Inference Based on Alternative Bootstrapping Methods in Spatial Models with an Application to County Income Growth in the United States

Daniel C. Monchuk, Dermot J. Hayes, and John A. Miranowski

Working Paper 08-WP 471
June 2008

Center for Agricultural and Rural Development
Iowa State University
Ames, Iowa 50011-1070
www.card.iastate.edu

Daniel Monchuk is assistant professor in the Department of Economics at the University of Southern Mississippi. Dermot Hayes and John Miranowski are professors in the Department of Economics at Iowa State University.

Questions or comments about the contents of this paper should be directed to Daniel Monchuk, #5072-118 College Dr., Department of Economics, University of Southern Mississippi, Hattiesburg, MS 39406; Ph: (601) 266-6094; Fax: (601) 266-4920; E-mail: dmonchuk@gmail.com.

Abstract

This study examines correlates with aggregate county income growth across the 48 contiguous states from 1990 to 2001. Since visual inspection of the variable to be explained shows a clear spatial relationship and to control for potentially endogenous variables, we estimate a two-stage spatial error model. Given the lack of theoretical and asymptotic results for such models, we propose and implement a number of spatial bootstrap algorithms, including one allowing for heteroskedasticity, to infer parameter significance. Among the results of a comparison of the marginal effects in rural versus non-rural counties, we find that outdoor recreation and natural amenities favor positive growth in rural counties, densely populated rural areas enjoy stronger growth, and property taxes correlate negatively with rural growth.

Keywords: county income growth, rural development, spatial bootstrapping.

Inference Based on Alternative Bootstrapping Methods in Spatial Models with an Application to County Income Growth in the United States

This study is motivated by the map shown in figure 1. This map shows the growth in total county income (a close proxy for measure of county gross domestic product) for 48 contiguous states measured in standard deviations from the mean value. It is quite clear that county income growth during the 1990s has some clear spatial trends. We see that growth in the middle United States tended to be lower than in the rest of the country given the fairly prominent stretch of below-average growth in counties running from eastern Montana and North Dakota southwards to the Texas panhandle. Low growth also stretches across the industrial Midwest. Another prominent spatial trend is the above-average growth experienced in the southeastern region of the United States. Growth appears higher in areas where outdoor amenities are plentiful, such as in the Rocky Mountain region and near large cities such as Minneapolis. South Dakota shows higher growth rates than in surrounding states, especially where counties adjoin those states. Iowa shows a growth pattern that is closer to Kansas and Nebraska than to Minnesota and Missouri.

This map stimulates some obvious questions. Is the lack of growth in the midsection and industrial Midwest associated with weather, lack of amenities, or dominance of agriculture? Are there policies that can be adopted at the county or state level to alleviate this growth? How important are large urban areas for stimulating growth, and are the forces that influence growth fundamentally different in urban and rural counties?

The growth patterns just discussed and several of the hypothesized explanatory variables have been studied by Khan, Orazem, and Otto (2001); Deller et al. (2001);

Huang, Orazem, and Wohlgemuth (2002); and Kusmin, Redman, and Sears (1996). However, these earlier analyses are based on data prior to 1995. They typically focus on regional growth or on non-metro growth and use measures of population, employment, or per capita income change rather than the more comprehensive total county income used here. This study includes almost all of the proposed explanatory variables included in these earlier studies, and it incorporates amenities, human capital, agriculture, and urban infrastructure in a more comprehensive way than any other study of which we are aware. We also allow for different responses to selected variables among rural and non-rural counties. The results show that certain policy responses that are suggested for the entire data are reversed when one considers rural areas.

The data shown in figure 1 shows a clear pattern of spatial correlation. When estimating spatial models, a common practice has been to assume, either explicitly or implicitly, that once spatial autocorrelation has been dealt with, often by means of a spatial error or spatially lagged dependent variable model, the necessary conditions required for valid inference are maintained. This includes the assumption of homoskedasticity. Further, if the model happens to be a multi-stage, spatial specification, such as those involving instrumental variable estimation, then inference based on simple asymptotic properties of estimators are no longer valid. At the same time, however, the analytic relationships needed for inference are either quite complex or not yet known.

With the exception of Kelejian and Prucha (2007) we are not aware of any other models that control for spatially correlated and possibly endogenous and heteroskedastic data, and, to the best of our knowledge, this is the first applied attempt to examine such data. However, unlike the generalized moments estimator of Kelejian and Prucha, we use simpler, more tractable spatial bootstrapping to achieve this objective. Unlike traditional analytic methods, which use asymptotic results to approximate the sampling distribution, bootstrapping is a method that uses computer brute force to estimate the sampling distribution of the model parameters. Three common bootstrap methods include (1) nonparametric residual bootstrap sampling from the model errors; (2) parametric residual bootstrap sampling, which involves sampling from the (usually) normal distribution; and (3) paired method sampling with replacement from the data. Of these three, only the paired approach provides consistent estimates if the true errors are heteroskedastic (Brownston and Valletta 2001). However, since the spatial structure of the data must be maintained, modifying bootstrap algorithms in spatial applications requires additional considerations. These three alternative bootstrap procedures for spatial estimation are considered and compared, and we apply these methods in an empirical application examining aggregate income growth in U.S. counties using a two-stage spatial model with instrumental variables to control for endogeniety.

The methods described here will facilitate inference from other spatial models where the data generating process has been completely described but for which analytic results for inference are either quite complicated or non-existent.

In the next section, we explain the conceptual model and variables used to describe aggregate county economic growth. Then we outline the spatial econometric model and describe how alternative bootstrapping methods can be applied to such spatial models. We then describe the data used and results of the empirical application.

Conceptual Framework

Other studies of county economic growth, including those focusing on rural counties, have examined a combination of indicators, including population, employment, and per capita income growth (Carlino and Mills 1987; Khan, Orazem, and Otto 2001; Deller et al. 2001; and Huang, Orazem, and Wohlgemuth 2002). A shortcoming of measuring economic performance with employment and population growth, however, is these measures are likely imperfect indicators when economic growth *within* the county is the variable of interest, as might be the case for local governments interested in greater incomes from which levied taxes provide for local services. Migrants that increase the population without generating significant income may free ride on already stretched local services such as education and medical care. At the same time, growth in employment may not generate as much additional government revenue as expected when new jobs are secured by out-of-county residents. The relationship between local employment growth and enhancements in locally provided public goods is highlighted by Renkow (2003), who finds that approximately one-third to one-half of new jobs are secured by non-resident commuters. Furthermore, in rural counties, which are by definition sparsely populated, relative measures of economic performance like wage and per capita income growth might be of limited consequence to local governments where achieving sufficient scale to allow for the provision of public goods and services might take precedence.

In light of the failings of the these indicators of economic performance, it is interesting that relatively little attention has been directed to explaining aggregate measures of economic welfare, such as total county income whereby the total size of the economic pie is at issue. A few exceptions are Kusmin, Redman, and Sears (1996); Aldrich and Kusmin (1997); Artz, Orazem, and Otto (2007); and Monchuk et al. (2007). In the first two studies, the variable of interest is total county earnings growth, ultimately a combination of wage and employment growth. The article by Artz, Orazem, and Otto includes aggregate county economic income growth in addition to wage and employment growth when considering the effect of the meat packing and processing industry in midwestern and southern counties. The article by Monchuk et al. also explains total county income growth by incorporating a broader set of variables than used by some of the studies, but the extent of the analysis is limited to midwestern counties.

Total county income (*TCI*) is the product of population and per capita income; total county income growth between the current period (t) and the next (t+1) is ln [TCI_{t+1} /TCI_{t}]. By using total county income growth, we consider the combined effects of population and per capita income growth. In our economic growth model, total county income growth is a function of a number of initial economic, social, and demographic conditions, region-specific characteristics, and government fiscal variables. Each of these variables and their relationship to (regional) county income growth is discussed next in greater detail.

Population Density, Per Capita Income, Demographics, and Entrepreneurs

Initial *population density* and *per capita income* variables allow us to control for conditional convergence. Which counties are getting richer: those with wealthy residents or the more densely populated ones? Since population densities vary in our cross-section of counties, considering initial population density as an explanatory variable allows us to assess the impact of population concentration on economic growth while holding the extent to which economies grow based on economic well-being of residents constant and vice versa. The role of human capital is a key variable in many growth models, and counties with high levels of human capital may potentially attract more firms, thereby increasing the demand for labor, which in turn raises wages and county incomes. That human capital has a positive effect on labor demand is documented by Wu and Gopinath

(2008), who examine variation in economic development across U.S. counties. However, high levels of human capital in rural counties can lead to a "brain drain," in which highly educated and skilled rural residents migrate to urban areas where the returns to human capital investment are higher, as documented in the study by Huang, Orazem, and Wohlgemuth (2002). To control for the level of human capital within the county, we use the *share of the population having a college degree or higher* as an initial condition. Many rural counties have tended to age as agricultural labor has been replaced by larger machinery and young people have left. These structural changes in agriculture and related agribusinesses have left many rural counties with aging populations and the question of who will maintain the county income base. To examine the effect of initial demographic distributions on county income growth, we include the *percentage of the population age 65 and over,* and to control for "the next generation," we include the *share of the population under age 20.*

An issue that often receives considerable attention in policy circles is the role of entrepreneurship in economic growth (see Carree et al. 2002); yet, empirical analysis is lacking in the area. One problem that arises when attempting to analyze the impact entrepreneurship has on growth is how best to measure it. As a measure of entrepreneurship we use *proprietors per capita* following the work of Acs and Armington (2004), who used a similar measure when studying the relationship between entrepreneurial activity and employment growth in cities in the early 1990s.

Location Characteristics

The role of spatial location and spillovers in the economic growth process has received much attention. Spatial externalities are believed to play a role in the new geographic economy (Fujita, Krugman, and Venables 1999). Khan, Orazem, and Otto (2001) found that wage growth in neighboring counties complemented population growth in the home county. However, agglomeration diseconomies arising from past manufacturing activity in urban areas (e.g., congestion, higher land values, pollution, higher labor costs) are one reason rural manufacturing was able to experience significant employment growth in the Midwest in the 1970s and 1980s (Haynes and Machunda 1987). Wu and Gopinath (2008) report that "remoteness" is a significant factor in explaining variation in economic development across U.S. counties. In any case, market access and close physical proximity to large metro markets may give a county a comparative advantage over a similar more remote county. We control for *adjacency to a metro* area using a dichotomous indicator variable.

The literature on agglomeration economies and economic spillovers suggests that the county location and access to major markets play an important role in the growth process (especially in rural areas). To control for these initial location-specific characteristics, we include the *percentage of the county population that commutes 30 minutes or more* to work. In a study of U.S. cities during the 1990s, Glaeser and Shapiro (2003) found that regions with high levels of commuting by automobile (as opposed to public transport) showed greater levels of economic growth. Growth enjoyed by commuter counties is one example of a spatial externality. That areas with high levels of commuting activity enjoy additional growth is consistent with Renkow's (2003) findings that as much as half of new jobs created locally are filled by non-resident commuters, although growth in these commuter areas might be said to be free riding on the economic development policies of others. We include a *micropolitan* variable, coded one if the county had a city population greater than 10,000 but also had a total county population of less than 50,000, and zero otherwise, to control for those rural counties that would lack an urban designation but at the same time are not among the most rural of counties.[1]

Amenity Index

Previous studies have indicated that amenities and quality of life play an important role in county-level economic growth. Quality of life is a multi-dimensional concept. Surveys focusing on quality of life attributes have found that recreational amenities are important to location decisions, especially for high technology and information-intensive firms relying on skilled workers. Other studies have found that positive amenities are capitalized into wages and higher housing values (Roback 1982, 1988) or land values (Cheshire and Sheppard 1995), while negative factors such as pollution have adverse impacts on labor market growth (Pagoulatos et al. 2004). To control for outdoor and recreation amenities, we compute an *outdoor recreation and natural amenity index*, which combines a variety of amenities (trails, park characteristics, recreational land and water areas, etc.) from the home plus neighboring counties (see Monchuk et al. 2007). To control for potential Sunbelt effects in southern regions, we also include the average number of *January sun hours*.

Local Government Fiscal Activity

An important decision facing local policymakers is the amount of revenue to collect through county taxes and fees. Local government fiscal policy can provide both incentives and disincentives for economic growth. In general, policies designed to induce growth (i.e., better government services) may be offset by taxes (i.e., property taxes) required to pay for those services. Huang, Orazem, and Wohlgemuth (2002) find local government expenditures on public welfare and highways contribute positively to rural population growth in the Midwest and South. However, they also suggest that the net effect of local fiscal expenditure and county taxation is neutral or even slightly negative on rural working-age populations.

Every five years, the U.S. Census of Governments collects detailed data for all county, town, city, and other local governments. The Census dataset is a comprehensive list of all revenue sources and expenditures for local governments, ranging from property to death and gift taxes on the revenue side and from government wages to library expenses on the expenditure side. We use the 1992 Census of Governments and aggregate over all government bodies within the county. To control for the local tax burden, we use initial *property tax revenues per capita*, the predominant source of discretionary local government revenue in rural areas.

Agricultural Influence

Since agriculture has traditionally held the greatest influence in many rural counties, we examine the impact of agriculture's income share within the county on economic growth to address the question. Is dependence on common agriculture good or bad for economic growth? To see how counties with a strong agricultural sector have fared, we compute the *share of county income from farming*, which is defined as farm income net of farm employer contributions for government social security divided by total county income.

While agricultural commodities in general have faced increasing competition and long-run declines in real prices, some counties have realized additional growth in value-adding livestock activities. To account for this increase in livestock receipts, we include *growth in livestock cash receipts within the county*, $\ln\left(LCR_{i,t+1}/LCR_{i,t}\right)$, over the period of analysis. To control for potential endogeneity between this variable and the dependent variable, county income growth, we use an instrumental variable approach in which growth in livestock cash receipts for the previous decade and initial livestock cash receipts are used as instruments to obtain fitted values for growth in livestock cash receipts, which are then included as an explanatory variable. In the next section, we discuss the estimation details for this type of two-stage, instrumental variable model with spatially correlated errors and the alternative bootstrap methods to conduct inference.

Empirical Model

In addition to specifying a typical spatial model, we also need to consider potential endogeneity issues that arise based on our selection of explanatory variables in our growth model. One method commonly used to control for such simultaneity is through a two-step process in which an instrumental variable, correlated with the endogenous explanatory variable but not model residuals, is used in a first-step regression to obtain predicted or fitted values. In the second stage, these fitted values are included as an explanatory variable in the regression on the dependent variable, here, county income growth. Asymptotic results to determine parameter significance and conduct inference are available for many "typical" regression models but are virtually non-existent for two-step models involving spatial estimation. Fortunately, we can still conduct meaningful inference and determine parameter significance in the absence of asymptotic results by approximating the sampling distributions for parameters using bootstrapping. So long as the data generating process has been fully described, bootstrapping provides a suitable alternative to conducting inference (Efron and Tibshirani 1986).

There are three general types of bootstraps we can apply; two of these concern sampling related to model errors, and the other is based on sampling from the data directly. In the case of the nonparametric residual bootstrap, the procedure involves sampling with replacement from the residuals of the estimated equation. The alternative residual procedure, parametric residual bootstrap, involves sampling with replacement from the distribution used to specify the behavior of the error, usually the Gaussian. The third method is referred to as the paired bootstrap, as it involves sampling with replacement from the data. Of these three methods, only the paired method will give consistent estimates if the true model errors are heteroskedastic (Brownstone and Valletta 2001).[2]

While in a standard linear regression the application of each of the three bootstrap methods mentioned above is straightforward, applications with more complex data generating processes, such as with many spatial models, usually require a slightly modified approach to make them operational. In the remainder of this section we describe how those bootstrap methods identified above might be applied to a spatial error model.[3]

Consider a model in which the dependent variable, county income growth, is an nx1 vector of cross-sectional growth rates represented by y, and **X** represents an nxk matrix of explanatory variables. Further, suppose there exist potentially unobservable factors that may be correlated across space and are captured in the model error (u), an nx1 vector that contains both a spatial and random error component (ε).The intensity of the unobserved spatial relationship is determined by the parameter λ, and the nature of the spatial relationship is determined by the spatial weights matrix, **W**, an nxn matrix with zeros along the main diagonal and whose non-zero off-diagonal elements, with row sums equal to unity, represent spatial neighbors. The model may be represented as follows:

$$
\begin{aligned}
y &= \mathbf{X}\beta + u \\
u &= \lambda \mathbf{W} u + \varepsilon \ . \\
\varepsilon &\sim N\left(0, \sigma^2\right)
\end{aligned}
\tag{1}
$$

When the matrix of explanatory variables, **X**, includes variables that are a potential source for endogeneity, a common method to deal with this involves a two-stage procedure. This procedure involves regression of the endogenous variable in the first stage on instrumental variables in addition to the complement of other explanatory variables to obtain a predicted value for the endogenous variable. So long as good instruments are used (i.e., correlated with the endogenous variable but not with the model residuals), the first-stage regression effectively purges the endogenous variable's correlation with the residuals. However, if confidence intervals and inference for estimated parameters are based on the residuals from the second-stage regression, as would be reported in a typical regression output, they will no longer be valid. Calculated in the usual manner, inference will be incorrect since standard errors used to calculate parameters' test statistics are computed based on the second-stage model alone and thus ignore the fact that an instrument has been used.

In situations such as this, one approach to valid inference is through the use of bootstrapping. The procedures outlined below describe how each of nonparametric residual, parametric residual, and paired bootstrap methods might be applied to a spatial error model such as that specified in equation (1).

Algorithm 1 — Nonparametric Residual Bootstrap

Step 1 – Predict the value for livestock growth and use as an explanatory variable in the model where county income growth is the dependent variable. Obtain an estimate of the parameters $\hat{\beta}$ and $\hat{\lambda}$ using the method of maximum likelihood.

Step 2 – Retrieve the residuals, $\hat{\varepsilon} = \left[I - \hat{\lambda}\mathbf{W}\right]y - \left[I - \hat{\lambda}\mathbf{W}\right]\mathbf{X}\hat{\beta}$.

Step 3 – Loop over the next three steps (3.1–3.3) *L* times to obtain bootstrap estimates of the model parameters $\{\beta_b, \lambda_b\}_{b=1}^{L}$:

3.1 – Using the vector of residuals from step 2, sample with replacement to construct a vector of bootstrap residuals ε_b.

3.2 – Using the bootstrap vector of residuals from step 3.1, next is computed a vector of pseudo-dependent variables: $y_b = \mathbf{X}\hat{\beta} + \left[I - \hat{\lambda}\mathbf{W}\right]^{-1}\varepsilon_b$.

3.3 – With this new vector of dependent variables y_b, estimate the following equation to obtain bootstrap parameter estimates: $y_b = \mathbf{X}\beta_b + \mathrm{u}$ where $\mathrm{u} = \lambda_b\mathbf{W}\mathrm{u} + \varepsilon$, and $\varepsilon \sim N\left(0, \sigma^2\right)$. Collect and store the estimates β_b and λ_b.

Steps 3.1–3.3 are repeated *L* times to create an empirical sampling distribution for each parameter. Creating a histogram using the sequence of bootstrap values for each parameter reveals an approximation of its distribution and can be used to determine whether or not a particular parameter was significantly different from zero at a given level of significance. A (1-α)*100% confidence interval for a particular parameter β_q is found by ordering the *L* bootstrap estimates from lowest to highest and then removing the lowest (α/2)*L observations from both the lower and upper end of the sequence. Denoting the lowest value in the remaining sample by $\beta^{l}_{q,\frac{\alpha}{2}}$ and the largest remaining value by $\beta^{h}_{q,\frac{\alpha}{2}}$, it follows that a (1-α)*100% confidence interval for β_q is given by

$\left[\beta^{l}_{q,\frac{\alpha}{2}}, \beta^{h}_{q,\frac{\alpha}{2}}\right]$. For a particular level of significance α, if this interval does not include zero we would reject the null hypothesis that the parameter β_q is equal to zero.

Algorithm 2 — Parametric Residual Bootstrap

Unlike algorithm 1, which does not impose a particular structure on the residuals, in algorithm 2 the distributional form of the residuals are taken as given, and the bootstrap routine involves sampling from that particular distribution. In most empirical models it is assumed that errors are distributed normally, in which case the bootstrap is based on sampling from that distribution.

Step 1 – Predict the value for livestock growth and use as an explanatory variable in the model where county income growth is the dependent variable. Obtain an estimate of the model parameters $\hat{\beta}$, $\hat{\lambda}$, and $\hat{\sigma}^2$ using the method of maximum likelihood.

Step 2 – Loop over the next three steps (2.1–2.3) L times to obtain bootstrap estimates of the model parameters $\{\beta_b, \lambda_b\}_{b=1}^{L}$:

2.1 – Draw randomly from the Gaussian distribution with mean zero and variance $\hat{\sigma}^2$ and create a vector of residuals ε_b.

2.2 – Using the vector of residuals from step 2.1, next is computed a vector of pseudo-dependent variables: $y_b = \mathbf{X}\hat{\beta} + \left[I - \hat{\lambda}\mathbf{W}\right]\varepsilon_b$.

2.3 – With this new vector of dependent variables, y_b, estimate the following equation to obtain bootstrap parameter estimates: $y_b = \mathbf{X}\beta_b + \mathrm{u}$ s.t. $\mathrm{u} = \lambda_b \mathbf{W}\mathrm{u} + \varepsilon$, and $\varepsilon \sim N\left(0, \sigma^2\right)$. Collect and store the estimates β_b, and λ_b.

Determining variable significance and inference proceeds in the same manner as indicated in algorithm 1.

Algorithm 3 — Paired Bootstrapping

The most general method is the paired bootstrap and involves sampling with replacement from the dataset itself rather than the residuals (parametric or nonparametric). However, the application of the paired method to spatial models requires a modified method that involves transforming the data to "remove" the spatial component by applying a Cochrane-Orcutt type of transformation.

Step 1 – Predict the value for livestock growth and use as an explanatory variable in the model where county income growth is the dependent variable. Obtain an estimate of the parameters $\hat{\beta}$ and $\hat{\lambda}$ using the method of maximum likelihood.

Step 2 – Using the estimate of spatial interaction term $\hat{\lambda}$, notice that we can write $[I - \lambda\mathbf{W}]y = [I - \lambda\mathbf{W}]\mathbf{X}\beta + \varepsilon$. Define $\tilde{y} = [I - \lambda\mathbf{W}]y$ and $\tilde{\mathbf{X}} = [I - \hat{\lambda}\mathbf{W}]\mathbf{X}$, and create the nx*(1+k)* matrix $\tilde{\mathbf{Z}} = [\tilde{y} \quad \tilde{\mathbf{X}}]$.

Step 3 – Loop over the next three steps (3.1–3.2) L times to obtain bootstrap estimates of the model parameters $\{\beta_b, \lambda_b\}_{b=1}^{L}$:

3.1 – Sample with replacement from the matrix $\tilde{\mathbf{Z}}$ to get a pseudo-dataset, $\tilde{\mathbf{Z}}_b = [\tilde{y}_b \quad \tilde{\mathbf{X}}_b]$, and use this to create a vector of dependent variables and explanatory variables $y_b = \left[I - \hat{\lambda}\mathbf{W}\right]^{-1}\tilde{y}_b$ and $\mathbf{X}_b = \left[I - \hat{\lambda}\mathbf{W}\right]^{-1}\tilde{\mathbf{X}}_b$, respectively.

3.2 – With this new vector of dependent variables y_b, and explanatory variables $\mathbf{X}_b$, estimate the following equation to obtain bootstrap parameter estimates: $\mathrm{Y}_b = \mathbf{X}_b\beta_b + \mathrm{u}$ where $\mathrm{u} = \lambda_b\mathbf{W}\mathrm{u} + \varepsilon$, and $\varepsilon \sim N\left(0, \sigma^2\right)$ Collect and store the estimates β_b and λ_b.

Determining variable significance and inference proceeds in the same manner as indicated in algorithm 1.

Data Description and Regional Overview

We examine the determinants of aggregate county income growth for U.S counties. Based on county data from the Bureau of Economic Analysis's Regional Economic Information Systems dataset, total county income growth over the years 1990-2001 averaged almost 55% for the nearly 3,000 contiguous counties in the United States for which we have a complete complement of data (table 1 and figure 1).

The average population density in 1990 was about 120 people per square mile, but these numbers varied considerably among counties, ranging from a low of approximately 3 persons per 10 square miles to a high of nearly 5,300 per square mile (table 1). As expected, population density is greatest along both the East and West Coasts and the Great Lakes region and is relatively low from about the midwestern to the non-coastal western region of the country (figure 2). In 1990, the average per capita income was $15,220 and although this figure was not too variable over the entire sample (coefficient of variation equal to 22%), the values ranged from about $5,500 to over $35,000, indicating considerable range between the poorest versus the richest counties on a per capita income basis. The representative county share of population under 20 years of age was 30% in 1990 while 15% were age 65 or older (table 1), leaving about 55% of the population aged 35 to 64 (the excluded category). As a measure of human capital, the share of the population aged 25+ with a college degree averaged just over 13%. Our measure of entrepreneurial ability, the number of proprietors per capita, in 1990 is 12 per 100 inhabitants. Across the county, the number of proprietors relative to population tends to be highest in the central and northwestern regions while many of the counties in the southern states are ranked among the lowest (figure 3).

Among the location characteristics, an average of about 16% of the sample population commutes 30 minutes or more in 1990. Counties with a city greater than 10,000 population but with a total county population of less than 50,000 are classified as micropolitan counties. A classification capturing counties that would not be classified as urban or rural in a traditional sense, micropolitan counties comprise 10% of all counties (table 1) and were located relatively uniform throughout the sample. Another location-specific variable to capture the potential spillover impacts of very large urban centers, and which would include some Micropolitan counties, we find 32% of counties were adjacent to a metropolitan area in 1993.[4] The amenity index comprises measures of outdoor recreational and natural amenities from the home as well as the contiguous counties that have been scaled and summed to create a single amenity index.[5] With an average value of 0.43, the amenity index indicates greater opportunities for outdoor recreation and natural amenities in the western states, pockets around the Great Lakes, the Northeast, and Florida (figure 4). The areas with a low amenity index value include east central, southern, and central states, except along the Gulf of Mexico and a vein of counties in the south central region. The average number of January sun hours was 152 and ranged from a low of 48 to a high of over 260 in counties located in Washington State and Arizona, respectively.

Using data from the 1992 Census of Governments, property taxes per capita range from $24 to over $5,400 with an average of $544. The pattern of property taxes per capita appears to follow some definite spatial patterns, with counties in southern states like Alabama, Arkansas, Kentucky, Louisiana, Missouri, New Mexico, and Oklahoma having lower property tax burdens than in northeastern and central regions (figure 5).

To control for the role of agriculture, an industry that is generally more important in rural areas, we consider two measures of agricultural influence, one to capture the relative importance in general and the other to capture the impact of value-added agriculture. The first incorporates all types of income-generating activities in agriculture. Farm earnings relative to county income in 1990 are approximately 5% on average and are highest in the Great Plains states running north and south (figure 6). Our measure of value-added agriculture, growth (point-logarithmic) in livestock cash receipts for the years 1990-2001, has an average value of -0.01, indicating the representative county has experienced a decline in farm incomes from livestock. Unlike most of the other variables considered, change in livestock cash receipts did not appear to exhibit a clear spatial relationship, except possibly that the high-growth counties tend to be located in southern and western states while the negative-growth counties are located in states like Arizona, Colorado, Illinois, Indiana, Ohio, and Kentucky (figure 7). The endogenous relationship between our dependent variable and growth in livestock cash receipts is dealt with using the estimation strategy outlined in the previous section. For the two-stage model to work, the growth relationship must be identified and at least one predetermined variable must be used to form the instrumental variable. Two instruments are used. The first is growth in livestock cash receipts in the previous decade 1980-90 and the second is livestock cash receipts in 1990; their averages were 0.19 and $33,000, respectively.

Because of our interest in rural areas, we include several rural interaction regressors. These include population density, the amenity index, and property taxes per capita in rural areas. These three are included from among a large range of rural interaction regressors considered, as other rural-interacted variables could not be included because they were highly correlated with one or more of the other explanatory variables.

Results

Estimation of the parameters of the spatial error model in (1) is by maximum likelihood[6] and the contiguity rule for the spatial weights matrix is constructed using the nearest four neighboring counties. To determine parameter significance, the empirical bootstrap distribution is used to compute confidence intervals and to inspect whether or not the value zero is contained within that interval. Rather than reporting actual estimates of these confidence intervals, to conserve space the values given in tables 2, 3, and 4 represent the *smallest* of the 10%, 5%, and 1% significance levels, corresponding to 90%, 95%, and 99% confidence intervals, respectively, that do not contain zero in the interval. These significance levels are reported for each of the three alternative bootstrap methods considered. By and large, the same general conclusions regarding parameter significance are reached using each of the three bootstrap methods considered. In figure 8 we have created histograms for each of four parameters under the three alternative bootstrap methods. We can see that some of these distributions do not appear to be symmetric but rather appear to be skewed (i.e., per capita income appears skewed to the left), in which case inference based on standard t-statistics, which assume symmetry, might lead to misleading inference. Inference based on the three bootstrap methods led to the same conclusions with only a few minor discrepancies.

We present the estimates from two models. The second column of table 2 contains parameter estimates from the model *excluding* state effects, while estimates in table 3 correspond to the model *including* a full complement of state indicator variables (estimates of state effects are reported in table 4). The adjusted R-square indicates that slightly more than 64% of the variation in total county income growth over 1990-2001 is explained in the model that includes state effects as compared to less than 61% when state controls are omitted. The third, fourth, and fifth columns report levels of significance corresponding to the nonparametric residual, parametric residual, and paired bootstrap methods, respectively. In addition to those explanatory variables described in the previous section, we also include three variables that have been interacted with a non-metro[7] dummy variable to capture certain rural-specific growth aspects. All of the variables are statistically significant at a conventional level of confidence except for the non-rural outdoor recreation and natural amenity variable, which is found to be not statistically significant in both specifications, and the micropolitan variable, which is not significant when state effects were excluded (table 2). This near-universal level of significance was not an accident. The model results presented here represents a very small sample of the runs that were considered and were selected because the inferences that can be drawn from these results are robust with respect to model specification and because the results can be interpreted in a way that is relevant to the questions posed in the introduction.

The results in table 2 indicate that counties that added livestock experienced more economic growth than those that did not. Given that livestock production is a form of value-added agriculture, this result would appear to be axiomatic; however, an alternative hypothesis from Monchuk et al. that we had thought worthwhile to examine in this much larger dataset was whether the presence of new livestock facilities drove population away from livestock-intensive counties. In their examination of meat packing and processing, Artz, Orazem, and Otto (2007) do not find evidence that the industry in general had a significant impact on aggregate county income growth. In contrast, we find that (instrumented) change in livestock cash receipts, a form of value-added agriculture originating more with producers, is associated with greater income growth.

We were surprised that counties with a high per capita income and high population density in 1990 experienced lower growth in total county income than those that did not have these attributes. In hindsight, it seems possible that high real estate prices in these counties deterred growth. However, a high population density in rural counties was associated with *greater* growth. Counties with a large proportion of older individuals in 1990 and those with a high percentage of young people in 1990 grew more slowly than would otherwise have been the case. Given the preference and ability of young people to move away from counties with stagnant local economies, it makes sense that those left with a larger proportion of older people would do poorly. However, this does not explain why counties with young people did not fare well. This result is due to our use of the proportion of college-educated people with a college degree as an additional explanatory variable. Having controlled for share with a college degree, the age group 20-65 (the excluded group) is associated with growth. Once we control for education level, the simple presence of people younger than 20 with their associated educational costs is not a predictor of growth.

As mentioned earlier, population-dense counties did poorly; however, those counties that were adjacent to a metropolitan area did well, as did counties with a high proportion of commuters. Our admittedly crude measure of entrepreneurship, the number of proprietors per capita, was also associated with higher growth. As can be seen from figure 3, this measure is highest in rural counties because farmers are typically classified as proprietors. The model was able to separate the generally negative influence of the agriculture sector from the positive influence of this entrepreneurial variable.

There are three measures of the quality of outdoor life presented in tables 2 and 3. January sunshine led to county income growth, as individuals moved or retired to the Sunbelt. The countrywide measure of outdoor recreation and natural amenity index did not contribute to growth. However, when this term is interacted with a rural indicator variable, it is a positive and significant variable. Likewise, rural counties with a high population density did well, especially in contrast to non-rural, high-density counties. It is possible that metro counties with a high level of amenities had already exploited these by 1990 or that amenities in combination with adjacency to a metro area were responsible for growth in those counties. Among those non-Sunbelt counties that remained rural in 1990, those endowed with amenities appeared to have generated growth. This was particularity true for rural counties that were already densely populated by 1990. The policy prescription here is that adding amenities to rural counties can generate increases in aggregate income through a combination of one or more of attracting employment or population or increasing individual incomes.

Several measures of the size and relative importance of local government were available to us. This included relative salaries of local government workers, total county tax burden, and intergovernmental transfers. We report on only one of these variables here, per capita property taxes, because all of these terms are highly correlated, especially with rural-interacted variables, and all provide essentially the same result. When applied to the entire dataset, the impact of per capita property taxes is positive and significant. However, when applied only to rural counties, the property tax variable is negative and significant. Our hypothesis is that as rural counties have attempted to fund the relatively large fixed costs associated with education, roads, and judicial system with a declining population base, they have increased local taxes to the point where they are deterring growth. There is clearly a minimum population level that is required to effectively fund the fixed costs associated with running a county, and some of these counties now appear to be below that critical level. The policy prescription here would be to find a way to pay for these costs in a manner that does not deter in-migration or outside investment. A shift in property taxes from commercial buildings to land would achieve this objective, as would cost sharing with state and federal governments.

A comparison of tables 2 and 3 shows the effect of including the 47 state dummies.[8] These results are essentially the same and indicate that the results are robust with respect to relatively large changes in model specification.

The state dummies themselves are presented in table 4. Unlike the previous two tables, in table 4 it is shown that different bootstrap methods might lead to different conclusions concerning parameter significance. Testing the null hypothesis, for example, that South Dakota has no effect on growth relative to the default state would be rejected at the 5% level under inference based on either type of residual bootstrap. However, inference under the paired bootstrap method does not lead to rejection of the null hypothesis at any conventional level and, if heteroskedasticity is the culprit, reveals the potential pitfalls of improper inference when the data-generating process has not been properly modeled. States with positive and significant effects include Arizona, Colorado, Idaho, Utah, and Washington. States with negative and significant results include Alabama, Arkansas, California, Connecticut, Iowa, Louisiana, Massachusetts, Maryland, Maine, Mississippi, North Carolina, North Dakota, New Hampshire, New Jersey, New York, Ohio, Oklahoma, Pennsylvania, South Carolina, Virginia, Vermont, and West Virginia. These state dummies are significant because we are missing a set of explanatory variables, but it is not clear what these variables should be. Because our interest here is in county-level growth, we did not focus on state-specific efforts, but clearly these are important. This may be a fruitful avenue for future research.

Table 5 shows the impact of a one-standard-deviation change in each explanatory variable on county population growth except for the two dummy variables, in which case the change in income is based on satisfying/not satisfying the criteria. These results attempt to place economic importance on the statistical results in tables 2 and 3 in a way that is generally comparable across the explanatory variables. These results generally support those described earlier, but they do suggest that counties with a large share of commuting more than a half hour and county income from farming have larger economic impacts than was suggested by the earlier results. The impact of growth in livestock is nearly double the next largest, the commuting variable, but cannot be interpreted in the same manner since the livestock impact is based on change in the growth rate. Still, the results do indicate that significant gains in county income can be made by growing the livestock sector.

Conclusions

This study updates and expands upon several earlier studies on the forces driving economic activity at the U.S. county level. As was true for several of the earlier studies, our work focuses on income and population loss in rural counties. This study is unique in that it looks at all counties in the lower 48 states and uses a comprehensive list of explanatory variables, including amenities, livestock and agricultural dependence, rural/non-rural comparisons, and property taxes. Our dependant variable, total county income, captures both income and population changes in a way that mimics county gross domestic product.

The results suggest that growth in total county income in the United States was lower in counties that had the following: larger per capita income in 1990, a higher population density in 1990, a higher proportion of older individuals, and a higher proportion of population under 20 years of age. Counties with a heavy dependence on agriculture grew more slowly in general, but those counties with growth in livestock grew faster. Counties that had the following grew at a faster rate: a high proportion with a college degree, close to a metropolitan area, a high proportion of commuters, and relatively more sunshine in January.

When the analysis is limited to rural counties by means of a rural interaction term, those counties with higher population density and more amenities grew at a higher rate. Property taxes were not a significant explanatory variable at the national level, but they had a negative influence on rural counties. Local taxes spent on apparently important activities, such as education, reduced county growth in rural counties, presumably because some of those that benefited from education were then in a position to leave. Taxes spent on improving the level of outdoor amenities had the opposite impact, presumably because these amenities attracted employers or more highly educated individuals. The results suggest that some rural counties may have lost so much population that per capita fixed costs associated with running the counties are contributing to further population outflow.

In addition to adding several years of new data to this line of inquiry, this analysis is the first to examine inference with spatially correlated and possibly endogenous and hetroskedastic data. We use computer brute force to estimate and compare the sampling distribution of the model parameters for three common bootstrapping methods. Although these procedures are tedious and intensive in their use of computing power, they facilitate inference from spatial data wherein analytic results for inference are either quite complicated or non-existent.

Footnotes

[1] The micropolitan variable was computed using the Economic Research Service urban-influence codes for 1993. The micropolitan variable equals 1 if the urban influence code was equal to either 3, 5, or 7, and the total county population was also less than 50,000 in 1990 and zero otherwise. For more details, see http://www.ers.usda.gov/Briefing/Rurality/urbaninf/1993UIC.htm.

[2] Additional discussion pertaining to the use of bootstrapping for hypothesis testing and computing confidence intervals may be found in Brownstone and Kazimi 2000; Efron and Tibshirani 1993; Horowitz 2001; and Jeong and Maddala 1993.

[3] While here we discuss these bootstrap procedures in the context of a spatial error model, analogous modifications would apply to bootstrapping other related spatial models such as those involving a spatially lagged dependent variable.

[4] Adjacency to a metro is determined by the following 1993 ERS rural-urban continuum codes: (i) 4 – Urban population of 20,000 or more, adjacent to a metro area; (ii) 6 – Urban population of 2,500 to 19,999, adjacent to a metro area; (iii) 8 – Completely rural or less than 2,500 urban population, adjacent to a metro area (http://www.ers.usda.gov/Briefing/Rurality/RuralUrbCon/priordescription.htm).

[5] Specifically, for a given amenity indicator (i.e. rails-to-trails bike path miles), the value for that particular amenity in the home county plus contiguous counties are combined and then scaled to be between zero and one for all counties in the sample and then summed over all amenity indicators to determine a total amenity index for a given county.

[6] See Anselin 1988 and Cressie 1993 for estimation involving spatial data.

[7] A county is defined as non-metro if the 1993 rural-urban continuum code equals 4, 5, 6, 7, 8, or 9.

[8] Texas is the omitted state.

References

Acs, Z.J., and C. Armington. 2004. "Employment Growth and Entrepreneurial Activity in Cities." *Regional Studies* 38(November):911–27.

Aldrich, L., and L. Kusmin. 1997. *Rural Economic Development. What Makes Rural Communities Grow?* Washington DC: U.S. Department of Agriculture, ERS, Agr. Info. Bull. No. 737, September.

Anselin, L. 1988. *Spatial Econometrics: Methods and Models.* Dordrecht: Kluwer.

Artz, G.M, P.F. Orazem, and D.M. Otto. 2007. "Measuring the Impact of Meat Packing and Processing Facilities in Nonmetropolitan Counties: A Difference-in-Differences Approach." *American Journal of Agricultural Economics* 89(August):557-70.

Brownstone, D., and R. Valletta. 2001. "The Bootstrap and Multiple Imputations: Harnessing Increased Computing Power for Improved Statistical Tests." *Journal of Economic Perspectives* 15(1, Fall):129-141.

Brownstone, D., and C. Kazimi. 2000. "Applying the Bootstrap." Working Paper, Department of Economics, University of California, Irvine. In *Handbook of Econometrics,* vol. 5. E.E. Leamer and J. J. Heckman, eds. Amsterdam: Elsevier.

Carlino G.A., and E.S. Mills. 1987. "The Determinants of County Growth." *Journal of Regional Science* 27(1):39-54.

Carree M., A. Van Stel, R. Thurik, and S. Wennekers. 2002. "Economic Development and Business Ownership: An Analysis Using Data of 23 OECD Countries in the Period 1976–1996." *Small Business Economics* 19:271–290.

Cressie, N. 1993. *Statistics for Spatial Data, Revised Edition*. New York: Wiley.

Cheshire, P., and S. Sheppard. 1995. "On the Price of Land and the Value of Amenities." *Economica* 62(May):247-67.

Deller, S.C., T. Tsai, D.W. Marcouiller, and D.B.K. English. 2001. "The Role of Amenities and Quality of Life in Rural Economic Growth." *American Journal of Agricultural Economics* 83(May):352-65.

Efron, B., and R. Tibshirani. 1993. *An Introduction to the Bootstrap.* New York: Chapman & Hall.

Efron, B., and R. Tibshirani. 1986. "Bootstrap Methods for Standard Errors, Confidence Intervals, and Other Measures of Statistical Accuracy." *Statistical Science* 1:54-75.

Fujita, M., P. Krugman, and A. Venables. 1999. *The Spatial Economy: Cites, Regions, and International Trade*. Cambridge MA: MIT Press, 1999.

Glaeser, E.L., and J.M. Shapiro. 2003. "Urban Growth in the 1990s: Is City Living Back?" *Journal of Regional Science* 43(1):139-65.

Haynes, K.E., and Z.B. Machunda. 1987. "Spatial Restructuring of Manufacturing and Employment Growth in the Rural Midwest: An Analysis for Indiana." *Economic Geography* 63(October):319-33.

Horowitz, J.L. 2001. "The Bootstrap." In *Handbook of Econometrics*, vol. 5. E.E. Leamer and J.J. Heckman, eds. Amsterdam: Elsevier Science Publishers.

Huang, T-L., P.F. Orazem, and D. Wohlgemuth. 2002. "Rural Population Growth, 1950-1990: The Roles of Human Capital, Industry Structure, and Government Policy." *American Journal of Agricultural Economics* 84(August):615-27.

Jeong, J., and G.S. Maddala. 1993. "A Perspective on Application of Bootstrap Methods in Econometrics." In *Handbook of Statistics*, vol. 11. C.R. Rao and H.D. Vinod, eds. Amsterdam: Elsevier Science Publishers, pp. 573–610.

Kelejian, H.H., and I.R. Prucha. 2007. "Specification and Estimation of Spatial Autoregressive Models with Autoregressive and Heteroskedastic Disturbances." *Working* *paper* available online at http://www.econ.umd.edu/~prucha/Research_WP.htm (accessed June 20, 2008).

Khan, R., P.F. Orazem, and D.M. Otto. 2001. "Deriving Empirical Definitions of Spatial Labor Markets: The Roles of Competing versus Complementary Growth." *Journal of Regional Science* 41:735-56.

Kusmin, L.D., J.M. Redman, and D.W. Sears. 1996. *Factors Associated with Rural Economic Growth. Lessons from the 1980's.* Washington DC: U.S. Department of Agriculture, Technical Bulletin No. 1850, September.

Pagoulatos, A., S.J. Goetz. D.I. Debertin, and T. Johannson. 2004. "Interactions between Economic Growth and Environmental Quality in U.S. Counties." *Growth and Change* 35(Winter):90-108.

Renkow, M. 2003. "Employment Growth, Worker Mobility, and Rural Economic Development." *American Journal of Agricultural Economics* 85(May):503-13.

Roback, J. 1982. "Wages, Rents, and the Quality of Life." *Journal of Political Economy* 90(December):1257-78.

———. 1988. "Wages, Rents, and Amenities: Differences among Workers and Regions." *Economic Inquiry* 26(January 1988):23-41.

Wu, J. and M. Gopinath. 2008. "What Causes Spatial Variations in Economic Development in the United States?" *American Journal of Agricultural Economics* 90(May):392-408.

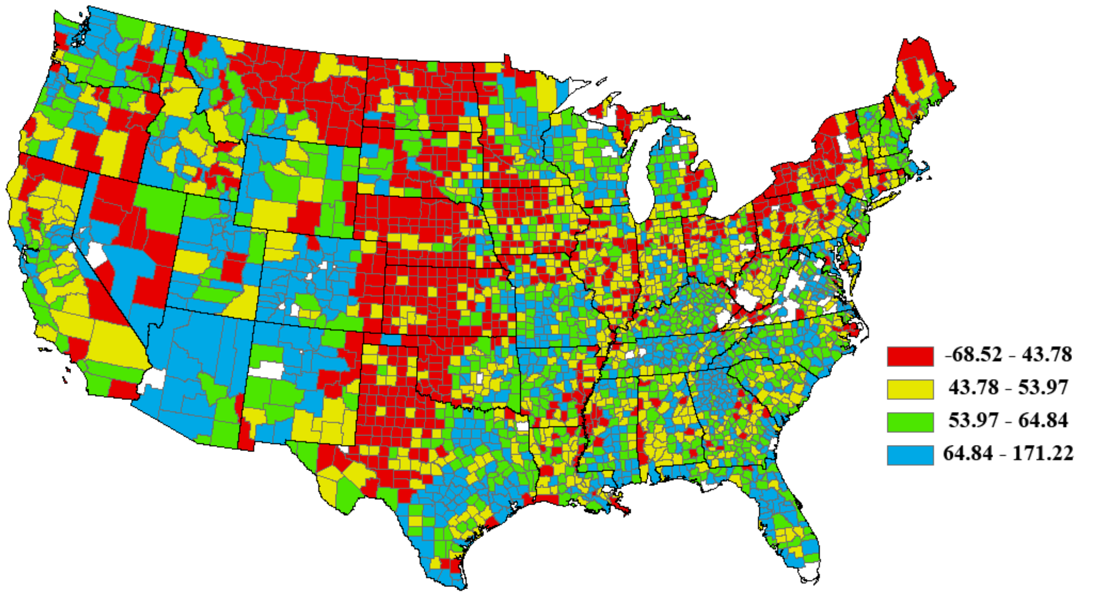


Figure 1. Aggregate county income growth, 1990–2001

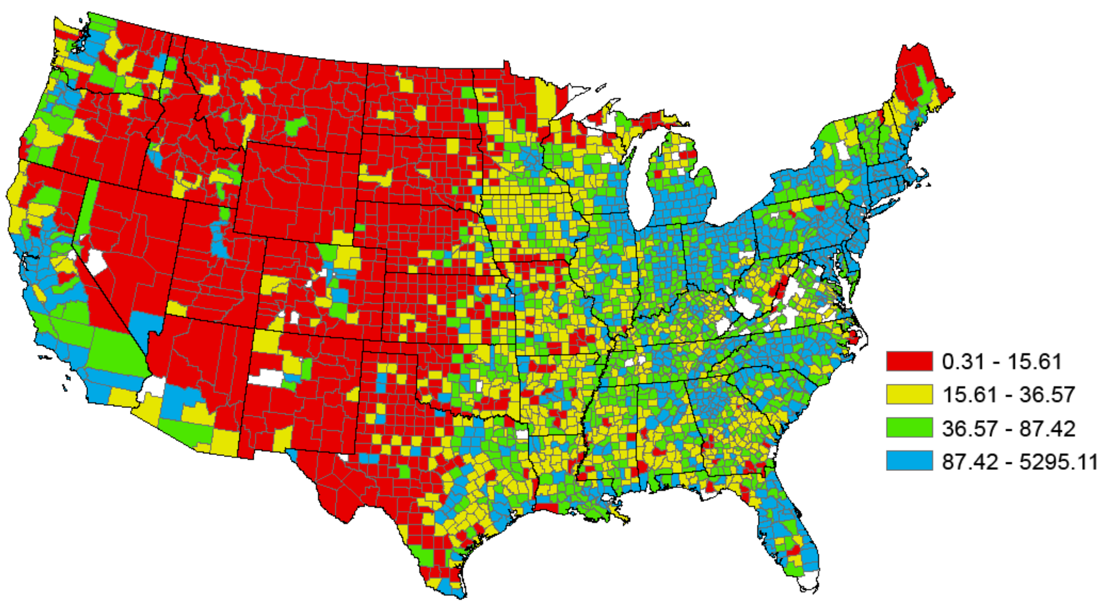


Figure 2. Population per square mile, 1990

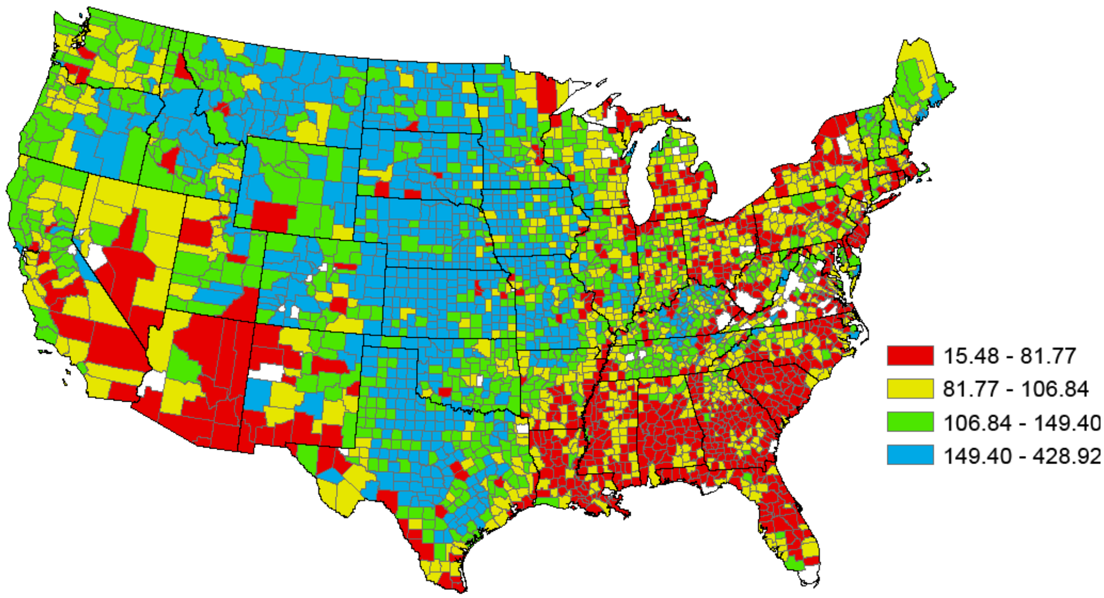


Figure 3. Proprietors per capita, 1990

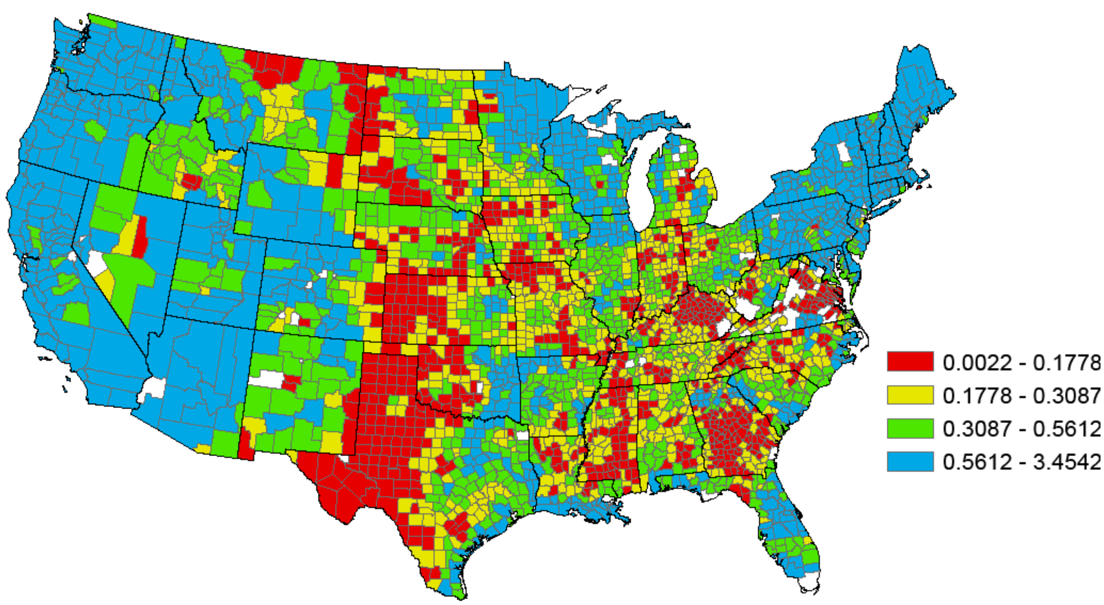


Figure 4. Outdoor recreation and natural amenity index

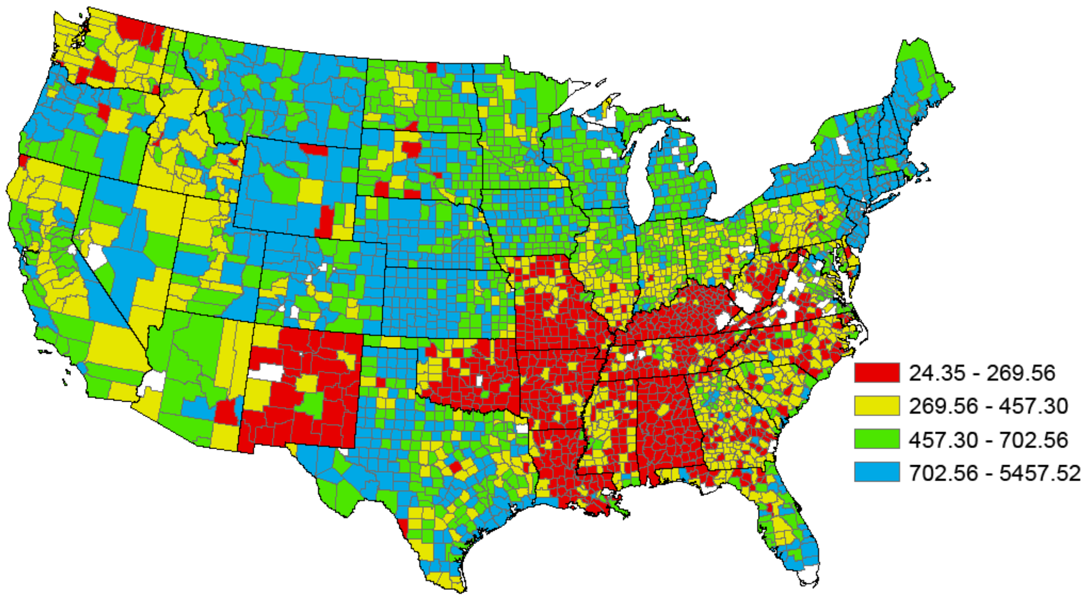


Figure 5. Property taxes per capita, 1992

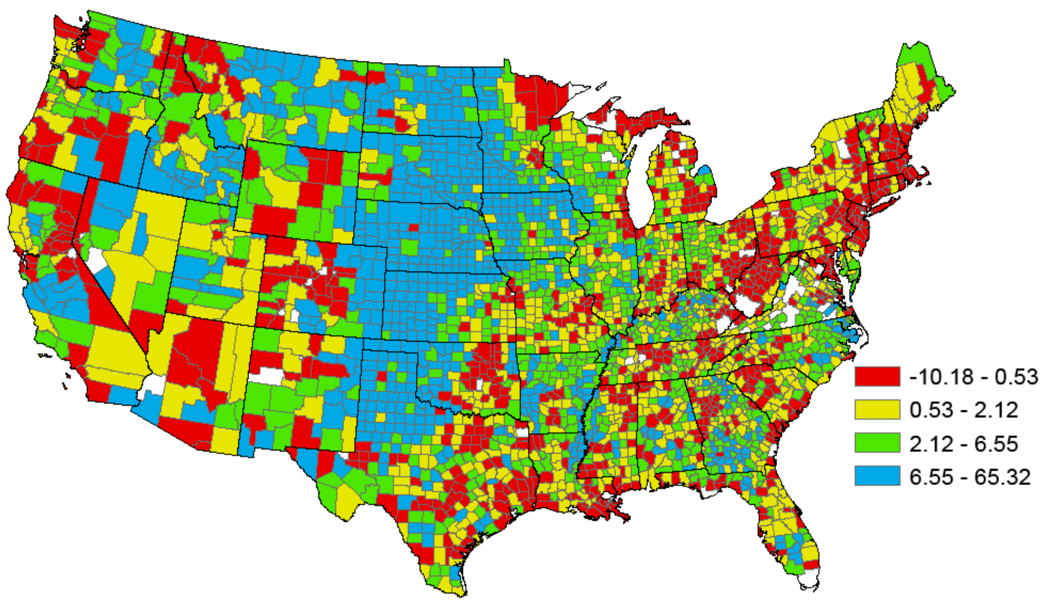


Figure 6. Farm income share of aggregate county income, 1990

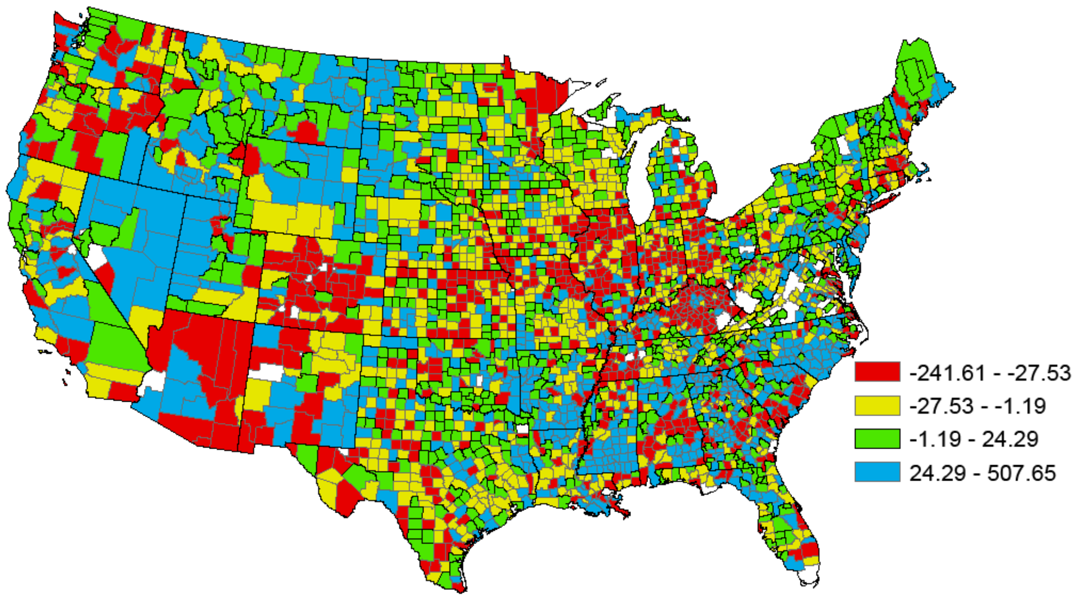
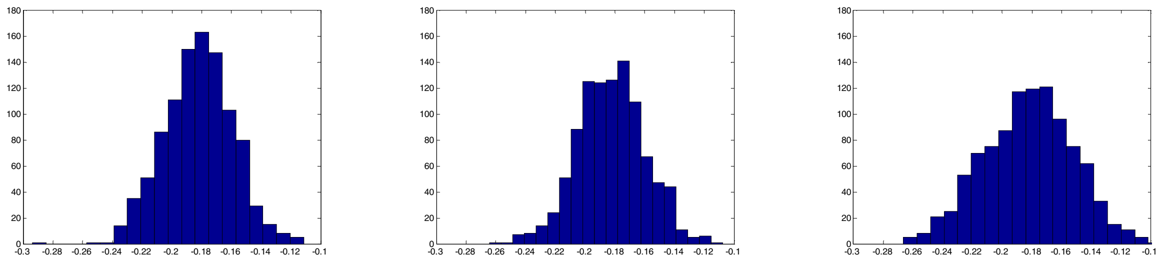


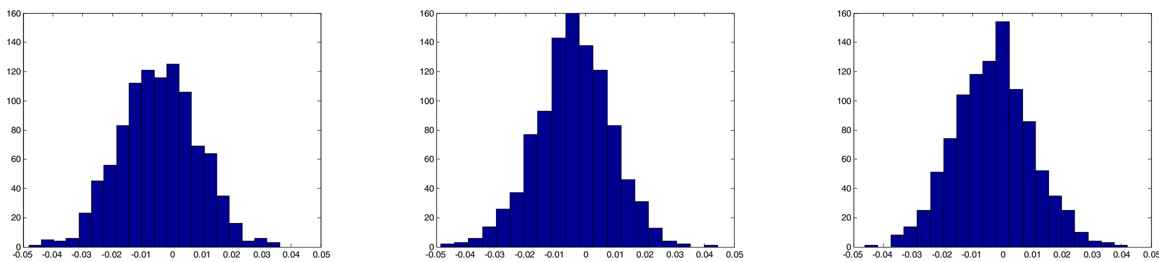
Figure 7. Change in livestock cash receipts, 1990–2001

Figure 8. Bootstrap sampling distributions for model parameters

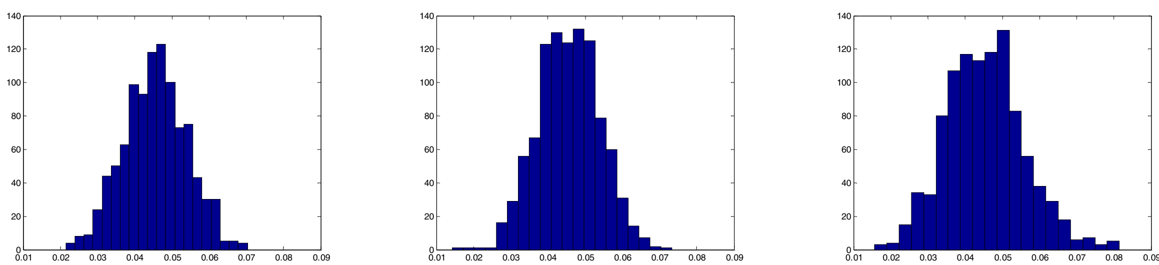
(i) Nonparametric residual | (ii) Parametric residual | (iii) Paired



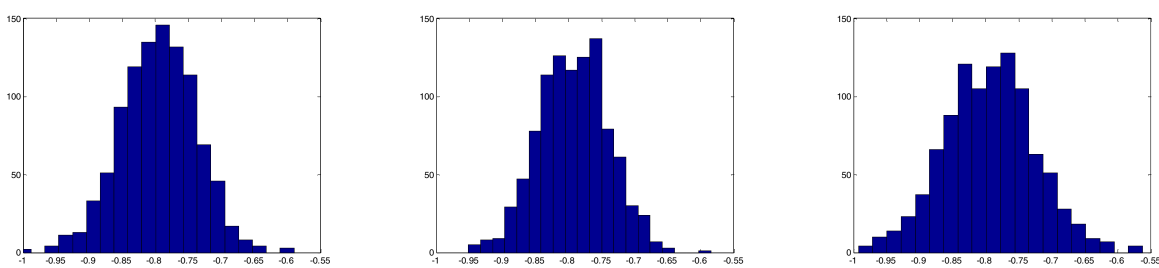
(a) Per capita income



(b) Outdoor recreation and natural amenity index



(c) Property taxes per capita



(d) Share of county income from farming

Note: The empirical approximations of the sampling distribution for these parameters were obtained using 1,000 bootstrap passes and are based on the model, which includes state dummies (table 3).

Table 1. Summary statistics

Variable	Mean	Std. Dev.	Min	Max
Dependent variable (n=2975)				
(logarithmic) Total county income growth 1990-2001	0.546	0.189	-0.685	1.712
Independent variables				
Per capita income 1990	15.224	3.387	5.479	35.318
Population per square mile 1990	119.974	322.772	0.312	5295.114
Percent of population 65+ 1990	15.002	4.324	1.388	34.090
Percent of population under age 20 1990	29.898	3.464	17.323	50.418
Percent of population 25+ with college degree 1990	13.303	6.227	3.689	49.944
Micropolitan variable (city 10-50K and total pop<50K)	0.099	0.299	0	1
Adjacent to a metropolitan area 1993	0.324	0.468	0	1
Percent of population commuting 30+ mins 1990	16.359	6.337	5.163	56.020
Proprietors per capita 1990	0.122	0.055	0.015	0.429
Outdoor recreation and natural amenity index	0.426	0.376	0.002	3.454
January sun hours	151.631	33.064	48	266
Property taxes per capita 1992	544.458	410.543	24.354	5457.516
Share of county income from farming 1990	0.054	0.081	-0.102	0.653
Rural interacted variables[a]				
Rural - Population per square mile 1990	35.689	41.971	0.312	998.387
Rural Outdoor recreation and natural amenity index	0.386	0.354	0.002	2.990
Rural - Property taxes per capita 1992	541.438	440.071	30.696	5457.516
Instrumented variable				
(logarithmic) Growth in livestock cash receipts 1990-2001	-0.006	0.523	-2.416	5.076
Instrument				
(logarithmic) Growth in livestock cash receipts 1980-90	0.190	0.396	-1.868	2.398
Livestock cash receipts 1990	9.658	1.303	4.804	13.840

[a] Based on the 2,200 rural counties alone.

Table 2. Regression results: County income growth, 1990-2001, no state effects

Variable	Coefficient estimate	Parameter Inference based on Alternative Bootstrap Methods[a] Nonparametric residual	Parametric residual	Paired
Instrumented change in livestock receipts 1990-2001	0.2074	1%	1%	1%
(ln) Per capita income 1990	-0.1653	1%	1%	1%
(ln) Population per square mile 1990	-0.0396	1%	1%	1%
Percent of population 65+ 1990	-0.0085	1%	1%	1%
Percent of population under age 20 1990	-0.0038	1%	1%	1%
Percent of population 25+ with college degree 1990	0.0054	1%	1%	1%
Micropolitan variable (city 10-50K and total pop<50K)	-0.0063	ns	ns	ns
Adjacent to a metropolitan area (=1) 1993	0.0201	5%	1%	1%
Percent of population commuting 30+ mins 1990	0.0089	1%	1%	1%
(ln) Proprietors per capita 1990	0.1064	1%	1%	1%
Outdoor recreation and natural amenity index	-0.0174	ns	ns	ns
(ln) January sun hours	0.0649	1%	1%	1%
(ln) Property taxes per capita 1992	0.0396	1%	1%	1%
Share of county income from farming 1990	-0.8438	1%	1%	1%
Rural interacted variables				
Rural - (ln) population per square mile 1990	0.0641	1%	1%	1%
Rural - Outdoor recreation and natural amenity index	0.0658	1%	1%	1%
Rural - (ln) Property taxes per capita 1992	-0.0608	1%	1%	1%
Constant	0.9848	1%	1%	1%
Spatial Error Interaction (λ)	0.4720	1%	1%	1%

[a] Parameter significance is based on 1,000 iterations for each of the three bootstrap methods. Given a level of significance α, the null hypothesis, H_o: the parameter is equal to zero, is rejected if a $(1-\alpha)*100\%$ confidence interval for that parameter from the empirical bootstrap distribution does not include the value zero. The level of significance is reported at the usual 1%, 5%, and 10% levels and parameters not found significant at these levels are denoted by "ns."

Table 3. Regression results: County income growth 1990-2001, state effects included

Variable	Coefficient estimate	Parameter inference based on alternative bootstrap methods: Nonparametric residual	Parametric residual	Paired
Instrumented change in livestock receipts 1990-2001	0.2423	1%	1%	1%
(ln) Per capita Income 1990	-0.1821	1%	1%	1%
(ln) Population per square mile 1990	-0.0306	1%	1%	1%
Percent of population 65+ 1990	-0.0080	1%	1%	1%
Percent of population under age 20 1990	-0.0063	1%	1%	1%
Percent of population 25+ with college degree 1990	0.0062	1%	1%	1%
Micropolitan variable (city 10-50K and total pop<50K)	-0.0157	5%	5%	5%
Adjacent to a metropolitan area (=1) 1993	0.0174	1%	1%	1%
Percent of population commuting 30+ mins 1990	0.0106	1%	1%	1%
(ln) Proprietors per capita 1990	0.0797	1%	1%	1%
Outdoor recreation and natural amenity index	-0.0041	ns	ns	ns
(ln) January sun hours	0.0719	1%	1%	5%
(ln) Property taxes per capita 1992	0.0456	1%	1%	1%
Share of county income from farming 1990	-0.7945	1%	1%	1%
Rural interacted variables				
Rural - (ln) Population per square mile 1990	0.0671	1%	1%	1%
Rural - Outdoor recreation and natural amenity index	0.0751	1%	1%	1%
Rural - (ln) Property taxes per capita 1992	-0.0610	1%	1%	1%
Constant	0.9294	1%	1%	1%
Spatial error interaction (λ)	0.2640	1%	1%	1%

[a] Parameter significance is based on 1000 iterations for each of the three bootstrap methods. Given a level of significance α, the null hypothesis, H_o: the parameter is equal to zero, is rejected if a $(1-\alpha)*100\%$ confidence interval for that parameter from the empirical bootstrap distribution does not include the value zero. The level of significance is reported at the usual 1%, 5%, and 10% levels and parameters not found significant at these levels are denoted by “ns”

Table 4. Regression results: State effects—county income growth, 1990-2001

State Effects[b]	Coefficient estimate	Parameter inference based on alternative bootstrap methods[a]: Nonparametric residual	Parametric residual	Paired
Alabama	-0.0580	5%	1%	5%
Arkansas	-0.0675	5%	1%	1%
Arizona	0.1323	1%	1%	1%
California	-0.1189	1%	1%	1%
Colorado	0.1810	1%	1%	1%
Connecticut	-0.2200	1%	1%	1%
Delaware	-0.1541	10%	5%	5%
Florida	0.0146	ns	ns	ns
Georgia	0.0052	ns	ns	ns
Iowa	-0.0593	1%	1%	1%
Idaho	0.0763	5%	5%	5%
Illinois	-0.0221	ns	ns	ns
Indiana	-0.0416	10%	10%	10%
Kansas	-0.0647	1%	1%	1%
Kentucky	0.0081	ns	ns	ns
Louisiana	-0.0854	1%	1%	1%
Maine	-0.1284	1%	1%	5%
Maryland	-0.1891	1%	1%	1%
Massachusetts	-0.2124	1%	1%	1%
Michigan	-0.0425	10%	10%	ns
Minnesota	-0.0320	ns	10%	10%
Missouri	-0.0315	ns	10%	10%
Mississippi	-0.0575	5%	5%	5%
Montana	-0.0893	1%	1%	5%
North Carolina	-0.0954	1%	1%	1%
North Dakota	-0.1168	1%	1%	1%
Nebraska	-0.0748	1%	1%	1%
New Hampshire	-0.1713	1%	1%	1%
New Jersey	-0.2621	1%	1%	1%
New Mexico	-0.0028	ns	ns	ns
Nevada	-0.0332	ns	ns	ns
New York	-0.2800	1%	1%	1%
Ohio	-0.0731	1%	1%	1%
Oklahoma	-0.1499	1%	1%	1%
Oregon	0.0386	ns	ns	ns
Pennsylvania	-0.1642	1%	1%	1%
Rhode Island	-0.1247	10%	10%	5%
South Carolina	-0.0941	1%	1%	1%

South Dakota	0.0474	5%	5%	ns
Tennessee	-0.0232	ns	ns	ns
Utah	0.1612	1%	1%	1%
Vermont	-0.1263	1%	1%	1%
Virginia	-0.2241	1%	1%	1%
Washington	0.0849	5%	5%	5%
Wisconsin	0.0008	ns	ns	ns
West Virginia	-0.0971	1%	1%	1%
Wyoming	0.0059	ns	ns	ns

[a] Parameter significance is based on 1,000 iterations for each of the three bootstrap methods. Given a level of significance α, the null hypothesis, H_o: the parameter is equal to zero, is rejected if a (1- α)*100% confidence interval for that parameter from the empirical bootstrap distribution does not include the value zero. The level of significance is reported at the usual 1%, 5%, and 10% levels and parameters not found significant at these levels are denoted by "ns."

[b] Suppressed in table 3, these state effects correspond to that model.

.

Table 5. Impact analysis

Variable	Mean starting value	Change in independent variable[a,b]	Resulting change in total county income (000's 1990 dollars)
Change in livestock cash receipts 1990-2001	-0.006	0.523	197,082
Per capita income 1990	15.224	3.387	-52,427
Population per square mile 1990	119.974	322.772	-57,104
Percent of population 65+ 1990	15.002	4.324	-49,632
Percent of population under age 20 1990	29.898	3.464	-31,646
Percent of population 25+ with college degree 1990	13.303	6.227	57,460
Micropolitan variable (city 10-50K and total pop<50K)	0.099	0 to 1	-22,684
Adjacent to a metropolitan area 1993	0.324	0 to 1	25,680
Percent of population commuting 30+ mins 1990	16.359	6.337	101,341
Proprietors per capita 1990	0.122	0.055	43,853
Outdoor recreation and natural amenity index	0.426	0.376	-2,269
January sun hours	151.631	33.064	20,851
Property taxes per capita 1992	544.458	410.543	37,860
Share of county income from farming 1990	0.054	0.081	-91,020
Rural interacted variables			
Rural - Population per square mile 1990	35.689	41.971	17,452
Rural - Outdoor recreation and natural amenity index	0.386	0.354	8,773
Rural - Property taxes per capita 1992	541.438	440.071	-11,617

Note: These economic impacts are based on the regression estimates from the model when state dummies are included (table 3).

[a] All estimated changes in total county income reflect a one-standard-deviation change in the independent variable with the exception of the micropolitan and adjacency to a metropolitan area. In the case of these two dummy variables, the change in income results from satisfying versus not satisfying that particular criteria.

[b] The resulting change in income accompanying the rural interacted variables are based on an average total county income of $325,878,000 for rural counties in 1990 (n=2200). The change in income for all other variables is based on a total county income of $1,458,364,000 for all counties in 1990 (n=2975).