5 SPATIAL INFLUENCES IN COUNTY ECONOMIC PERFORMANCE

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"Task 1, Part 4: Empirical Analysis""
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5.1 Introduction

To better understanding what causes some non-metro Appalachian counties to make economic strides forward, while others remain distressed, a set of empirical studies were conducted with the aim of elucidating the role exerted by economic areas linked to a county. Our objective here is to (a) identify the nature of that linkages among counties, (b) define the geographic extent and features (contiguous/ non-contiguous) of this spatial neighborhood, (c) assess the roles of mountain topography, market access and highway links in affecting those results, and (d) identify how these factors affect levels of economic distress and changes in those levels over time.

In this section, we present an exploratory analysis of the factors affecting the current economic conditions and trends in Appalachia's non-metropolitan (non-metro) counties. We extract four types of variables that we consider to be closely related to the USDA/ERS typology of Appalachian Region counties, because regional analysts generally consider county type to play a significant role in determining county economic performance. We explore the statistical features and spatial patterns of the variables using statistical software and mapping and spatial analysis tools available in ArcGIS, geographic information systems, SPSS statistical analysis software and GeoDa, spatial statistics software developed by the Spatial Analysis Laboratory (SAL) in the Geography Department at the University of Illinois, Urbana-Champaign.

5.2 Exploratory Statistical Analysis

The analysis conducted for this study focused on the development of various forms of regression models to assess the role of explanatory factors in explaining and predicting patterns and trends in the economic well-being of non-metro Appalachian counties. Specifically, the types of county data that we use include:

Dependent variables:

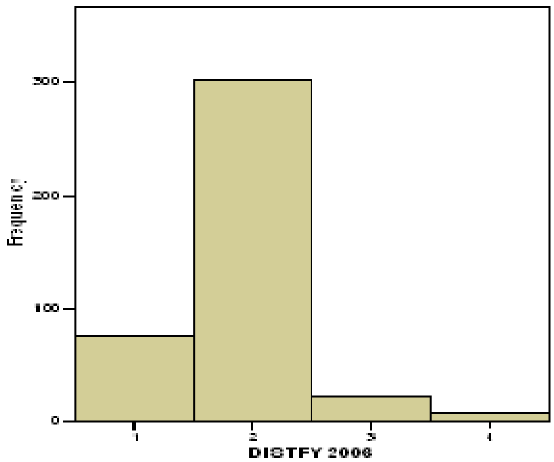
- ***Measures of economic health***: As a dependent variable, to be explained through the empirical analysis, we examine several measures (current levels or growth change) of each county's economic health. One key measure is the ARC county economic-status classification, whereby counties are classified a "attainment," "competitive," "transitional," or "'distressed" for each (fiscal) year. This classification is based on employment, income, and poverty measures (relative to the US average). The "Pickard Index" combines the three measures into a single, continuous index of economic level. In order to distinguish these two variables, we name the four-level, categorical variable as the ARC county Economic Status Class (ESC), and the continuous variable (the Pickard Index) as the county Economic Level Index (ELI). Another measure of economic health that we utilize is the county employment *growth* between 1990 and 2000, adjusted (using shift-share analysis) to control for national trends. This measure is obtained from IMPLAN based on Bureau of Economic Analysis and their Regional Economic Information System.
- ***Change in economic health:*** We assess patterns of change over time in terms of (a) the rate of growth or decline in the ELI rating, and (b) the rate of employment growth rate in the county as a whole.

Independent (explanatory) variables:

- ***Demographic data***: US Census demographic data from 2000 for such variables as the age, education, minority status, mobility, and urban/rural residential location of the county population,
- ***Geographic characteristics***: terrain, elevation, natural amenity, and highway data describing the geographic features and transportation infrastructure of the counties. The terrain and elevation data are from the US Geological Survey (USGS), the transportation data are from ARC and the US Department of Transportation's Bureau of Transportation Statistics. The natural amenity scale is an index of the density of attractiveness of geographic features developed by the Economic Research Service (ERS) of the United State Department of Agriculture (USDA)
- ***Industrial mix and commuting patterns:*** measures of industrial mix, types and business, and commuting patterns within the Appalachian counties. BEA/REIS data break down earned income by industry for 1980, 1990, and 2000. We also develop entrepreneurship indicators from BEA/REIS data on the diversity and value-added components of earned income. Commuting patterns are based on 1990 US Census ''journey-to-work' data.
- ***Density and Urban Influence:*** measures of population density and urbanization for each county and for sub-county regions. These indicators include USDA/ERS measures of population-based rural-urban continuum codes and urban-influence codes; and the delineation of metropolitan and micropolitan areas.

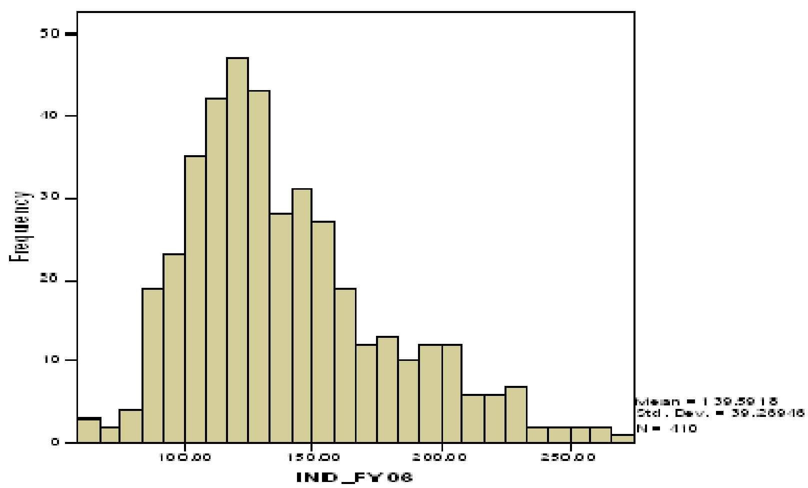
Exhibit 5-1 shows the frequency distributions of ARC's Economic Status Classes (ESC). Exhibit 5-2 plots the frequency distribution of the ELI index. The ELI measure (labeled IND_FY06 for Fiscal Year 2006) is a continuous function of the three measures (unemployment, income, and poverty) used to determine the ESC category. Compared with the four discrete ESC categories, the continuous ELI variable provides more differentiation among counties and, hence, an increased opportunity to explain variations in economic health across counties in terms of the independent variables that we have identified.

Exhibit 5-1: Distribution of County Economic Status Class (ESC)
(Labeled as "DISTFY2006")



Source: ARC's Economic Status Classification.

Exhibit 5-2: Distribution of the county Economic Level Index
(ELI, Labeled as "IND_FY06" for Fiscal Year 2006)



5.3 Models to Predict County Economic Level

A number of researchers have used econometric methods to model economic health (at county levels) as a function of various demographic and socio-economic factors, and industrial mix. However, relatively little work has been done to understand how geography and transportation infrastructure affect the interaction among counties and population centers and, as a result, the pattern and pace of economic development.

We focus our efforts on investigating measures of geographic and infrastructure features that might influence economic health through facilitating, or hindering, the interconnectedness of Appalachian counties – and the resulting speed at which economic growth might occur. GeoDa software allows us not only to run classic ordinary least-squares (OLS) regression models, but also to estimate "spatial-lag" and "spatial-error" regression models that account for additional spatial "spillover" effects that reflect the influence of economic neighbors.

Explanatory Variables. In order to see how much of the variation in ELI across the Appalachian counties can be explained by demographic, geographic, and market segmentation factors, we begin with the following set of measures for various factors that the literature suggests are correlated with economic health. Listed below are the basic explanatory variables used in regression models to predict county ELI levels.

Demographics	
PCTHSGRAD	Percentage of people with high school diploma
PER_MINORI	Percentage of people who are minority
PER_POP65P	Percentage of people over 65 years old
Mobility	
PCTSAMCNT	Percentage of people who resided in the same county 5 years earlier
Amenities	
ASCALE	Natural amenity scale
Entrepreneurship	
BREADTH	Economic breadth = # non-farm proprietors / total non-farm emp
DEPTHINC2	Non-farm proprietor income/# non-farm proprietors
DEPTHVALAD	Non-farm proprietor income, BEA/non-employer receipts
Industrial mix	
AGRIC00	Percentage of income from agriculture in 2000
MIN00	Percentage of income from mining in 2000
CNSTR00	Percentage of income from construction in 2000
MANFC00	Percentage of income from manufacturing in 2000
TRNSP00	Percentage of income from transportation in 2000
WHTRD00	Percentage of income from wholesale trade in 2000
RETRD00	Percentage of income from retail trade in 2000
FIRE00	Percentage of income from finance, insurance, real estate in 2000
SERV00	Percentage of income from services in 2000
GOV00	Percentage of income from government employment in 2000
County interdependence	
RADJ97_EMP	Income adjustment to account for workers' county of residence

(normalized by employment)

In this section, we develop two basic forms of regression model. The first one estimates the role of various county attributes (previously listed) on the Economic Level index (ELI) of each ARC county as of FY2006. The second one adds geography and infrastructure factors to increase explanatory power. For both forms of regression model, a set of four variations is estimated. (Additional regression models of *changes* in county economic health are discussed in the section which follows.)

Exhibit 5-3 summarizes results for the first set of regression models under three different formulations: Ordinary Least Squares, Spatial Lag and Spatial Error. Findings from each of these model variations are summarized below:

Model 1-A. Ordinary Least Squares Regression. Using GeoDa softrware, the ELI rating of each county was regressed onto each of the 18 variables. The R-squared of 0.71 indicates that a linear combination of the independent variables explains 71% of the variance in ELI across counties – a modestly good fit. Most estimated coefficients have the expected sign. For example, the coefficient for education (PCTHSGRAD) implies a predicted decrease of 2.32 in the ELI indicator (i.e., an improvement in economic health because ELI measures the extent of poverty and unemployment) for every percentage point increase in the county's adults who have at least a high school graduate level of education. One other demographic variable was highly significant (with a positive relationship), the percentage of the population who are minority (PER_MINORI). The mobility indicator (PCTSAMCNT) was also significant. This measure is the percentage of persons who lived in the same county five years earlier. High values suggest an immobile population. Both these variables had positive signs indicating that higher percentages were correlated with higher ELI values –i.e. distressed economic conditions.

The ASCALE index measures the quantity and quality of scenic natural features and recreation areas in each county. It was not statistically significant as an explanatory factor. It could be that the economic benefits of natural amenities are accrued not so much by the county in which they reside, but by particular, proximate counties that are key points of access to the amenities, e.g., the valley along a major highway connecting population centers to scenic mountains and national parks. Likewise, the mere presence of a natural amenity does not imply that the county or proximate counties are able to leverage their assets into a thriving tourism economy.

The three entrepreneurship measures show mixed results. The breadth of proprietorship measure (BREADTH) is not significantly different from zero, and the two proprietorship "depth" measures (DEPTHINC2 and DEPTHVALAD) are significant but have opposite signs. Increases in DEPTHINC2 are associated with improved economic health (lower IND_FY06) and increases in DEPTHVALAD are associated with declines in economic health (higher IND_FY06). The standardized beta coefficients indicate that their effects are opposite in sign.

Exhibit 5-3: Coefficient Comparison of MODEL-1 Statistical Variations

	Model 1-A (OLS)			Model 1-B (Spatial Lag)			Model 1-C (Spatial Error)		
Variable	Coeff.	T-Stat	Prob.	Coeff.	Z-Val.	Prob.	Coeff.	Z-Val.	Prob.
CONSTANT	**246.707**	**10.346**	**0.000**	**156.208**	**24.141**	**.0000**	**302.088**	**11.998**	**0.000**
PCTHSGRAD	**-2.326**	**-14.528**	**0.000**	**-1.629**	**0.169**	**0.000**	**-2.636**	**-13.082**	**0.000**
PER_MINORI	**0.555**	**5.198**	**0.000**	**0.513**	**0.094**	**0.000**	**0.507**	**3.901**	**0.000**
PER_POP65P	-0.615	-1.172	0.242	0.004	0.461	0.993	0.387	0.768	0.442
PCTSAMCNT_	**1.374**	**5.800**	**0.000**	**1.078**	**0.208**	**0.000**	**0.696**	**3.089**	**0.002**
ASCALE	-1.338	-1.243	0.215	-0.302	0.948	0.750	0.560	0.523	0.601
BREADTH	-8.386	-0.476	0.634	5.057	15.508	0.744	-2.680	-0.180	0.857
DEPTHINC2	**-2.399**	**-5.865**	**0.000**	**-1.674**	**0.368**	**0.000**	**-1.631**	**-4.182**	**0.000**
DEPTHVALAD	**71.183**	**4.958**	**0.000**	**42.311**	**12.948**	**0.001**	**42.494**	**3.042**	**0.002**
RADJ97_EMP	**-0.682**	**-3.440**	**0.001**	**-0.389**	**0.176**	**0.027**	**-0.411**	**-2.453**	**0.014**
AGRIC00	-297.529	-1.385	0.167	-493.950	188.851	0.009	**-482.146**	**-2.861**	**0.004**
MIN00	-7.076	-0.397	0.691	-9.769	15.634	0.532	-6.054	-0.355	0.723
CNSTR00	-63.832	-1.768	0.078	-69.330	31.674	0.029	-50.697	-1.631	0.103
MANFC00	**-79.504**	**-7.133**	**0.000**	**-61.381**	**9.890**	**0.000**	**-52.132**	**-5.346**	**0.000**
TRNSP00	-37.585	-1.379	0.169	-39.687	23.914	0.097	-52.058	-2.368	0.018
WHTRD00	**-154.474**	**-2.825**	**0.005**	**-150.903**	**47.999**	**0.002**	**-105.494**	**-2.312**	**0.021**
RETRD00	34.988	0.899	0.369	1.825	34.172	0.957	-10.766	-0.346	0.729
FIRE00	-115.927	-1.617	0.107	-102.956	62.869	0.102	-82.349	-1.387	0.165
SERV00	**-45.419**	**-2.558**	**0.011**	**-46.495**	**15.577**	**0.003**	**-32.775**	**-2.158**	**0.031**
LAMBDA							**0.647**	**13.998**	**0.000**
Log-likelihod	-1823			-1786			-1777		
R-Squared	71.0%			77.6%			80.1%		

Dependent variable is the economic level index for FY2006 (ind_fy06).
Coefficients significant at the 0.05 level or better are in bold face.

Source: MIT-DUSP ARC Research Team.

Three of the nine industrial mix variables in MODEL-1A were statistically significant. They are manufacturing, wholesale trade, and services. All three have coefficients with negative signs indicating that sector size increases are associated with reductions in ELI scores which represent improvements economic well-being. The industrial mix coefficients are larger than those for the demographic variables, but that is because the industrial mix measures are fractions ranging from zero to 1.0 while the demographic factors range from 0 to 100%. The standardized coefficients adjust for differences in measurement units and show the much weaker effect.

The negative residential income adjustment (RADJ97_EMP) coefficient indicates that a county is better off (lower IND_FY06) if its residents bring in more wage income from out-of-county than the county's non-resident workers export to their home counties. This is one type of "spatial multiplier" effect whereby counties tend to have improved ELI scores if they experience net gains when earned income accounting is shifted from place of work to place of residence. That is, earned income tends to be spent closer to one's home than to one's workplace, so counties gain an economic stimulus if they house more out-commuters than they employ non-resident workers.

Model 1-B: Spatial-lag Regression. This model regresses ELI on the same 18 variables as before, but now using a "spatial-lag model." That type of regression model assumes that the value of an independent variable in one county spills over to affect the corresponding values in adjacent counties (Anselin, 2003). The model is a weighted regression where the weights are non-zero for counties that are adjacent to one another and the coefficients are estimated using maximum likelihood estimation.

The likelihood ratio test indicates that accounting for spatial-lag is worthwhile, and the effective R-squared increases to 78%. We are not surprised that the estimated coefficients for the most significant variables are somewhat reduced in the spatial lag model. For example, consider the education effect. Spillover effects from better education in neighboring counties could account for what otherwise might be lumped into a larger same-county coefficient in the ordinary least squares regression.

One change is that the size of the agricultural sector (AGRIC00) is now significant, and inverse in its effect, which is counterintuitive. A separate histogram shows that this variable is highly skewed with most values at or near zero and a right tail reaching only to 3 %. We would be better off treating AGRIC00 as a dummy variable indicating which counties had a measurably large agricultural sector.

Model 1-C: Spatial-Error Regression. This model regresses ELI on the same 18 variables as before, but now using "a spatial-error model" in place of the spatial-lag model. The "spatial-error" regression model assumes that the county-to-county spillover occurs indirectly through spatial correlation in the error terms for neighboring counties. That is, the independent variables have only local effects, but factors missing from the model specification are spatially correlated.

The signs and significant variables for the spatial-error model are similar to those for the spatial lag, although the residential persistence variable (pctsamcnt) is now marginal and the transportation sector size becomes significant. Overall, the log-likelihood is slightly higher and the effective R-squared is increased slightly (to 80%).

Both the spatial lag and spatial error runs use simple measures of proximity – spillover effects are assumed to come exclusively from neighboring counties and each adjacent county contributes in the same manner. Even with these simple assumptions, we see evidence of significant spillover effects. The RADJ97_EMP variable adjusts income earned by workers in a county in order to account for the county of residence of the employee. The fact that the RADJ97_EMP (expressed on a per-employee basis) is significant in the OLS regression indicates that income earned elsewhere can matter. The variable is less significant with a much smaller coefficient in the spatial lag and spatial error models, because some of the county-to-county influence is explicitly captured in the spatial lag or spatial error term.

Model 1-D. Consolidating the Industrial Mix. The industry specific variables in all of the preceding models had "multicollinearity" (meaning that a high share of employment in any one industry would tend to bring a lower share of employment in other industries). That makes their coefficient estimates subject to error. To address that, we used *factor analysis* to identify linear combinations of industrial sector percentages that capture most of the variation across counties.

Exhibit 5-4 show the component score coefficients for the extracted factors. For example, a county's 2000 factor score for Factor 1 would be computed by multiplying the coefficients in the Factor 1 column by the corresponding industry mix percentages for agriculture, mining, construction, etc. We see that Factor 1 has a large negative coefficient for manufacturing and large positive coefficients for wholesale and retail trade, fire, and services. So, counties with a high share of employment in services or trade and little manufacturing (relative to the other ARC counties) will have a high score on Factor 1. Alternatively, Factor 2 deemphasizes manufacturing and emphasizes mining, government, and transportation. So, counties with a high share of employment in mining and government, and little in manufacturing and wholesale will have a high score on Factor 2. Similarly, Factor 3 emphasizes government, agriculture, and construction without wholesale trade; and Factor 4 emphasizes construction, transportation, agriculture without government, or services.

Exhibit 5-5 (left side) shows the results of rerunning Model-1C (the spatial error model) with the four composite industry factors substituted in place of the nine industrial sector percentages (labeled as Model 1-D). We see that the fit is slightly better than before, with five fewer variables. Note that the most significant factor among the four is Factor-2 (which is higher where there is more reliance on mining or government activities and less on manufacturing or wholesale trade activities). The large positive coefficient (7.75) indicates that a one standard deviation increase in a county's Factor-2 value correlates with a 7.75 point increase (that is, diminished economic condition) in the ELI score for that county.

Exhibit 5-4, Factor Analysis Results

(Component Score Coefficient Matrix)

	Component			
	Factor-1	Factor-2	Factor-3	Factor-4
agric00	.107	-.031	.443	.519
min00	-.168	.260	-.201	.359
cnstr00	.191	.005	.494	.233
manfc00	-.148	-.472	-.041	-.113
trnsp00	.002	.168	-.401	.433
whtrd00	.264	-.210	-.234	.200
retrd00	.295	.075	-.053	-.331
fire00	.358	-.005	-.035	-.061
serv00	.292	.162	-.218	-.083
gov00	-.099	.365	.278	-.340

Factor Interpretation:
Factor-1: service/trade without manufacturing
Factor-2: mining/government without manufacturing/wholesale
Factor-3: government/agriculture/construction without wholesale trade
Factor-4: construction/transportation/agriculture without government/services

Exhibit 5-5: Coefficient Comparison for Models Using Industry Factors

	Model 1-D (spatial error model using industry factors)			Model 1-E (commuting shed model using industry factors)		
Variable	**Coeff.**	**Z-Val.**	**Prob.**	**Coeff.**	**Z-Val.**	**Prob.**
CONSTANT	**243.932**	**9.425**	**0.000**	**268.711**	**10.030**	**0.000**
PCTHSGRAD	**-2.534**	**-13.048**	**0.000**	**-2.781**	**-14.409**	**0.000**
PER_MINORI	**0.443**	**3.683**	**0.000**	**0.616**	**5.370**	**0.000**
PER_POP65P	0.291	0.609	0.542	0.740	1.593	0.111
PCTSAMCNT_	**0.904**	**4.159**	**0.000**	**0.608**	**2.807**	**0.005**
ASCALE	0.577	0.552	0.581	1.376	1.411	0.158
BREADTH	3.227	0.227	0.820	16.695	1.207	0.227
DEPTHINC2	**-1.306**	**-3.470**	**0.001**	**-1.017**	**-2.752**	**0.006**
DEPTHVALAD	**33.612**	**2.486**	**0.013**	**28.460**	**2.125**	**0.034**
FAC1_2000	**-4.173**	**-3.582**	**0.000**	**-4.403**	**-3.827**	**0.000**
FAC2_2000	**7.753**	**6.992**	**0.000**	**6.495**	**5.605**	**0.000**
FAC3_2000	1.639	1.591	0.112	1.279	1.275	0.202
FAC4_2000	**-3.487**	**-3.884**	**0.000**	**-3.317**	**-3.798**	**0.000**
RADJ97_EMP	**-0.507**	**-3.120**	**0.002**	**-0.356**	**-2.270**	**0.023**
LAMBDA	**0.625**	**13.066**	**0.000**	**0.900**	**109.477**	**0.000**
Log-likelihod	-1769			-1754		
R-Squared	80.7%			80.0%		

Model 1-E. Alternative Measures of County Connectivity – Commuting Zones. Both the spatial-lag and spatial-error models presented so far employ a simple notion of spillover, which assumes that each county is only affected by its "nearest neighbors" – with equal weight given to each neighbor. Given the mountainous terrain over much of Appalachia, we might expect that hills, rivers, interstates, and other major obstacles, and convenient infrastructure, could distort the meaning of "adjacency." For example, counties with highly inter-connected development paths might be those along a major interstate running through a valley.

The economic interdependence of counties can amplify the beneficial impact of economic development. If we know how counties are interdependent, then we can devise more effective economic development strategies. Prior versions of Model 1 provided some evidence of significant spillover effects among immediately adjacent counties. The best way to measure county connectivity is likely to depend on the type of development being considered. Analysts who use traditional economic growth models focus on residence/workplace linkages, and they might use commute-sheds to identify well-connected counties. But we envision other development strategies that may use a different notion of connectivity. Consider, for example, asset-based development, such as tourism or mining. In such cases, connectivity and interdependence might involve convenient highway and rail infrastructure connecting the local site to population centers or resource users. Alternatively, a knowledge-based development strategy may require an understanding of alumni networks and university connections. For example, the zip code frequency for home addresses of university students may be a good measure of where a university's education and technology transfer efforts are most likely to be felt.

To explore the usefulness of alternative connectivity measurement beyond "adjacency," we examine the commute-sheds (or commute-zones) for Appalachian counties. The USDA has developed commute-shed data for Appalachia based on US Census Bureau Year 2000 journey-to-work data. Each of the 410 counties is clustered into a commute-shed with other counties that most often share commuters who work in one county and live in the other. GeoDa software can use "commute sheds" to calibrate spatial weights that offer an alternative to the "adjacent county" approach.

Exhibit 5-5 (Model 1-E) shows the results of rerunning the prior model with spatial weights based on the commute-sheds, rather than on county adjacency. The results show little change in the model's explanatory power. Given the significant overlap of commute-sheds and "nearest neighbor" adjacent counties, we are not surprised that the results are similar for these two ways of identifying proximate counties that have intertwined economies. Also, the commute-shed results would probably be improved if we included counties at the edge of Appalachia that fall within commute-sheds that include one or more Appalachian counties.

Model 2-A and 2-B: Adding Geography and Access Factors. The final variation of the economic health models adds considerations of terrain slope, road density and worker accessibility.

- *Terrain Ruggedness – Slope Computations.* Because much of Appalachia is mountainous terrain, we might expect that hills, rivers, interstates, and other major obstacles (and convenient infrastructure) could warp the meaning of "connectedness" to be quite different from "as the crow flies." To investigate such possibilities, we computed a measure of terrain ruggedness based on slope computations. We obtained USGS elevation data, projected it to the Alber's area-preserving coordinate system used by ARC, and then converted it to a raster-elevation model in ArcGIS. We overlaid the grid cell slope (rise/run) estimates with the county boundaries, to estimate average slopes within each county (variable name SLOPE).

- *Nearby Terrain Slopes.* We also computed average slopes for all counties whose centroid fell within 66 kilometers of the target county (variable name SLOPE66). Exhibit 5-6 is a thematic map of the estimated slope of the Appalachian Region with lighter colors indicating locations with steeper slopes. Note the sharp change between the Cumberland Plateau and the Great Smoky Mountains where the Tennessee River Valley corridor runs Northeast and Southwest of Knoxville.

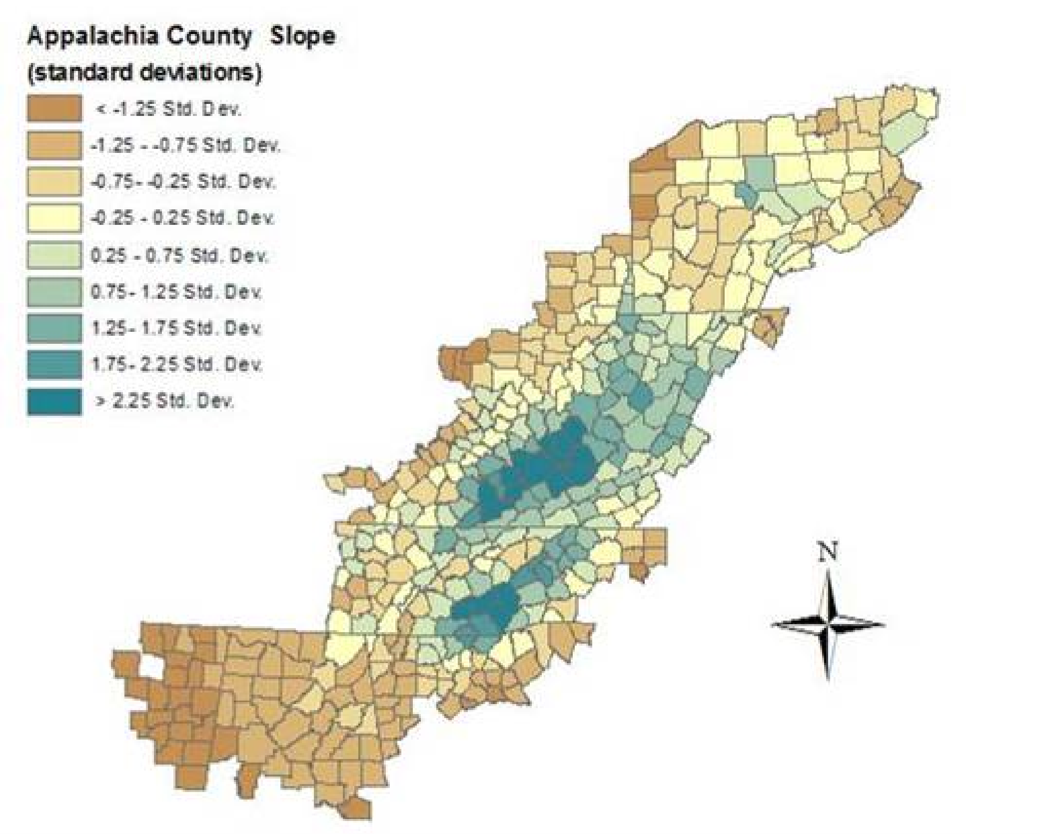
- *Transportation Infrastructure – Road Density.* Our team obtained National highway data from 2004 National Highway Planning Network (NHPN), Federal Highway Administration, U.S. Department of Transportation. We also obtained additional, more detailed, Appalachian Development Highway System (ADHS) data from the ARC. With these data, we developed estimates of road density within each county (variable name ROADWT)

- *Worker Accessibility.* Using data compiled for the Local Economic Assessment Package, we obtained a data set estimating the number of workers who live within 50 minutes driving time of each county. We use this data as a measure of each county's labor market accessibility (variable name EMP50M).

We first ran a new regression model in which we added the access measures and geography measures as cited above. Both a standard OLS regression (Model 2-A) and as a spatial error regression (Model 2-B) were run. However, the results showed that none of the access and geography measures was statistically significant in explaining county-level economic health. It was believed that the reason for this result is that the effect of access and geography is likely to differ for metro and non-core counties. Accordingly, a new variation on the model was run in which coefficients for the explanatory variables were interacted with dummy variables for metropolitan and non-metro areas. That attempt, using metro/ non-metro interaction variables, was more successful. It is referred to as Models 2-C and 2-D, and is discussed and shown next.

(Results for the earlier Models 2-A and 2-B are not shown in this summary although they are shown in the full report.)

Exhibit 5-6: Slope Estimate for the Appalachian Region (Based on USGS 90m Elevation Data from the National Map)



Source: MIT-DUSP ARC Research Team using ArcGIS.

Model 2(C-F): Interaction of Metro Status with Geography and Access. The alternative model specifications included interactions between type-of-county and the other explanatory variables. The interaction of labor market and non-metro status was added in Models 2-C (OLS model version) and 2-D (spatial error model version). The further interaction of slope factors and non-metro status was added in Models 2-E (OLS model version) and 2-F (spatial error model version). In both cases, the spatial error version provided a better fit than the OLS version, although the coefficient estimates were generally consistent across both model types. For brevity, results are shown only for the spatial error versions in Exhibit 5-7 (though results for the other model variations are shown in the full report.)

The spatial error results for Models 2-D and 2-F confirm that the effects of several variables do differ depending on whether a county's status is metro or non-metro. Results are shown in Exhibit 5-7 just for the statistically significant variables. Note that variables interacted with the metro dummy variable are denoted by an "M_" prefix and those interacted with a non-metro dummy variable are denoted by an "N_" prefix.

The results show that slope and labor force access measures do have statistically significant effects in predicting economic health level, but only in the non-metro counties (indicated by coefficients for variables N_SLOPE, N_SLOPE66, and N_EMP50). We are not surprised by the overlapping effects of employee access and terrain, because we expect that employee accessibility will be lower in mountainous areas and that non-core counties might benefit if the counties that surround them are relatively mountainous and inaccessible.

The coefficient values for the slope variables also show that above average slopes *within a non-core county* (N-SLOPE) are associated with weaker economic levels, while above average slopes *in surrounding areas* (N_SLOPE66) are associated with stronger economic levels. Those findings are plausible. In metro areas, density and infrastructure make the slope and employee access measures less relevant. Also, place-of-residence and place-of-workplace are more likely to span counties in metro areas[16].

Exhibit 5-7: Coefficient Comparison of MODEL-2 Variations

	Model 2-D *Spatial-error model with worker access and road density*			**Model 2-F** *Spatial-error with local and nearby slopes*		
Variable	**Coeff.**	**Z-Val.**	**Prob.**	**Coeff.**	**Z-Val.**	**Prob.**
CONSTANT	**5.67570**	**35.3827**	**0.00000**	**5.66271**	**34.8558**	**0.00000**
PCTHSGRAD	**-0.01688**	**-13.9391**	**0.00000**	**-0.01702**	**-14.0408**	**0.00000**
PER_MINORI	**0.00324**	**4.5158**	**0.00001**	**0.00343**	**4.6660**	**0.00000**
PCTSAMCNT_	**0.00590**	**4.9752**	**0.00000**	**0.00594**	**5.0046**	**0.00000**
DEPTHINC2	**-0.00860**	**-3.6808**	**0.00023**	**-0.00895**	**-3.8275**	**0.00013**
DEPTHVALAD	**0.19684**	**2.2972**	**0.02161**	**0.20793**	**2.4263**	**0.01525**
FAC1_2000	**-0.02636**	**-3.6787**	**0.00023**	**-0.02727**	**-3.8094**	**0.00014**
FAC2_2000	**0.04371**	**6.1400**	**0.00000**	**0.04153**	**5.7560**	**0.00000**
FAC4_2000	**-0.02371**	**-4.3558**	**0.00001**	**-0.02379**	**-4.3710**	**0.00001**
M_RADJ97	**-0.00545**	**-5.7599**	**0.00000**	**-0.00488**	**-4.3712**	**0.00001**
M_ROADWT	**-0.00814**	**-3.7559**	**0.00017**	**-0.00626**	**-2.3412**	**0.01922**
N_EMP50M	**-0.00825**	**-2.6881**	**0.00719**			
N_SLOPE				**0.00584**	**2.6972**	**0.00699**
N_SLOPE66				**-0.00588**	**-2.1887**	**0.02862**
LAMBDA	**0.884**	**92.985**	**0.000**	**0.89497**	**104.1315**	**0.00000**
Log-likelihod		320.9			320.2	
Akaike info		-617.8			-614.5	
R-Squared		83.3%			83.2%	

Source: MIT-DUSP ARC Research Team.

[16] An alternative explanation is that the commute-sheds do a better job of capturing high economic impact regions within metro areas since the weights matrices are not sensitive to the number of cross-county employees.

5.4 Modeling Changes in Economic Health

We have made several attempts to measure *changes* in economic status, so that we could have a stronger econometric underpinning for modeling economic growth over time and space (Anselin, 2003; Feser, 2005). We consider changes in the ELI measure during the last decade, and attempt to estimate and analyze the change in value added (per employee) as a dependent variable between 1997 and 2002 using IMPLAN data. In both cases, the results were limited with, for example, R-square values in the teens. Although we expect lower R-square values when modeling differences, a closer look at the data suggested deeper problems. The time series of annual income and poverty data underlying the ELI measure are based on sample sizes and estimation methods that vary somewhat from year to year. Large samples, such as for the decennial census, are not repeated annually. Hence, year-to-year changes tend to track simple trends. Then, when the next large data sample becomes available, big changes occur all at once in those places that have not followed the fitted curve. The measurement noise that is thereby added to the data can be significant when studying small counties or developing indices that fuse data from different sources or analysis subsectors of the economy.

The most success that we have had with modeling temporal changes in economic indicators for Appalachia has been in studying employment growth during the 1990s after controlling for labor-market conditions and other factors, such as labor mobility, natural amenities, and market size. One member of the research team, worked on this analysis for her Master of City Planning Thesis, "Industrial Structure and Employment Growth in the 1990s in Appalachian Counties."

Before presenting the *economic change* models, we will explain and summarize the measures that we use to characterize economic growth of Appalachian counties during and since the 1990s.

Changes in ELI. It is important to note that the Economic Level Index (ELI) was developed by averaging the county unemployment rate, poverty rate, and per capita market income levels (all expressed as a percentage of the US average). These components are developed from different samples taken at different points in time. When selecting two points in time for use in modeling change, we should be cognizant of the sampling and accuracy issues in the datasets. The ELI estimate for 2004 is the most recent estimate that could be computed using datasets available at the time (in 2005) that we assembled the data – and is the first 2000+ estimate that includes the results of the 2000 US Census. Analysis of the changes in ELI (variable NEW_DELI) showed that the larger improvements tended to be along the edge of Appalachia east of Cincinnati and Louisville or northwest of Atlanta.

Changes in Employment during the 1990s. Because the ELI measure is a composite index of poverty, employment, and income outcomes, it is difficult to construct an economic model of growth that can directly account for spatial and temporal impacts on ELI. As an alternative measure of changing economic conditions, we examined changes in employment in Appalachia counties during the 1990s. We used the percentage change in employment and adjusted the results (using shift-share analysis) to account for national trends in industrial sectors. The variable CMPT_CAP measures each county's percent change in employment during the 1990s above and beyond whatever change might have occurred if the county followed national trends.

These competitively adjusted changes in employment levels represent a measure of economic growth that can be regressed against demographic, industrial mix, geographic, and other factors in order to identify the conditions that resulted in faster (or slower) growth and to estimate the extent of spatial spillover effects whereby neighboring counties amplified (or, possibly, diminished) the local rate of growth[17]. Tan (2005) explains the methodology in detail.

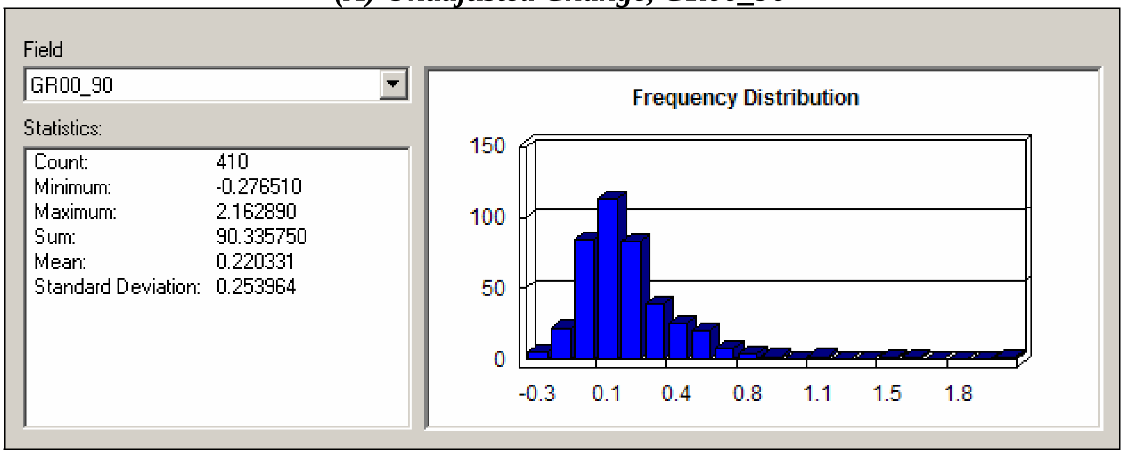
Exhibit 5-8 contains the histogram plots of 1990-2000 employment changes for ARC counties. Part A shows the unadjusted percent changes, GR00_90, and Part B shows the competitively-adjusted changes in employment levels, CMPT90_00. The 1990s were a period of economic growth for the entire nation so the 22% mean percentage increase in employment is no surprise. However, the large range and standard deviation is noteworthy. The distribution of competitively adjusted employment changes is similar in shape and standard deviation but shifted negative (with a mean of -15.9%) because Appalachia counties did not fare as well as the nation on the whole.

Exhibit 5-9 plots these changes in employment thematically across the 410 Appalachia counties. The map on the left shows the competitively adjusted employment changes whereas the map on the right shows the unadjusted employment-change results. A cluster of high-growth counties is evident in the Southeast (that is, northwest of Atlanta). Another group of low-growth counties is visible in the Eastern Kentucky and West Virginia area, but the competitive adjustment tends to temper the magnitude of these changes.

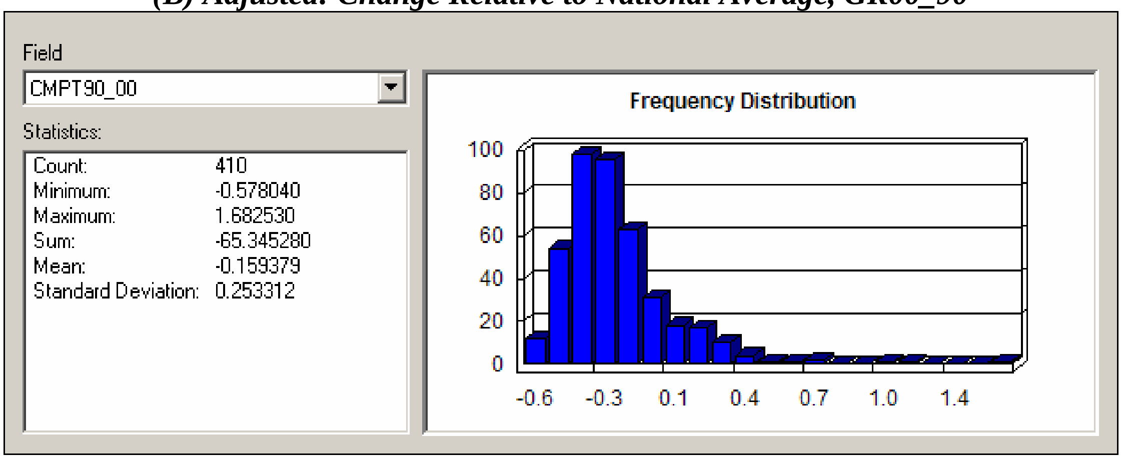
[17] Anselin (2003) has explained how weighted regression fits of such models can estimate first-order spatial-lag and spatial-error effects and Boarnet (1994), Feser and Isserman (2005), and others have developed simultaneous-equation models of employment and population size that can be used to model economic growth and estimate spatial-spillover effects.

Exhibit 5-8: Histogram of 1990-2000 Percent Change in Employment

(A) Unadjusted Change, GR00_90

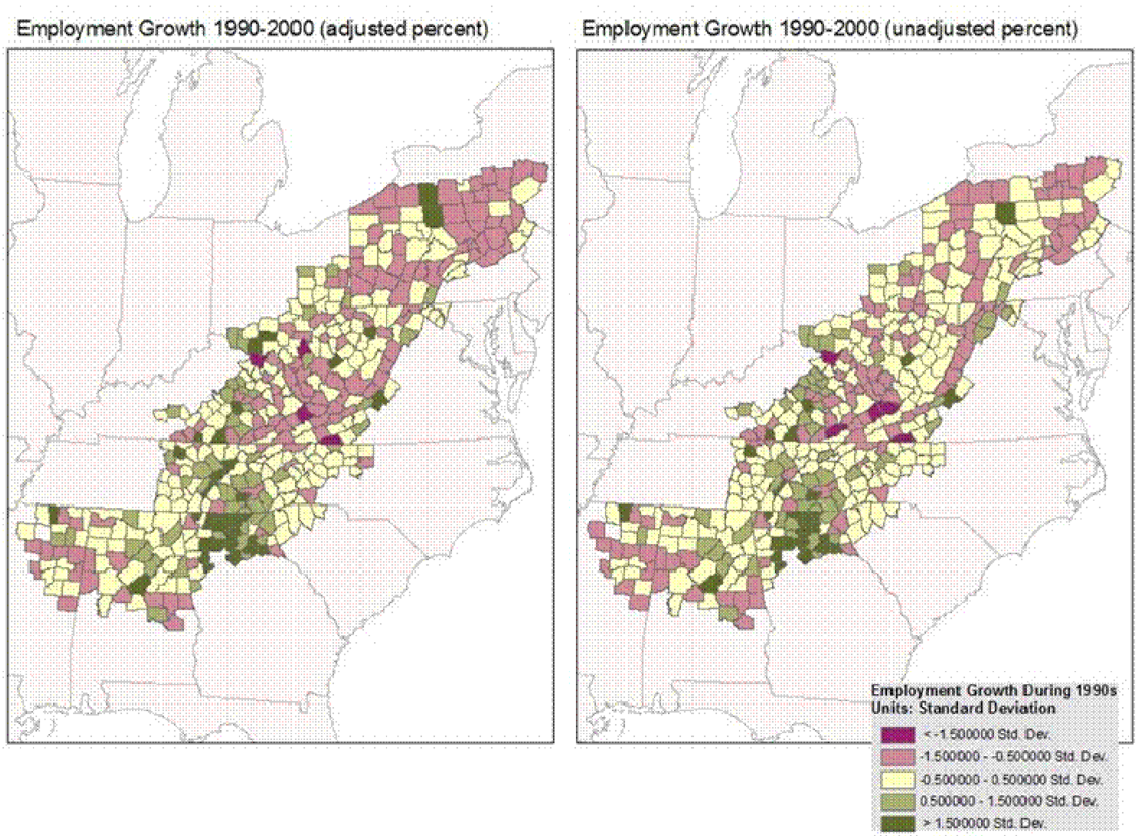


(B) Adjusted: Change Relative to National Average, GR00_90



Source: MIT-DUSP ARC Research Team.

Exhibit 5-9: Employment Change within Appalachian Counties (1990 -2000)
Source: MIT-DUSP ARC Research Team using ArcGIS.



Model 3 and Model 4-A: ELI Rating Change vs. Employment Change. We begin the discussion of *economic change* models by considering the same right-hand-side variables that we used earlier to estimate effects on recent *economic health levels* in Models 1 and 2. Some minor changes are in order, however, because we want the measures of the right-hand side variables at or near the start of the period for which change is observed – 1997 for change in Economic Level Index (NEW_DELI) or 1990 for the competitively adjusted and capped employment change (CMPT_CAP).

Initially, parallel OLS regressions were run to estimate effects on ELI change (in Model 3) and effects on employment change (in Model 4A). The results indicated a poor fit, particularly for the ELI change, where the R^2 indicated that only 16% of the variance was being explained by the model. A substantially better R^2 of 32% was achieved for the model of employment change. Actually, this difference was expected, given the coarse and discrete nature of the ELI rating changes and the smoother nature of variation in the employment change measure. Based on these findings, it was decided that better results could be obtained by focusing on the determinants of employment change, and that the spatial lag and spatial error model forms were likely to yield better fits to the data. Those results are presented and discussed next. (For brevity, results of Model 3 and 4-A are not shown here though they are presented in the full report.)

Model 4(B-C): Change in Employment. Exhibit 5-10 shows the results of models to predict employment change, using both spatial lag approach (Model 4-B includes the rhs variable **W_CMPT_CAP**) and spatial error approach (Model 4-C). Both models attempt to predict the employment change variable using the same right-hand side variables (or their early-90 equivalent) that were previously used in Model 2-A to predict current ELI levels. The results for both new models show better explanatory power (R^2 = 38%) than the previously discussed OLS results. However, the model fit for explaining *economic change* is still far lower than the explanatory power of similar regressions that explained current *economic performance levels*. That is not unexpected, since there is greater variation in the dependent variable depicting a growth rate and the explanatory variables have some updating limitations that were previously discussed.

There are some surprising findings shown in the employment change results. Educational attainment (PCTHSGRAD) is now showing a significant but counter-intuitive relationship on employment growth (this interpretation was acceptable when the dependent variable was current ELI). Adjusted employment growth outcomes in neighboring counties will exert a significant influence on a county's employment changes in the same direction. The key importance of prior industry mix also remains strong, though there are some differences. In the earlier Model 2-A of ELI *levels*, industry factors 1, 2, and, 4 were significant. For the new models of employment *changes*, factors 3 and 4 are significant. They both exert positive effects on the adjusted employment growth that occurred between 1990 and 2000.

Some of the other results are less expected. The industry concentration measure (BEAGINI_9) appears insignificant, as do the economic breadth (BREADTH) and amenity (ASCALE) variables. However, all of these unexpected results can be attributed to correlation with other variables and equally importantly, differences in their impacts within metro vs. non-metro areas.

Model 4(D-F) Metro and Non-Metro Differences. To test this last hypothesis, separate model runs were made for those counties designated by USDA as metropolitan, micropolitan, and non-core counties. The explanatory variables included the demographic variables measuring education, minority and senior citizen presence, and mobility (percent of population living in the same county for at least 5 years); the four industrial mix factors from the factor analysis plus a measure of industry concentration (BEAGINI_9); the three worker access measures counting (counting workers within 40, 50, and 60 minutes) plus the place-of-residence adjustment of worker-based-county income, RADJ97_EMP; and the various geography and infrastructure measures: ASCALE for the USDA amenity index, ROADWT for the weighted percentage of land used for major roads, SLOPE for the average slope, and AVG_SLOPE6 and AVG_SLOPE1 for the average slope of neighboring counties within 66 and 100 km. The results are shown in Exhibit 5-11, and they reveal that the impact of the same explanatory variables differed considerably across the three types of counties.

EXHIBIT 5-10 Model 4-B,C: Models of Employment Change Over Time

	Model 4-B *Spatial-lag model*			**Model 4-C** *Spatial-error model*		
Variable	**Coeff.**	**Z-Val.**	**Prob.**	**Coeff.**	**Z-Val.**	**Prob.**
W_CMPT_CAP	**0.497**	**14.405**	**0.000**			
CONSTANT	**1.213**	**5.123**	**0.000**	**1.241**	**4.460**	**0.000**
PHSGRAD90	**-0.005**	**-4.254**	**0.000**	**-0.006**	**-3.678**	**0.000**
PMINORI90	**-0.004**	**-3.872**	**0.000**	**-0.004**	**-3.218**	**0.001**
PSAMECNT90	**-0.011**	**-6.033**	**0.000**	**-0.010**	**-5.310**	**0.000**
BEAGINI_9	-0.092	-0.470	0.638	-0.036	-0.190	0.849
F1_1990	-0.023	-1.741	0.082	-0.016	-1.196	0.232
F2_1990	0.008	0.709	0.478	0.005	0.361	0.718
F3_1990	0.026	**2.238**	**0.025**	**0.031**	**2.697**	**0.007**
F4_1990	0.034	**3.307**	**0.001**	**0.030**	**3.075**	**0.002**
RADJ97_EMP	-0.002	-1.327	0.184	**-0.004**	**-2.199**	**0.028**
SLOPE	-0.002	-0.702	0.483	-0.006	-1.836	0.066
ROADWT	0.000	-0.104	0.917	-0.001	-0.150	0.881
EMP50MINK	0.002	1.857	0.063	0.001	0.984	0.325
AVG_SLOPE6	-0.001	-0.267	0.790	-0.002	-0.408	0.683
LAMBDA				**0.698**	**29.578**	**0.000**
Log-likelihod	121.0			121.1		
Akaike info	-211.9			-214.1		
R-Squared	.38			.38		

The results in Exhibit 5-11 show that the best fit was obtained for the metropolitan counties (Model 4-D), with 57 percent of the variability in employment growth explained by the model. For micropolitan counties (Model 4-E), the explanatory power dropped to 33%, and for non-core counties (Model-4-F), the explanatory power dropped to 18.5%.

Not only did the goodness of fit vary, but the selected variables and coefficients vary as well. High school graduation rates (PHSGRAD90) matter for metro and non-core counties (not for micropolitan counties) yet the sign once again is negative as seen above in results for Models 4-B and 4-C – indicating *slower* growth rates in counties with more educated populations. The minority share of the population does not matter in metropolitan counties, matters most in micropolitan counties, and matters somewhat less in non-core counties. In both cases, the sign is negative indicating that counties with higher minority shares grow at slower rates. The adult population share, PROP65_90, matters only for micropolitan counties and also has a negative coefficient. The mobility measure, PSAMECNT90, is significant for all three county types but is estimated to have less than half the impact in non-core counties. Once again, the sign is negative.

Exhibit 5-11: MODEL-4 Stepwise OLS Fits for Metro/Micro/Non-Core Submarkets

		Model 4-D Metropolitan Counties *(109 as of 1993)*				**Model 4-E** Micropolitan Counties *(118 as of 1993)*				**Model 4-F** NonCore Counties *(183 as of 1993)*			
Theme	**Variable**	**B***	**Beta***	**T**	**Sig.**	**B***	**Beta***	**T**	**Sig.**	**B***	**Beta***	**T**	**Sig.**
	Constant	1.848		7.312	0.000	1.265		2.920	0.004	1.071		4.320	0.000
Demographics	PHSGRAD90	-0.009	-0.263	-4.025	0.000					-0.007	-0.435	-5.646	0.000
"	PMINORI90					-0.007	-0.287	-3.261	0.001	-0.002	-0.158	-2.270	0.024
"	PPOP65_90					-0.020	-0.169	-2.142	0.034				
"	PSAMECNT90	-0.018	-0.536	-7.729	0.000	-0.019	-0.347	-4.234	0.000	-0.007	-0.288	-3.812	0.000
Concentration	BEAGINI_9					0.825	0.233	2.665	0.009	-0.439	-0.170	-2.196	0.029
Industry Mix	F1_1990												
"	F2_1990									0.053	0.326	4.200	0.000
"	F3_1990					0.081	0.318	3.615	0.000				
"	F4_1990	0.053	0.212	3.196	0.002	0.044	0.180	2.223	0.028				
Worker Access	EMP40MINK												
"	EMP50MINK					0.026	0.171	2.049	0.043				
"	EMP60MINK	0.003	0.267	3.692	0.000								
Residence	RADJ97_EMP												
Amenity	ASCALE												
Infrastructure	ROADWT												
Terrain	SLOPE												
"	AVG_SLOPE6												
"	AVG_SLOPE1												
	Steps**		4				7				5		
	Adjusted R^2		0.570				0.332				0.185		

** B = the coefficient estimate and Beta = the standardized coefficient estimate*

*** Stepwise ordinary least squares regression of CMPT_CAP (capped, competitively-adjusted employment percent growth 1990-2000) for 410 ARC Counties on the eighteen variables. Separate runs by 1993 USDA County type: Metropolitan, Micropolitan, Non-Core.*

Source: MIT-DUSP ARC Research Team.

The industry concentration GINI measure (BEAGINI_9) is not significant for metro counties but was significant – with different signs – for micro and non-core counties. In micropolitan counties, increased industry concentration correlates with faster growth, but in non-core counties, increased industry concentration correlates with slower growth (and the coefficient estimate was half as large). The results for the industry mix factors are also interesting. Only the fourth factor, F4_1990, matters in metro counties. This factor emphasizes construction/transportation/agriculture without government/services and higher factor scores correlates with faster growth. For micropolitan counties factor 4 still matters (a little less), but factor 3 is even stronger (and also positive). Factor 3 emphasizes government/agriculture/construction without wholesale trade. On the other hand, for non-core counties, only factor 2 matters (positively). Factor 2 emphasizes manufacturing and wholesale trade without mining and government.

The worker access measures matter most for micropolitan counties and not at all for non-core counties. The worker count within 50 minutes, EMP50MINK, performs best for micro counties, but the 60-minute count, EMP60MINK, performs best for metro counties. Note that the coefficient is much smaller for metro counties (0.003 vs. 0.026) but, based on the standardized Beta coefficient, is more influential for metro counties (0.267 vs. 0.171). The worker access distribution is skewed with a long right tail for counties close enough to large metropolitan areas. Hence, the smaller coefficient will tend to be applied to a much larger worker access count, EMP60MINK, for metro counties than for the micropolitan counties that are further from the large metro centers and where the best fitting variable is the 50-minute count, EMP50MINK.

The place-of-residence adjustment, RADJ97_EMP, was not significant for any of the three county types and neither were the amenity, infrastructure, and terrain measures. Because these models predict employment growth by place of employment, we are not surprised that the place-of-residence income adjustment is not relevant (even though it was for earlier ELI models that focused on unemployment, poverty, and income by place of residence). The amenity variable, ASCALE, focuses (as explained earlier) on the scenic and recreational features of a county and other counties might be the ones that benefit economically from these features (e.g., a county along the highway that leads to a national park located in the next county). The terrain measures could well have less effect on 10-year growth than they did for the earlier cross-sectional models. For example, there could be a long-standing advantage to counties in the valley vs. in the hills that explains the much lower density, income, etc. in the hills, even if the recent 10-year employment growth rate is similar.

Another possible explanation for the limited effects of geography in Exhibit 5-11 is that the OLS fits do not account for spatial-spillover effects. The spatial-lag and/or spatial-error models that account for spillover effects within commuting zones consistently outperform the OLS fits. From earlier runs, we see that these spatial models alter the significant variables as well as the coefficient values. Unfortunately, the models and estimation algorithms needed to handle both county stratification and spatial effects are beyond the scope of this study. For example, commuting zones often include a mix of metro, micro, and non-core counties. We cannot meaningfully run the GeoDa models separately for metro, micro, and non-core counties.[18] Nevertheless, our analyses have provided useful insights into both the factors (and county differences) that influence growth rates and the spatial relationships that influence county interactions. In this section, we summarize these findings and draw conclusions regarding decision tools that can assist in identifying promising development strategies.

5.5 Uses and Limitations of the Findings

The analyses demonstrate the importance of demographic, industry mix, and spatial interactions in explaining differences across ARC counties in their economic health and growth rates. The most interesting results relate to the explicit inclusion of detailed geography, infrastructure, and spatial dependencies in models of economic health and growth. We demonstrated that useful measures of geographic influence could be computed, using modern GIS tools, from readily available data in a manner that is practical and consistent across an area as large as Appalachia. Use of GeoDa has also demonstrated the importance of modeling spatial dependencies explicitly in order to avoid fitting miss-specified ordinary least-squares models that can overstate individual factor coefficients as a result of ignoring spatial dependencies. We have also demonstrated circumstances (the commute shed) in which the nearest-neighbor adjacency was *not* the best way to model spatial dependency.

Nevertheless, despite the progress with improved spatial-analysis tools, the model specifications do not go as far as we would like in linking policy options and development strategies to predicted outcomes. The employment growth model does, indeed, use change data to calibrate the parameters. However, we have not explicitly modeled the development process responsible for observed employment changes. We have not, for example, specified an underlying "economic-growth" model that postulates primary industries, demand for ancillary services, import and export flows, and the like, in order to identify which public investments are most likely to yield the biggest returns through exports and local multiplier effects.

Acquiring the data (e.g., freight flows) needed to calibrate such models is impractical at present, and, in the parts of Appalachia that are most in need of assistance, traditional economic-base analysis is likely only a piece of the tool-kit needed to help inform the right development questions. In the small, non-metro counties that are transitional, the size of the multiplier effect associated with project investment

[18] In order to use tools such as GeoDa to estimate spatial spillover effects for mixed models that allow differing variable coefficients by county type with clusters of 'connected' counties, we would have to transform all the variables and include county-type interaction terms that measured deviations from the main (non-interacting) effects. This is beyond the scope of the current study.

depends on many local factors that are not readily observed and estimated. How much of the new money will recycle locally may not be evident or easily modeled from standard data sources. Also, the “connectivity” mechanism that facilitates spillover and other multiplier effects may not be visible and may be relatively different from a ”next-door” adjacency model. A “tourism” strategy, for example, might involve spillover effects along the transportation corridors to the tourist sites, whereas a “knowledge economy” strategy might build social networks that leapfrog counties or even states. The appropriate connectivity matrix for studying (and forecasting) spatial dependencies in these cases could look very different from either the nearest-neighbor or the commute-shed examples that we considered.

Consider, for example, that the employment growth models worked best for metropolitan counties (57% explained) and least well in non-core counties (18% explained). Upon reflection, these variations are not surprising because the traditional export-base model of economic growth is likely to work better for metropolitan areas with sizeable economies, and well developed infrastructure and commute sheds. A further analysis of the Appalachian commute sheds also showed that most include a mix of at least two county types.[19] Many of the more distressed counties are in commute sheds that include no metropolitan county.

Rather than try to identify a single, complex model for explaining growth across all county types, it may be more useful to turn the question around and ask which of several types of models is most appropriate for a county depending upon the characteristics of that county and its neighbors. If, for example, a county has favorable demographics and is in a commuter shed that includes a metropolitan area, then a traditional economic development strategy aimed at the commuter shed may be beneficial and able to capitalize on favorable spillover effects for that county. However, if the commuter shed includes only non-core counties without favorable demographics and industry mix, then traditional development strategies may not be effective, and growth in neighboring commuter sheds might even have unfavorable “backwash” effects.[20] For these counties, more promising development strategies might focus less on commuter-shed ‘neighbors’ and more on supply-chain possibilities or amenity-driven development. Would it make sense for the county to grow its warehouse facilities, is the county along the path from a population center to potentially attractive amenities, etc.?

Research our team conducted for the white papers and other aspects of the project suggests that, for many transitional counties, the development choice is not a matter of fine-tuning the investment strategy and choosing the one with the biggest multiplier. Instead, it is likely to involve sizing up whether one or another of a few plausible growth paths is practical, given the current circumstances for the county and its

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[19] The map also highlights the need to include non-ARC border communities in further analysis because many one- or two-county commute sheds at the edge of the Appalachia region are really part of a larger commute shed, including sheds oriented toward metropolitan centers outside ARC.
[20] A recent study by Feser and Isserman (2005) of employment and population growth in all US counties provides evidence of both favorable spillover and unfavorable backwash effects for non-metro counties.

neighbors. In order to make tourism work, a county needs access to tourists, desirable venues, highways and motels, etc. For a retirement community, or industrial park to work, a different set of questions would be asked. The most effective use of empirical analyses may be to support these evaluations with good (electronic) bookkeeping and visualization. How many people are less than two hours driving distance away from their work? Which counties will benefit from (or contribute to) a new development in a county if the county undertakes certain type of strategies? What gaps exist in the supply or demand for services, infrastructure, skilled workers, etc. What questions should a county ask in order to see if one or another growth model is plausible for the county? Is the county near a metropolitan area, along a transportation corridor, etc.? Modern web-mapping tools and online services are making it practical to acquire data and develop visualization tools and indicator systems that can greatly facilitate "what if" dialogues with citizens and local agencies. Fieldwork and case studies will help when combined with the kind of empirical analysis we have done to measure geographic constraints, neighborhoods, and opportunities. Also, analysts might use outlier counties identified by models, such as the ones we calibrated, to identify places to look for success/failure examples.

Such an approach suggests a policy-oriented decision strategy that:

(a) identifies different sets of potential partners for each county based on the growth model that might be emphasized (for example, counties in the same commuting zone for traditional export-base growth, but counties along the TVA riverway for particular supply-chain analyses, or counties along a highway corridor for certain amenities strategies),

(b) compares the characteristics of the county (and its "neighbors") with those suggested by the relevant right hand side variables for *the growth model that matches the particular development strategy being contemplated* to see whether one or more of these strategies has the factor levels needed to suggest a high likelihood of success (e.g., do not use an export-base strategy for an isolated county with poor transportation infrastructure),

(c) checks whether the type of economic development that is anticipated will be structured in a way that leaves value-added in the county (e.g., mining can benefit locals a lot or a little depending on whether most of the value-added is recirculated in the community or shifted to remote shareholders), and

(d) identifies complementary investments (e.g., in other "neighboring" counties) that would help the group of "neighbors" assemble the factors needed to tap local synergy and enhance the likelihood of success.

5.6 References

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