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Business Establishment Growth in the Appalachian Region, 2000–2007: An Application of Smooth Transition Spatial Process Models

Wan Xu and Dayton M. Lambert

Business establishment growth in the Appalachian region (2000–2007) was regressed on industry sector composition controlling for demographic, physical, and economic determinants. We test the hypothesis that local response to growth determinants is geographically heterogeneous using Smooth Transition spatial process models. This class of models exhibiting endogenous regime switching behavior provides another tool for exploring the spatially heterogeneous effects of local determinants on economic growth.

Key Words: Appalachia, business establishment growth, smooth transition models, spatial processes

JEL Classifications: C21, C51, O47, R11

Models explaining geographic heterogeneity of economic growth are ubiquitous. For example, Partridge et al. (2008) found that the effects of fiscal policies and other local characteristics on growth varied considerably across rural areas in the United States using Geographically Weighted Regression (GWR). Lambert and McNamara (2009) explained food manufacturer location decisions using discrete spatial regimes, finding that the importance of local determinants varied depending on how counties were classified as metropolitan, micropolitan, or noncore. Wojan, McGranahan, and Lambert (2010) allowed parameters to vary across metropolitan–micropolitan–noncore counties and three resource amenity categories, finding that the interaction effects between individuals in creative class occupations and entrepreneurs on economic indicators were heterogeneous across regimes. Arbia, Basile, and Piras (2005) applied a nonparametric regression estimator to examine geographic nonlinearities of factors explaining the regional heterogeneity of growth in Italy. Other examples of spatial econometric models admitting individual or group-specific responses are numerous, including spatial adaptive filters (SAF) (Foster and Gorr, 1986), quantile regression (Lambert et al., 2007), Quant's (1958) regime switching regression, Casetti's (1972) spatial expansion model, multilevel hierarchical modeling

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(Voss, White, and Hammer, 2004), and random coefficient models (Anselin, Wendy, and Cho, 2002). Regional studies using these approaches typically regress some economic indicator on local factors hypothesized to explain growth according to parameters or functional forms unique to spatial units. The underlying tenets of these methods are generally consistent with the conventional idea that the constraints, opportunities, and politics guiding growth are ultimately context-dependent and that development strategies are more likely to succeed when tailored to local conditions (Irwin et al., 2010). Global solutions implied by models that restrict responses to local determinants to be the same everywhere may also understate important sources of heterogeneity that could provide insight about connections to wider economies and specific solutions to regionwide resource allocation problems.

This research applies a relatively new spatial econometric model to explain business establishment growth in the Appalachian region from 2000–2007, the Smooth Transition Regression (STAR) model of Pede (2010) and Pede, Florax, and Holt (2009). Like the GWR and SAF methods, parameter estimates of the STAR model assume different values at different locations. However, GWR and SAF models are extreme examples of the incidental parameter problem because each spatial unit has its own vector of coefficients; probabilistic statements about the coefficients are impossible, and interpretation is restricted to the idiosyncrasies of the sample (Anselin, 1988). In addition, the calibration of the GWR model is sensitive to outliers, heteroskedasticity, and possibly spatial error dependence (Cho, Lambert, and Chen, 2010). Poor calibration of GWR models may also lead to data oversmoothing. An advantage of the STAR model is that the incidental parameter problem is circumvented and the usual robust covariance estimators can be applied to make inferential statements. Unlike the SAF or GWR models, nonlinear relationships across space are modeled using "autocatalytic" switching functions under the STAR specification. From a theoretical perspective, the notion of endogenous regimes is also consistent with the "New Economic Geography" results that focus on the causes and consequences of regional economic asymmetries (e.g., Fujita, Krugman, and Venables, 1999; Brakman et al., 2001). To the extent that the STAR's autocatalytic function sorts spatial units along a continuous hierarchy, the smooth transition model also lends itself to identifying endogenous break points across space resulting from (for example) differential trade costs; access advantage to urban economies; job and people migration; and "catastrophic agglomeration", the superconcentration of industries into a few regions (Fujita and Thisse, 2002; Baldwin et al., 2003). The endogenous sorting process so applied complements other modeling efforts that explain rural–urban growth interactions resulting from hierarchical access advantages (e.g., Partridge et al., 2008).

This article demonstrates the capabilities of the STAR family of spatial process models by examining the factors associated with business establishment growth in the Appalachian region, 2000–2007. Despite significant economic improvement over the last four decades, nearly one fourth of the counties in the region continue to struggle in terms of key economic indicators (Keefe, 2009). Improvement in relative economic well-being is evident in many Appalachian communities from 1960–2011 but spatial inequities persist. Like many rural areas, the challenges facing Appalachian communities are often reduced to tradeoffs between scale economies, transportation costs, external market demand, and resource endowments and how these factors influence business location and job creation (Irwin et al., 2010).

This article has two objectives. The first objective is to motivate a relatively new class of spatial regression models—STAR models—which allow for endogenous sorting of spatial units into growth regimes. The approach is useful for modeling the effects of access advantage and transport costs on local growth as a data-driven process, bypassing the need for artificial dichotomies such as "rural" or "urban" county classification schemes. The second objective is to identify which counties in Appalachia were positioned to withstand challenging economic times in terms of sustained business establishment growth given initial levels of existing infrastructure, demographic attributes, and industry structure. The 2000–2007 period includes the low point of a brief recession (in 2001) and the economic recovery that lasted through 2007. Some industry sectors may have positively contributed to business establishment growth during this period. However, in other locations, different industry sectors may have no effect, or even a negative impact, on employment and income growth (Feser, Renski, and Goldstein, 2008; Spencer et al., 2010). Identifying which industry sectors contributed to business establishment expansion during this period may inform regional economic development policy in terms of business retention and industry recruitment.

Empirical Model

Local factors hypothesized to influence business establishment growth include demographic characteristics, settlement patterns, growth momentum, infrastructure, human and social capital, physical and natural amenities, and industry structure. The baseline log-linear model in reduced form is:

$$\begin{aligned} \Delta estabs_{i2000-2007} = {} & \alpha \cdot lnestden_{i2000} + \beta_0 + \beta_1 \cdot percomm_i + \beta_2 \cdot emprt_i + \beta_3 \cdot perestab20_i + \beta_4 \cdot perestab100_i \\ & + \beta_5 \cdot \Delta pop_{9000i} + \beta_6 \cdot \Delta emp_{9000i} + \beta_7 \cdot \Delta estab_{9000i} + \beta_8 \cdot perblk_i + \beta_9 \cdot permind_i \\ & + \beta_{10} \cdot perhsp_i + \beta_{11} \cdot perpop2064_i + \beta_{12} \cdot perpop65up_i + \beta_{13} \cdot perhsdip_i + \beta_{14} \cdot percc_i \\ & + \beta_{15} \cdot amenity_i + \beta_{16} \cdot landpub_i + \beta_{17} \cdot interstate_i + \beta_{18} \cdot adhs_i + u_i, \; i = 1 - 1{,}070 \text{ counties} \end{aligned} \tag{1}$$

which is summarized as $\Delta y = Z\beta + u$. Variable names, data sources, and descriptive statistics are summarized in Table 1.

Change in the number of business establishments ($\Delta estabs_{2000\text{–}2007}$) was measured as natural log ratio of the total number of business establishments in a county with the initial (terminal) years of 2000 (2007). The initial year for business establishments was normalized by county area (*lnestden*). Access advantage to economic centers was measured with two variables. The percent of workers commuting outside a county (*percomm*) is expected to be positively associated with business establishment growth given the physical amenity advantages afforded by urban areas (Partridge et al., 2008). Counties with relatively higher employment rates were expected to grow faster than counties with fewer available jobs (*emprt*). Employment rates are from the Regional Economic Information System files compiled by the Bureau of Economic Analysis (2007) and the percent of workers commuting to other counties is from the 2000 U.S. Census.

Change measures from the previous decade (1990–2000) were included for business establishments ($\Delta estab_{9000}$), employment (Δemp_{9000}), and population (Δpop_{9000}) and are hypothesized to proxy growth sustainability (Wojan, McGranahan, and Lambert, 2010). Population growth in the preceding decade may be indicative of favorable demand conditions, and the relationship between growth in business establishments and jobs has also been found to have some lag (Fritsch and Mueller, 2004). These variables were calculated as the logged ratio of the end-of-the-decade to start-of-the-decade measures.

Demographic variables include the percent of the population aged 20–64 years (*perpop2064*), a measure of labor availability, and the proportion of the population older than 65 years (*perpop65up*), both enumerated in 2000. Some counties in the Appalachian region have become destinations for retirees (Lambert et al., 2007; Clark et al., 2009). Retirees may be inclined to start small businesses but with no intention of becoming major employers (Rogoff, 2008). Therefore, the expected relationship is ambiguous. The proportions of the black (*perblk*), Hispanic (*perhsp*), and Native American (*peramind*) populations were also included in the model because these groups and whites may have different opportunities to participate in different job markets or start new businesses (Wojan, McGranahan, and Lambert, 2010).

Human capital is hypothesized to be associated with economic growth and is represented

Table 1. Summary Statistics of Growth Indicators, Industry Sector Shares, and Local Determinants

Variable	Description	Data Source	Mean	Standard Deviation
lnestden00	Log establishments/area, 2000	CBP/1	0.546	1.338
distmet	Distance to metro county, 1993	ERS/2	33.466	28.860
percomm	Percent commute outside county, 2000	2000 Census/3	39.963	
emprt	Percent employment rate, 2000	REIS/4	95.394	1.580
lnmedhhi	Log median household income, 2000	2000 Census	10.444	0.246
perestab20	Percent of firms with < 20 employees, 2000	CBP	88.030	
perestab100	Percent of firms with > 100 employees, 2000	CBP	2.193	
Δpop9000	Δ Population, 1990–2000	2000 Census	0.103	0.140
Δemp9000	Δ Employment, 1990–2000	2000 Census	0.122	0.125
Δestabs9000	Δ Establishments, 1990–2000	2000 Census	0.181	0.182
perblk2000	Percent black, 2000	2000 Census	16.885	
peramind2000	Percent American Indian, 2000	2000 Census	0.428	
perhsp2000	Percent Hispanic, 2000	2000 Census	2.220	
pctpop2064	Percent Pop. 20–64 years old, 2000	2000 Census	58.717	
c00p65ov	Percent Pop. 64+ years old, 2000	2000 Census	13.434	
hsdip2000	Percent high school diploma, 2000	2000 Census	73.099	
pctcc	Percent population creative occupations, 2000	ERS	16.941	
amenity	Natural amenity index	2000 Census	–0.200	1.178
pubpct	Percent public land	2000 Census	7.410	
interstate	Interstate (=1)	ESRI/5	0.469	
adhs	Appalachian Development Highway (=1)	ARC/6	0.136	
Industry sectors (% Establishments)				
ag	Percent agriculture, forestry	CBP	1.60	
mining	Percent mining	CBP	0.60	
manu	Percent manufacturing	CBP	5.70	
retail	Percent retail trade	CBP	20.2	
infor	Percent information	CBP	1.50	
prof	Percent professional services	CBP	6.30	
art	Percent arts, entertainment, and recreation	CBP	1.30	
accfood	Percent accommodation and food services	CBP	7.40	

1. CBP, County Business Pattern.
2. ERS, Economic Research Service.
3. 2000 Census, U.S. Census, 2000.
4. REIS, Regional Economic Information System.
5. ESRI, ESRI ArcView GIS.
6. ARC, Appalachian Region Commission.

by the percent of the population with bachelor's degrees (*perhsdip*) and the percent of persons working in creative occupations (*percc*). In previous decades, rural areas with low education attainment attracted employers offering low-skill, low-wage jobs, but many of these firms relocated operations abroad or adopted new technologies requiring higher skilled labor in the 1990s (Johnson, 2001). Demand markets may also harbor relatively more creative individuals capable of solving market logistic problems or combining old ideas in new ways, which may influence business growth (Jacobs, 1965). We include the percent of persons working in so-called creative occupations (Wojan and McGranahan, 2007) to proxy the stock of local talent and intellectual capacity.

Natural amenities and public land availability may influence business establishment growth by attracting new firms and people to locations with open space, wilderness, or scenic environments (Deller et al., 2001; McGranahan, 2008). In low-amenity places, growth may depend primarily on changes in demand for producer services driven by expansion of basic economic sectors (Wojan, McGranahan, and Lambert, 2010). However, high-amenity areas may also be remote and difficult to access. A natural amenity index (*amenity*) was included to measure the relationship between economic growth and locations abundant in natural amenities (McGranahan, 1999). The variable is an aggregate index of sunlight, humidity, temperature, topography, and water resources. The percent of the county in public land was included to control for the effects of public access to unbuilt areas on business establishment growth (*landpub*).

Dummy variables indicating the presence of a national interstate (*interstate*) or an Appalachian Development Highway (*adhs*) in a county were included in the regression to control for the influence of transportation infrastructure on business establishment growth. The expected sign is generally ambiguous. Good roads may be attractive to prospective firms, which would increase the likelihood of attracting new investment. However, good roads may encourage out-commuting, which could encourage growth elsewhere, thereby offsetting growth in local retail or service sectors (Kahn, Orazem, and Otto, 2001).

Industry structure is measured by the percentage of manufacturing establishments with less than ten employees (*perestab20*) and the percentage of manufacturing establishments with more than 100 employees (*perestab100*). Both variables intend to capture effects attributable to agglomeration economies and economies of scale internal to firms (Lambert, Brown, and Florax, 2010). The relationship between industry sectors and business establishment growth was measured as sector shares at the two-digit NAICS level; $S^k_{i2000} = \frac{E^k_{i2000}}{E^{tot}_{i2000}}$, where E^k_{i2000} is the number of business establishments in sector k, county i, and E^{tot}_{i2000} is the total number of business establishments in a county. There were eight industry sectors considered: agriculture and forestry (NAICS 11), mining (NAICS 21), manufacturing (NAICS 31–33), retail (NAICS 44), information services (NAICS 51), professional services (NAICS 54), arts and entertainment (NAICS 71), and food and accommodations (NAICS 72) (Table 1). Of interest is the extent to which the initial level (or "stock") of an industry sector was associated with aggregate business establishment growth. Feser, Renski, and Goldstein (2008) found that clustering did not guarantee employment growth but was associated with new business formation from 1998–2002 in the Appalachian region. Therefore, we maintain no priors on the expected relationships specific sectors might have on business establishment growth.

Spatial Processes, Regional Adjustment, and Endogenous Growth Regimes

The family of STAR models developed extends Pede (2010) and Pede et al.'s (2010) previous work on STAR process models to the regional adjustment model. In addition to endogenous stratification of counties into separate growth regimes, we hypothesize that business establishment growth is simultaneously determined by business establishment growth in neighboring counties, for example, $\sum_{j=1,i\neq j}^{n} w_{ij}y_j$, where W denotes spatial connectivity. Local growth may be influenced by information spillovers, thick labor markets, or forward–backward linkages to other spatial units (Anselin, 2002; Moreno et al., 2004). Most studies incorporating spatial dependence typically use a spatial process model attributable to Whittle (1954) whereby an endogenous variable specifies interaction between spatial units plus a disturbance term. Anselin and Florax (1995) called this a spatial lag autoregressive (SAR) model. The SAR model with autoregressive disturbances of order (1,1) (ARAR) (Anselin and Florax, 1995) contains a spatially lagged endogenous variable (Wy) and spatially dependent disturbances: $y = \rho Wy + X\beta + \varepsilon$, $\varepsilon = \lambda W\varepsilon + u$, where u is independently and identically distributed with mean zero and covariance Ω, and W is a matrix defining relationships between spatial units. When the weights are defined as contiguous neighbors or groups of observations bounded by some distance metric, local shocks are transmitted to all other locations with the intensity of the shocks decreasing over space. The reduced form of the ARAR model is $y = A^{-1}X\beta + A^{-1}B^{-1}u$, with (respectively) $A = (I - \rho W)$ lag autoregressive and $B = (I - \lambda W)$ error autocorrelation spatial filters. The inverted matrices A^{-1} and B^{-1} are spatial multipliers that relay feedback/feed-forward effects of shocks between locations

(Fingleton, 2008), thereby distinguishing this class of models from other econometric models.

We use a "gravity weight" specification to model spillover potential between counties. Gravity weight specifications are hypothesized to proxy market potential across regions (Fujita, Krugman, and Venables, 1999; Fingleton, 2008). Each element in W is

$$w_{ij} = \frac{pop_i^{98} \cdot pop_j^{98}}{d_{ij}}$$

where pop_i is the population of county i in 1998 and d_{ij} is the network distance between counties i and j. The elements of W are presumed to be exogenous; hence, the 2-year lag of population. The spatial weight matrix was row-standardized, rendering it scale-neutral (Anselin, 1988).

The reduced form of the SAR-type models suggests that estimation of the marginal effects is more complicated than the typical marginal effects of log-linear models. There are a variety of methods whereby the marginal effects associated with SAR-type models can be calculated (e.g., LeSage and Pace, 2009, pp. 34–39). In this application, the influence of the lag multiplier is approximated as a geometric series (see also Anselin and Lozano-Gracia, 2008). For example, the "total effect" of a covariate k is the global impact of that variable on a given spatial unit: $A^{-1}(I_n \cdot \beta_k) = [I_n + \rho W + \rho^2 W^2 + \rho^3 W^3 + \rho^4 W^4 + \rho^5 W^5 + \ldots \rho^q W^q]\beta_k$, where the order q refers to the location itself ($q = 0$), the impact of the neighbors ($q = 1$), the impact of the neighbors of the neighbors ($q = 2$), etc. In the limit, A^{-1} tends to $(1 - \rho)^{-1}$ and the "total" marginal effect can be written as $\beta_k^{Total} = \beta_k(1 - \rho)^{-1}$. The "indirect effect" is the difference between the total and direct effect or the impact neighboring locations (on average) has on a given spatial unit given an incremental change in the covariate at that location $\left(\beta_k^{Indirect} = \frac{\rho}{1-\rho}\beta_k\right)$. Provided a consistent covariance estimator, standard errors of the total and indirect effects may be estimated using the delta method (Greene, 2000).

Smooth Transition Regime Model

Smooth transition models are well developed in time-series analysis (Terasvirta and Anderson, 1992; Van Dijk and Franses, 2000; Holt and Craig, 2006) and the biological sciences (Schabenberger and Pierce, 2002), but less so in the spatial econometric literature. A spatial analogue of the STAR model was introduced by Gress (2004), Basile and Gress (2005), and Basile (2008). Pede, Florax, and Holt (2009) and Pede (2010) modified Lebreton's (2005) spatial version of the time-series STAR model by including a spatially lagged variable in the transition function. Pede, Florax, and Holt also modified the spatial STAR model to accommodate spatial lag and error multiplier effects. The approach applied here is parametric and extends their work.

The economic geography literature generally predicts that friction caused by heterogeneous transport costs may induce "catastrophic agglomeration" such that the distribution of firms and jobs across space concentrates into one or a few regions (Brakman, Garretsen, and van Marrewijk, 2001). The endogenous sorting of regions admitted by the smooth transition model are hypothesized to identify these so-called "bifurcations" that could emerge in regional economies resulting from uneven trade costs. The STAR model provides a direct test for identifying these structural breaks and the extent to which access to agglomeration economies affects the relationship between local resource constraints and growth. Let $G(\gamma, c; v)$ be an autocatalytic function (Schabenberger and Pierce, 2002) such as the logistic function, $[1 + \exp(-\gamma[v - c]/\sigma_v)]^{-1}$, with (respectively) slope and location parameters γ and c and a transition variable v. The parameters are approximately scale-neutral when they are normalized by the standard deviation of the transition variable (σ_v). The adjustment model with regime-switching potential is

$$\Delta y = G \cdot Z\beta_1 + (1-G) \cdot Z\beta_2 + u, \quad (2)$$

where "·" is the Hadamer product operator, Z a matrix of covariates, and (β_1, β_2) coefficients corresponding with regimes 1 and 2. Equation 2 can be rearranged accordingly (Maddala, 1983):

$$\Delta y = Z\beta_2 + G \cdot Z(\beta_2 - \beta_1) + u, \rightarrow \Delta y = Z\beta + G \cdot Z\delta + u, \quad (3)$$

with the interaction between the transition function and the covariates permitting nonlinear parameter variation among spatial units. As γ increases, spatial units are sorted into more distinct groups. Intermediate values of γ identify spatial units along a continuum that are "in transition" as determined by the transition variable, v (for example, Figure 1). The parameter c is a location parameter that determines the inflection point on the regime splitting curve according to the transition variable (Figure 1). For larger values of γ (e.g., greater than 100), spatial units split into distinct regimes with the interaction coefficients (δ) the difference from the reference group mean response to local determinants (the β's) and the alternative regime. Rejection of the null hypothesis $\delta = 0$ suggests a nonlinear relationship between local covariates and business establishment growth. For large values of γ, (3) behaves "as if" counties were categorized using dummy variables (e.g., "metropolitan" or "nonmetropolitan") and then interacted with every explanatory variable. There are no regimes when $\delta = 0$ and the effects of the covariates are geographically invariant. Thus, when there are regimes, the location-specific marginal effects (ME) of the basic STAR model are $ME_i = \beta + G_i\delta$.

Of particular importance is the choice of the transition variable (v), which is hypothesized to drive the sorting process. Ideally, v conveys information about connectivity between spatial units and is also exogenous. We use the road network distance of a county to the nearest metropolitan county (defined by the Office of Management and Budget) as the transition variable (*distmet*). A number of alternative transition variables are conceivable (e.g., Pede, 2010), but using the distance to the nearest metropolitan county is appealing to the extent that 1) the geographic effects of trade costs on business establishment growth are hypothesized to be nonlinear, possibly causing bifurcations in regional growth trajectories (e.g., Fujita and Thisse, 2002); and 2) that the urban–rural hierarchy is important with respect to firm location decisions and economic growth (Partridge et al., 2008; Lambert and McNamara, 2009).

Spatial Regimes and Spatial Process Models

The basic smooth transition model is more complex when *local spillovers* between counties *and regime splitting* potential are possible. For example, combining the STAR with the ARAR spatial process model suggests the following reduced form specification:

$$\text{ARAR-STAR: } \Delta y = A^{-1}Z\beta + A^{-1}G{\cdot}Z\delta + A^{-1}B^{-1}u \rightarrow \Delta y = \rho W\Delta y + Z\beta + G{\cdot}Z\delta + B^{-1}u. \tag{4}$$

This specification suggests the following hypotheses with respect to a baseline a-spatial model that could be estimated using Ordinary Least Squares (OLS) or the usual spatial error (SEM) and spatial lag (SAR) process models:

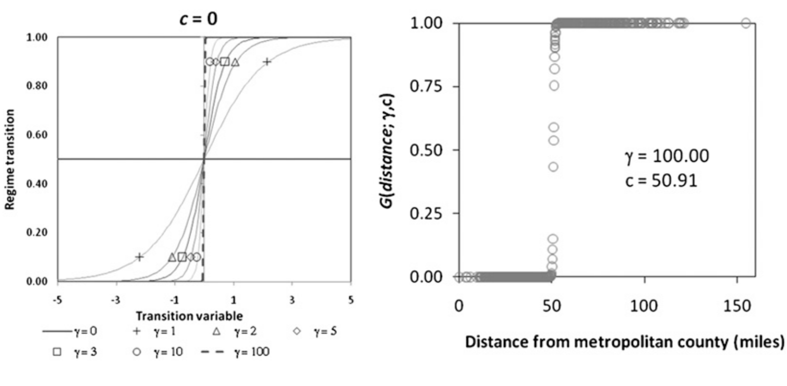

Figure 1. Example of the Transition Function $G(\gamma, c; v)$ and Different Levels of the Smoothing Parameter, γ. (left panel) Note That Two Distinct Regimes Emerge When $\gamma = 100$, Whereas There Are No Regimes Identified When $\gamma = 0$. The Parameter c Functions as a Location Parameter; the Inflection of the Transition Function is Centered on c. Transition Function of the Regime-Splitting Variable, $G(\gamma, c; distmet)$, for $\Delta estabs_{2000–2007}$ (right panel)

(5) H1: $\rho = 0,\ \lambda = 0,\ \delta = 0$ (a-spatial model, suggesting estimation with OLS),

(6) H2: $\rho = 0,\ \lambda = 0,\ \delta \neq 0$ (STAR model with geographic heterogeneity),

(7) H3: $\rho = 0,\ \lambda \neq 0,\ \delta \neq 0$ (error process model with geographic herterogeneity, SEM-STAR),

(8) H4: $\rho \neq 0,\ \lambda = 0,\ \delta \neq 0$ (lag process model with geographic heterogeneity, SAR-STAR),

(9) H5: $\rho \neq 0,\ \lambda \neq 0,\ \delta \neq 0$ (lag-error process model with geographic hertrogeneity, ARAR-STAR),

(10) H6: $\rho \neq 0,\ \lambda \neq 0,\ \delta = 0$ (lag-error process model, ARAR),

(11) H7: $\rho \neq 0,\ \lambda = 0,\ \delta = 0$ (spatial lag process model, SAR),

(12) H8: $\rho = 0,\ \lambda \neq 0,\ \delta = 0$ (spatial error process model, SEM).

Each specification has implications with respect to estimating marginal effects. Under H2 and H3, the *ceteris paribus* effect of an additional unit increase in local determinant k is

(13) $$ME_i^k = \beta_k + G_i.\delta_k.$$

Evidence supporting models H4 and H5 suggests more complicated marginal effects because of the interaction between neighbors through the spatial lag multiplier:

(14) $$ME_i^k = (\beta_k + G_i.\delta_k)(1-\rho)^{\uparrow(-1)},$$

with the indirect effects,

(15) $$ME_i^k = \rho/(1-\rho)(\beta_k + G_i.\delta_k).$$

Estimation and Specification of the Smooth Transition Regression Family of Models

Pede (2010) and Pede et al. (2010) outline the estimation procedures for recovering the STAR spatial process model parameters using maximum likelihood (ML). We relax the distributional assumption of normality maintained under ML and propose a general method of moments (GMM) estimator suggested by Arraiz et al. (2010) and Kelejian and Prucha (2010) for the STAR versions of the SAR, SEM, and ARAR models. Nonlinear estimation of the basic STAR model is discussed first followed by the procedure used to estimate the STAR model with lag dependence and/or correlated innovations using instrumental variables. Finally, we introduce a procedure whereby the number of spatial units considered neighbors in W are determined based on the threshold parameter of the transition function, c.

Nonlinear Least Squares Estimation of the Smooth Transition Regression Model

Nonlinear least squares is used to estimate the basic STAR model. Determining good starting values is critical for convergence. To calibrate the optimization procedure, we use a grid search over the shape and location parameters with the objective of minimizing the concentrated sum of squared errors (SSE):

(16) $$SSE = \min_{\gamma,c} \sum_{i=1}^{N} \left(\Delta y_i - \beta(\gamma,c;distmet_i)'Z_i\right)^2.$$

Conditional on the shape and location parameters, the closed-form solution for the parameters is $\beta(distmet;\gamma,c) = \left(\tilde{Z}'\tilde{Z}\right)^{-1}\tilde{Z}'y$, with $\tilde{Z} = [Z,\ \ G \cdot Z]$ (Terasvirta and Anderson, 1992). Note that concentrating the objective in (16) reduces the problem of finding reasonable starting values to a two-dimensional grid search (Holt and Craig, 2006). The expected value of γ is ≥ 0, so the outer grid domain ranged from 0 to 100 in increments of 0.5. The grid domain for the location parameter (c) was based on the 5%-tiles of the transition variable distribution. The shape and location parameters that minimized the SSE objective were used as starting values for a constrained nonlinear optimization routine to estimate the STAR and its spatial process variants.

Instrumental Variable Estimation of Smooth Transition Regression Spatial Process Models

Estimation of the SAR-STAR model with instrumental variables applies the same principle as the procedure typically used to estimate the SAR model with instruments (e.g., Anselin, 1988, p. 86; Kelejian and Prucha, 1999). Anselin (2006) surveyed a variety of instruments that could be used to generate predicted values of the endogenous, spatially lagged dependent variable: $\tilde{W}y = \tilde{P}Wy$ where $\tilde{P}$ is symmetric, positive definite, and idempotent projection matrix. Replacing Wy with its predicted values, the outcome variable is regressed on $\tilde{Z} = [X, \tilde{W}y]$, yielding the SAR-IV estimator; $\delta_0 = (\tilde{Z}'\tilde{Z})\tilde{Z}'y$. Standard errors for the estimator are adjusted for the "first-stage" regression such that $AsyCov(\delta_0) = \sigma_{IV}^2 \left(\tilde{Z}'\tilde{Z}\right)^{-1}$ (assuming homoskedastic errors) with variance $\sigma_{IV}^2 = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \delta'_0 Z_i\right)^2$, where Z includes the original data (Greene, 2000). A heteroskedastic-robust version could be estimated as

$$AsyCov(\delta)_{HET} = \left(\frac{n}{n-k}\right)\left(\tilde{Z}'\tilde{Z}\right)^{-1}\tilde{Z}'\Omega\tilde{Z}\left(\tilde{Z}'\tilde{Z}\right)^{-1}, \tag{17}$$

with Ω denoting the diagonal matrix of the squared residuals and the sample size divided by the degrees of freedom a small sample correction factor. Examples of instrumental variables (IVs) typically used in the applied literature include $Q_0 = [X, WX, W^2X]$ (e.g., Kelejian and Prucha, 1999). An alternative set of instruments, which is adopted here, includes Lee's (2003) "best" set of IVs such that $Q_{BEST} = [X, W(\mathrm{I} - \hat{\rho}_0\mathrm{W})^{-1}\mathrm{X}\hat{\beta}_0]$, with $(\hat{\beta}_0, \hat{\rho}_0)$ obtained from the IV regression with instruments Q_0. Modification of the SAR–IV to the SAR–STAR IV estimator is straightforward.

1. Replace Wy by its predicted values in the design matrix Z (as previously shown).
2. Find good starting values of the shape (γ) and location (c) parameters of the transition function $G(\gamma_0, c_0; v)$ using a grid search.
3. Given reasonable starting values, use a constrained nonlinear optimization routine to minimize the objective:

$$min_{(\gamma,c)} y'\left(1 - Z_G\left(\tilde{Z}_G'\tilde{Z}_G\right)^{-1}\tilde{Z}_G'\right)y,$$

where $Z_G = [X, G{\cdot}X, Wy]$, and $\tilde{Z}_G = [X, G \cdot X, \widetilde{Wy}]$.

4. Estimate standard errors using a heteroskedastic-robust covariance matrix (e.g., Equation 17).

Similar steps may be applied to estimate the ARAR–STAR with the instruments defined following Kelejian and Prucha (2010) (K&P) general moments procedure with some minor modifications. For instance, an iterative procedure is applied to estimate a heteroskedastic-robust version of the error autoregressive parameter (λ). The algorithm used in this application to estimate that ARAR–STAR version follows.

1. Estimate the STAR model, yielding G;
2. Given G, construct a residual vector with the IV estimator based on Z_G; $\tilde{Z}_G$.
3. Find the error autoregressive parameter following K&P's procedure for estimating the ARAR process model with autoregressive and heteroskedastic disturbances;
4. Detrend the outcome and design matrix variables with the Cochran–Orcutt transformation as $y^* = y - \lambda Wy$; $Z_G^* = Z_G - \lambda WZ_G$.
5. Update the STAR parameters (γ, c) given (y^*, Z_G^*); and
6. Return to step 1, and iterate until convergence (e.g., 0.000001, in this application).

Standard errors of the ARAR–STAR parameters are estimated using the asymptotic covariance matrix suggested by K&P (p. 60).

The stepwise iterative procedure used for the ARAR–STAR may be extended to cases where only error autocorrelation and spatial nonlinearities are considered, as in the case of the SEM with endogenous regimes (SEM–STAR). In this case, the IV matrix is an identity and Wy is omitted from the design matrix (Z). Standard errors may be estimated using an appropriate heteroskedastic-robust covariance matrix as previously.

If maximum likelihood were used to estimate the STAR-type models, then a stepwise "specific-to-general" (Florax, Folmer, and Rey, 2003) specification search could be applied using the Lagrange Multiplier tests developed by Pede, Florax, and Holt. In this application, a "general-to-specific" approach (Hendry, 2006; Larch and Walde, 2008) was considered. Therefore, hypotheses about spatial nonlinearity, lag, error, ARAR processes, and their combinations (H1–H8) were tested by calculating Wald statistics based on the robust covariance matrix of the full ARAR–STAR model (Equation 4, see K&P, p. 60).

Neighborhood Threshold Determination of W Based on Transition Parameters

In general, there is no consensus that spatial weights are most appropriate for any spatial econometric study, and the selection of appropriate weight matrices remains a challenge in applied research (Anselin, 1988; LeGallo and Ertur, 2003). Anselin, Florax, and Rey (2004) discuss the problems that may arise when spatial weights matrices are poorly selected. Some research has addressed selection of W using data-driven methods (e.g., Kooijman, 1976; Boots and Dufournaud, 1994; Getis and Aldstadt, 2004; Aldstadt and Getis, 2006). In this application, we determine neighborhood inclusion based on the location parameter—c—of the transition function. The elements of the "gravity matrix" are therefore determined as

$$w_{ij}^{*} = \begin{cases} \dfrac{pop_i^{98} \cdot pop_j^{98}}{d_{ij}} & if\ d_{ij} < c^{*} \\ 0 & otherwise \end{cases},$$

where c^* belongs to the set of G-function parameters minimizing the concentrated objective. The elements of W^* are updated, the instruments are reconstructed, and the minimization algorithm continues until an optimal neighborhood inclusion bandwidth is codetermined along with the transition parameters (γ, c). That the transition variable used in this application measures the distance between counties to the closest metropolitan county provides some intuition regarding the selection of neighbors. The parameter c is the distance (in miles) determining which counties are sorted into fast- or slow-growing regimes and is a natural cutoff point whereby neighborhoods are defined.

Results and Discussion

We focus discussion of the econometric results on 1) model specification; 2) the spatial patterns of the transition function G; and 3) the total marginal effects of the local determinants. The null hypothesis that business establishment growth was not contagious between counties was rejected at the 5% level (Table 2, Wald statistic = 8.05, degrees of freedom [df] = 1). However, the null hypothesis that the error terms were uncorrelated between spatial units could not be rejected (Wald = 1.68, df = 1). The joint lag/error test was rejected at the 5% level, which suggests the adjustment model could be specified as an ARAR process model. Not surprisingly, however, when the ARAR process model was estimated, the standard error of the error autoregressive parameter was relatively large and not significant. The null hypothesis that the effects of the covariates on growth were geographically invariant ($\delta = 0$) was rejected at the 5% level (Wald = 87.74, df = 29), suggesting that the growth trajectories exhibited heterogeneity across the region. Based on these results, we conclude that the SAR-STAR appropriately described the data-generating process determining business establishment growth during this period. The squared correlation coefficient of the SAR-STAR was $r^2 = 0.63$, suggesting that more than 60% of the variation in the data was explained by the model (Table 3). The relationship between local business establishment and growth in neighboring counties was modest but significant (lag autoregressive coefficient, $\rho = 0.17$, $p < 0.01$, Table 3). The transition function parameters were $\gamma = 100$ (the shape parameter) and $c = 51$ (the location parameters, in miles). The shape parameter was "binding" such that the estimated value was equal to the upper-bound constraint of the grid search. For this reason, the standard error of the shape parameter was difficult to estimate. The relatively large value of the shape parameter suggests the presence of two distinct growth regimes (Figure 1) with a transition threshold of approximately $c = 51$ miles. Therefore, the effects of the covariates on business establishment growth are remarkably different moving past the 50-mile marker of a metropolitan

Table 2. Model Specification for Change in Business Establishments

	Wald Statistic	P Value
Spatial lag AR, H_0: $\rho = 0$	8.05	0.00
Spatial error AR, H_0: $\lambda = 0$	1.68	0.19
Joint lag/error, H_0: $\rho = \lambda = 0$	18.90	0.00
Spatial nonlinearity, H_0: $\delta = 0$	87.74	0.00
Joint nonlinearity/lag/error, H_0: $\delta = \rho = \lambda = 0$	110.83	0.00

Table 3. Growth Regression Results for Change in Business Establishments, 2000–2007

Dep. Variable: $\Delta estabs_{2000-2007}$	Relation to Metropolitan County							
	Closest				Farthest			
	Direct Effect		Total Effect		Direct Effect		Total Effect	
Variable	Coefficient	*P* Value	Coefficient	*P* Value	Coefficient	*P* Value	Coefficient	*P* Value
Constant	–1.60	0.00	–1.94	0.00	1.30	0.20	1.58	0.19
ln Establishments, 2000	–0.04	0.00	–0.05a	0.00	0.05	0.00	0.06 a	0.00
Percent commute outside county, 2000	0.0886E–02	0.00	0.0107E–01	0.00	–0.0720E–02	0.29	–0.0872E–02	0.30
Employment rate, 2000	1%	0.01	0.01 a	0.00	–0.0986E–02	0.86	–0.0120E–01	0.86
Median household income, 2000	0.12	0.00	0.14 a	0.00	–14%	0.10	–0.18	0.09
Percent of firms with < 20 employees, 2000	–0.0375E–01	0.08	–0.0454E–01	0.09	0.0316E–01	0.43	0.0383E–01	0.43
Percent of firms with > 100 employees, 2000	0.0246E–01	0.64	0.0299E–01	0.64	–1%	0.44	–1%	0.44
Δ Population, 1990–2000	–0.10	0.06	–0.12	0.06	0.35	0.02	0.42	0.02
Δ Employment, 1990–2000	0.41	0.00	0.50 a	0.00	–0.33	0.01	–0.40	0.01
Δ Establishments, 1990–2000	0.06	0.09	0.07	0.10	0.02	0.81	3%	0.81
Percent Black, 2000	0.0678E–02	0.03	0.0821E–02 a	0.02	–0.0179E–01	0.00	–0.0217E–01 a	0.00
Percent American Indian, 2000	0.0202E–01	0.05	0.0245E–01	0.05	–0.0447E–01	0.03	–1%	0.03
Percent Hispanic, 2000	0.0382E–01	0.00	0.0462E–03 a	0.00	0.0700E–03	0.98	0.0850E–03	0.98
Percent population 20–64 years old, 2000	–1%	0.01	–1%	0.01	–0.0291E–01	0.47	–0.0352E–01	0.47
Percent population 64+ years old, 2000	–0.0933E–02	0.61	–0.0113E–01	0.61	–0.0709E–02	0.85	–0.0859E–02	0.85
Percent high school diploma, 2000	0.0820E–02	0.37	0.0993E–02	0.38	0.0959E–02	0.64	0.0116E–01	0.64
Percent population creative occupations, 2000	1%	0.00	1a%	0.00	–1%	0.12	–1%	0.12
Natural amenity index	0.02	0.00	0.02a	0.00	–0.01	0.37	–1%	0.37
Percent public land	0.0593E–02	0.15	0.0718E–02	0.15	–0.0756E–02	0.23	–0.0915E–02	0.23
Interstate	–0.01	0.22	–0.01	0.22	0.01	0.51	0.01	0.51
ADHS	0.01	0.50	0.01	0.51	0.01	0.62	0.01	0.62
ρ	0.17	0.00						
γ	100.00	0.70						
c	50.91	0.00						
Sq. Corr.	0.63							
Industry Sector Establishments								
Percent agriculture	–0.47	0.05	–0.57	0.05	0.92	0.01	1.11	0.01

Table 3. Continued

Dep. Variable: $\Delta estabs_{2000\text{–}2007}$	Relation to Metropolitan County							
	Closest				Farthest			
	Direct Effect		Total Effect		Direct Effect		Total Effect	
Variable	Coefficient	*P* Value	Coefficient	*P* Value	Coefficient	*P* Value	Coefficient	*P* Value
Percent mining	0.22	0.48	0.27	0.48	−0.13	0.83	−0.15	0.83
Percent manufacturing	−0.20	0.27	−0.24	0.27	−0.05	0.89	−0.06	0.89
Percent retail trade	−0.23	0.12	−0.27	0.12	0.92	0.01	1.12	0.01
Percent information	−0.52	0.33	−0.63	0.34	−0.65	0.50	−0.79	0.50
Percent professional services	−0.64	0.01	−0.77	0.01	0.78	0.17	0.94	0.18
Percent arts, entertainment, and recreation	0.48	0.39	0.58	0.39	−1.01	0.38	−1.23	0.38
Percent accommodation and food services	−0.31	0.13	−0.38	0.13	0.43	0.26	0.52	0.26

Note: an "a" in the Total Effect column indicates the indirect effect (total effect – direct effect) is significant at the 5% level. Total effects were estimated as $(1-\rho)^{-1}\beta$. Standard errors were estimated using the delta method (Greene, 2000).

county. On average, this value corresponds closely with the diameter of most counties in the region. The counties in the top percentile (the counties where $G = 1$) are generally associated with nonmetropolitan counties, and counties in the bottom of the hierarchy (e.g., those where $G = 0$) are associated with metropolitan counties. There are a few counties that appear to be "in transition" with respect to business establishment growth. The spatial distribution of the transition probabilities generated by the G function was mapped (Figure 2). The pattern closely follows the distribution of the Pickard index used by the ARC to categorize the economic disposition of counties (Figure 2; for example, see www.arc.gov/research/MapsofAppalachia.asp).

In Table 3, the "closest" regime ($G = 0$) corresponds with counties located in or near metropolitan counties, whereas the "farthest" regime ($G = 1$) is associated with more remote counties. Interpretation of the regime coefficients follows focusing on the relationship between business establishment growth and the change in employment over the previous decade. Previous decade employment and business establishment growth was heterogeneous between the growth regimes. That is, in counties near metropolitan areas, a 1% change in employment growth in the previous decade was associated with a 0.5% change in the number of business establishments. The effect was reversed in counties farther away from core urban areas, which may suggest that the employment opportunities that emerged in these counties during the 1990s did little to stimulate growth in other sectors, including nonbasic sectors; a 1% change in employment growth was associated with a 0.5–0.4 = 0.1% change in business establishment growth in counties farther away from urban core areas. This observation might be attributable to employers locating in rural counties whose supply chains were elsewhere, resulting in weak or nonexistent backward linkages to the local economy. Interpretation of the other coefficients would proceed similarly.

Conclusions

The objectives of this article were to (1) extend a relatively new econometric method, the Smooth

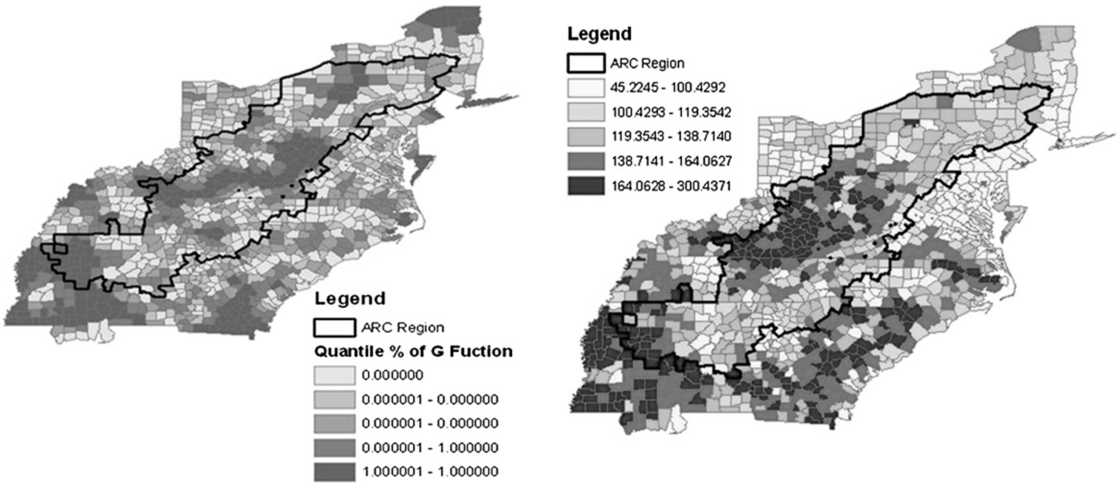

Figure 2. Spatial Distribution of the Transition Variable $G(\gamma, c; distmet)$ for $\Delta estabs_{2000–2007}$ (left panel) and the ARC Economic Distress Index (right panel)

Transition model of Pede, Florax, and Holt, to a regional growth model; and 2) analyze the relationship between local demographic and physical attributes, industry sectors, and business establishment growth in the Appalachian region using this method. The change in business establishment was regressed on industry sector composition controlling for local demographic, physical, and economic determinants. The hypothesis that the relationship between industry sectors on growth was geographically heterogeneous was tested using a relatively new spatial econometric approach, a STAR model. Findings suggest the relationship between the local determinants and growth was nonlinear across the region, and the association between local attributes and business establishment growth could be characterized into two distinct growth regimes. The spatial distribution of the regime members was remarkably similar to the distribution of the ARC's "economic distress" index.

The STAR family of models is relatively new to the spatial economic toolbox. The method contributes in terms of its ability to identify regimes using a data-driven approach as opposed to one in which regimes are identified using conventions potentially fraught with definitional problems (i.e., "urban" vs. "rural" dichotomies). The STAR model also relaxes the assumption that a single parameter completely summarizes an entire region but bypasses the incidental parameter problem commonly associated with local regression methods like GWR. The STAR model also provides a method for testing some of the fundamental theories espoused by the economic geography literature that predict the effects of transport costs and agglomeration economies on regional growth. To the extent that the STAR family of spatial models is able to identify structural breaks across space, the method provides an interesting avenue for future research testing theories about labor migration, wage earnings, and firm location patterns as related to localization and urban agglomeration economies.

Much work remains to be done in terms of comparing estimation procedures suitable for modeling smooth transition growth processes. Although the advantages and disadvantages of ML and GMM estimation are well known, the performance of the STAR model and its spatial process variants under different experimental circumstances remains to be documented. The performance of diagnostics used to specify STAR-class models should also be thoroughly investigated. In this application, a "general-to-specific" approach was taken to specify the regression model. How this specification search compares with a "specific-to-general" approach could provide information regarding which types of tests should be used under different assumptions (e.g., Lagrange Multiplier tests, assuming a normal distribution vs. Wald tests in which distributional assumptions are relaxed).

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