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Tennessee Agriculture and Forestry Industry Clusters and Economic Performance, 2001–2006

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Industry cluster identification methods determine linkages between purchasers and suppliers at the county level for 447 economic sectors in Tennessee. Using an econometric model, the cluster analysis is extended to estimate which value chains contributed to economic growth between 2001 and 2006. Businesses making up the agriculture and forestry clusters enjoyed increased output per job in 34% and 32%, respectively, of Tennessee's counties. The spatial pattern of these findings was significant, suggesting that some counties may benefit from regional coordination of projects designed to enhance or retain businesses in these industry clusters.

Key words: comparative advantage, economic development, industry clusters, nonparametric clustering, value chains

Introduction

Regional economists and policy makers increasingly emphasize the identification of industry clusters as an important component of regional development strategies (Barkley and Henry, 1997; Porter, 1998; Stimson, Stough, and Roberts, 2006; St. John and Pouder, 2006; Feser, Renski, and Goldstein, 2008). This research applies the industry cluster concept to examine the transformation of the Tennessee economy amid recent changes in regional and global economies. From 1997 to 2007, Tennessee lagged behind other states with respect to job and population growth, which led to a decrease in labor force participation (Center for Business and Economic Research, 2008). Identifying sectors that flourished in Tennessee during this period may provide insight to potential economic development strategies for counties in terms of business retention and industry recruitment.

We examine the 2001–2006 time frame, which includes the lowest point of a brief recession in 2001 and much of the economic rebound that lasted through 2007. By identifying industry clusters that thrived during this period, along with the value chains supporting them, it is possible to determine which counties or regions were positioned to withstand difficult economic times in terms of continued job growth, business retention or expansion, and increased output per job. Some industry clusters may have

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positively contributed to county or regional economic growth during this short business cycle. But in other instances, the presence of a given industry cluster may have had no effect, or even a negative impact, on growth. Locations where an industry cluster persisted or expanded during 2001–2006, and concomitantly contributed to economic growth, may suggest a county has a comparative advantage with respect to a given value chain in particular, or an industry cluster in general.

This paper provides a conceptual overview of industry clusters and value chains, and then develops an econometric model to identify the sectors comprising industry clusters in counties and their impact on economic growth in Tennessee over the period 2001–2006. A three-step procedure accomplishes this goal. The first step applies a non-parametric clustering method (Feser, 2005; Feser, Renski, and Koo, 2009; Feser and Isserman, 2009) to county-level sector data to isolate value chains defining and supporting industry clusters. The second step measures the impact industry clusters had on economic growth using a partial adjustment model. The third step determines the spatial distribution of the industry clusters associated with economic growth. The paper concludes with a summary of the findings and offers suggestions for further research.

The empirical analysis focuses on Tennessee's agriculture and forestry clusters and how they contributed to economic growth in Tennessee's 95 counties from 2001–2006. Tennessee's agricultural and forestry industries are important to the state's economy, contributing more than $60 billion to the state economy in total industry output and employing over 490,000 individuals in 2003 (Menard, Jensen, and English, 2003). In 2006, about one in five dollars in the state's economy resulted from farming and primary forest products, with about 80% derived from further handling and processing of these products. Raw food and fiber products produced by the state's farms and forests are transported, handled, processed, and marketed, adding value and jobs to the economy. Potential exists for enhancing farm incomes by increasing producer prices and/or providing investment opportunities for producers. If value is added to raw materials or intermediate goods produced in the state, jobs will be generated that would otherwise be added out-of-state or out-of-country. Identification of the linkages between sectors making up the agroforestry complex is important for community leaders and those who advise them with respect to targeting programs geared toward business attraction and retention with a regional perspective.

Conceptual Overview of Industry Clusters and Value Chains

Industry clusters are built around core export-oriented businesses that bring new wealth into a region and help drive regional economic growth (Barkley and Henry, 1997; Stimson, Stough, and Roberts, 2006; St. John and Pouder, 2006; Renski, Koo, and Feser, 2007). The source of competitive advantage for industry clusters is in local qualities, such as shared knowledge, relationships, and motivation, which are more difficult for distant competitors to obtain (St. John and Pouder, 2006). Gibbs and Bernat (1997) characterized industry clusters as firms in similar industries seeking comparative advantage by co-locating near natural resources, and product, input, and labor markets. Cluster interactions promote competition between industries while maintaining channels of cooperation. Industry clusters influence competition by fostering innovation, research, and development, which in turn support growth in labor productivity, increase the depth and breadth of labor skill sets, and stimulate new business formation (Renski, Koo, and Feser, 2007). These actions facilitate additional rounds of interaction which advance the core industry sectors and reinforce the cluster itself (Porter, 1998), resulting in an agglomeration of competing but collaborating industries with similar resource and labor demands (Fujita and Thisse, 2002). Businesses in clusters benefit from greater access to suppliers and customized support services while building a framework for companies to work together to meet common needs and promote common interests (Center for Community and Economic Development, 2008). In many ways, cluster members enjoy the benefits of scale economies without sacrificing autonomy (Porter, 1998).

Business and retention programs designed to enhance the forward and backward linkages of industry clusters will likely increase local multiplier effects if dollars are invested locally (Shaffer, Deller, and Marcouiller, 2004). Spatial concentrations of activity increase local income by increasing factor productivity, decreasing production costs, and providing access to specialized goods and services (Johnson, 2001). In other words, output will be higher for a given dollar of input due to the cost savings from agglomeration economies created by industry clusters. With regard to wages and income, Gibbs and Bernat's (1997) analysis of rural industry clusters suggests rural worker earnings are about 13% higher than those of comparable workers outside clusters. The end result is that through regional cooperation, groups of counties may consider cluster recruitment as a mutual economic development strategy because of the network externalities resulting from business transactions and communications stemming from cluster formation across a region (Feser and Isserman, 2009).

Strategies designed to add value to a region's resources are an important component of rural development policy (Kraybill and Johnson, 1989). Identifying so-called industry clusters enables professionals, policy makers, and their advisors to determine empirically whether a particular industry cluster adds value to local resources and contributes to local economic growth. An understanding of these linkages provides local planners, industry leaders, and entrepreneurs with information to make complex decisions regarding new business opportunities, creative financial arrangements, product market potential, and material supply acquisition. In addition, identifying which combinations of sectors contribute to economic growth in a given county or region may be useful for local planners with respect to allocating limited financial resources to business retention or recruitment projects, or regional cooperation efforts where several local governments or interest groups target similar development objectives.

Methods

There are numerous methods for identifying and analyzing industry clusters. Survey approaches use interviews, focus groups, and questionnaires to learn about supply chain structures (Stimson, Stough, and Roberts, 2006). Quantitative approaches typically analyze industrial sector data to gauge industry size and change, as measured by employment, wage earnings, the number of establishments, and related dynamics (Stimson, Stough, and Roberts). Quantitative methods also include the regional analysis of input-output linkages and location quotients (e.g., Czamanski, 1974; Barkley and Henry, 1997; Feser and Bergman, 2000; Feser and Isserman, 2009; Feser, Renski, and Koo, 2009). Recent studies have also used exploratory spatial data analysis to identify and analyze the geographic distribution of regional clusters (Gibbs and Bernat, 1997; Feser, Renski, and Goldstein, 2008).

Nonparametric Identification of Industry Clusters with Sector Transaction Data

Other quantitative approaches have used factor analysis to identify industry clusters, based on intersectoral purchasing/sales ratios derived from input-output (IO) tables (e.g., Czamanski, 1974; Czamanski and Ablas, 1979; Feser and Bergman, 2000; Feser, Sweeney, and Renski, 2005, among others). This method identifies interindustry linkages by calculating a set of ratios $x_{ij} = a_{ij}/a_{+j}$ and $y_{ij} = a_{ij}/a_{i+}$, which represent, respectively, the total intermediate good sales and purchases between industries i to j (Renski, Koo, and Feser, 2007). The a_{ij}'s are elements of an IO transaction matrix, $\mathbf{A}$. An entry in any column vector of $\mathbf{X}$ represents the ratio of purchases by column industry j from row industry i to total intermediate purchases by industry j. The ratio of sales from row industry i to column industry j to total intermediate sales by industry i is represented by $\mathbf{Y}'$. The ratios are interpreted as correlations between industries, e.g., how closely they are linked. In all, there are four possible ratios: buyers-to-buyers, sales-to-sales, buyers-to-sales, and sales-to-buyers. Typically, the largest of the set of ratios between sector pairs is selected to produce an $s \times s$ matrix (s is the number of sectors). Given $\mathbf{X}$ and $\mathbf{Y}'$, the sector composition of industry clusters is determined using the factor pattern associated with this matrix.

Feser and Bergman (2000) identified several problems with this approach. Because industries i and j commonly make relatively large purchases from a comparatively smaller set of producer service industries, this does not always mean industries i and j are closely linked (Feser and Isserman, 2009). But correlation between these industries would be high using the approach outlined above, making it difficult to identify distinct value chains (Feser and Bergman, 2000). Correlations exclusively based on purchases and sales may be skewed by very large flows between a few industries, which may have the unintended consequence of producing large, aggregated clusters.

To address these potential problems, this study uses a qualitative nonparametric clustering procedure suggested by Feser (2005), Feser and Isserman (2009), and Feser, Renski, and Koo (2009). Define sets S_i and B_i, where S_i is the set of supplier industries (sellers) to industry j, and B_j is the set of purchasing industries (buyers) from industry i. In practice, the researcher might assign a threshold (α) that purchasing and sales ratios must attain before a sector is included as a cluster member. Given S and B, define:

(1)
$$\begin{aligned} I_{ij}^{SS} &= S_i \cap S_j, & U_{ij}^{SS} &= S_i \cup S_j, \\ I_{ij}^{BB} &= B_i \cap B_j, & U_{ij}^{BB} &= B_i \cup B_j, \\ I_{ij}^{SB} &= S_i \cap B_j, & U_{ij}^{SB} &= S_i \cup B_j, \\ I_{ij}^{BS} &= B_i \cap S_j, & U_{ij}^{BS} &= B_i \cup S_j, \end{aligned}$$

where I and U are sets of buyer and/or supplier intersections and unions, respectively. From these qualitative relationships, the following measures are constructed:

(2) $$R_{ij}^{SS} = \frac{I_{ij}^{SS}}{U_{ij}^{SS}}, \quad R_{ij}^{BB} = \frac{I_{ij}^{BB}}{U_{ij}^{BB}}, \quad R_{ij}^{SB} = \frac{I_{ij}^{SB}}{U_{ij}^{SB}}, \text{ and } R_{ij}^{BS} = \frac{I_{ij}^{BS}}{U_{ij}^{BS}}.$$

These ratios measure the proportion of shared linkages between sectors i and j along four dimensions. R^{SS} is the number of supplier industries that sectors i and j have in common over the total number of supplier industries to i and j. Larger values of R^{SS} indicate a stronger value chain linkage between i and j because of joint sourcing from the same suppliers. Likewise, R^{BB} is the share of common buyer industries. The R^{SB} and R^{BS} measures may be different because the IO matrix representing intersectoral transactions is not necessarily symmetric. R^{SB} measures second-level relationships between sector pairs, and increases as one industry's suppliers become another industry's buyers. R^{BS} measures second-level relationships between sector pairs, and increases as one industry's buyers become another industry's suppliers. The maximum value of these measures is chosen to construct an $s \times s$ intersectoral linkage matrix, with the (i, j) elements, $R_{ij}^{\text{MAX}} = \max(R_{ij}^{SS}, R_{ij}^{BB}, R_{ij}^{BS}, R_{ij}^{SB})$. It is important to note that every industry is potentially linked to every other industry, with the strength of linkages ranging from $R_{ij}^{\text{MAX}} = 0$ (no joint buyers or suppliers) to $R_{ij}^{\text{MAX}} = 1$ (identical buyer and supplier linkages). Industries making up the clusters have stronger linkages than other groups, but it is still the case that any given industry may have reasonably tight linkages with other sectors defining specific value chains. It is also important to note that cluster membership is not mutually exclusive. A sector may belong to a value chain in more than one cluster.

In addressing the problems of the factor analysis approach, Feser (2005), Feser, Renski, and Koo (2009), and Feser and Isserman (2009) suggest several adjustments in constructing $\mathbf{R}^{\text{MAX}}$. First, local serving sectors are eliminated from the value chain analysis including null sets (i.e., a sector may not be present in any county), local consumer and personal services, primary and secondary schools, and government enterprises (table 1).

Second, thresholds are set to capture a high majority of significant suppliers/buyers for each industry. The thresholds ensure there are enough linkages to reflect the industry's unique sales/purchase pattern, but not so many whereby it becomes difficult to differentiate between industries. The thresholds are selected by inspecting the matrices to ensure lower levels of relatively small flows are captured (Feser and Isserman, 2009). In this study, a linkage threshold of 0.02 was set for purchases, and 0.01 for sales for the local serving sectors. The threshold requires that industry j must represent at least 2% or more of industry i's total intermediate input purchases to be considered one of i's key suppliers. Likewise, industry j must account for at least 1% or more of industry i's intermediate sales to be considered one of i's key buyers. Thus, if the share of total dollar sales or purchases is lower than these thresholds, and the transaction between i and j is discounted, industries i and j are not considered key buyers or sellers to each other.

Once this step is completed, sectors such as wholesale trade, information, legal services, advertising, finance, and insurance are defined as "enabling industries" (appendix table A1). Enabling industries were assigned a weight of 0.33, which reduces their influence in the calculation of the R_{ij} measures. Discounting the enabling sectors allows distinct linkages between industries to define value chains rather than the joint

Table 1. Singleton, Local Serving, and Government Industrial Enterprise Sectors Excluded from the Value Chain Analysis, Following Feser and Isserman (2009)

Industry Code	Description	Industry Code	Description
16	Fishing	470	Social Assistance – except Child Daycare Services
21	Iron Ore Mining	476	Fitness and Recreational Sports Centers
23	Gold- Silver- and Other Metal Ore Mining	477	Bowling Centers
49	Rice Milling	481	Food Services and Drinking Places
50	Malt Manufacturing	482	Car Washes
56	Sugar Manufacturing	483	Automotive Repair and Maintenance – except Car Wash
78	Roasted Nuts and Peanut Butter Manufacturing	486	Household Goods Repair and Maintenance
81	Flavoring Syrup and Concentrate Manufacturing	487	Personal Care Services
90	Cigarette Manufacturing	488	Death Care Services
127	Flexible Packaging Foil Manufacturing	489	Drycleaning and Laundry Services
208	Alumina Refining	490	Other Personal Services
214	Primary Smelting and Refining of Copper	491	Religious Organizations
303	Computer Storage Device Manufacturing	495	Federal Electric Utilities
310	Electron Tube Manufacturing	496	Other Federal Government Enterprises
331	Household Laundry Equipment Manufacturing	497	State and Local Government Passenger Transit
348	Motor Home Manufacturing	498	State and Local Government Electric Utilities
354	Guided Missile and Space Vehicle Manufacturing	499	Other State and Local Government Enterprises
355	Propulsion Units and Parts for Space Vehicles	500	Noncomparable Imports
356	Railroad Rolling Stock Manufacturing	501	Scrap
360	Military Armored Vehicles and Tank Parts Manufacturing	502	Used and Secondhand Goods
412	Nonstore Retailers	503	State and Local Education
432	Automotive Equipment Rental and Leasing	504	State and Local Non-Education
433	Video Tape and Disc Rental	505	Federal Military
435	General and Consumer Goods Rental – except Video Tapes	506	Federal Non-Military
461	Elementary and Secondary Schools	507	Rest of the World Adjustment to Final Uses
469	Child Daycare Services	509	Owner-Occupied Dwellings

consumption of similar mixes of producer services, while still entirely including linkages with producer services (Feser, Renski, and Koo, 2009). The weighting scheme moderates linkages between industries *i* and general enabling industries to emphasize more concretely the linkage among more specialized industries (Feser and Isserman, 2009).[1]

[1] A sensitivity analysis was performed to determine the extent to which these thresholds influenced value chain identification. The $\mathbf{R}^{MAX}$ matrix was recalculated using different threshold levels. The thresholds used in the final analysis were those that produced statistically distinct chains (discussed below). Exogenously assigning such thresholds may be a shortcoming of this method. A more desirable approach would be to use endogenously determined thresholds. Future refinement of the Feser, Renski, and Koo (2009) method could consider a data-driven approach toward this end.

Feser, Renski, and Koo (2009) suggest a pseudo z-score as a cutoff point to determine cluster membership: $z_{ij} = [\bar{r}_{ij} - \text{mean}(\bar{r}_{ij})]/\text{s.d.}(\bar{r}_{ij})$, with $\bar{r}_{ij}$ the average value of the maximum linkage between sector i and the set of primary sectors in core cluster j.[2] The cutoff for the z-score was set to 1.96.

The next step entails identifying sectors having few linkages with other sectors. These sectors are either insular (i.e., "within" themselves; sectors with no purchases or sales to other sectors) or have connections with primarily local serving industries. These sectors were eliminated from the linkage matrix prior to applying Ward's (1963) hierarchical cluster analysis.

In the final step, Ward's cluster algorithm analyzes the linkage matrix to discern industry clusters. The $\mathbf{R}^{\text{MAX}}$ matrix is converted to a "dissimilarity" ($\mathbf{D}$) matrix and used in the clustering algorithm. We used the simple distance measure $d_{ij} = (1 - R_{ij}^{\text{MAX}})$ as the basis for the dissimilarity matrix. The larger d_{ij} is, the less closely related sales and purchases are between sectors, and the less likely sectors i and j will be included in the same cluster.

Hotelling's pseudo T^2-value was used to determine the optimal number of industry clusters following analysis of the linkage matrix with Ward's algorithm (Milligan and Cooper, 1985). The pseudo T^2-statistic generally decreases as the algorithm disaggregates the linkage matrix. Inspection of the T^2-statistics calculated for each candidate number of clusters provides guidance as to an appropriate number of clusters that best describe the data (Johnson and Wichern, 2002). Candidate clusters are determined by identifying a peak in the distribution of the T^2-statistics, and then "moving back" once (an example follows).

In this analysis, Tennessee IO data from IMPLAN (year 2001) were used to benchmark the value chains. The $\mathbf{R}$ matrices are estimated at the state level.

Empirical Model Measuring the Influence of Industry Clusters on Labor Productivity Growth

Once a set of industry clusters has been identified, we test whether a given cluster influenced output per job growth in a county from 2001–2006. A partial adjustment model is used to estimate sector-specific change in labor productivity. Adjustment models have been used in a wide variety of empirical applications, and are frequently applied to study the dynamics of employment-population migration (e.g., Carlino and Mills, 1987; Carruthers and Vias, 2005; Carruthers and Mulligan, 2007). Other regional studies have used adjustment models to explain changes in county per capita income (Monchuk et al., 2007).

As applied here, the partial adjustment model assumes that sector (s) output per job (y) is constantly adjusting toward some unknown equilibrium level (*) at time t, $y_{st}^* = \boldsymbol{\beta}'\mathbf{x}_{t-1} + e_{st}$, where e_{st} is a random disturbance, x are variables hypothesized to explain the equilibrium state, and $\boldsymbol{\beta}$ a vector of parameters. The adjustment process is $\Delta y_{st} = (y_{st} - y_{s,t-1}) = \lambda(y_{st}^* - y_{s,t-1})$, where t and $t-1$ are two points in time, y_{st} is output per worker adjusting toward equilibrium over time, and λ is an adjustment parameter that

[2] A variety of distance measures could be imagined for this purpose. However, the pseudo z-score provides a rule of thumb to gauge cluster membership. Future studies using this clustering procedure may benefit from establishing more rigorous membership decision rules.

is strictly positive and less than one. Observed labor productivity lies somewhere between the targeted equilibrium level (y^*_{st}) and labor productivity in the previous period ($y_{s,t-1}$). Rearranging the adjustment process suggests that labor productivity at time t is the weighted average of output per job in the previous period plus the target equilibrium level: $y_{st} = \lambda y^*_{st} + (1-\lambda)y_{s,t-1}$. On substituting y^*_{st}, actual output per job at time t is $y_{st} = \lambda(\boldsymbol{\beta}'\mathbf{x}_{t-1} + e_{st}) + (1-\lambda)y_{s,t-1}$. Rearranging the expression produces a linear, reduced-form equation that can be estimated with least squares under the usual assumptions:

$$(3) \qquad \Delta y_{st} = \tilde{\boldsymbol{\beta}}'\mathbf{x}_{t-1} + \lambda^* y_{s,t-1} + e^*_{st}, \quad \text{with } \tilde{\boldsymbol{\beta}} = \lambda\boldsymbol{\beta},\ \lambda^* = -\lambda, \text{ and } e^*_{st} = \lambda e_{st},$$

where e^* is an independent and identically distributed shock with $E(e^*) = 0$ and $E[e^* e^{*\prime}] = \boldsymbol{\Omega}$. When the variables are in logs, the coefficients are short-run elasticities (Greene, 2000).

Because the goal is to isolate the effects of a single industry cluster k on sector output per job from 2001–2006 across all counties, labor productivity of the $s = 1, \ldots, 508$ sectors is estimated simultaneously by including fixed effects for each county (c_i, $i = 1, \ldots, 95$) and k value chains identified in 2001 ($g^s_{k,2001}$), indicating that the sth sector is a member of industry cluster k. The cluster-specific fixed effects allow for heterogeneity in labor productivity across clusters, while the county fixed effects allow for the growth in output per job to vary across the state. The spatial distribution of a cluster on the labor productivity of its members is estimated by interacting a target cluster with the county fixed effects. For example, focusing on the agriculture (AG) industry cluster ($l = AG$) and how sectors belonging to that cluster contributed to cluster member growth in county i, the interaction term for the ith county is $h_{i,AG} = c_i g^s_{AG,2001}$.

The change in sector- and county-specific labor productivity from 2001–2006 is measured as $\Delta y_{si,2006} = \ln[(Y^{2006}_{is}/L^{2006}_{is})/(Y^{2001}_{is}/L^{2001}_{is})]$, where Y is output from sector s (in 2001 dollars), and L is employment in sector s. Including the county and industry cluster variables and the industry cluster by county interaction terms in (3):

$$(4) \qquad \Delta y_{is,2006} = \tilde{\boldsymbol{\beta}}'\mathbf{x}_{i,2001} + \lambda^*\ln(y_{is,2001}) + c_i + h_{il} + g^s_{l,2001} + \sum_{k=1,k\neq l}^{K-1} g^s_{k,2001} + e^*_{is}.$$

An orthogonal restriction was applied to the county fixed effects such that $\Sigma_i c_i = 0$ (Neter et al., 1998). The restriction shifts the distribution of the county fixed effects away from a reference county (i.e., the usual "compare counties to a reference county" specification) to one where the county labor productivity of a cluster member is compared to the overall average sector output per job growth of the state. The null hypothesis for each h_{il} is that industry cluster l had no effect on the change in output per job of the cluster members in a county. For each county, the interaction coefficient is the difference in the change in labor productivity due to cluster l in county i, relative to the state average effect of cluster l on labor productivity growth of the cluster members.

The reference groups for the industry fixed effects were sectors that did not belong to an industry cluster. Therefore, the industry cluster effects are the average growth in output per worker of the value chain relative to all other sectors not belonging to an industry cluster.[3]

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[3] About 24% of the sample observed in 2001 and 2006 did not belong to a cluster.

In addition to the industry cluster and county mean effects, labor markets and industry structure are hypothesized to influence the change in sector output per job from 2001–2006, and are represented in $\mathbf{x}$. The percentage of persons employed in manufacturing, agriculture and forestry, and mining, and the percentage employed in business support services proxy county industry structure. In general, output will be higher for a given dollar of input due to cost savings of manufacturers locating near each other (Johnson, 2001). We expect this variable to be positively correlated with growth in output per job. Mining typically occurs in relatively remote and poor Tennessee counties where other job opportunities may be limited. We expect the share of employed persons in mining to be negatively correlated with change in output per job. Similar to counties where mining is an important source of employment, counties with comparative advantage in agriculture or forestry may be unattractive to footloose or demand-oriented businesses attracted to agglomeration economies. All else equal, we expect that the county share of jobs in agriculture and forestry will be negatively correlated with changes in labor productivity. Access to business support services may lower costs for other firms. Intuitively, one would expect that counties with relatively more business services would experience, on average, relatively higher gains in labor productivity.

The $\log_e$ of employment density (jobs/county area), $\log_e$ of median household income, and the $\log_e$ of the change in employment between 1990–2000 proxy the influence labor markets have on changes in output per worker. All else equal, the momentum of job growth in counties could spill over into the birth of new establishments and more jobs. Employment density is often included in firm location studies to control for the agglomerative effects of many firms locating in the same area. However, more jobs or employment density do not necessarily translate into increases in labor productivity. If worker skills do not match well with current technology, or if the production technology lags behind new innovations, then labor productivity could decrease. Median household income proxies job earnings. Workers earning higher wages may be more skilled in a variety of technologies, which correlates with higher labor productivity. In sum, there are $8 + 2 \times 95 + k - 1$ (including a constant) parameters to estimate in equation (4), where k is the number of clusters identified with Feser and Isserman's (2009) procedure.

Estimation Methods

Ideally, ordinary least squares (OLS) would be used to estimate equation (4). The regression includes 508 sectors in Tennessee's 95 counties ($n = 95 \times 508 = 48{,}260$), but some sectors may not have existed in a county in 2001 or 2006 (e.g., output and employment was zero). Alternatively, a given sector in a county may have existed in 2001, but exited by 2006. Or a sector may have been absent in 2001, but entered the local economy by 2006. Output in both periods was observed in 23% of the sample ($n = 11{,}139$), and not observed in any periods in 68% of the data. This makes calculation of a change in labor productivity impossible between the periods for some sectors. However, simply eliminating these sectors with zero output during one or both of the periods and focusing only on the sectors existing in 2001 and 2006 may bias OLS estimates. If the pattern of missing sectors is random, then selection bias is not an issue. Yet, it is entirely possible that such a pattern in the data set is not random due to imperfect competition, market power, or other unobserved local factors systematically influencing firm birth and death.

Taking into consideration this potential selection bias, we estimate the system using Heckman's (1979) sample selection model. The null hypothesis is that the disturbance terms between the outcome and selection equations are not correlated. A significant correlation coefficient (ρ) between the disturbance terms of the selection and outcome equations is evidence that sample selection bias exists, the observed pattern of missing sectors is not random, and the properties of the OLS estimator are compromised.

Factors hypothesized to influence whether sector output was observed in 2001 and 2006 include county-level labor market characteristics and industry composition, as well as demographic characteristics. The industry structure variables are common to the selection and outcome equations (percentage employed in mining, manufacturing, agriculture and forestry, and business support services). But when the same variables are included in the outcome and selection equations of the sample selection model, correlation between the disturbances arises only from the nonlinearity of the system. As such, correlation between the disturbance terms may be spurious (Puhani, 2000).

To address this potential problem, we make some variable substitutions for the labor market characteristics, using the unemployment rate as an instrument instead of employment density. In addition, we include demographic profiles of counties in the selection equation, counting the shares of the population aged 8–17 and above 60. Skilled labor may be scarce in counties with relatively more persons who are of school age or easing out of the workforce. The percentage of the population with a college degree measures availability of skills needed at all levels of management. Counties with relatively more persons with college degrees may be more likely to retain businesses. The percentage of workers commuting to jobs in other counties, the $\log_e$ of population density, and the $\log_e$ of the change in population density (1990–2000) proxy settlement patterns. More persons commuting to work in other counties may be indicative of relatively thin job markets in home counties, and therefore increases in the likelihood of business churn, which decreases the likelihood of firm observability in both periods. Higher population densities correlate with thick demand markets, and hence the likelihood for local product demand and labor supply. Counties that attracted relatively more persons from 1990–2000 could also be more attractive for prospective firms as they seek expanding demand and labor markets. County and industry cluster fixed effects were also included in the selection model. In total, there were $95 + k + 13$ parameters included in the selection model.

Standard errors of the sample selection model were estimated with White's (1980) heteroskedastic robust covariance matrix. Likelihood-ratio tests were calculated to test the null hypothesis that the county and industry cluster fixed effects and their interactions were redundant in the agriculture and forestry sample selection models. The null hypothesis that the selection and outcome equations were independent was tested with a Wald statistic.

Spatial Clustering of County by Value Chain Coefficients

In an ex post analysis, local indices of spatial association (LISAs) (Anselin, 1995) were estimated to measure the extent to which counties shared similar growth in labor productivity over a geographic region, conditional on the presence of a value chain. LISAs are an adaptation of Moran's I (1950), and focus on local variations in patterns of spatial dependence. LISAs measure the degree to which a target value is similar to

Table 2. Descriptive Statistics of Control Variables

Variable	Data Source	Mean	Std. Dev.
Log labor productivity, 2001 [a]	IMPLAN	11.47	3.94
Industry Structure:			
% Employment in Manufacturing, 2000 [b]	REIS [c]	26.55	7.20
% Employment in Agriculture/Forestry, 2000 [b]	REIS	2.56	1.55
% Employment in Mining, 2000 [b]	REIS	0.34	0.45
% Employment in Business Services, 2000 [b]	REIS	7.04	3.29
Labor Market Characteristics:			
Log Median Household Income, 2000 [b]	U.S. Census	10.37	0.19
Log Employment Density, 2000 [b]	REIS	3.58	0.96
Log Employment, 2000/1990 [b]	REIS	4.81	0.15
Unemployment Rate, 2000 [b]	U.S. Census	5.63	1.28
Demographic Characteristics:			
Log Population Density, 2000 [b]	U.S. Census	8.02	0.84
% Jobs Commuting, 2000 [b]	U.S. Census	39.40	15.51
Log Population, 2000/1990 [b]	U.S. Census	4.77	0.08
% Age 8–17, 2000 [b]	U.S. Census	13.78	1.15
% Age over 62, 2000 [b]	U.S. Census	16.59	2.74
% College Degree [b]	U.S. Census	13.08	7.09
Dependent Variable: Change in Sector Output/Employment [a]	IMPLAN	0.21	0.80

[a] Calculated for observations where sector output and employment was greater than zero in 2001 and 2006 (n = 11,139).
[b] Calculated for full sample (N = 48,260).
[c] Bureau of Economic Analysis' Regional Economic Information System.

the values observed in adjacent counties. In the ex post analysis, the coefficients of the industry cluster by county interaction effects (the h_{il}'s) were analyzed with this procedure to identify regional linkages between value chains and member productivity. A row-standardized, first-order contiguity matrix was used to identify spatial neighborhoods.

Data

Tennessee IMPLAN 2001 gross absorption coefficients (GACs) were used to construct the input-output transaction matrix, which served as the base for the industry clustering procedure. The GACs contain information for 508 intersectoral purchases and sales. Sector employment information was also gathered from the 2001/2006 IMPLAN files, as well as the value-added output for each sector (in 2001 dollars). Eliminating local retail and personal serving sectors, singletons, and government industries reduced the transactions matrix to a 447 × 447 dissimilarity matrix evaluated by Ward's cluster algorithm.

Covariates in the growth and selection equations come from the *2000 U.S. Census of the Population* STF4 files and the 2000 Bureau of Economic Analysis' Regional Economic Information System (REIS) (table 2). After eliminating observations with missing data, the full sample size used in the regression analysis was 48,260, with 11,139 observations

(23% of the sample) where output and employment in a given sector were observed in 2001 and 2006.[4]

Results and Discussion

We focus discussion of the results on two industrial clusters—agriculture and forestry—due to the strength of the connections between member sectors as well as the importance of these industries to the Tennessee economy (tables 3 and 4). In 2001 (2006), Tennessee's agriculture sector employed 304,880 (311,711) persons, and produced \$27,763 (\$35,018) million in value-added output. Value-added output from the forestry sector increased 33% over the 2001–2006 period, from \$5,548 million to \$7,382 million, but employment in this sector slightly decreased from 21,237 employees in 2001 to 20,987 employees in 2006.

In general, the *z*-scores of the agricultural and forestry clusters indicate strong membership between representative sectors, but the linkage values are relatively low compared to findings reported in Feser and Isserman's (2009) study at the national level. The relatively lower values are expected, however, because the focus here is on the state and county levels, and many sector linkages are lost. Discussion of the results follows the three steps used to identify the value chains making up the forestry and agriculture industry clusters, and their impact on economic growth across counties.

Step One: Industry Cluster Identification with 2001 Sector Transaction Data

According to the Hotelling T^2-statistics, there are three candidate cluster populations: 18 (19 – 1), 42 (43 – 1), and 45 (46 – 1) (figure 1). Clusters were too aggregated using 18 distinct clusters, making it difficult to discern any particular relational patterns between sectors. The second and third candidates—42 and 45 individual clusters—produced memberships that were easily discernable with relatively strong linkages. The lower, more parsimonious value (42 clusters) was used in the growth regressions.[5]

As Feser, Renski, and Koo (2009) note, the descriptors assigned to clusters cannot completely capture all of the relationships between industries in each value chain, and should be interpreted carefully and not too literally. The top 30 clusters were ranked in term of jobs (see appendix table A2). Most jobs (61% of 3,472,042 jobs in Tennessee, 2001) were associated with the group of sectors identified as the retail and wholesale merchandising cluster. The so-called health delivery cluster employed about 17% of all jobs, followed by a cluster comprised of higher education institutions and supporting services (12% of all jobs). The agricultural (8% of all jobs) and forestry (0.61% of all jobs) clusters ranked 4th and 27th, respectively, in terms of employment. The remainder of this discussion focuses on these latter two industry clusters.

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[4] Sixty-eight percent of the observations reported no output in 2001 and 2006. About 4% of the sectors reported output in 2001, but not in 2006.

[5] Feser and Isserman (2009) identified 45 clusters in their national analysis. The threshold levels of $\alpha = 1\%$ and 2% for local serving sector purchases and sales, and $\alpha = 33\%$ for the enabling industries found here were similar to those used by Feser and Isserman.

Table 3. Agriculture Value Chain Cluster for Tennessee, 2001

Description	IMPLAN Code	Pseudo z-Score	Linkage
Agriculture and Forestry Support Activities	18	3.009915	0.172008
Logging	14	1.991986	0.187577
Forest Nurseries, Forest Products, and Timber	15	2.862023	0.139594
Hunting and Trapping	17	5.488078	0.121962
Waste Management and Remediation Services	460	2.061137	0.187577
Other Accommodations	480	2.218950	0.166274
Other Ambulatory Health Care Services	466	2.444034	0.154060
Hospitals	467	2.597388	0.171351
Veterinary Services	449	3.535342	0.207195
Animal Production – except Cattle and Poultry	13	3.687510	0.267512
Cattle Ranching and Farming	11	3.951774	0.285717
Pipeline Transportation	396	2.189191	0.145240
Rail Transportation	392	2.117743	0.103620
Air Transportation	391	2.171898	0.103620
Transit and Ground Passenger Transportation	395	2.802904	0.207195
Insurance Carriers	427	2.043781	0.134041
Insurance Agencies, Brokerages, and Related	428	2.727789	0.047447
Sand, Gravel, Clay, and Refractory Mining	25	2.076744	0.103889
Greenhouse and Nursery Production	6	3.960904	0.260501
Cotton Farming	8	5.014096	0.363562
Grain Farming	2	5.020745	0.342455
All Other Crop Farming	10	5.084112	0.322934
Tree Nut Farming	4	5.124218	0.363366
Oilseed Farming	1	5.142249	0.340588
Vegetable and Melon Farming	3	5.149934	0.317689
Tobacco Farming	7	5.231438	0.364079
Fruit Farming	5	5.274651	0.364079

Variable:	**Sum Total**
Value-Added Output, 2001	$27,763 mil.
Value-Added Output, 2006	$35,018 mil.
Employment, 2001	304,880
Employment, 2006	311,711

There were 27 sectors identifying what we named the agricultural industry cluster (table 3). Members are consistent with what one might typically consider agricultural activities (e.g., cotton farming, grain farming, and livestock production). Allied industries include sectors closely affiliated with farming (e.g., veterinary services, agriculture and forestry support services) and farm by-products [waste management, logging, and refractory mining (from conversion of forest to farmland, or farmland to other uses), hunting and trapping (a positive amenity of agriculture)]. Potentially less obvious relations include insurance carriers (possibly for crop and livestock insurance), various transport services (rail and ground transportation), and timber and forest products.

Table 4. Forestry Value Chain Cluster for Tennessee, 2001

Description	IMPLAN Code	Pseudo *z*-Score	Linkage
Reconstituted Wood Product Manufacturing	114	2.043653	0.217388
Pulp Mills	124	2.162288	0.214560
Paper and Paperboard Mills	125	2.417742	0.234518
Wood Windows and Door Manufacturing	117	2.111225	0.186967
Veneer and Plywood Manufacturing	115	2.418956	0.220455
Cut Stock, Resawing Lumber, and Planing	118	2.513328	0.280556
Wood Preservation	113	2.514049	0.280556
Wood Container and Pallet Manufacturing	120	2.514049	0.280556
Hunting and Trapping	17	2.686536	0.062500
Logging	14	2.725694	0.225000
Sawmills	112	2.847003	0.281566
Forest Nurseries, Forest Products, and Timber	15	4.711249	0.219444

Variable:	**Sum Total**
Value-Added Output, 2001	$5,548 mil.
Value-Added Output, 2006	$7,382 mil.
Employment, 2001	21,237
Employment, 2006	20,987

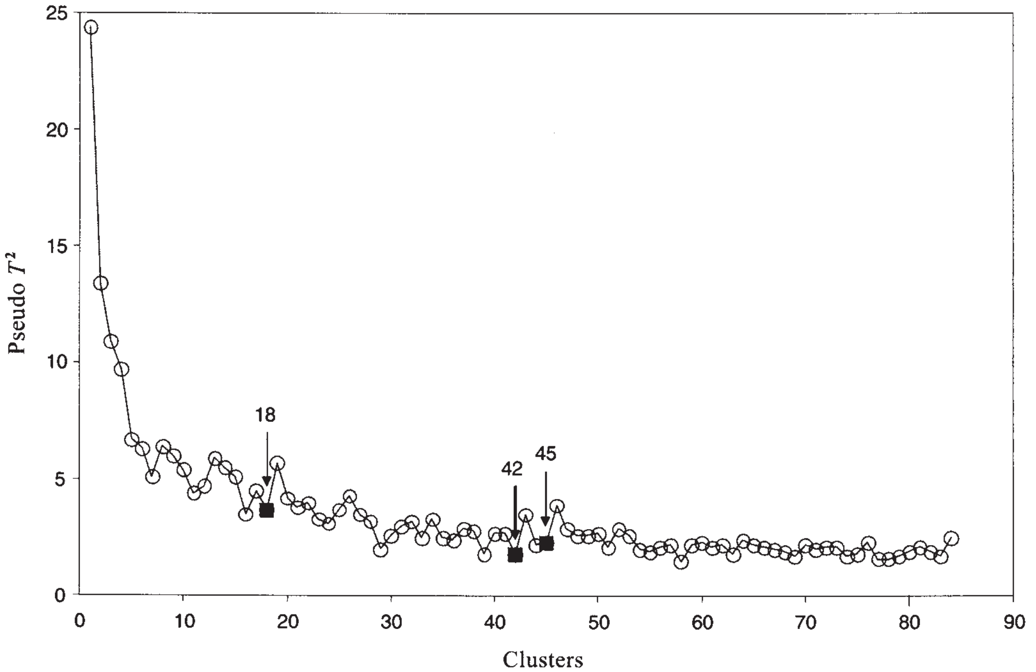

Figure 1. Candidate industry cluster sizes identified with Ward's clustering algorithm

Some surprising members include hospitals (possibly due to the risks associated with agriculture, or perhaps identifying a linkage with the veterinary sector), air transportation (perhaps catering to some perishable agricultural products, seeds, or animal products delivered from/to far-away locations), and pipeline transportation (possibly associated with natural gas or petrochemical distribution).

The forestry cluster (table 4) included 12 sectors. The forest nurseries, forest products, and timber sectors stand out as the forestry cluster core, along with the logging and sawmill industries. Supporting sectors included pulp mills, paper mills, wood window frames and door manufacturing, and reconstituted wood product manufacturing.

Step Two: Estimating Where These Clusters Contributed to Growth in Labor Productivity

The effect of agricultural and forestry clusters on labor productivity growth at the county level was estimated with equation (4). We report the results from the Heckman sample selection model because the null hypothesis that the disturbance terms between the selection and growth equations was strongly rejected for both models (tables 5 and 6). Industry cluster, county fixed effects, and the interaction terms were not redundant in the agriculture or forestry models (the respective likelihood-ratio statistics were 76,238 and 14,774). In terms of identifying the effect of industry clusters on labor productivity growth, the relevant estimates are the interaction terms of the county fixed effects and the target industry cluster; hence, the relationship between the control variables, sector observability in both periods, and labor productivity growth is discussed only briefly.

Probit Selection Equation and Control Variables

The signs, significance patterns, and magnitudes of the covariates included in the agriculture and forestry cluster selection models were generally similar (tables 5 and 6). The relationship between the local determinants and the existence of a given sector in a county in both periods were generally unsurprising. Sectors in counties with relatively more jobs in manufacturing or in agriculture and forestry were less likely to be observed in 2001 or 2006. Demographic characteristics were important determinants of business persistence. Businesses in counties with high commuter flow were less likely to be observed in 2001 or 2006. Sectors in counties with relatively older (younger) populations were less (more) likely to be observed in both periods. Somewhat surprisingly, sectors in counties with relatively more college educated persons were less likely to be observed in 2001 and 2006.[6] A possible explanation could be that these persons are relatively mobile compared to other individuals. The brief recession in 2001 could have motivated these individuals to relocate elsewhere, which could have adversely affected firm survivability up to 2006. More likely, 68% of the 48,260 observations reported zero output in 2001 and 2006, suggesting that of the 23% of the sample reporting output in both periods, these sectors may not require the human capital levels (as measured by persons with college degrees) which might be expected in other sectors.

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[6] The results of the selection equation should be put into perspective. For instance, as currently formulated, the probit model explains which local attributes influence sector observability in both periods. A compelling analysis could employ a more sophisticated model to estimate which factors contributed to business establishment birth and death, as well as persistence.

Table 5. Marginal Effects of Agriculture Industry Value Change and Labor Productivity Growth, 2001–2006

Variable	Selection Equation: Positive Output and Employment from 2001–2006	Outcome Equation:[a] Change in Labor Productivity from 2001–2006
Log Labor Productivity, 2001		–0.002***
Industry Structure:		
% Employed in Manufacturing, 2000	–0.003*	0.002**
% Employed in Agriculture/Forestry, 2000	–0.034***	–0.031***
% Employed in Mining, 2000	0.011	0.011
% Employed in Business Services, 2000	0.009	0.027***
Labor Market Characteristics:		
Log Median Household Income, 2000	0.174	–0.059
Log Employment Density, 2000		–0.028***
Log Employment, 2000/1990		–0.229***
Unemployment Rate, 2000	–0.021	
Demographic Characteristics:		
Log Population Density, 2000	–0.018	
% Jobs Commuting, 2000	–0.005***	
Log Population, 2000/1990	–0.369	
% Age 8–17, 2000	–0.013	
% Age over 62, 2000	–0.016***	
% College Degree	–0.005**	
Constant	3.419	19.689**
Covariates	134[b]	224[b]

ρ	–0.889***
No. of Observations	48,260
Censored	37,121
Uncensored	11,139
Log Likelihood	–30,546[c]
Wald – H_0: All coefficients = 0 (222 df)	853***
Wald – H_0: ρ = 0 (1 df)	40***

Note: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

[a] Marginal effects calculated as E [*Change in Labor Productivity* | Pr(*Output* > 0 in 2001 and 2006)].

[b] Because the covariates were measured at the county level, 15 county fixed effects were dropped due to collinearity. County fixed effects for the growth and selection equations are suppressed, but available from the authors on request.

[c] The log likelihood for the restricted model was –38,119.

Sector Output per Job Growth Equation and Control Variables

The signs and magnitudes of the short-run elasticities were also generally similar in the agriculture and forestry cluster equations measuring changes in output per job (tables 5 and 6). The lagged output per worker was significant but relatively small in both models, with implied adjustment parameters of 0.002. On average, sector output per worker decreased over the period in counties where agriculture and forestry were

Table 6. Marginal Effects of Forestry Industry Value Change and Labor Productivity Growth, 2001–2006

Variable	Selection Equation: Positive Output and Employment from 2001–2006	Outcome Equation:[a] Change in Labor Productivity from 2001–2006
Log Labor Productivity, 2001		–0.002***
Industry Structure:		
% Employed in Manufacturing, 2000	–0.003	–1.E-05
% Employed in Agriculture/Forestry, 2000	–0.036***	–0.032***
% Employed in Mining, 2000	0.019	0.021
% Employed in Business Services, 2000	0.011	0.017*
Labor Market Characteristics:		
Log Median Household Income, 2000	0.215**	0.157
Log Employment Density, 2000		–0.030***
Log Employment, 2000/1990		–0.219***
Unemployment Rate, 2000	–0.012	
Demographic Characteristics:		
Log Population Density, 2000	–0.014	
% Jobs Commuting, 2000	–0.006***	
Log Population, 2000/1990	–0.244	
% Age 8–17, 2000	–0.017*	
% Age over 62, 2000	–0.017***	
% College Degree	–0.007**	
Constant	–0.777	8.852*
Covariates	134[b]	218[b]

ρ	–0.880***
No. of Observations	48,260
Censored	37,121
Uncensored	11,139
Log Likelihood	–30,732[c]
Wald – H_0: All coefficients = 0 (202 df)	845***
Wald – H_0: ρ = 0 (1 df)	38***

Note: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

[a] Marginal effects calculated as E[*Change in Labor Productivity* | Pr(*Output* > 0 in 2001 and 2006)].

[b] Because the covariates were measured at the county level, 15 county fixed effects were dropped due to collinearity. Six forestry cluster by county interaction effects were dropped as well because the forestry industry cluster was not represented in these counties. County fixed effects for the growth and selection equations are suppressed, but available from the authors on request.

[c] The log likelihood for the restricted model was –38,119.

important job sources. Labor productivity also decreased most in counties with relatively higher employment densities that attracted jobs in the previous decade, while counties with more persons working in the business service sector enjoyed gains in labor productivity. Counties with more persons employed in manufacturing enjoyed gains in labor productivity in the agriculture cluster model. The other covariates in the growth equation were generally unremarkable.

Table 7. Value Chain Cluster Coefficients ($g^{s}_{k,2001}$) for the Agriculture and Forestry Regressions

	Agriculture Model		Forestry Model	
Value Chain	Coeff.	Pr > |z|	Coeff.	Pr > |z|
Agriculture	–0.607	0.0000	–0.580	0.0000
Construction	–0.927	0.0000	–0.908	0.0000
Textiles	0.303	0.0000	0.296	0.0010
Forestry	0.265	0.0000	0.270	0.0000
Paper Products	–0.122	0.0380	–0.126	0.0310
Cement/Ceramics	0.546	0.0000	0.520	0.0000
Concrete Products	–0.101	0.1550	–0.078	0.2680
Metal Products	0.327	0.0000	0.325	0.0000
Metallurgy	0.413	0.0000	0.414	0.0000
Mining	0.088	0.2320	0.081	0.2690
Home/Office Supplies	0.904	0.0000	0.896	0.0000
Fluid Machinery	–0.198	0.0060	–0.197	0.0060
Semiconductors	0.080	0.7450	0.087	0.7210
Retail I	–0.041	0.4910	–0.042	0.4870
Health Delivery, Administration, and Education Complex	0.180	0.0000	0.175	0.0000
Higher Educational and Supporting Services	–0.201	0.0000	–0.200	0.0000
Hospital and Dental Profession	–0.403	0.0000	–0.411	0.0000
Electrical Conduit Manufacturing	0.632	0.0000	0.618	0.0000
Plastics	0.141	0.0190	0.143	0.0180
Household Goods/Furnishing Manufacturing	0.071	0.3900	0.051	0.5350
Retail II	–0.837	0.0000	–0.825	0.0000
Food and Home Appliance Manufacturing	0.538	0.0000	0.529	0.0000
Industrial Machinery	0.187	0.0000	0.190	0.0000
Tool Manufacturing	0.487	0.0000	0.481	0.0000
Dairy	0.205	0.0000	0.213	0.0030
Animal Food Manufacturing	–0.682	0.0000	–0.672	0.0000
Milling and Industrial Materials	0.650	0.0000	0.633	0.0010
Sanitary Products	1.219	0.0000	1.225	0.0000
Energy/Power Generation	0.511	0.0070	0.496	0.0090
Wood Products	0.228	0.0000	0.227	0.0000
Rubber Products	0.833	0.0000	0.824	0.0000
Navigation Instruments	0.882	0.0000	0.889	0.0000
Transportation	0.046	0.4820	0.048	0.4580
Recreational Vehicle Manufacturing	0.426	0.0250	0.401	0.0350
Electrical Wiring and Allied Industries	1.169	0.0000	1.161	0.0000
Media	0.491	0.0000	0.483	0.0000
Hotels/Leisure/Entertainment	0.397	0.0000	0.394	0.0000
Insurance/Finance	–0.084	0.2040	–0.093	0.1600
Computer Programming Services	0.033	0.8540	0.018	0.9170
Business Management	0.009	0.9550	0.004	0.9790
Business/Administration Support Services	0.241	0.0000	0.230	0.0000

Labor productivity growth in the agriculture cluster was, on average, 49% lower than the average growth in labor productivity of sectors not belonging to an industry cluster (table 7, −49% = exp[−0.67] − 1). For sectors making up the forestry industry cluster, the change in labor productivity was 31% higher compared to sectors not belonging to an industry cluster (table 7).

Step Three: County-Industry Cluster Interactions on Labor Productivity Growth

Turning to the interaction between the county fixed effects and the industry cluster effects, about 34% of the counties with sectors belonging to the agricultural cluster experienced growth in labor productivity over the 2001–2006 study period. As shown by figure 2, the interaction terms between the county fixed effects and the forestry cluster were positive in 32% of Tennessee's counties. The spatial distribution of the quantiles for the interaction terms are mapped in figure 2. Quantile maps reporting corn and soybean acres planted and head of cattle in 2006 are provided as a reference.

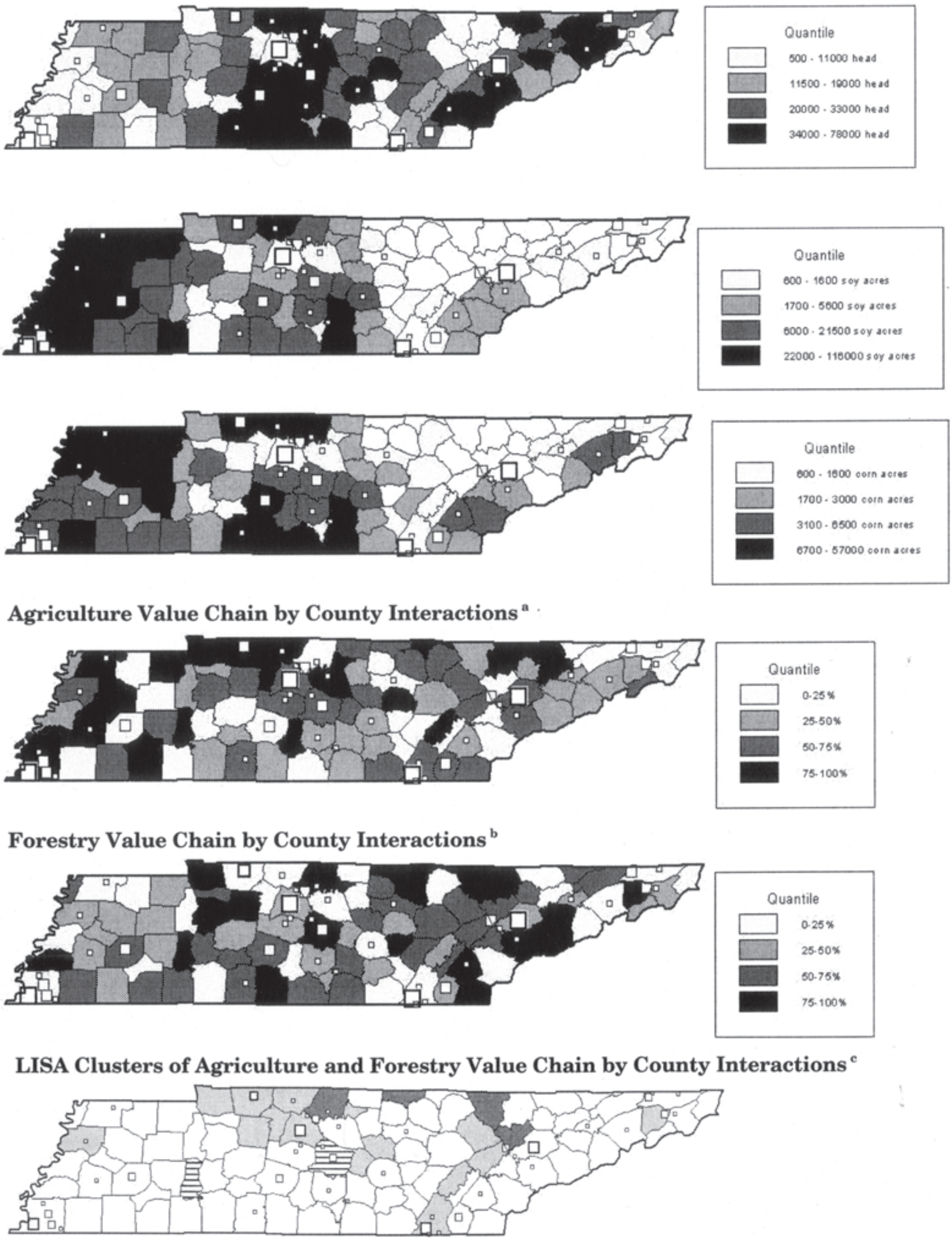
Local indices of spatial association (LISAs) were estimated using the interaction coefficients (h_{il}'s) from the agriculture and forestry cluster regressions (figure 2, bottom). While the raw correlations between the cluster interaction coefficients and corn/soybean and cattle production are not too revealing, the LISAs show that the boosts in the agriculture and forestry value chain members' labor productivity are significantly clustered across counties. Most of the LISAs overlap the region where beef and corn production is comparatively high. In addition, some of the agriculture and forestry cluster LISAs overlap, suggesting the presence of an agroforestry complex near the Nashville-Davidson metropolitan statistical area (MSA) and the Kentucky border. The Nashville-Davidson MSA has experienced tremendous population growth in recent times, and represents a rapidly expanding demand market.

These spatial patterns suggest that counties belonging to these respective clusters might benefit from regional coordination with respect to focusing limited resources on business recruitment or retention strategies targeting sectors belonging to these specific value chains. In other cases where an industry cluster positively influenced labor productivity growth during this time period, but did not belong to a highly productive spatial cluster, counties may also consider focusing scarce resources to develop and enhance businesses belonging to these sectors, but with less emphasis on efforts to establish channels of regional cooperation with other counties.

Summary and Conclusions

Identification of industry clusters is an important component of regional economic development strategies. By determining the sector composition of industry clusters, more accurate information regarding recruitment of traditional value-added activities (such as manufacturing) or the incubation of innovative endeavors (such as niche agricultural marketing) is possible when a community or region is able to identify which industries make up value chains, and the extent to which industry costs are minimized through these linkages.

We applied a three-step approach to identify industry clusters, determine how these clusters influenced economic growth at the local and regional levels, and estimate the



Note: All panels: Cities are boxes; small box = cities with 10,000–24,999 persons, next box size = cities with 25,000–49,999 persons, next box size = cities with 50,000–99,999 persons, and largest box = cities with 100,000+ persons.

[a] Quantile breaks are –0.82 to –0.23, –0.23 to –0.01, –0.01 to 0.06, and 0.06 to 1.74 for the 0–25%, 25–50%, 50–75%, and 75–100% quantiles.

[b] Quantile breaks are –0.50 to –0.12, –0.12 to –0.01, –0.01 to 0.13, and 0.13 to 0.62 for the 0–25%, 25–50%, 50–75%, and 75–100% quantiles.

[c] Agriculture and forestry clusters are light and dark gray, respectively.

Figure 2. Spatial distribution of cattle head, and corn and soybean acres planted (2006, NASS), counties by cluster interactions, and corresponding LISAs, 2001–2006

extent to which these value chains were integrated over a wider geographic region. The first step applied a nonparametric method to identify industry clusters based on input-output transactions. The goal was to identify industry clusters in Tennessee (in 2001), and how these clusters influenced labor productivity growth between 2001 and 2006. The second step used regression analysis to gauge the performance of counties hosting one or more sectors of an industry cluster. The third step examined the spatial distribution of counties where the labor productivity of sectors making up the agriculture and forestry industry clusters increased. County and regional comparative advantage was determined by testing whether the presence of a particular value chain in a given county contributed to increased labor productivity during the study period, controlling for other local determinants of economic performance.

Based on 2001 sales transaction data for Tennessee, 42 industry clusters were identified. Regression analyses indicate that, on average, labor productivity of agriculture and forestry cluster members increased in 34% and 32% of the counties, respectively. Spatial exploratory data analysis revealed these effects were geographically heterogeneous. Significant positive spatial clustering in some regions suggests that counties with businesses making up the agriculture and forestry clusters may enjoy increases in output per worker by coordinating development strategies to promote or enhance the sectors belonging to these value chains. However, in this analysis, the spatial patterns may not necessarily be indicative of regional network effects because the agriculture and forestry industries are largely resource based, and are more likely to cluster across space based on raw material availability. Indeed, this is generally the case for Tennessee. In addition, holding output constant, increases in labor productivity could be due to job loss or downsizing. But even if the location determinants of the firms belonging to these clusters are resource based, county leaders may still consider regional cooperation as a component of a broader development strategy. Examples are the Mississippi River Hills project, the Kentucky Bourbon Trail, the Overhill Heritage Association in Tennessee, and other agritourism operations or regional appellation initiatives.[7] The enterprises making up these operations are resource and amenity based, but regional coordination is essential for these programs to exist.

Future studies applying this methodology will include a broader regional analysis using IO data from counties in neighboring states, producing a more detailed county-level analysis. Additional work could also match O*NET occupational data with identified clusters, which combined would provide targeting analysis from an occupational clustering perspective (e.g., Thompson and Thompson, 1985; Renski, Koo, and Feser, 2007). And while the forestry and agriculture industries are important with respect to Tennessee's economy, analysis of other industry clusters identified using the algorithm applied in this research may yield policy-relevant information regarding other value chains as related to local economic growth. From an economic development standpoint, the analysis could be improved using a general equilibrium framework, rather than the partial equilibrium approach used here.

Finally, while care was taken to check the robustness of the value chain cluster analysis with respect to the thresholds used to determine cluster membership, more general linkage-based methods that do not rely so much on data-reduction methods could take a "bottom-up" instead of a "top-down" approach toward identifying industry linkages.

[7] The websites are, respectively, www.showme.net/MRH, www.kybourbontrail.com, and www.tennesseeoverhill.com.

Such an approach would not depend on threshold choices that need to be made to form distinct groups from the many industries. While we are confident the thresholds used in this analysis produced clusters representative of Tennessee's agroforestry complex, other approaches that build clusters around each individual industry would avoid the use of somewhat arbitrary thresholds.

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Table A1. Enabling Sectors, Tennessee IMPLAN, 2001

Sector	Sector
Wholesale Trade	Real Estate
Air Transportation	Machinery & Equipment Rental & Leasing
Rail Transportation	Lessors of Nonfinancial Intangible Assets
Water Transportation	Legal Services
Truck Transportation	Accounting & Bookkeeping Services
Transit & Ground Passenger Transportation	Architectural & Engineering Services
Pipeline Transportation	Specialized Design Services
Scenic & Sightseeing Transportation & Support	Custom Computer Programming Services
Couriers & Messengers	Computer Systems Design Services
Warehousing & Storage	Other Computer Related Services- including Facilities
Newspaper Publishers	Management Consulting Services
Periodicals Publishers	Environmental & Other Technical Consulting Services
Book Publishers	Scientific Research & Development Services
Database- Directory- & Other Publishers	Advertising & Related Services
Software Publishers	Photographic Services
Motion Picture & Video Industries	Veterinary Services
Sound Recording Industries	All Other Miscellaneous Professional & Technical
Radio & Television Broadcasting	Management of Companies & Enterprises
Cable Networks & Program Distribution	Office Administrative Services
Telecommunications	Facilities Support Services
Information Services	Employment Services
Data Processing Services	Business Support Services
Nondepository Credit Intermediation & Related Serv.	Travel Arrangement & Reservation Services
Securities- Commodity Contracts- Investments	Investigation & Security Services
Insurance Carriers	Services to Buildings & Dwellings
Insurance Agencies- Brokerages- & Related Services	Other Support Services
Funds- Trusts- & Other Financial Vehicles	Waste Management & Remediation Services
Monetary Authorities & Depository Credit Intermed.	

Table A2. Top 30 Employing Industry Clusters Identified in Tennessee, 2001

Cluster	Sectors in Cluster	2001 Employment	Rank
Retail I and II	86	2,131,392	1
Health Delivery, Administration, and Education Complex	24	587,191	2
Higher Educational and Supporting Services	13	406,365	3
Agriculture	27	304,880	4
Construction	17	274,640	5
Media	21	231,165	6
Transportation	12	185,202	7
Insurance/Finance	5	115,672	8
Business/Administration Services I	9	87,052	9
Hospital and Dental Profession	2	85,691	10
Industrial Machinery	27	70,385	11
Household Goods/Furnishing	28	59,151	12
Hotels/Leisure/Entertainment	9	53,923	13
Tool Manufacturing	40	47,891	14
Paper Products	23	47,799	15
Electrical Conduit Manufacturing	23	41,799	16
Business/Administration II	4	40,043	17
Rubber Products	20	38,195	18
Dairy	8	36,284	19
Plastics	21	33,237	20
Textiles	14	32,575	21
Metallurgy	19	30,174	22
Animal Food	6	26,931	23
Wood Products	13	26,811	24
Food and Home Appliance	24	26,649	25
Milling and Industrial Materials	20	23,159	26
Forestry	12	21,237	27
Computer Programming Services	1	19,697	28
Metal Products	15	15,599	29
Energy/Power Generation	11	14,754	30

Notes: This table presents the top 30 clusters according to employment determined with Feser and Isserman's (2009) procedure using 2001 Tennessee IMPLAN transaction data. Clusters were determined at the state level. Employment in clusters is not mutually exclusive, i.e., jobs are double-counted across clusters, and the sum does not represent the total number of jobs in Tennessee in 2001 (3,472,042).