) Research on internal migration in the United States: A survey. *Journal of Economic Literature* 13: 397–433

Greenwood MJ, Hunt GL, McDowell JM (1986) Migration and employment change: Empirical evidence on spatial and temporal dimensions of the linkage. *Journal of Regional Science* 26: 223–234

Hamalainen K, Bockerman P (2004) Regional labour market dynamics, housing, and migration. *Journal of Regional Science* 44: 543–568

Hashmati A (2001) On the causality between GDP and health care expenditure in the augmented Solow growth models. URL: http://ideas.repec.org/p/hhs/hastef/0423.html

Hausman J (1983) Specification and estimation of simultaneous equations models. In: Griliches Z, Intriligator M (eds) *Handbook of econometrics*. North Holland, Amsterdam

Helms LH (1985) The effects of state and local taxes on economic growth: A time series-cross sectional approach. *Review of Economics and Statistics* 67: 574–582

Henderson JM (1968) Local government expenditures: A social welfare analysis. *Review of Economics and Statistics* 50: 156–163

Henry MS, Barkley DL, Bao S (1997) The hinterland's stake in metropolitan growth: Evidence from selected southern regions. *Journal of Regional Science* 37: 479–501

Henry MS, Schmitt B, Kristensen K, Barkley DL, Bao S (1999) Extending Carlino-Mills models to examine urban size and growth impacts on proximate rural areas. *Growth and Change* 30: 526–548

Henry MS, Schmitt B, Piguet V (2001) Spatial econometric models for simultaneous systems: Application to rural community growth in France. *International Regional Science Review* 24: 171–193

Herzog, HW, Schlottmann AM, Boehm TP (1993) Migration and spatial job search: A survey of empirical findings. *Regional Studies* 27: 327–340

Higgins MJ, Levy D, Young AT (2006) Growth and convergence across the US: Evidence from county-level data. *Review of Economics and Statistics* 88: 671–681

Hunt GL (1993) Equilibrium and disequilibrium in migration modelling. *Regional Studies* 27: 341–349

Jones BD (1990) Public policies and economic growth in the American States. *The Journal of Politics* 52: 219–233

Kapoor M, Kelejian HH, Prucha IR (2007) Panel data models with spatially correlated error components. *Journal of Econometrics* 140: 97–130

Kelejian HH, Prucha IR (1998) A generalized two-stage least squares procedure for estimating a spatial autoregressive model with spatial autoregressive disturbances. *Journal of Real Estate, Finance and Economics* 17: 99–121

Kelejian HH, Prucha IR (1999) A generalized moments estimator for the autoregressive parameter in a spatial model. *International Economic Review* 40: 509–533

Kelejian HH, Prucha IR (2001) On the asymptotic distribution of the Moran *I* test statistic with applications. *Journal of Econometrics* 104: 219–257

Kelejian HH, Prucha IR (2004) Estimation of simultaneous systems of spatially interrelated cross sectional equations. *Journal of Econometrics* 118: 27–50

Kelejian HH, Robinson DP (1993) A suggested method of estimation for spatial interdependent models with autocorrelated errors, and an application to a county expenditure model. *Papers in Regional Science* 72: 297–312

Krugman PR (1991a) Increasing returns and economic geography. *Journal of Political Economy* 99: 483–499

Krugman PR (1991b) *Geography and trade*. MIT Press, Cambridge, MA

Krugman PR, Venables AJ (1995) Globalization and the inequality of nations. *Quarterly Journal of Economics* 110: 857–880

LeSage J, Pace PRK (2009) *Introduction to spatial econometrics*. Chapman & Hall/CRC Press, Boca Raton, FL

Lewis DJ, Hunt GL, Plantinga AJ (2002) Does public land policy affect local wage growth. *Growth and Change* 34: 64–86

Lucas RE (1988) On the mechanics of economic development. *Journal of Monetary Economic* 22: 3–42

Lucas RE (1993) Making a miracle. *Econometrica* 61: 251–272

Lundberg J (2003) On the determinants of average income growth and net migration at the municipal level in Sweden. *Review of Regional Studies* 32: 229–253

MacDonald JF (1992) Assessing the development status of metropolitan areas. In: Mills ES, MacDonald JF (ed) *Sources of metropolitan growth*. Center for Urban Policy Research, New Brunswick, NJ

Mackinnon JG, White H, Davidson R (1983) Tests for model specification in the presence of alternative hypotheses: Some further results. *Journal of Econometrics* 21: 53–70
Marlow ML, Shiers AF (1999) Do law enforcement expenditures crowd-out public education expenditures? *Applied Economics* 31: 255–266
Martin P, Ottaviano GIP (1999) Growing locations: Industry location in a model of endogenous growth. *European Economic Review* 43: 281–302
Martin P, Ottaviano GIP (2001) Growth and agglomeration. *International Economic Review* 42: 947–968
Mead AC (1982) A simultaneous equations model of migration and economic change in non-metropolitan areas. *Journal of Regional Science* 22: 513–327
Mills ES, Price R (1984) Metropolitan suburbanization and central city problems. *Journal Urban Economics* 15: 1–17
Mutl J, Pfaffermayr M (2010) The spatial random effects and the spatial fixed effects model: The Hausman test in a Cliff and Ord panel model. URL: https://editorialexpress.com/cgi-bin/conference/download.cgi?db_name=paneldata 2010&paper_id=94
Obermiller PJ, Howe SR (2004) Moving mountains: Appalachian migration patterns 1995–2002. *Journal of Appalachian Studies* 10: 359–371
Painter G, Bae K (2001) The changing determinants of state expenditure in the United States: 1965–1992. *Public Finance and Management* 1: 370–392
Persson J (1997) Convergence across the Swedish counties 1911–1993. *European Economic Review* 41: 1834–1852
Pollard KM (2003) Appalachia at the millennium: An overview of results from census 2000. Population Reference Bureau, Washington, DC. URL: http://www.arc.gov/index.do?nodleld=1847
Rappaport J (1999) Local growth empirics. URL: http://ideas.repec.org/p/wop/cidhav/23.html
Rauch JE (1993) Productivity gains from geographic concentration of human capital: Evidence from cities. *Journal of Urban Economics* 34: 380–400
Rey SJ, Boarnet MG (2004) A taxonomy of spatial econometric models for simultaneous equations systems. In: Anselin L, Florax RJGM, Rey SJ (eds) *Advances in spatial econometrics: Methodology, tools and applications*. Springer, Berlin
Romer PM (1990) Endogenous technical change. *Journal of Political Economy* 98: S71–S102
Romer PM (1986) Increasing returns and long run growth. *Journal of Political Economy* 94: 1002–1037
Rupasingha A, Goetz SJ, Freshwater D (2006) The production of social capital in US counties. *The Journal of Socioeconomics* 35: 83–101
Schachter J, Althaus PG (1989) An equilibrium model of gross migration. *Journal of Regional Science* 29: 143–160
Simon C, Nardinelli C (2002) Human capital and the rise of American cities 1900–1990. *Regional Science and Urban Economics* 32: 59–96
Sjaastad LA (1962) The costs and returns of human migration. *Journal of Political Economy* 70: 80–93
Solé-Ollé A (2003) Electoral accountability and tax mimicking: The effects of electoral margins, coalition government, and ideology. *European journal of Political Economy* 19: 685–713
Steinnes DN, Fisher WD (1974) An econometric model of intra-urban location. *Journal of Regional Science* 14: 65–80
Thorne D, Tickameyer A, Thorne M (2004) Poverty and income in Appalachia. *Journal of Appalachian Studies* 10: 341–357
Tiebout CM (1956) A pure theory of location expenditure. *Journal of Political Economy* 64: 415–424
Wood LE, Bishak GA (2000) *Progress and challenges in reducing economic distress in Appalachia: An analysis of national and regional trends since 1960*. Appalachian Regional Commission, Washington, DC
Wu Y, Hendrick R (2009) Horizontal and vertical tax competition in Florida local governments. *Public Finance Review* 37: 289–311
Young AT, Higgins MJ, Levy D (2007) Sigma convergence versus beta convergence: Evidence from US county-level data. *Journal of Money, Credit and Banking* 40: 1083–1093

Appendix 1: Method of estimation in panel data spatial simultaneous equations model

To estimate the parameters of our model, we developed a five-step estimation procedure. In the first step, the parameter vector $[\alpha', \beta', \lambda', \gamma']$ is estimated by generalized two-stage least squares (G2SLS) using an instrument matrix, $\mathbf{Q}$ consisting of a subset of $\mathbf{X}$, $(\mathbf{I} \otimes \mathbf{W})\mathbf{X}$, and $(\mathbf{I} \otimes \mathbf{W})^2$ $\mathbf{X}$.$\mathbf{X}$ is the matrix of all control variables in the model, $\mathbf{I}$ is the identity matrix of dimension T, and $\mathbf{W}$ is a row-standardized queen-based contiguity spatial weights matrix.

The disturbances for each equation are computed by using the estimates for $\alpha', \beta', \lambda', \gamma'$ from the first step. In the second step, the program first defines two orthogonal and symmetric idem potent matrices, $\mathbf{P}$ and $\mathbf{H}$, where $\mathbf{P}$ is the matrix averaging the observations across time for each individual, and **H** is the matrix obtaining the deviations from the individual means. Then, the computed disturbances from the first step are used to estimate the spatial autoregressive parameter ρ and variance components, σ_w^2 and σ_1^2, using the generalized moments procedure suggested by Kapoor, et al. (2007). **P** and **H** are used to define the generalized moments estimators of ρ, σ_w^2 and σ_1^2 in terms of six moments conditions.

The second step has two parts. In the first part, initial generalized moments estimators of ρ, σ_w^2 and σ_1^2 are computed. These are un-weighted GM estimators. In the second part, weighted GM estimates of ρ, σ_w^2 and σ_1^2 are computed. In the third step, first, the data undergo a Cochran-Orcutt-type transformation, using the weighted GM estimators of the spatial autoregressive parameter ρ. Then, the transformed data are further transformed using $\mathbf{\Omega}^{-1/2}$ from Equation (8), after replacing the variance components σ_w^2 and σ_1^2 by their weighted GM estimators. In the fourth step, feasible generalized spatial two-stage least squares (FGS2SLS) estimates for $[\alpha', \beta', \lambda', \gamma']$ are obtained by estimating the transformed model using a subset of the linearly independent columns of $[\mathbf{X}, (\mathbf{I} \otimes \mathbf{W})\mathbf{X}, (\mathbf{I} \otimes \mathbf{W})^2 \mathbf{X}]$ as the instrument matrix. GS2SLS does not, however, utilize the information available across equations because it does not take into account the potential cross equation correlation in the innovation vectors $\boldsymbol{\omega}_{t,r}, r = 1, \ldots, 5$. Therefore, the full system information is utilized by stacking the transformed equations (from the third step) to estimate them jointly. Thus, in the fifth step the FGS3SLS estimators of $[\alpha', \beta', \lambda', \gamma']$ are obtained by estimating this stacked model. The codes for this program are written in TSP matrix programming language.

Appendix 2: Data types and sources

Data for the empirical analysis are for all 418 Appalachian counties. They have been compiled from County Business Patterns, Bureau of Economic Analysis, Bureau of Labour Statistics, Current Population Survey Reports, County and City Data Book, US Census of Population and Housing, US Small Business Administration, and Department of Employment Security. County-level data for employment, gross in-migration, gross out-migration, local government expenditures and median household income have been collected for 1990 and 2000. In addition, data for a number of control variables have been collected for 1990 and 1980 (see Table A1 for the data description).

Dependent variables

The dependent variables are the growth rates of employment, gross in-migration, Gross out-migration, median household income, and per capita direct local government expenditures.

Growth rate of employment (EMPR)

The growth rate of employment is measured by the log-difference between the 2000 and 1990 and between the 1990 and 1980 levels of private non-farm employment.

Growth rate of gross in-migration (INMR)

The growth rate of gross in-migration is measured by the log-difference between the levels of gross in-migration into a given county in 2000 and 1990, and 1990 and 1980.

Growth rate of gross out-migration (OTMR)

This variable is measured by the log-difference between the levels of gross out-migration away from a given county in 2000 and 1990, and 1990 and 1980. The use of gross in-migration and gross out-migration variables is preferable to the use of net-migration (see Bowman and Myers 1967 and Sjaastad 1962) for details on this issue). Greenwood (1975) also argued that the use of net-migration would involve a substantial loss of information and offer no apparent advantages that cannot also be achieved by regarding the effects of net migration as the sum of the effects of gross in- and gross out-migration. Note that the effects of migration on the sending and on the receiving counties depend critically on the characteristics of the migrants themselves, and that for any county in-migrants and out-migrants are unlikely to have identical characteristics.

Growth rate of median household income (MHYR)

The log-difference between the 1999 and 1989 levels, and between the 1989 and 1979 levels, respectively, of median household income in a given county is used to measure the growth rate of median household income. Median household income is used as an average overall measure of county-level income. Median household income is preferable to mean or average household income because, unlike the mean, the median is not influenced by the presence of a few extreme values.

Growth rate of direct local government expenditures (GEXR)

Local governments spend money on local public services such as education, recreation, police, and infrastructure. Total local government expenditures at county-level on local public services divided by the total county population are used to measure local public services. The growth rate of direct local government expenditures per capita is measured by the log-difference between the 2002 and 1992, and between the 1992 and 1982 levels of per capita local government expenditures.

The spatial lags of the growth rate of employment (($\mathbf{I} \otimes \mathbf{W}$) **EMPR**), growth rate of gross in-migration (($\mathbf{I} \otimes \mathbf{W}$) **INMR**), growth rate of gross out-migration (($\mathbf{I} \otimes \mathbf{W}$) **OTMR**), growth rate of median household income (($\mathbf{I} \otimes \mathbf{W}$) **MHYR**), and growth rate of direct local government expenditures (($\mathbf{I} \otimes \mathbf{W}$) **GEXR**) are included on the right hand side ofeach equation of the system in (2). These spatially lagged endogenous variables are created by multiplying each of the dependent variables by ($\mathbf{I} \otimes \mathbf{W}$).

Independent variables

Independent variables include demographic, human capital, labour market, housing, industry structure, and amenity and policy variables. In line with the literature, unless otherwise indicated, the initial values of the independent variable are used in the analysis. This formulation reduces the problem of endogeneity. All independent variables are in log form except those that can take negative or zero values. The descriptions of the independent variables are given in Table A1.

Appendix 3: Interpretations of the coefficients of the spatial model

To interpret the coefficients of the spatial model, first let us rewrite Equation (2) as follows:

$$\mathbf{Y}_t = \mathbf{Y}_t\mathbf{B} + \mathbf{X}_t\mathbf{\Gamma} + \mathbf{W}\mathbf{Y}_t\mathbf{\Lambda} + \mathbf{U}_t \quad \text{for } t = 1, 2$$

where all the variables and the parameters are as defined is Equation (2).

A vector transformation of Equation (2) gives the following:

$$\begin{aligned} vec(\mathbf{Y}_t) &= vec(\mathbf{Y}_t\mathbf{B}) + vec(\mathbf{X}_t\mathbf{\Gamma}) + vec(\mathbf{WY\Lambda}) + vec(\mathbf{U}_t) \\ &= (\mathbf{B}' \otimes \mathbf{I}_N)vec(\mathbf{Y}_t) + (\mathbf{\Gamma}' \otimes \mathbf{I}_N)vec(\mathbf{X}_t) + (\mathbf{\Lambda}' \otimes \mathrm{W})vec(\mathbf{Y}_t) + \mathrm{vec}(\mathbf{U}_t) \end{aligned}. \tag{A1}$$

Letting $\mathbf{y}_t = vec(\mathbf{Y}_t)$, $\mathbf{x}_t = \mathrm{vec}(\mathbf{X}_t)$, and $\mathbf{u}_t = \mathrm{vec}(\mathbf{U}_t)$, it follows from Equation (A1) that

$$\begin{aligned} \mathbf{y}_t &= (\mathbf{B}' \otimes \mathbf{I}_N)\mathbf{y}_t + (\mathbf{\Gamma}' \otimes \mathbf{I}_N)\mathbf{x}_t + (\mathbf{\Lambda}' \otimes \mathbf{W})\mathbf{y}_t + \mathbf{u}_t \\ &= [(\mathbf{B}' \otimes \mathbf{I}_N) + (\mathbf{\Lambda}' \otimes \mathbf{W})]\mathbf{y}_t + (\mathbf{\Gamma}' \otimes \mathbf{I}_N)\mathbf{x}_t + \mathbf{u} \end{aligned}. \tag{A2}$$

The reduced form of Equation (A2) is given by:

$$\mathbf{y}_t = (\mathbf{I}_{5N} - [(\mathbf{B}' \otimes \mathbf{I}_N) + (\mathbf{\Lambda}' \otimes \mathbf{W})])^{-1}(\mathbf{\Gamma}' \otimes \mathbf{I}_N)\mathbf{x} + (\mathbf{I}_{5N} - [(\mathbf{B}' \otimes \mathbf{I}_N) + (\mathbf{\Lambda}' \otimes \mathbf{W})])^{-1}\mathbf{u}_t. \tag{A3}$$

Letting $\mathbf{B}^* = [(\mathbf{B}' \otimes \mathbf{I}_N) + (\mathbf{\Lambda}' \otimes \mathbf{W})]$ *and* $\mathbf{\Gamma}^* = (\mathbf{\Gamma}' \otimes \mathbf{I}_N)$, Equation (A3) can also be written as:

$$\begin{aligned} \mathbf{y}_t &= \mathbf{B}^*\mathbf{y}_t + \mathbf{\Gamma}^*\mathbf{x}_t + \mathbf{u}_t \\ \mathbf{y}_t &= (\mathbf{I}_{5N} - \mathbf{B}^*)^{-1}\mathbf{\Gamma}^*\mathbf{x}_t + (\mathbf{I}_{5N} - \mathbf{B}^*)^{-1}\mathbf{u}_t \text{ (in reduced-form)} \end{aligned}. \tag{A4}$$

where $(\mathbf{I}_{5N} - \mathbf{B}^*)^{-1}$ is an *5N x 5N* inverse matrix.

The own- and cross-partial derivatives: $\frac{\delta y_t}{\delta x'_{tR}}$ for our model takes the form of $5N \times 5N$ matrix that can be given by:

$$\frac{\delta y_t}{\delta x'_{tR}} = (\mathbf{I}_{5N} - \mathbf{B}^*)^{-1}\mathbf{I}_{5N}\gamma_R, \tag{A5}$$

where $(\mathbf{I}_{5N} - \mathbf{B}^*)^{-1}$ is the spatial multiplier.

The marginal effect can be decomposed into various effects using the formula for a sum to infinity:

$$\begin{aligned} (\mathbf{I}_{5N} - \mathbf{B}^*)^{-1}\mathbf{I}_{5N}\gamma_R &= (\mathbf{I}_{5N} + \mathbf{B}^* + \mathbf{B}^{*2} + \mathbf{B}^{*3} + \cdots)\mathbf{I}_{5N}\gamma_R \\ &= \mathbf{I}_{5N}\gamma_R + [\mathbf{B}^*\gamma_R + \mathbf{B}^{*2}\gamma_R + \mathbf{B}^{*3}\gamma_R + \cdots] \end{aligned} \tag{A6}$$

Using LeSage and Pace's (2009) conjecture, we can calculate scalar summaries of the own- and cross-partial derivatives. The total effect of the same marginal change in any of the exogenous variables, say Pop 25–44, across all N counties on employment growth rate at location '*i*', say county 1, at time *t*is the average of the sum across the *i*th row of the 5N × 5N matrix given in (A5) above. This total effect can be decomposed into direct (own-region) effect and indirect (other region) effect. The direct effect is the average of the sum of the main diagonal elements $(\partial y_{it}/\partial x'_{itR})$ of the matrix given in (A5). This direct effectfor county *i* includes feedback loop effects that arise as a result of impacts passing through neighbouring counties *j* and back to county i. The indirect effect is the average of the sum of the off-diagonal elements across the ith row $\left(\sum_{j=1}^{N-1} \partial y_{it} / \partial x'_{itR}, \text{ for } j \neq i\right)$. In terms of (A6), the direct effect is the average of all own-partial derivatives which are on the diagonals of $\mathbf{I}_{5N}\gamma_R$ and the indirect effect is the average of all cross-partial derivatives which are on the off-diagonal positions of $[\mathbf{B}^*\gamma_R + \mathbf{B}^{*2}\gamma_R + \mathbf{B}^{*3}\gamma_R + \cdots]$. Hence, the diagonal elements of the 5N × 5N matrix given in (13) contain the direct effects and the off-diagonal elements represent the indirect effects (see LeSage and Pace 2009; Anselin and LeGallo 2006; and Debarsy et al. 2010).

Table A1. Variable description and data sources

Variable code	Variable description	Source
Endogenous variables		
EMPR	Growth rate of employment 1980–1990, 1990–2000	Computed
INMR	Growth rate of gross in-migration 1980–1990, 1990–2000	Computed
OTMR	Growth rate of gross out-migration 1980–1990, 1990–2000	Computed
MHYR	Growth rate of median household income 1979–1989, 1989–1999	Computed
GEXR	Growth rate of local public expenditures per capita 1982–1992, 1992–2002	Computed
Spatially lagged endogenous variables		
($\mathbf{I} \otimes \mathbf{W}$) EMPR	Spatial Lag of EMPR	Computed
($\mathbf{I} \otimes \mathbf{W}$) INMR	Spatial Lag of INMR	Computed
($\mathbf{I} \otimes \mathbf{W}$) OTMR	Spatial Lag of OTMR	Computed
($\mathbf{I} \otimes \mathbf{W}$) MHYR	Spatial Lag of MHYR	Computed
($\mathbf{I} \otimes \mathbf{W}$) GEXR	Spatial Lag of GEXR	Computed
Initial condition variables		
EMPt-1	Employment 1980, 1990	County & City Data Book
INMt-1	In-migration 1980, 1990	Internal Revenue Service
OTMt-1	Out-migration 1980, 1990	Internal Revenue Service
MHYt-1	Median Household Income 1979, 1989	Bureau of Economic Analysis
GEXt-1	Local Public Expenditures per Capita 1982, 1992	US Bureau of the Census
Regional and policy variables		
AREA	Land area in square miles 1980, 1990	US Bureau of the Census
POPs	Population 1980, 1990	US Bureau of the Census
POP2	Population-square 1980, 1990	US Bureau of the Census
POP5-17	Per cent of population between 5–17 years 1980, 1990	US Bureau of the Census
POP25-44	Per cent of population between 25–44 years old 1980, 1990	US Bureau of the Census
FHHF	Per cent of female householder, family householder 1980, 1990	County & City Data Book
SCRM	Serious crime per 100,000 population 1980, 1990	County & City Data Book
POPHD	Persons 25 years and over, % high school 1980, 1990	County & City Data Book
POPCD	Persons 25 years and over, % at least bachelor's degree 1980, 1990	County & City Data Book
OWHU	Owner-occupied housing unit in per cent 1980, 1990	US Bureau of the Census
MCRH	Median contract rent of specified renter-occupied 1980, 1990	US Bureau of the Census
UNEMP	Unemployment rate 1980, 1990	Bureau of Labour Statistics
MANU	Per cent employed in manufacturing 1980, 1990	County & City Data Book
WHRT	Per cent employed in wholesale and retail trade 1980, 1990	County & City Data Book
DFEG	Direct federal expenditures and grants per capita 1982, 1992	County & City Data Book
PCTAX	Per capital local tax 1982, 1992	County & City Data Book
PCPTAX	Property tax per capita 1982, 1992	County & City Data Book
PCTD	Total debt outstanding per capita 1982, 1992	County & City Data Book
LTD	Long-term debt, utility 1982, 1992	County & City Data Book
SCIX	Social capital index 1990, 1997	Rupasingha et al. 2006
NAIX	Natural amenities index 1980, 1990	USDA
HWD	Highway density 1980, 1990	US Highway Authority
ESBd	Establishment density 1980, 1990	County Business Pattern
EXPTAX	Personal income tax/local general expenditure 1980, 1990	Computed

Table A2. Descriptive Statistics for Appalachia Counties 1990–2000

Variable	Description	Mean	Std Dev	Minimum	Maximum
EMPR	Growth Rate of Employment 1990–2000	0.17672	0.24499	–0.69448	1.7868
INMR	Growth Rate of Gross In-Migration 1990–2000	0.096241	0.24922	–0.92655	1.08588
OTMR	Growth Rate of Gross Out-Migration 1990–2000	0.096679	0.22048	–1.09537	0.99832
MHYR	Growth Rate of Median Household Income 1989–1999	0.47743	0.30826	–0.49426	1.39569
GEXR	Growth Rate of Local Public Expenditures Per Capita 1992–2002	0.61617	0.44636	–0.54832	4.95896
(**I** ⊗ **W**) EMPR	Spatial Lag of EMPR	0.17629	0.13013	–0.12982	0.84378
(**I** ⊗ **W**) INMR	Spatial Lag of INMR	0.094796	0.22541	–0.45875	0.80957
(**I** ⊗ **W**) OTMR	Spatial Lag of OTMR	0.092459	0.15939	–0.33829	0.57753
(**I** ⊗ **W**) MHYR	Spatial Lag of MHYR	0.47791	0.16818	0.076696	1.00418
(**I** ⊗ **W**) GEXR	Spatial Lag of GEXR	0.61467	0.17942	0.1598	1.83703
AREA	Land Area in square miles 1990	6.00903	0.74824	1.09861	7.27656
POPs	Population 1990	10.29714	0.94766	7.87664	14.10553
POP2	Population-squared 1990	106.9271	19.95609	62.04143	198.9659
POP5-17	Per cent of population between 5–17 years 1990	2.92443	0.12003	2.17475	3.22287
POP25-44	Per cent of population between 25–44 years old 1990	3.37993	0.077483	2.78501	3.74479
FHHF	Per cent of Female Householder, Family Householder 1990	2.32185	0.20314	1.81143	3.18787
SCRM	Serious crime per 100,000 population 1990	2,284.809	1,561.256	0	8,487
POPHD	Persons 25 years and over, % high school 1990	4.10041	0.1706	3.56953	4.4682
POPCD	Persons 25 years and over, % bachelor's degree or above 1990	2.26938	0.40654	1.30833	3.7305
OWHU	Owner-Occupied Housing Unit in per cent 1990	4.32524	0.076094	3.86703	4.47278
MCRH	Median Contract Rent of Specified Renter-Occupied 1990	5.64139	0.20586	4.94164	6.35784
UNEMP	Unemployment Rate 1990	2.15356	0.34816	1.22378	3.24649
MANU	Per cent employed in manufacturing 1990	26.24019	11.29556	2.2	53.6
WHRT	Per cent employed in wholesale and retail Trade 1990	18.82775	3.53195	8.7	27.7
DFEG	Direct Federal Expenditures and Grants per Capita 1992	7.98688	0.3758	6.98286	10.1766
PCTAX	Per Capital Local Tax 1992	5.91452	0.52985	4.50736	7.42253
PCPTAX	Property Tax per Capita 1992	5.5236	0.61602	3.91202	7.36265
PCTD	Total Debt Outstanding per Capita 1992	1,180.022	2,271.215	0	30,332
LTD	Long-Term Debt, Utility 1992	11,728.35	71,189.12	0	1,368,142
SCIX	Social Capital Index 1990	–0.59298	0.95959	–2.5266	5.64457
NAIX	Natural Amenities Index 1990	0.14333	1.15867	–3.72	3.55
HWD	Highway Density 1990	0.69039	0.40412	–0.33914	2.63189
ESBs	Establishment Density 1990	2.92833	0.3351	1.87398	4.09316
EXPTAX	Personal Income Tax/Local General Expenditure 1990	0.8429	0.51449	–0.98373	2.60823
EMPt-1	Employment 1990	8.82649	1.25425	5.42054	13.38131
INMt-1	Gross In-Migration 1990	7.08755	1.00192	4.54329	10.51994
OTMt-1	Gross Out-Migration 1990	7.03768	0.97551	4.49981	10.54952
MHYt-1	Median Household Income 1989	9.9439	0.2261	9.05894	10.68093
GEXt-1	Local Public Expenditures per Capita 1992	7.22576	0.27948	6.49224	8.10832

Note: All variables except SCRM, PCTD, LTD, SCIX and NAIX are in log form.

doi:10.1111/j.1435-5957.2012.00388.x

Estimamos un modelo de crecimiento de panel espacial regional por ecuaciones simultaneas, utilizando una nueva estrategia de estimación de cinco pasos que generaliza una enfoque descrito en Kelejian y Prucha. La región de estudio comprende los 418 condados Apalaches 1980-2000. Las estimaciones muestran simultaneidades de retroalimentación entre las variables endógenas, convergencia condicional con respecto a las variables endógenas respectivas, y un retardo espacial autorregresivo y efectos de retardo regresivos cruzados espaciales con respecto a las variables endógenas. Una conclusión clave sobre políticas es que los programas sectoriales específicos deberían estar integrados y armonizados, y que las políticas de desarrollo diferenciadas regionalmente podrían producir mejores retornos que si se tratasen todas las localizaciones del mismo modo.

我々は、KelejianとPruchaが概略を提示するアプローチを一般化した5段階の新しい推定戦略を用いて、地域空間パネル同時連立方程式成長モデルを推計した。対象地域は1980年から2000年までのアパラチアの418郡からなる。推計は、内生変数間のフィードバックの同時性、各内生変数に関する条件収束、内生変数について空間的自己回帰ラグおよび空間的クロス回帰ラグ効果を示す。重要な政策的結論は、特定セクター向けプログラムは総合調整されるべきであり、すべての地域を同一に扱う政策よりも地域別に差別化された開発政策の方が高いリターンが得られるというものである。