7.1 Appendix A: Basic Technology Industry Clusters

Basic Chemicals
Petrochemical manufacturing
Plastics material and resin manufacturing
Other basic organic chemical manufacturing
Synthetic rubber manufacturing
Non-cellulosic organic fiber manufacturing
Adhesive manufacturing
Surface active agent manufacturing
Cellulosic organic fiber manufacturing
Other miscellaneous chemical product manufacturing
Custom compounding of purchased resins
Pesticide and other agricultural chemical manufacturing
Nitrogenous fertilizer manufacturing
Printing ink manufacturing
Industrial process variable instruments

Engine Equipment
Fluid power pump and motor manufacturing
Speed changers and mechanical power transmission equipment
Pump and pumping equipment manufacturing
Air and gas compressor manufacturing
Other engine equipment manufacturing
Metal valve manufacturing
Fluid power cylinder and actuator manufacturing
Measuring and dispensing pump manufacturing
Turbine and turbine generator set units manufacturing
Small arms manufacturing
Scales, balances, and miscellaneous general machinery
Power-driven hand tool manufacturing
Motor and generator manufacturing
Motor vehicle parts manufacturing
Welding and soldering equipment manufacturing
Military armored vehicles and tank parts manufacturing

Precision Instruments
Industrial process variable instruments
Watch, clock, and other measuring and controlling device manufacturing
Analytical laboratory instrument manufacturing
Automatic environmental control manufacturing
Optical instrument and lens manufacturing
Totalizing fluid meters and counting devices
Electricity and signal testing instruments
Relay and industrial control manufacturing

Computer and Electric Equipment
Computer storage device manufacturing
All other electronic component manufacturing
Other computer peripherals and manufacturing
Broadcast and wireless communications equipment
Electricity and signal testing instruments
Search, detection, and navigation instruments
Electronic computer manufacturing
Telephone apparatus manufacturing
Semiconductors and related device manufacturing
Computer terminal manufacturing
Irradiation apparatus manufacturing
Electron tube manufacturing
Electro-medical apparatus manufacturing

Pharmaceuticals
Polish and other sanitation good manufacturing
Toilet preparation manufacturing
Soap and other detergent manufacturing
Pharmaceutical and medicine manufacturing
Pesticide and other agricultural chemical manufacturing

Information Services
Data processing services
Other computer related services, including facilities management
Computer systems design services
Software publishers
Custom computer programming services
Information services
Telecommunications
Cable network and program distribution

Industrial Machinery and Distribution Equipment
Conveyor and conveying equipment manufacturing
Industrial truck, trailer, and stacker manufacturing
Mining machinery and equipment manufacturing
Construction machinery manufacturing
Elevator and moving stairway manufacturing
Overhead cranes, hoists, and monorail systems
Oil and gas field machinery and equipment
Packaging machinery manufacturing
Industrial process furnace and oven manufacturing
Railroad rolling stock manufacturing
Semiconductor machinery manufacturing
Electric power and specialty transformer manufacturing

Basic Technology Industry Clusters (continued)

Cable Manufacturing
Other communication and energy wire manufacturing
Fiber optic cable manufacturing
Paint and coating manufacturing
Wiring device manufacturing
Switchgear and switchboard apparatus manufacturing

Fertilizer and Chemical Products
Fertilizer, mixing only, manufacturing
Other basic inorganic chemical manufacturing
Explosives manufacturing
Synthetic dye and pigment manufacturing
Carbon and graphite product manufacturing
Industrial gas manufacturing
Nitrogenous fertilizer manufacturing
Petrochemical manufacturing

Aerospace
Aircraft manufacturing
Other aircraft parts and equipment
Propulsion units and parts for space vehicle and guided missiles
Aircraft engine and engine parts manufacturing
Guided missile and space vehicle manufacturing

Motor Vehicles
Miscellaneous electrical equipment manufacturing
Automobile and light truck manufacturing
Heavy duty truck manufacturing
Motor vehicle parts manufacturing
Audio and video equipment manufacturing

Wiring Devices and Switches
Switchgear and switchboard apparatus manufacturing
Wiring and device manufacturing
Other communications equipment manufacturing
Motor and generator manufacturing
Architectural and engineering services

Medical Instruments and Optics
Surgical and medical instrument manufacturing
Ophthalmic goods manufacturing
Photographic film and chemical manufacturing
Surgical appliance and supplies manufacturing
Primary battery manufacturing
Dental equipment and supplies manufacturing
Storage battery manufacturing
Other ordnance and accessories manufacturing
Photographic and photocopying equipment manufacturing
Audio and video equipment manufacturing
Ammunition manufacturing
Miscellaneous electrical equipment manufacturing

Architectural and Engineering
Architectural and engineering services
Other communications equipment manufacturing
Environmental and other technical consulting services
Management consulting services
Specialized design services

Technical and Research Services
Environmental and other technical consulting services
Management consulting services
Scientific research and development services
Specialized design services
Other ambulatory health care services
Architectural and engineering services
Custom computer programming services

Note: Industry clusters are based on Feser and Isserman (2009) value chain analysis of the 1997 United States Benchmark Input/Output accounts. A complete set of cross references between I/O sector identification with NAICS listings are available at www.ace.illinois.edu/Reap/Feser_051015_BenchmarkValueChain.xls.

7.2 Appendix B: Statistical Methods and Procedures

7.2.1 Growth Regression Model

The log-linear model used in this analysis is:

$$\ln(y_{i2007}/y_{i2000}) = \alpha \cdot \ln y_{i2000} + \beta_0 + \beta_1 \cdot percomm_i + \beta_2 \cdot emprt_i + \beta_3 \cdot perestab20_i + \beta_4 \cdot perestab100_i + \beta_5 \cdot peragmi_i + \beta_6 \cdot permanf_i + \beta_7 \cdot \Delta pop_{9000\,i} + \beta_8 \cdot \Delta emp_{9000\,i} + \beta_9 \cdot \Delta estab_{9000\,i} + \beta_{10} \cdot perblk_i + \beta_{11} \cdot peramind_i + \beta_{12} \cdot perhsp_i + \beta_{13} \cdot perpop2064_i + \beta_{14} \cdot perpop65up_i + \beta_{15} \cdot perhsdip_i + \beta_{16} \cdot percc_i + \beta_{17} \cdot amenity_i + \beta_{18} \cdot landpub_i + \beta_{19} \cdot interstate_i + \beta_{20} \cdot adhs_i + u_i,\ i = 1 \text{ to } 1{,}070 \text{ counties},$$

which is summarized hereon as, $\Delta y = Z\beta + u$. Dummy variables were used to identify ARC (*arc*) and non-ARC counties (*nonarc*), and interacted with the local determinants which allows slopes and intercepts to vary between ARC and non-ARC counties;

$$\Delta y = \delta_{nonarc} \cdot nonarc + nonarc \cdot Z \cdot \beta_{nonarc} + \delta_{arc} \cdot arc + arc \cdot Z \cdot \beta_{arc} + u.$$ [128]

The matrix Z contains the local determinants and industry concentration indices but omits a constant. McGranahan, Wojan, and Lambert (2010) applied the same method in their analysis of creative capital and entrepreneurship on growth. The convention allows us to focus on ARC counties specifically, acknowledging that these counties are connected to a wider regional economy by allowing for geographic dependence between ARC and non-ARC counties through the spatial process models developed below.

7.2.2 Spatial Process 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; $y = \rho Wy + X\beta + \varepsilon$, $\varepsilon = \lambda W\varepsilon + u$, u is independently and identically distributed with mean zero and covariance Ω, and W is a matrix defining relationships between spatial units. 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, thereby distinguishing this class of models from other econometric models.

When the weights are contiguity matrices 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. We use two weight matrices to hypothesize about neighborhood dependencies. The first is a queen contiguity matrix (W_1), and the second is an inverse distance matrix that only considers adjacent counties (W_2). The distances are the network road distances between county seats. Both matrices are row standardized. The average number of neighbors was 5.56, with 5,951 nonzero links.

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[128] In the absence of spatial dependence, the growth/local determinant relationships could be estimated separately for ARC and non-ARC counties, where δ_{arc} and δ_{nonarc} would be the overall slopes and intercepts for each group.

7.2.3 Endogenous Growth Regime Specification

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,

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

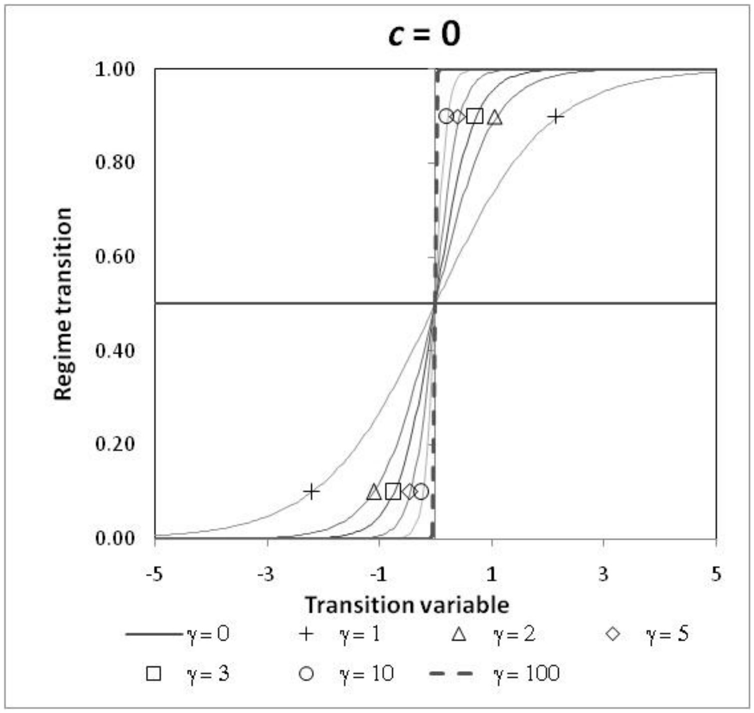
which can be rearranged as:

$$\Delta y = Z\beta + G \cdot Z\delta + u,$$

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. 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., >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 confers 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 [OMB]) 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., 2008b; Partridge and Rickman, 2008; Lambert and McNamara 2009).

Figure 7-1: Example of the transition function $G(\gamma, c; v)$, and different levels of smoothing parameter, γ. *Note that two distinct regimes emerge when γ = 100, whereas no regimes are identified when γ = 0. The parameter c functions as a location parameter; the inflection of the transition function is centered on c.*



7.2.4 Growth 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 (the "null" model);

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

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:

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

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

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

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

H5: $\rho \neq 0$, $\lambda \neq 0$, $\delta \neq 0$ (lag-error process model with geographic heterogeneity, ARAR-STAR), H6: $\rho \neq 0$, $\lambda \neq 0$, $\delta = 0$ (lag-error process model, ARAR),

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

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;

$$ME_i^k = \beta_k + G_i \cdot \delta_k.$$

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

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

with the indirect effects,

$$ME_i^k = \frac{\rho}{1-\rho}(\beta_k + G_i \cdot \delta_k).$$

In this application, a "general-to-specific" approach (Hendry, 2006; Larch and Walde 2008) is considered to specify each model according to the contiguity and inverse distance specifications. Hypotheses about spatial nonlinearity, lag, error, ARAR processes and their combinations (H2 – H8) are tested by calculating Wald statistics based on the heteroskedastic-robust covariance matrix of the full ARAR–STAR model.

T-statistics are used to test the null hypothesis that the local determinants had no effect on growth. We choose a Type-I error rate of 5%. The squared correlation coefficient was used a measure of fit because of the nonlinear instrumental variables approach used to estimate the models. Estimation procedures are summarized in Xu and Lambert (2011).

7.3 Appendix C: County Cohort Selection

The matching method is summarized as follows. For example, if *X* contains the local economic indicators in 1960, then *WX* is the weighted average of the local economic indicators in neighboring counties. The Mahalanobis distance metric (*d*) takes the form:

$$d(Z_T, Z_C) = (Z_T - Z_C)'\Sigma^{-1}(Z_T - Z_C),$$

where *T* represents a target county (i.e., those selected based on the cut-off criteria defined above), *C* represents a candidate matching county, and *Z* = [*X*, *WX*] is the vector of selection variables, and Σ is the covariance of possible matching counties. The term *WX* are the averages of these values for neighboring counties (also measured in 1960) were included in the algorithm.

Averages were weighted by the proportion of common border shared between counties discounted for the distance between county centroids. This weighting scheme (*W*) is often referred to as Cliff-Ord type array (Cliff and Ord, 1981). This additional information incorporates geographic information into the matching criteria as potential "spillovers" between neighbors.

7.4 Appendix D: Regression Model Specification

The Wald tests specifying each regression model are reported in Table 7.4.5. The test statistics are based on the null model in Appendix B, "Growth Regimes and Spatial Process Models."

7.4.1 Table: Model Specification for Change in Employment and Per Capita Income Measures

	Δemp_{0007}	$\Delta estabs_{0007}$	Δpci_{0007}
W_{ID}, Inverse Network Distance			
Spatial lag AR, H_0: $\rho = 0$	14.10	0.59	9.82
Spatial error AR, H_0: $\lambda = 0$	0.06	5.80	3.42
Joint lag/error, H_0: $\rho = \lambda = 0$	22.02	12.77	46.29
Spatial nonlinearity, H_0: $\delta = 0$	194.15	276.73	171.12
Joint nonlinearity/lag/error, H_0: $\delta = \rho = \lambda = 0$ /3	223.27	287.31	264.57
W_{Queen}, Order 1			
Spatial lag AR, H_0: $\rho = 0$	12.33	1.17	11.43
Spatial error AR, H_0: $\lambda = 0$	0.19	6.17	3.57
Joint lag/error, H_0: $\rho = \lambda = 0$	18.64	17.13	46.77
Spatial nonlinearity, H_0: $\delta = 0$	197.85	276.27	162.57
Joint nonlinearity/lag/error, H_0: $\delta = \rho = \lambda = 0$	215.18	291.14	263.39

Notes:

1/ 5% critical value = 3.84

2/ 5% critical value = 5.99

3/ 5% critical value = 7.81.

7.4.2 Summary Statistics of Growth Indicators, Technology Cluster Location Quotients, and Local Determinants.

Variable	Description	Source	Mean	Std. Dev.
lnempdens	Log employment density, 2000	REIS[129]	3.694	1.236
lnpci	Log real per capita income, 2000	REIS	13.533	1.359
distmet	Distance to metro county (miles), 1993	ESRI[130]	33.466	28.860
percomm00	% Commute outside county, 2000	Census 2000	39.963	17.226
emprt	Employment rate, 2000	REIS	95.394	1.580
lnmedhhi	Median HH Income, 2000	Census 2000	10.444	0.246
pctest20	% of firms with < 20 employees, 2000	CBP[131]	88.030	3.120
pctest100	% of firms with > 100 employees, 2000	CBP	2.193	1.034
peragmi	% Emp. Ag & Mining, 2000	REIS	3.816	3.266
permanf	% Emp. Manufact., 2000	REIS	20.455	8.672
Δpop9000	Population, 1990-2000	REIS	0.103	0.140
Δemp9000	Employment, 1990-2000	REIS	0.122	0.125
Δestabs9000	Establishments, 1990-2000	CBP	0.181	0.182
perblk	% Black, 2000	Census 2000	16.885	18.809
peramind	% American Indian, 2000	Census 2000	0.428	1.689
perhsp	% Hispanic, 2000	Census 2000	2.220	3.030
pctpop2064	% Pop. 20-64 years old, 2000	Census 2000	58.717	2.428
c00p65ov	% Pop. 64+ years old, 2000	Census 2000	13.434	2.875
hsdip	% high school diploma, 2000	Census 2000	73.099	8.600
pctcc	% Pop. Creative occupations, 2000	ERS[132]	16.941	6.101
amenity	Natural amenity index (index)	ERS	-0.200	1.178
pubpct	% Public land	US Forest Service	7.410	11.367
Interstate	Interstate (1 = yes)	ESRI	0.469	
adhs	Appalachian Development Highway (1 = yes)	ARC[133]	0.136	

[129] REIS = Regional Economic Information System (http://www.bea.gov/bea/regional/reis)

[130] ESRI = Environmental Systems Research Institute (http://www.esri.com/data/free-data)

[131] CBP = County Business Patterns (http://www.census.gov/epcd/cbp)

[132] ERS = Economic Research Service (http://www.ers.usda.gov/data)

[133] ARC = Appalachian Regional Commission (http://www.arc.gov/research/RegionalDataandResearch.asp)

Table (continued): Summary Statistics of Growth Indicators, Technology Cluster Location Quotients, and Local Determinants.

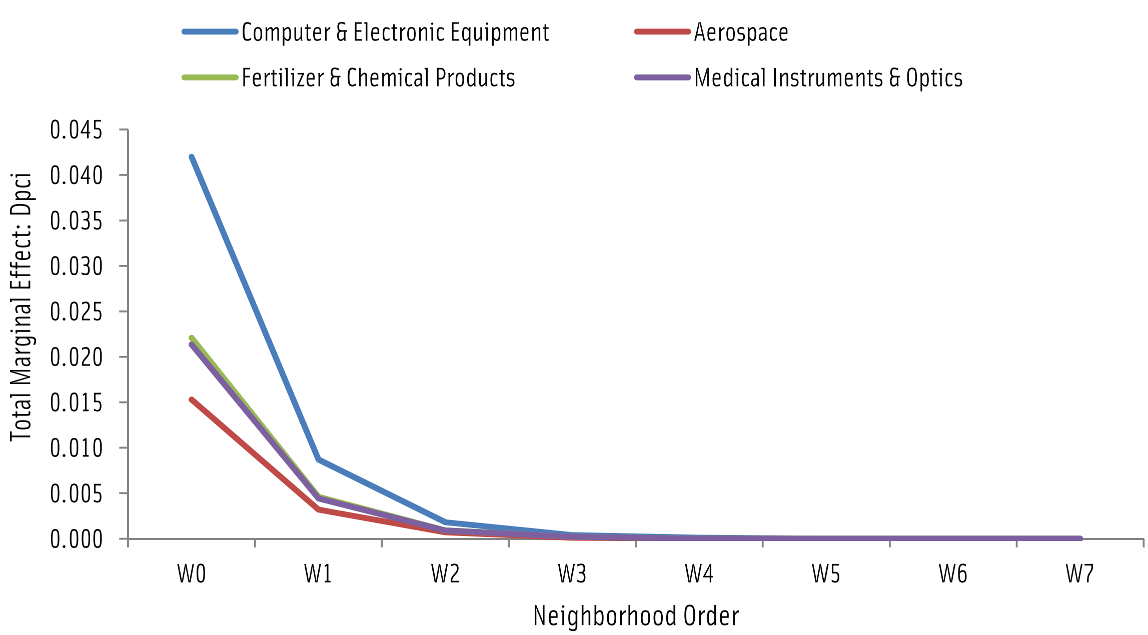
CI1	Basic Chemicals	0.360	0.684
CI2	Precision Instruments	0.156	0.379
CI3	Engine Equipment	0.357	0.476
CI4	Computer & Electronic Equipment	0.143	0.273
CI5	Information Services	0.180	0.139
CI6	Pharmaceuticals	0.192	0.839
CI7	Fertilizer & Chemical Products	0.524	1.279
CI8	Industrial Machinery & Distribution Equipment	0.324	0.655
CI9	Aerospace	0.155	0.605
CI10	Medical Instruments & Optics	0.201	0.407
CI11	Motor Vehicles	0.364	2.041
CI12	Wiring Devices & Switches	0.288	0.979
CI13	Technical & Research Services	0.185	0.128
CI14	Cable Manufacturing	0.275	1.024
CI15	Architectural & Engineering Services	0.206	0.144

7.5 Appendix E: Marginal Effects of Technology Clusters

Discussion of the marginal effects focuses of the technology clusters that were significantly correlated with jobs and income growth. Four sets of parameters correspond with the direct and total effects of the technology clusters on income growth for each regime. The association between job growth and the basic chemicals (BCH) and wiring and device switch (WDS) technology clusters was nonlinear, with a clearly defined switching point of 20 miles beyond urban core counties. Own-county job growth was also positively correlated with employment growth in neighboring counties.

The BCH cluster was associated with a modest decrease in jobs in counties located within 20 miles of metropolitan counties, but farther away from urban areas the relationship changed. For example, a 10% increase in the BCH concentration index in relatively remote counties corresponded with (on average) a 0.004% change in jobs, but in metropolitan counties, the relationship was negative, with a corresponding elasticity of –0.02%. The association between job growth and the WDS cluster was effectively zero moving away from metropolitan to more remote counties. Per capita income in counties where the computer and electronic equipment (CEE) production and manufacturing cluster was relatively concentrated grew, on average, more slowly in counties located within 44 miles of a metropolitan county. A 10% change in the CEE index corresponded with a relatively small decrease in per capita income (-0.09%) in ARC counties located near urban core areas. The relationship was nonlinear, with the association becoming positive beyond the 44 mile threshold. For ARC counties located farthest from metropolitan counties, the marginal effect was – 0.06 + [G = 1]*0.11; a 10% change in the CEE concentration index corresponded with a relatively small but positive increase (0.01%) in per capita income in more remote counties.

Figure 7-2: Marginal effect partitioning of selected technology clusters with income growth in the ARC region, 2000-2007.



Partitioning the marginal effects suggests that expansion of this cluster in relatively remote counties could be associated with modest increases in income in neighboring counties up to order 2 (e.g., the "2-deep" ring of counties surrounding a given county, Figure 7-2). Nonlinear trends were also evident in the aerospace (AER), medical and optical instruments (MED), and fertilizer and chemical technology clusters (FCH), except the trends were reversed. All else equal, these sectors were correlated with modest increases in income in urban areas. At the 44-mile threshold, the concentration indices associated with the AER and MED clusters were negatively correlated with income growth in more remote counties. The association between the FCH product cluster and income growth was always positive, but the magnitude of the association decreased moving away from metropolitan core counties. Partitioned marginal effects associated with these clusters with respect to income growth approached zero beyond neighborhood order 2, which is mainly due to the modest lag autocorrelation coefficient of ρ = 0.21.

7.5.2 LISA Groupings, Technology Clusters, and Regional Impact Multipliers

In the empirical application, we focus on the results of the per capita income model to motivate the geographic targeting of industry clusters. The analysis considers the FCH, AER, MED, and CEE technology clusters and their relationship with income growth. The elasticity of income growth with respect to a percentage change in the cluster concentration indices were calculated for each county and mapped (Figure 7-4). Local Moran's I statistics were estimated to analyze the spatial distribution of the elasticities. The resulting LISAs identify the "core" counties of a technology cluster (Figure 7-5). Given a set of core counties, peripheral counties were appended to the core group based on the marginal effect partition as in Figure 1, which delineate an "impact region" (Figure 7-4). Each technology cluster is associated with a different set of core-periphery counties, but impact regions may overlap.

As an example, a selected impact region of the CEE technology cluster corresponds with the cities of Beckley and Braxton, West Virginia. Beckley has undergone extraordinary growth since the last decade, and is a regional hub for more than 200,000 residents. The region is also known for its local artisans, and historical and scenic tourism. Interestingly, Braxton is the population weighted center of the state located in the mountain lake region of the state. The impact region selected for the aerospace, medical/optical, and fertilizer/chemical technology clusters all include the Knoxville, Tennessee, greater metropolitan statistical area, including Oak Ridge National Laboratory, and the counties included in the medical/optical technology cluster extend into eastern and central North Carolina, specifically the Raleigh-Durham-Chapel Hill research triangle. The core counties associated with the fertilizer/chemical technology cluster appear correlated with the interstate and the ADHS highway systems, suggesting the importance of transportation costs associated with production and marketing of fertilizer and chemical products.

We estimate the Type SAM (social accounting matrix) regional impact multipliers associated with each impact region and technology cluster separately using IMPLAN software (Figure 7-3). Type SAM multipliers take into account the expenditures resulting from increased household income and inter-institutional transfers resulting from the economic activity. Therefore, Type SAM multipliers assume that as final demand changes, incomes increase along with inter-institutional transfers. Increased spending by people and institutions leads to increase demand from local industries. The average of the location quotient inside the CEE and MED impact regions was less than one, but at least one county inside each impact region had a location quotient greater than one, suggesting that these counties may be the leaders within the group with respect to concentration. Type SAM (Social Accounting Matrix) multipliers were estimated for the each impact region (Figure 7-3). For example, a $1 million increase in final demand for products manufactured by the computer and electronic equipment cluster in the impact region results in a $0.55 million increase in total economic activity in the area, which is associated with 1.83 new jobs for each job created in the CEE cluster of these counties.

Figure 7-3: Regional impact multipliers associated with the identified "core and periphery" clusters

	Cluster Core	Cluster Core and Periphery				
Cluster	LQ (Mean)	LQ (Mean)	LQ (Max)	Type SAM Multiplier		
				Total Value Added	Total Employment	Total Output
Computer and Electronic Equipment	0.257	0.116	1.896	1.988	2.825	1.552
Aerospace	1.137	0.243	3.828	2.060	2.537	1.537
Fertilizer and Chemical Products	1.785	0.358	5.804	2.306	3.641	1.746
Medical Instruments and Optics	0.715	0.368	5.027	2.023	2.556	1.704

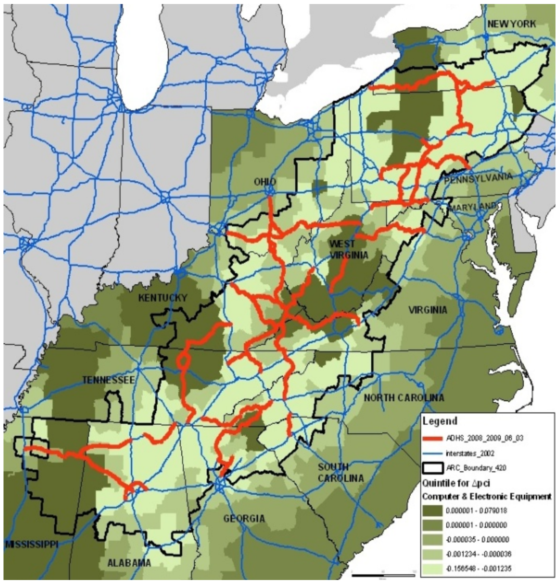
Employment, Output, and Earnings				
Cluster	Employment	Total Industry Output*	Total Value Added*	Wage Earnings*
Computer and Electronic Equipment	303	111.21	34.36	12.69
Aerospace	1181	412.57	113.58	82.16
Fertilizer and Chemical Products	4912	2388.93	731.72	379.97
Medical Instruments and Optics	9454	2638.93	960.03	519.78

**=in Millions of dollars.*

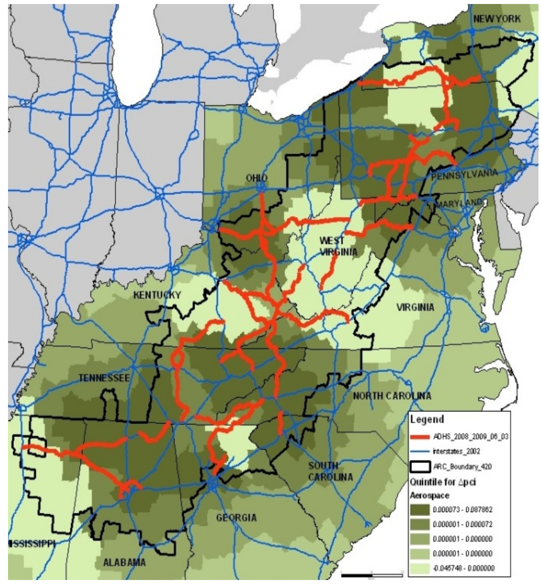
Regional multipliers for each technology cluster estimated using 2006 IMPLAN data;

Figure 7-4:   Spatial distribution of estimated elasticities for $\Delta pci_{2000\text{-}2007}$ (breaks are quintiles).

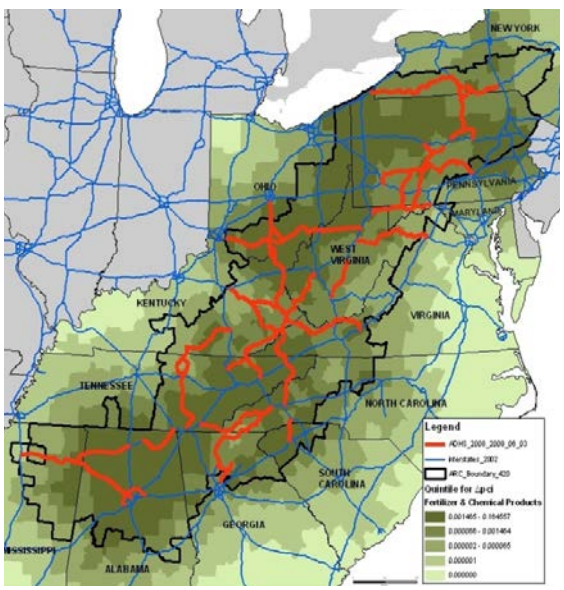
Computers and Electronic Components



Aerospace



Fertilizer and Chemical Products



Medical and Optical Instruments

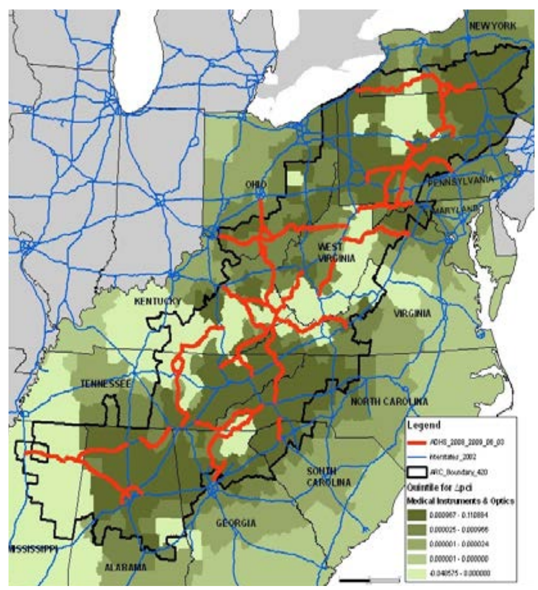
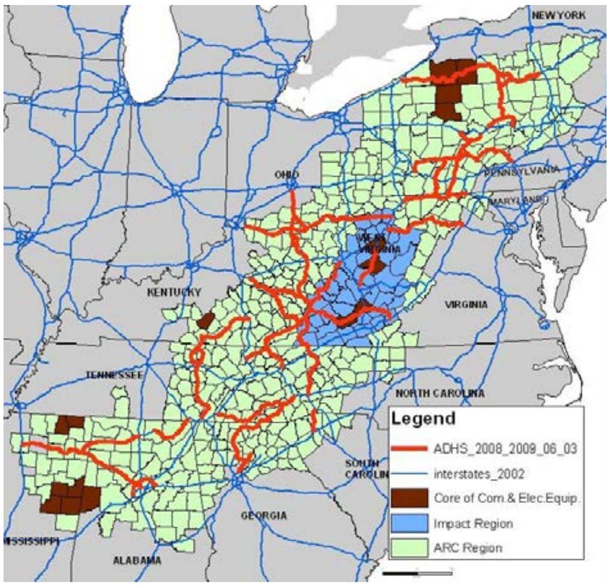
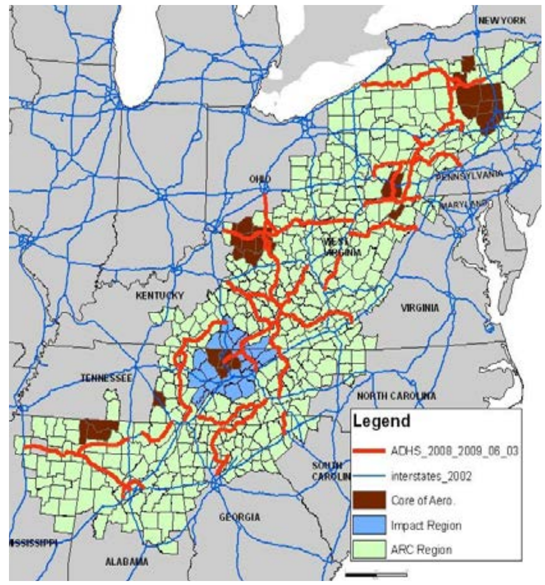


Figure 7-5: "Core and periphery" counties of selected impact regions. Core counties are those where industry cluster elasticities formed significant LISA clusters corresponding with the positive orthant of global Moran's I scatter plot. Periphery counties include the second order neighbors surrounding the core counties, as described in Figure 7-2.

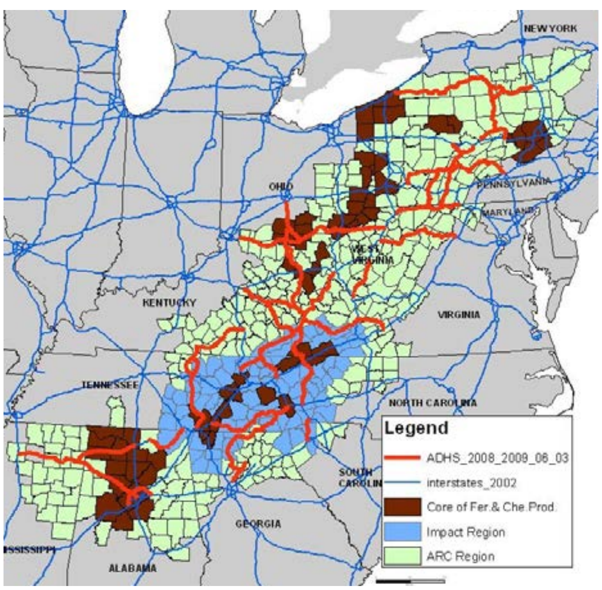
Computers and Electronic Components



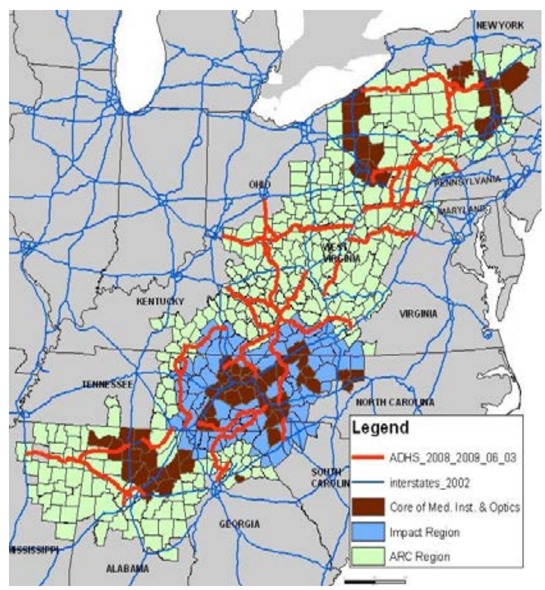
Aerospace



Fertilizer and Chemical Products



Medical and Optical Instruments



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