# Spatial Analysis of Rural Economic Development Using a Locally Weighted Regression Model

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This study uses locally weighted regression to identify county-level characteristics that serve as drivers of creative employment throughout the southern United States. We found that higher per capita income, greater infrastructure investments, and the rural nature of a county tended to promote creative employment density, while higher scores on a natural amenity index had the opposite effect. We were also able to identify and map clusters of rural counties where the marginal effects of these variables on creative employment density were greatest. These findings should help rural communities to promote creative employment growth as a means of furthering rural economic development.

***Key Words:*** creative class, locally weighted regression, natural amenities, rural economic development

The post Industrial Revolution period in the United States has been a time of rapidly increasing agricultural productivity. During this time, the economy has gradually moved from one primarily based on agricultural production, to one based heavily on industrial production, and more recently to one based increasingly on service provision. These changes have led to a steady decline in the importance of agriculture to the economic base of rural America. For many geographic areas, the decline has not been offset by equivalent increases in other economic sectors, and the population has followed the jobs into other, generally more urban areas. As a result, the population of rural areas has been shrinking relative to that of urban areas and many rural areas are facing population losses. In fact, more than 25 percent of the nation's non-metro counties experienced a net loss of total population during the 1990s, and more than 85 percent of the U.S. counties that experienced net population losses during the 1990s were rural (McGranahan and Beale 2002). There is some concern that the depopulation of rural areas could gradually erode the ability of many of these communities to provide the public services necessary for their citizens (Huang, Orazem, and Wohlgemuth 2002).

While overall population and economic growth in the southern United States over the past few decades has been strong, averages obscure some disturbing trends.[1] For example, a pattern of dualistic development—where rapid economic growth in and around urban areas like Atlanta and Nashville is accompanied by economic stagnation and persistent poverty in more isolated areas—has come to characterize much of the South. This dualistic development tends to increase the disparity between wealthy urban areas and poorer, more isolated rural areas. As a result, the rural South has the highest concentration of persistent

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[1] The U.S. Census Bureau defines the southern United States as including the District of Columbia and the following 16 states: Alabama, Arkansas, Delaware, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, and West Virginia.

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poverty in the nation, with 280 of the 340 nonmetro persistent poverty counties identified in the 2000 U.S. Census as being located in the South (Jolliffe 2004). Thus, stimulating rural economic development in the South remains a vitally important goal for policymakers at the local, state, and national levels.

Policymakers hoping to promote economic development have often focused on creating employment opportunities. Murdoch (2000) categorized policies designed to promote rural economic development on the basis of whether they promote “horizontal” or “vertical” networks. In Murdoch’s terminology, “horizontal” networks link rural spaces to more general, non-agricultural processes of economic change. Policies based on “vertical” networks attempt to develop a rural economy by enhancing the links among various stages of the agro-food sector. The primary focus of the literature on rural economic development has been on “horizontal” networks. For example, rural economic growth has been examined with respect to transport costs (Kilkenny 1998), natural amenities, and quality of life characteristics (Deller et al. 2001), farm subsides (Kilkenny 1993), sustainable energy for rural development (Byrne, Shen, and Wallace 1998), off-farm work decisions of husbands and wives (Huffman and Lange 1989), and more recently on “creative employment” opportunities (Rosenfeld 2004a, 2004b, 2005).

The recent emphasis on creative employment opportunities follows a decline in a number of traditional rural employment opportunities in addition to agriculture (Renkow 2003). According to Florida (2002, 2003), the distinguishing characteristic of the “creative class” is that its members engage in work whose function is to “create meaningful new forms,” and more than 30 percent of the nation’s workforce belongs to this class. In Florida’s view, creativity is the driving force of economic growth and, as a result, the creative class has become the most influential class in modern society. If true, then the presence of an expanding creative class could be an important determinant of future economic growth in rural areas.

A significant strand of the rural economic development literature focuses on analyzing factors that promote population and employment growth in rural areas. For example, a number of models have been developed that consider the employment decisions made by firms along with a variety of natural, social, and cultural amenities (Deller et al. 2001, Ashley and Maxwell 2001). Although these studies have been able to highlight a variety of factors that can promote rural economic development, the policy implications may be limited due to the necessarily site-specific nature of these factors. For example, a study that finds natural amenities to be a significant factor in promoting rural economic development in the Rocky Mountain West may be of little relevance to other regions of the country and, perhaps more importantly, may not adequately account for spatial variation within the region being analyzed. This limitation raises the question of whether spatial variations in the structure of rural economic development can be more successfully accommodated.

There are a couple of implicit assumptions made in the models that have examined the factors that promote population and employment growth. First, they implicitly assume that the spatial distribution of errors from both the population and employment growth equations is independent. When growth is spatially autocorrelated, the assumption of independence is invalid, and the effects of covariates that are themselves spatially autocorrelated tend to be exaggerated. Second, the model assumes that the relationships between growth and the economic drivers of this growth are constant across geographic space. If spatial variations in these relationships do exist, this assumption will result in model misspecification and potentially misleading results. Spatial variation in this relationship is referred to as spatial heterogeneity.

The spatial lag and spatial error models developed by Anselin (1988) are typically used to correct for spatial autocorrelation caused by spatial dependency. Spatial dependence is a systematic spatial variation that results in observable clusters or a systematic spatial pattern (Florax and Nijkamp 2003). Unfortunately, Anselin’s models do not address spatial heterogeneity. However, both spatial dependency and spatial heterogeneity can be accommodated with a locally weighted regression approach, as first proposed by Cleveland and Devlin (1988). The locally weighted regression approach allows regression coefficients to vary and cluster across space in terms of the first law of geography: “Everything is related to everything else, but near things are more related than distant things" (Tobler 1970, p. 236). The approach has recently been used to incorporate spatial autocorrelation and spatial heterogeneity into a variety of functional relationships (e.g., Brunsdon, Fotheringham, and Charlton 1996, 1999, Fotheringham 2000, Fotheringham, Brunsdon, and Charlton 1998, 2002, Huang and Leung 2002, Leung, Mei, and Zhang 2000a, 2000b, Paez, Uchida, and Miyamoto 2002a, 2002b, Yu and Wu 2004).

The focus of this study is on identifying the characteristics of rural communities that serve as drivers of creative employment density in a way that accommodates any spatial heterogeneity in the relationship between these drivers and creative employment density. More specifically, this study uses a locally weighted regression to examine creative employment density at the county level for the southern United States. Because locally weighted regression allows regression coefficients to vary across space, the partial derivatives of the employment density function, taken with respect to the explanatory variables, are estimated at an individual county level. By enabling such spatial variability, the locally weighted regression captures spatial dependency and heterogeneity at the county level over the southern United States.

These spatially varying, partial derivatives are used to categorize clusters of counties on the basis of the relative impact that the county characteristics have on creative employment density. These relative impacts may imply comparative advantages in promoting creative employment growth. For example, counties with positive partial derivatives for creative employment density with respect to natural amenities may have some comparative advantage in attracting creative employment through the preservation and promotion of their natural amenities. Thus, by understanding the nature of the relationship between individual characteristics and creative employment density at both a regional and local level, policymakers may be better able to tailor policies to promote this growth.

## Empirical Model

A two-stage least squares (2SLS) modeling system is used to estimate the interactions between creative employment density and population density. The modeling system, which is based on a lagged adjustment model (Carlino and Mills 1987), consists of estimating two different equations—one representing creative employment density and one representing population density—as follows:

$$(1)\quad cd_{it} = \beta_0 + \beta_1 pd_{it} + \beta_2 cd_{it\text{-}1} + \beta_3 \mathbf{Z}_{it\text{-}1} + \beta_4 u_{it} + \varepsilon_{it}^{cd}$$

$$(2)\quad pd_{it} = \delta_0 + \delta_1 cd_{it} + \delta_2 pd_{it\text{-}1} + \delta_3 \mathbf{Z}_{it\text{-}1} + \delta_4 u_{it} + \varepsilon_{it}^{pd},$$

where $cd_{it}$ and $cd_{it-1}$ are creative employment density of county $i$ in years 2000 and 1990 respectively, $pd_{it}$ and $pd_{it-1}$ are population density of county $i$ in years 2000 and 1990 respectively, $\mathbf{Z}_{it\text{-}1}$ is a vector of independent variables affecting both creative employment and population densities in year 1990, $u_{it}$ is an urban/rural dummy variable, $\beta_0, \beta_1, \beta_2, \beta_3$, and $\beta_4$ are conformable parameter vectors for the creative employment density equation, $\delta_0, \delta_1, \delta_2, \delta_3$, and $\delta_4$ are conformable parameter vectors for the population density equation, and $\varepsilon_{it} \sim N(0, \sigma^2)$ represents the stochastic error terms.

The lagged values of each dependent variable and of the independent variables are used to capture the lagged effects of these variables on creative employment and population densities (Boarnet, Chalermpong, and Geho 2003, Carlino and Mills 1987, Carruthers and Vias 2005). The county-level independent variables used in the model include various demographic characteristics, a measure of local government expenditure on public infrastructure, and a natural amenity index. The demographic characteristics included in the model are per capita income, the percentage of homes that are owner-occupied ("owner-occupied housing ratio"), the percentage of the population that is at least 55 years old ("senior ratio"), and the percentage of the population that is Hispanic ("Hispanic ratio"), all in 1990. Higher per capita income is hypothesized to be a key economic driver of both creative employment and population densities. This hypothesis is simply an extension of the finding that income is a key economic driver for population and employment more generally (e.g., Carlino and Mills 1987). Carruthers and Vias (2005) found that higher levels of senior citizens and owner-occupied housing had a positive and significant effect on employment density. Similarly, the percentage of the population that is Hispanic has also been found to be a significant factor in population and employment growth (Rogers 1999, Whitener and McGranahan 2003). Average rental rate and educational attainment are excluded because of high correlation with per capita income. The correlation between per capita income and average rental rate is 0.857, and the correlation between average education level and per capita income is 0.807.

A number of different studies have found that higher levels of governmental expenditure on infrastructure tend to enhance population growth and employment creation (Congressional Budget Office 1998, Huang, Orazem, and Wohlgemuth 2002, Jones 1995). More specifically, highways, sewage, and solid waste management expenditures were found to have a significant impact on rural poverty reduction and non-agricultural employment growth (Carruthers and Vias 2005). In this analysis, the sum of highway, sewage, and solid waste management expenditures at the county level is used as a measure of local government expenditure on public infrastructure. The expenditures include intergovernmental expenditures, current operations, capital outlays, assistance and subsidies, interest on debt, insurance benefits and repayment, and salaries and wages, but exclude amounts for debt retirement, and for loan, investment, agency, and private trust transactions.

The local government expenditures variable includes county but not city and municipality spending for a couple of reasons. First, because the data on county-level expenditures includes intergovernmental expenditures, including city and local municipality spending would lead to double counting in some instances. Second, since some cities and municipalities cross county boundaries, it would be difficult to allocate expenditures of these cities and municipalities to a county level. Since spending patterns among counties, municipalities, and state governments on highway, sewage, and solid waste management may vary to some extent from one state to another, a set of state dummy variables are included in both the population and creative employment density equations to control for these and other state-level differences among the counties.

McGranahan (1999) found that rural areas that rated higher in natural amenities enjoyed higher levels of population and employment growth. Following McGranahan (1999), this study uses a natural amenity index created by the Economic Research Service (2004) of the U.S. Department of Agriculture to capture variation in natural amenities among the counties. The scale combines six different measures reflecting warm winters, winter sun, temperate summers, low summer humidity, topographic variation, and water area.[2] Higher levels of natural amenities are expected to play a positive role in fostering growth in both creative employment and population density. Finally, a dummy variable denoting that the county is a rural county (i.e., a county assigned a code of four or greater on the Economic Research Service's 2003 Rural/Urban Continuum Code)[3] is also included to capture the effects of the rural/ urban distinction on population and creative employment densities.

Greene (1990, p. 603) suggests a two-stage technique for estimating a simultaneous equation system. In the first stage, we estimate the reduced-form equations (1) and (2) using ordinary least squares (OLS) regression. In the second stage, the parameters in the structural equations are estimated, first by applying OLS and then locally weighted least squares regression, after replacing $cd_{it}$ and $pd_{it}$ with their predicted values from the reduced-form equations from the first stage. The locally weighted regression will be superior to OLS if the functional relationships summarized in equations (1) and (2) vary across geographic space. This variation could occur in two different ways. First, the effects of the characteristics of other counties on creative employment and population densities may decrease with distance, so that the characteristics of an adjoining county may have a greater effect than the characteristics of a more distant county. Second, the nature of the relationship between the creative employment and population densities of one county and a characteristic of that county's neighbors may vary from one set of counties to another. For example, the relationship between a characteristic and employment or population den-

[2] More information on the Economic Research Service's natural amenity scale can be found at http://www.ers.usda.gov/Data/NaturalAmen[-]ities/.

[3] More information on the Economic Research Service's Rural/Urban Continuum Codes can be found at http://www.ers.usda.gov/Data/ Rural UrbanContinuumCodes/.

sities may be quite different for rural counties that are adjacent to urban areas than for rural counties that are surrounded only by other rural counties.

Following Fotheringham, Brunsdon, and Charlton (2002), the second-stage creative employment and population density equations using the locally weighted least squares approach are specified as

$$(3) \qquad cd_{it} = (\beta \otimes \hat{\mathbf{X}}^{pd})\mathbf{1} + \varepsilon$$

$$(4) \qquad pd_{it} = (\delta \otimes \hat{\mathbf{X}}^{cd})\mathbf{1} + \varepsilon \,,$$

where $\hat{\mathbf{X}}^{pd}$ is a vector of independent variables including predicted value of population density $\widehat{pd}_{it}$ in 2000, $\hat{\mathbf{X}}^{cd}$ is a vector of independent variables including predicted value of creative employment density $\widehat{cd}_{it}$ in 2000, $\otimes$ is a logical multiplication operator in which each element of matrixes β and δ are multiplied by the corresponding element of $\hat{\mathbf{X}}^{pd}$ and $\hat{\mathbf{X}}^{cd}$, respectively, **1** is a conformable vector of 1's, and ε is a vector of random errors. If there are $n$ counties and $m$ explanatory variables including the constant term, β, δ, $\hat{\mathbf{X}}^{pd}$, and $\hat{\mathbf{X}}^{cd}$ will have dimensions $n \times m$. β is an $n \times m$ matrix of local parameters with the following structure:

$$(5) \quad \beta = \begin{bmatrix} \beta_0(u_1,v_1) & \beta_1(u_1,v_1) & \ldots & \beta_m(u_1,v_1) \\ \beta_0(u_2,v_2) & \beta_1(u_2,v_2) & \ldots & \beta_m(u_2,v_2) \\ \ldots & \ldots & \ldots & \ldots \\ \beta_0(u_n,v_n) & \beta_1(u_n,v_n) & \ldots & \beta_m(u_n,v_n) \end{bmatrix},$$

where $(u_i, v_i)$ denotes the coordinates of the county $i$. δ has the same structure as β.

Using locally weighted regression in the second stage of the 2SLS constitutes a "local model," while using OLS regression in the second stage creates a "global model." In the local model the weights allow the observations from counties in closer proximity to county $i$ to have more influence in the estimation of the local parameters than counties located farther away. That is,

$$(6) \quad \hat{\beta}(u_i,v_i) = (\hat{\mathbf{X}}^{pd\prime}\mathbf{W}(u_i,v_i)\hat{\mathbf{X}}^{pd})^{-1}\hat{\mathbf{X}}^{pd\prime}\mathbf{W}(u_i,v_i)\mathbf{cd}$$

$$(7) \quad \hat{\delta}(u_i,v_i) = (\hat{\mathbf{X}}^{cd\prime}\mathbf{W}(u_i,v_i)\hat{\mathbf{X}}^{cd})^{-1}\hat{\mathbf{X}}^{cd\prime}\mathbf{W}(u_i,v_i)\mathbf{pd},$$

where $\hat{\beta}(u_i,v_i)$ represents an estimate of $\beta(u_i,v_i)$, $\mathbf{W}(u_i,v_i)$ is an $n \times n$ spatial weighting matrix, $\hat{\delta}(u_i,v_i)$ represents an estimate of $\delta(u_i,v_i)$, **cd** is a vector of creative employment densities, and **pd** is a vector of population densities. The elements of the spatial weight matrix, $w_{ij}$, are defined as

$$(8) \qquad w_{ij} = [1-(d_{ij}/b)^2]^2 \ \text{ if } d_{ij} < b,$$

$$= 0 \text{ otherwise},$$

where $j$ represents the centroid of a county for which data are observed, $i$ represents the centroid of any county for which parameters are estimated,[4] $d_{ij}$ is the Euclidean distance in kilometers between centroids $i$ and $j$, and $b$ is a chosen bandwidth or radius of the circle of influence around each observation. The bandwidth is a measure of the maximum distance included in the weighting function. At the regression point $i$, the weight of the data point $j$ is unity, which becomes zero when the distance between $i$ and $j$ is greater than or equal to the bandwidth.

As $b$ tends toward infinity, $w_{ij}$ approaches 1 regardless of $d_{ij}$, in which case the parameter estimates become uniform, and locally weighted regression is equivalent to the global model. Conversely, as $b$ becomes smaller, the parameter estimates will increasingly depend on observations in close proximity to location $i$ and hence have increased variance. A cross-validation (CV) approach is used for selection of the optimal bandwidth (Cleveland 1979). CV takes the following form:

$$(9) \qquad \mathrm{CV} = \sum_{i=1}^{n}[y_i - \hat{y}_{\neq i}(b)]^2 \,,$$

where $\hat{y}_{\neq i}(b)$ is the fitted value of $y_i$ (creative employment density or population density) with the observations for point $i$ omitted from the fitting process. The bandwidth is chosen to minimize CV. Thus, in the locally weighted regression model, only counties up to the optimal level of $b$ are assigned non-zero weights for the nearest

[4] The point of each county is represented by the geographic centroid of that county.

neighbors of county *i*. The weight of these points decrease with their distance from the regression point. This process is almost identical to the least squares estimator except for the fact that the observation for point *i* is omitted. The choice of bandwidth represents a trade-off between bias and variance of the estimates from the data. Sensitivity analysis was conducted for bandwidths of plus and minus 50 percent of the *b* selected by the CV approach, the results of which are discussed along with the results of the models.

The global model is estimated using the software package StataSE 9, and the locally weighted regression in the local model is estimated using the software package GWR 3.0, which was developed by Fotheringham, Brunsdon, and Charlton (2002).

## Study Area and Data

This study focuses on the 1,424 counties in the 17 states considered the southern United States by the U.S. Census Bureau. The study employs five county-level datasets in a geographical information system (GIS): (i) employment data for 1990 and 2000 from the Bureau of Labor Statistics, U.S. Department of Labor, (ii) data on population for 1990 and 2000 from the GeoLytics®, Inc., Census CD, (iii) other demographic data for 1990 derived from the GeoLytics®, Inc., Census CD, (iv) the Economic Research Service's 1999 Natural Amenities Scale, (v) 1992 data on county governmental expenditures on public infrastructure from the U.S. Census Bureau's Census of Governments, and (vi) the Economic Research Service's 2003 Rural/Urban Continuum Code. The 1992 governmental expenditures data was chosen to capture the lagged effect. The 2003 Rural/Urban Continuum Codes were used as a proxy for rural/urban counties in 2000. The more recent data was used to capture current differences in rural and urban counties as opposed to any lagged effect of these differences.

One obvious issue that has to be addressed in this type of research is how "creative employment" is to be distinguished from employment more generally. Florida's (2002) perception of the creative class encompasses two different levels of creativity—a rather narrow "super-creative core" and a broader group of "creative professionals." His classifications of the creative class are based on major categories from the U.S. Bureau of Labor Statistics, 2000 Standard Occupational Classification System (SOC) (SOC 2000). The categories from the SOC included in Florida's creative class, distinguished on the basis of whether they fit within the super-creative core or simply qualify as creative professionals, are listed in Table 1.

Unfortunately, employment data grouped according to the SOC classification system is available only at the state level. In contrast, county-level employment data categorized by North American Industry Classification System (NAICS) codes is available. To translate Florida's SOC codes into NAICS codes, we begin by selecting those NAICS codes that fit within Florida's general definition of the creative class, i.e., someone offering for sale products and/or services of which they are the originator. Seven different 2-digit and six different 3-digit NAICS codes were selected on this basis and are listed in Table 2.

**Table 1. Florida's Definition of the Creative Class**

| SOC Code | Major Groups |
|---|---|
| *Super-Creative Core* | |
| 15-0000 | Computer and mathematical occupations |
| 17-0000 | Architecture and engineering occupations |
| 19-0000 | Life, physical, and social science occupations |
| 25-0000 | Education, training, and library occupations |
| 27-0000 | Arts, design, entertainment, sports, and media occupations |
| *Creative Professional* | |
| 11-0000 | Management occupations |
| 13-0000 | Business and financial operations occupations |
| 23-0000 | Legal occupations |
| 29-0000 | Health care practitioners and technical occupations |
| 41-1000 | Supervisors, sales workers |
| 41-3000 | Sales representatives, services |
| 41-4000 | Sales representatives, wholesale and manufacturing |
| 41-9010 | Models, demonstrators, and product promoters |
| 41-9020 | Real estate brokers and sales agents |
| 41-9030 | Sales engineers |

Source: Florida (2002, p. 328).

**Table 2. NAICS Codes (2002) of Creative Employment**

| NAICS Code | Creative Professionals | Percentage of Florida's (2002) Class |
|---|---|---|
| *2-Digit NAICS Codes (2002)* | | |
| 51 | Information | 48.41% |
| 52 | Finance and insurance | 44.33% |
| 54 | Professional, scientific, and technical services | 64.25% |
| 55 | Management of companies and enterprises | 51.12% |
| 61 | Educational services | 70.41% |
| 71 | Arts, entertainment, and recreation | 29.09% |
| 92 | Public administration | 30.09% |
| *3-Digit NAICS Codes (2002)* | | |
| 451 | Sporting goods, hobby, book, and music stores | 18.28% |
| 487 | Scenic and sightseeing transportation | 7.06% |
| 533 | Lessors of non-financial intangible assets (except copyrighted works) | 47.51% |
| 562 | Waste management and remediation services | 13.23% |
| 622 | Hospitals | 58.54% |
| 813 | Religious, grant-making, civic, professional, and similar organizations | 35.11% |

Although these thirteen industries generally fit within the typical definition of the creative class, not all of the workers employed by these industries are likely to fit within Florida's (2002, 2003) definition of the creative class. For example, employment in NAICS 622, hospitals, will include health practitioners that are likely to fall within Florida's definition and hospital maintenance personnel that are not likely to be included. Thus, we used SOC data to calculate the percentage of workers within each of the thirteen NAICS industries at the national level (as shown in Table 2) and multiplied each county's employment in each industry by the applicable percentage. This sum for each county was then divided by the county's area in square miles to produce creative employment density for each county.

These categories of employment account for about 2.5 percent of total employment in the South and about 3.6 percent of total employment in the country as a whole. The 1.1 percent gap between the level of creative employment in the South and the country as a whole highlights the need to increase creative employment in the 17 southern states. Creative employment density in the South is much higher in urban counties than rural counties, following employment density more generally. The mean values for creative employment density in rural counties and urban counties of the South in 2000 are 1.64 and 34.44 per square mile, respectively.

For privacy reasons, the U.S. government does not disclose county employment levels below a certain threshold, which presents a significant obstacle to using more disaggregated employment data for rural counties. For example, in the 2000 Census data, only 6 percent of rural counties in the South had observations for the 3-digit NAICS code 711 (artists, entertainment, and recreation), while about 30 percent of the workforce is listed as self-employed. Those listed as self-employed are not classified by NAICS code and, thus, there may be a substantial number of self-employed artists, craftspeople, and other members of Florida's super-creative core who escape detection. The problem of having a large number of missing observations is avoided by using fairly aggregated employment data. Specifically, we attempt to adjust this data in accordance with the percentage of workers employed in creative professions for each industry at a national level. Definitions and descriptive statistics for the variables used in the model are presented in Table 3.

**Table 3. Variable Definitions and Descriptive Statistics**

| Variable | Definition | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|---|
| *Dependent variable* | | | | | |
| Creative employment density | Creative employment in 2000 divided by square miles of land | 14.43 | 107.79 | 0.00 | 2986.72 |
| Population density | Total population in 2000 divided by square miles of land | 209.29 | 646.08 | 0.39 | 9080.30 |
| *Explanatory variables* | | | | | |
| Lagged creative employment density | Creative employment in 1990 divided by square miles of land | 12.00 | 105.38 | 0.00 | 3036.43 |
| Lagged population density | Total population in 1990 divided by square miles of land | 186.92 | 598.81 | 0.39 | 9733.33 |
| Per capita income | Total income divided by 1,000 multiplied by total population in 1990 | 10.57 | 2.62 | 4.15 | 26.73 |
| Senior ratio | Number of people over 55 divided by total population in 1990 | 0.23 | 0.05 | 0.03 | 0.51 |
| Owner-occupied housing ratio | Number of owner-occupied housing units divided by the total number of housing units in 1990 | 0.63 | 0.08 | 0.19 | 0.82 |
| Hispanic ratio | Number of Hispanic residents divided by total number of population in 1990 | 0.05 | 0.13 | 0.00 | 0.98 |
| Natural amenities scale | Standard deviations from the mean with higher values representing higher amenity values | 0.36 | 1.37 | -3.98 | 6.05 |
| Infrastructure expenditure | Amount of money spent on roads and sewage in 1992 divided by 1,000 multiplied by total population in 1990 | 0.09 | 0.30 | 0.00 | 10.77 |
| Rural county | Urban = 0, rural = 1 | 0.61 | 0.49 | 0.00 | 1.00 |

## Empirical Results

The results of the global model and a summary of the local model for the creative employment density equation are presented in Table 4. Similar results for the population density equation are presented in the Appendix. For the purposes of this study, we limit our discussion to the results from the creative employment density equation. The adjusted $R^2$ in both the global and local models for the creative employment density equation is 0.99. The results from the global model of creative employment density show that population density, lagged creative employment density, per capita income, natural amenities scale, infrastructure expenditure, rural county dummy, and thirteen of the sixteen state dummy variables are statistically significant at the 5 percent level. The reference state used for the state dummy variables is Maryland. The positive and significant signs of these dummy variables indicate that creative densities in these thirteen states are higher than in Maryland, given control for the other explanatory variables. Given the number of factors that can vary at a state level, it is difficult to interpret these findings, but it is worth noting that Maryland is geographically clustered near the three states that were not statistically different from Maryland (Delaware, the District of Columbia, and Virginia).

Rather than reporting coefficient estimates for 1,408 counties from the local model, a shading tool in ArcMap is used to create the six maps that follow for coefficients of the explanatory variables that are statistically significant at the 5 percent level in the global model. The shading of the maps corresponds to the coefficient quartiles reported in Table 3. The lightly shaded or "LOW" areas correspond to the bottom quartile, the darkest or "HIGH" areas refer to the top quartile, and

**Table 4. Estimation Results for the Creative Employment Density Equation from the Global and Local Models**

| Variable | Global Model | Local Model | | | | |
|---|---|---|---|---|---|---|
| | | Min. | Lower Quartile | Median | Upper Quartile | Max. |
| Intercept | -13.737** (4.852) | -16.433 | -14.179 | -13.112 | -10.873 | -7.296 |
| *Endogenous Variable* | | | | | | |
| Population density | 0.017** (0.001) | 0.017 | 0.017 | 0.017 | 0.017 | 0.018 |
| *Exogenous Variables* | | | | | | |
| Lagged creative employment density | 0.925** (0.007) | 0.920 | 0.925 | 0.928 | 0.933 | 0.944 |
| Per capita income | 1.201** (0.000) | 0.618 | 0.981 | 1.199 | 1.301 | 1.515 |
| Senior ratio | -9.363 (6.911) | -15.814 | -12.645 | -11.027 | -7.405 | -2.179 |
| Owner-occupied housing ratio | -7.712 (4.568) | -9.215 | -8.304 | -7.890 | -7.209 | -6.099 |
| Hispanic ratio | 5.797 (3.363) | 2.418 | 4.210 | 5.658 | 6.615 | 9.737 |
| Natural amenities scale | -0.739** (0.289) | -0.981 | -0.791 | -0.708 | -0.543 | -0.331 |
| Infrastructure expenditure | 2.779* (1.041) | 2.232 | 2.761 | 2.848 | 2.864 | 2.892 |
| Rural county | 1.515* (0.765) | 0.576 | 1.115 | 1.540 | 1.753 | 2.224 |
| Alabama | 6.591** (2.814) | 4.692 | 6.351 | 7.480 | 8.037 | 9.242 |
| Arkansas | 8.348** (2.797) | 5.104 | 7.000 | 8.268 | 8.888 | 10.213 |
| Delaware | 3.899 (6.894) | 2.774 | 3.473 | 3.862 | 4.038 | 4.392 |
| District of Columbia | 13.877 (20.506) | -42.965 | -5.354 | 10.270 | 16.674 | 29.293 |
| Florida | 6.729* (2.853) | 3.843 | 5.525 | 6.734 | 7.318 | 8.582 |
| Georgia | 8.606** (2.589) | 6.259 | 7.587 | 8.502 | 8.955 | 9.955 |
| Kentucky | 7.059** (2.676) | 4.200 | 5.872 | 6.981 | 7.523 | 8.688 |
| Louisiana | 7.174* (2.874) | 4.208 | 5.915 | 7.037 | 7.581 | 8.774 |
| Mississippi | 8.419** (2.819) | 5.225 | 7.078 | 8.296 | 8.893 | 10.174 |
| North Carolina | 7.555** (2.638) | 5.475 | 6.718 | 7.543 | 7.940 | 8.794 |
| Oklahoma | 7.205** (2.757) | 4.330 | 6.001 | 7.210 | 7.785 | 9.020 |
| South Carolina | 6.316* (2.947) | 3.726 | 5.185 | 6.179 | 6.668 | 7.740 |
| Tennessee | 6.739* (2.709) | 4.007 | 5.583 | 6.674 | 7.217 | 8.408 |
| Texas | 6.117* (2.601) | 3.947 | 5.231 | 6.137 | 6.524 | 7.217 |
| Virginia | 1.829 (2.574) | -0.539 | 1.095 | 1.928 | 2.297 | 3.018 |
| West Virginia | 7.283* (2.893) | 4.390 | 6.131 | 7.264 | 7.812 | 8.974 |
| Number of observations | 1,408 | 1,408 | | | | |
| Adjusted $R^2$ | 0.99 | 0.99 | | | | |
| Bandwidth distance | | 1,448 km | | | | |

Notes: ** and * denote statistically significant at the 1 percent and 5 percent level, respectively. Parentheses in global model refer to standard deviation.

the gray or "MID" areas refer to the two middle quartiles. The coefficients of the state dummy variables are not mapped because they capture variation only at the state level. The maps are drawn to identify the spatial variations of local marginal effects for the South's rural counties.

The positive and statistically significant coefficient on population density from the global model indicates that creative employment density was higher in more densely populated counties. Figure 1 shows the extent of spatial variation in the local marginal effects of population density across all rural counties in the South. The counties with the highest marginal effects are clustered in Texas and Okalahoma. Counties for which population density has low marginal effects are located in a cluster covering South Carolina, Georgia, Florida, southeastern Mississippi, and central and southern Alabama. One interpretation is that sparse populations in rural areas in west Texas and Oklahoma present a significant constraint to creative employment formation.

The positive and statistically significant coefficient on lagged creative employment density in the global model is not surprising. Clearly, the level of creative employment in 2000 is likely to be a function of the 1990 level. Figure 2 shows the geographic distribution of the coefficients from the local model. This distribution, with the marginal effects decreasing as one moves from west to east, implies that the effect of the level of creative employment density in 1990 on the level of creative employment density in 2000 declines as one moves from west to east. Thus, creative employment density in counties located toward the west is generally increasing faster than creative employment density in counties with roughly equal initial stocks of creative density that are located more towards the east.

The positive and statistically significant coefficient for 1990 per capita income from the global model indicates that income is a significant driver in creative employment density. Figure 3 displays the spatial variation in coefficient values from the local regression. The counties are clustered into three distinct sections, with the marginal effects of per capita income on growth in creative employment density increasing in moving from west to east.

The negative and statistically significant coefficient for the natural amenity scale in the global model was surprising. Based on previous results, we hypothesized that higher levels of natural amenities would have a positive influence on creative employment density. These results may indicate that either the scale does not adequately capture the level of natural amenities in a particular southern county or the model suffers from omitted variable bias or simply looking at 1990 and 2000 fails to capture the effects of natural amenities on creative employment density prior to 1990. Alternatively, it could be that while natural amenities attract population and employment more generally, they do not serve to attract creative employment. Figure 4 shows the spatial distribution of the local regression coefficients, which are high in Texas and Oklahoma. This result, once again, seems to imply that the process driving creative employment density is markedly different in the western counties than it is in the rest of the South.

The positive and statistically significant coefficient on county government expenditure on public infrastructure in the global model mirrors the results from the literature indicating that expenditures are positively related to future population and employment density levels. Thus, local governments can, in general, draw the conclusion that increased infrastructure spending is likely to promote growth in creative employment. As shown in Figure 5, the local coefficients for a band of counties in Florida, Georgia, South Carolina, and western North Carolina have high marginal effects, implying that the level of creative employment density there is more highly related to infrastructure expenditures than in the rest of the South.

Finally, the positive and statistically significant coefficient on the rural dummy variable in the global model implies that creative employment is, *ceteris paribus*, higher in rural counties throughout the South than in urban counties. This finding should be encouraging to rural counties, to the extent that one believes that increasing creative employment portends future economic growth. In fact, the local coefficients for all counties are positive, indicating broad support for this general finding from the local model. Similar to other patterns, the marginal effect of being a rural county appears to increase as one travels from west to east, and is highest in the more urbanized eastern seaboard, as shown in Figure 6.

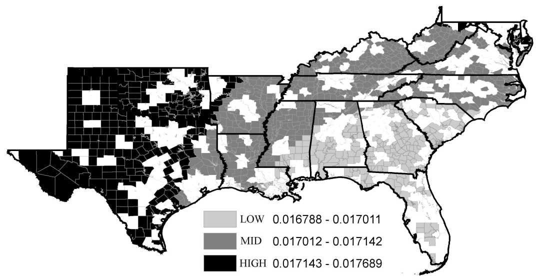


**Figure 1. Local Marginal Effect of Population Density (2000) in Rural Counties**

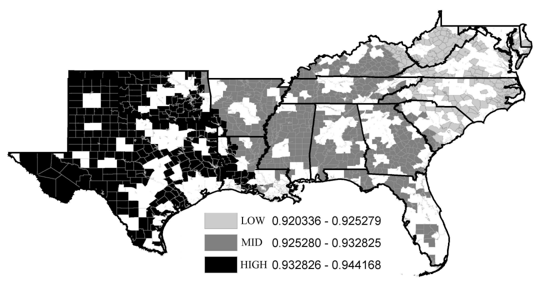


**Figure 2. Local Marginal Effect of Lagged Creative Employment Density (1990) in Rural Counties**

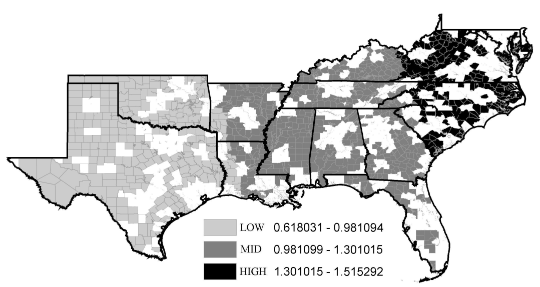


**Figure 3. Local Marginal Effect of Per Capita Income (1990) in Rural Counties**

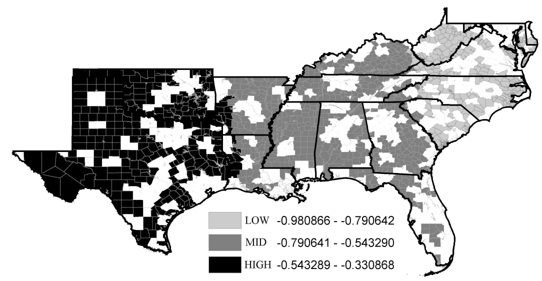


**Figure 4. Local Marginal Effect of Natural Amenity Scale in Rural Counties**

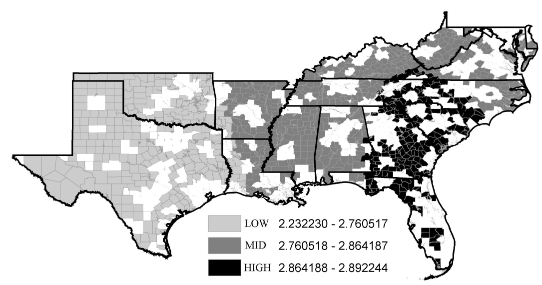


**Figure 5. Local Marginal Effect of Infrastructure Expenditure (1992) in Rural Counties**

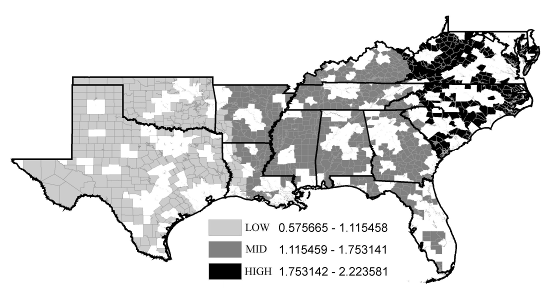


**Figure 6. Local Marginal Effect of Urban/Rural Dummy Variable in Rural Counties**

To examine the volatility of the local regression estimates, the local model is estimated using a bandwidth that is 50 percent larger and 50 percent smaller than the bandwidth found using the CV approach described earlier. The median value of the local marginal effects using both 724 and 2,172 kilometer bandwidths is reasonably close to the median estimates using the CV approach that identified an optimal bandwidth of 1,448 kilometers. However, with a bandwidth of 2,172 kilometers, almost no variation in local marginal effects exists. As the bandwidth widens, the locally weighted regression approach is unable to capture spatial heterogeneity, and the local estimates approach those estimated by the global model. This sensitivity analysis emphasizes the trade-off between a smaller bandwidth that retains the spatial heterogeneity inherent in the variables and the need to use a larger bandwidth to produce estimates that vary smoothly over the spatial regions of the study area.

## Conclusion

We found that creative employment density shares common characteristics with employment density more generally, but also has some unique features. The positive lagged effects of creative employment, and the positive roles of higher income and greater investment in infrastructure, are the common characteristics. In contrast, the negative effects of higher levels of natural amenities differ from earlier findings related to employment growth more generally. In addition, creative employment density appears to differ from employment density in that there seems to be higher creative employment density in rural than in urban counties all else equal. This finding should be good news for rural counties, as increasing creative employment may promote economic growth. Rural counties may also be heartened to know that increased expenditure on public infrastructure appears to promote creative employment.

Under the assumption that creative employment can promote rural economic growth, the results of our study could have significant value to policymakers interested in promoting rural economic development in the rural South. The use of a locally weighted regression approach allows us to tailor these results to particular counties. The clusters of counties that have comparative advantages in promoting creative employment are established on the basis of the maps for coefficients of the explanatory variables from the local model. Interestingly enough, creative employment density in counties located toward the west is generally increasing faster than creative employment density in counties with roughly equal initial stocks of creative employment density that are located more toward the east. A band of counties in Florida, Georgia, South Carolina, and western North Carolina have high marginal effects of infrastructure expenditures, implying that the level of creative employment density there is more highly related to infrastructure expenditures than in the rest of the South. Finally, the marginal effect of being a rural county appears to increase as one moves from west to east across the South.

These results suggest a number of different things to policymakers in the rural South. First, creative employment can be attracted to rural areas in the South, particularly in the more western counties. Second, since existing creative employment appears to attract additional creative employment, policymakers should adopt policies designed to build momentum by highlighting existing sources of creative employment. Third, the cluster of counties with high marginal effects of infrastructure expenditures may be in a position to significantly increase creative employment through increased infrastructure expenditures. Finally, the high marginal effect of per capita income suggests that the more affluent rural counties have an advantage in attracting creative employment. While this result may not be surprising, it may be somewhat disheartening for the poorer counties, which are likely to have fewer other economic development options.

As a final concluding comment, it is worth noting some of the difficulties in analyzing creative employment in rural areas. The first has to do with the difficulty of measuring creative employment in rural counties. Any definition of creative employment will be plagued by a certain amount of arbitrariness. However, empirically analyzing creative employment is made even more difficult by the large number of missing observations for disaggregated employment categories in rural counties. It might be possible to ameliorate this problem, if the U.S. Census Bureau were to create a definition of creative employment that aggregated across a relevant range of disaggregated NAICS codes and then reported creative employment on a county level.

A second difficulty is that the underlying assumption of this study—that growth in creative employment density will stimulate rural economic development—is not particularly well understood. Although our study is based on this assumption, there is little empirical evidence to support it. For example, estimating the multiplier effect of creative employment in rural economies could improve our understanding of the role of creative employment in rural economies and strengthen the argument for focusing on rural creative employment.

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## APPENDIX

## Estimation Results for the Population Density Equation from the Global and Local Models

| | Global Model | Local Model | | | | |
|---|---|---|---|---|---|---|
| | | Min. | Lower Quartile | Median | Upper Quartile | Max. |
| Intercept | -160.156** (31.816) | -179.775 | -164.848 | -156.575 | -137.854 | -106.840 |
| *Endogenous variable* | | | | | | |
| Creative employment density | 0.001 (0.046) | -0.011 | 0.002 | 0.009 | 0.0179 | 0.029 |
| *Exogenous variables* | | | | | | |
| Lagged population density | 1.090** (0.006) | 1.085 | 1.088 | 1.089 | 1.090 | 1.093 |
| Per capita income | 0.010** (0.001) | 0.007 | 0.009 | 0.010 | 0.011 | 0.012 |
| Senior ratio | -258.307** (44.881) | -363.525 | -303.135 | -275.638 | -223.382 | -148.022 |
| Owner-occupied housing ratio | 102.740** (29.996) | 53.411 | 82.323 | 101.828 | 111.140 | 131.091 |
| Hispanic ratio | 28.951 (21.966) | 18.933 | 23.836 | 28.932 | 33.237 | 44.866 |
| Natural amenities scale | 0.233 (1.886) | 0.273 | 0.359 | 0.393 | 0.440 | 0.492 |
| Infrastructure expenditure | -7.274 (6.802) | -8.227 | -7.145 | -6.592 | -5.769 | -4.991 |
| Rural county | 10.165* (4.995) | 1.752 | 7.433 | 11.006 | 12.788 | 16.602 |
| Alabama | 45.067* (18.392) | 32.182 | 39.847 | 44.997 | 47.276 | 51.822 |
| Arkansas | 61.197** (18.290) | 43.326 | 54.192 | 61.598 | 65.024 | 72.198 |
| Delaware | 37.437 (44.973) | 29.935 | 34.645 | 37.599 | 38.897 | 41.387 |
| District of Columbia | -1441.050** (126.363) | -1553.139 | -1480.620 | -1444.935 | -1429.972 | -1402.117 |
| Florida | 66.621** (18.634) | 48.729 | 59.412 | 66.504 | 69.719 | 76.298 |
| Georgia | 56.757** (16.930) | 47.088 | 52.758 | 56.457 | 58.082 | 61.336 |
| Kentucky | 47.304** (17.487) | 34.533 | 42.283 | 47.325 | 49.576 | 53.770 |
| Louisiana | 43.876* (18.782) | 30.033 | 38.277 | 43.394 | 45.623 | 49.996 |
| Mississippi | 53.588** (18.432) | 40.465 | 48.229 | 53.226 | 55.442 | 59.550 |
| North Carolina | 50.501** (17.238) | 39.474 | 46.123 | 50.593 | 52.606 | 56.748 |
| Oklahoma | 54.235** (18.017) | 37.458 | 47.630 | 54.667 | 57.845 | 64.406 |
| South Carolina | 39.483* (19.253) | 29.774 | 35.354 | 39.020 | 40.671 | 43.765 |
| Tennessee | 48.815** (17.702) | 36.818 | 44.095 | 48.950 | 51.107 | 55.567 |
| Texas | 53.650** (16.999) | 38.595 | 48.366 | 54.579 | 57.257 | 61.927 |
| Virginia | 5.756 (16.793) | -7.294 | 1.457 | 5.841 | 7.689 | 11.290 |
| West Virginia | 44.264* (18.902) | 28.139 | 38.183 | 44.834 | 47.769 | 53.871 |
| Number of observation | 1,408 | 1,408 | | | | |
| Adjusted $R^2$ | 0.99 | 0.99 | | | | |
| Bandwidth distance | | 1,448 km | | | | |

Notes: ** and * denote statistically significant at the 1 percent and 5 perce Notes: ** and * denote statistically significant at the 1 percent and 5 percent level, respectively. Parentheses in global model refer to standard deviation.