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The Journal of
Regional
Analysis
& Policy

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Modeling and Explaining County-level Prosperity in the U.S.

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Abstract. This paper explores the impact of space on prosperity. In order to do this, it develops a spatial model for locating prosperous counties and for identifying factors associated with prosperity. Using principal component analysis, a county-level prosperity index is created that comprises four measures: high school dropouts, housing conditions, unemployment, and poverty rates. Five categories of independent variables—demographic, economic, geographic, agricultural, and human and social capital—are used in the analysis. The spatial autocorrelation method has been used to determine the spatial pattern of prosperous counties, and the spatial econometric method has been used to develop a model that explains prosperity. The result shows that more prosperous counties have lower minority populations, more economic opportunities, and higher social and human capital. A policy reformulation is important in addressing the issues of less prosperous counties by creating jobs and enhancing social and human capital at regional levels.

1. Introduction

It is well-known that the degree of prosperity across U.S. counties varies widely. While some individual counties enjoy prosperity, others suffer persistent poverty. Arguably, one plausible function of public policy is to offer and develop programs and policies that alleviate poverty and facilitate economic growth in order to achieve prosperity. The mainstream literature talks mostly about county-level inequality, population loss, and persistent poverty in a sort of "distress manner", but very few researchers discuss county-level prosperity (Isserman et al., 2009, 2007; Rasker et al., 2013). One of the challenges of using prosperity as a variable in the analysis is the difficulty in defining and operationalizing the term. Economists look at the economic determinants of prosperity, while sociologists consider other social and structural factors (Cotter, 2002; Fuentes et al., 2013; Rupasingha and Goetz, 2003).

Isserman et al. (2007) were pioneers in defining and operationalizing prosperity in United States (U.S.) counties. According to these authors, "… prosperity is defined with a broader set of measures than typically used for distress. It includes education and housing as well as poverty and employment opportunities. The community's ability to keep its children in school through high school and the housing conditions its residents face seem to be uncontroversial, reasonable indicators of a community's prosperity" (Isserman et al., 2007, p. 6). The authors mention that the four measures — poverty, unemployment, education, and housing characteristics — are frequent targets of public policy. The authors constructed an index for measuring prosperity based on the sum of the difference of the county's rate from the national rates of poverty, unemployment, high school dropouts, and housing problems (Isserman et al., 2007; McGranahan et al., 2010).

This study uses Isserman et al.'s (2007) measures to explain county-level prosperity but applies a slightly different approach in locating and explaining county-level prosperity. For example, it focuses on spatial approach by introducing Morans' I for finding clusters of counties with high and low prosperity. A spatial approach in data analysis is preferred if the data are spatially distributed (LeSage, 1997; Monchuk and Miranowski, 2010). Four county-level rates—poverty, unemployment, high school dropout, and housing characteristics—are used to develop the prosperity index. The study uses principal component analysis (PCA) to develop a prosperity index from the Isserman et al. (2007) dataset. PCA helps to reduce the number of variables into a smaller number of components (Hatcher, 1994; Linting et al., 2007). Basically, PCA is a variable reduction procedure that develops a smaller number of artificial variables (called principal components) that account for most of the variance in the observed variables.

Isserman et al. (2009, 2007) also use spatial approach in exploring prosperity where the authors use multiple regression models, including spatial lag model. However, their work focuses primarily on prosperity of rural counties. In the estimated models, they include 42 independent variables related to geography, economy, human and social capital, demography, and regional control variables (Isserman et al., 2007). This study includes 16 independent variables, most of them different from what Isserman et al. have used in their models.

2. Data and methods

The first variable used to construct the prosperity index is the high school dropout rate. The dropout rate is the number of teenagers, 16 to 19, who are not enrolled in school and who are not high school graduates divided by the total population aged 16 to 19. High school graduates have greater chances of completing a good education, of qualifying for a well-paying job, and of having a better life (Fuentes et al., 2013). The second variable used for the index is the county-level unemployment rate. The unemployment rate is the number of unemployed divided by the civilian labor force, that is, the sum of employed and unemployed civilians aged 16 and older (Census Bureau, 2000; Isserman et al., 2007). A higher unemployment rate is found to be negatively correlated with an increased number of welfare recipients in counties (Crandall and Weber, 2004; Irwin et al., 2002). The third variable is housing quality. The "housing problems rate" is the percentage of households with one or more of four housing conditions that the Census Bureau has combined into a single indicator: (1) lacking complete plumbing facilities, (2) lacking complete kitchen facilities, (3) having 1.01 or more occupants per room, and (4) paying selected monthly owner costs or gross rent greater than 30% of the household income (Isserman et al., 2007; McGranahan et al., 2010). The lower the number of housing problems, the better the living conditions. The fourth variable is the poverty rate, which is defined here as the number of persons whose income was below the poverty level in 1999 divided by the total number of people whose poverty statuses were determined, which is everyone except for institutionalized people, people in military group quarters, people in college dormitories, and unrelated individuals under 15 years old (Census Bureau, 2000; Isserman et al., 2007).

Sixteen different independent variables, described below, have been identified based on an extensive literature review and are used in the analysis. These independent variables can be grouped into five main categories: demography (two variables), economy (eight variables), geography (two variables), agriculture (one variable), and human and social capital (three variables).

Other measures could also be important in defining and explaining prosperity and well-being. For example, Ashby and Sobel (2008) have used the economic freedom index in explaining income inequality among U.S. states. A number of studies, including those of Belasen and Hafer (2013), Cebula (2011, 2013), Clark and Lawson (2008), and Cole (2003), examine the relationship between economic freedom and well-being, with the authors finding that improvements in economic freedom lead to an increase in personal well-being. Similarly, scholars have used economic freedom variables to explain migration in U.S. states (Ashby, 2007; Cebula and Clark, 2011; Ruger and Sorens, 2009), where the authors demonstrate that the states with higher economic freedom have more opportunities that drive higher in-migration. Ideally, an index of economic freedom could be included in this paper, but no such data exist at the county level. Further, some researchers explore the relationships between natural amenities, and economic growth (Deller et al., 2001; Green, 2001; Kwang-Koo et al., 2005; Rasker et al., 2013). While this approach may add another dimension of looking at county-level prosperity, using county-level physical characteristics is beyond the scope of this paper.

This paper combines the identified categories of explanatory variables in the analysis. Each category is intended to complement the others. The goal is to provide a balanced and broad set of insights regarding the issues considered in this study.

2.1. Demographic variables

Percent minority population

The racial composition of a county affects poverty and prosperity (Kodras, 1997; Peters, 2009). Studies have shown that minority populations are more likely to live in poverty (Crandall and Weber, 2004; Voss et al., 2006). This implies that the higher the percentage of the minority population, the lower the level of prosperity (Beeghley, 1988).

Median age of population

The median age of the population is used to determine the effect of the population age structure on prosperity in counties. U.S. counties have witnessed a rapid change in demographic structure in recent years. Younger generations are leaving areas with fewer opportunities and are moving to city centers (Monchuk and Miranowski, 2010). The implication is that counties with fewer economic opportunities have populations with higher median ages. An older population is associated with lower economic activity (Dudenhefer, 1993). However, some rural retirement counties have large baby-boomer populations, who are considered to be better educated, wealthier, and more likely to work, at least part-time, after they retire (Bass, 2000; Chi and Marcouiller, 2012; Korczyk, 2001). It is possible that we may see the impact of this phenomenon in the prosperity index.

2.2. Economic variables

Median household income

Income is often associated with prosperity. Median household income is a good indicator of household income (Ryscavage, 1999). The median household income is considered a better indicator than the average household income, as it is not dramatically affected by unusually high or low values, so it will be used in this study to assess the relationship between income and prosperity.

Gini index

Higher income inequality is negatively associated with county prosperity. The Gini coefficient is used as a measure of inequality or income inequality. Studies have shown that higher inequality is associated with people's poor quality of lives (Ryscavage, 1999). In this study, the Gini coefficient for 2000 is used as an independent variable for examining the relationship between inequality and prosperity in the county.

Change in Gini coefficient between 1990 and 2000

The decrease in the Gini coefficient between 1990 and 2000 reflects a reduction in the inequality in a county (Ryscavage, 1999). When lower income inequality exists among the people in a county, this could positively increase the prosperity levels in the county.

Percent poverty change between 1990 and 2000

A lag variable was created in order to see the effect of change in the poverty rate between the years 1990 and 2000. Weber et al. (2005) state that many rural counties were able to lower their poverty rates between 1990 and 2000 and are enjoying more prosperous lives. The assumption is that a decrease in the poverty rate positively affects prosperity in these counties.

Percent population in manufacturing jobs

Employment is considered to be a factor associated with higher income (Beeghley, 1988; Cannaughton and Madsen, 2012; Irwin et al., 2002; Peters, 2009; Weber, 2007). However, the impact on prosperity of employment in a particular job is a matter of inquiry. Typically, income from manufacturing employment is considered to be higher, on average, than is income from other sectors such as service. The percent population in manufacturing jobs is used to determine the effect of employment in manufacturing jobs on a county's overall prosperity level.

Percent in service sector

This variable is introduced in order to determine the effect of the population employed in the service sector on the prosperity levels of counties. Miller and Rowley (2002) found that high-poverty counties had higher proportions of people working in the service sector.

Percent employed female

Studies have shown that a higher percentage of female employees in a county decreases the poverty rate (Crandall and Weber, 2004; Rupasingha and Goetz, 2003), as this generally indicates the number of two-income families as well as lower underemployment. This variable is introduced in order to determine the effect of the percentage of employed females on a county's prosperity.

Percent small manufacturing establishments

Many studies have suggested that a higher number of larger manufacturing industries decreases the welfare of people (Goldschmidt, 1978; Lobao, 1990; Lyson, 2005). This type of enterprise is more often owned by individuals or entities outside of the local community, and profits are exported from the county to other places, thus placing the local community at an economic disadvantage. It is assumed that a higher percent of small manufacturing establishments would increase the county prosperity. A small manufacturing establishment is defined as an establishment that employs fewer than nine people.

2.3. Geographic variables

Population per square mile

The population does not distribute itself equally across space. Some places have a higher population concentration, while others have lower population densities. This study aims to use this variable to see the relationship between the number of people per square mile and the county's prosperity. Generally speaking, rural areas that are not densely populated are shown to be less prosperous than more urbanized areas (Monchuk and Miranowski, 2010).

Urban Influence Code 2003

The United States Department of Agriculture (USDA) Economic Research Service (ERS) developed a set of county-level urban influence categories that divides metro counties into "large" areas with at least one million residents and "small" areas with fewer than one million residents. Nonmetro micropolitan counties are divided into groups according to their locations in relation to metro areas — adjacent to a large metro area, adjacent to a small metro area, and not adjacent to a metro area. Nonmetro noncore counties are divided into seven groups based on their adjacency to metro or micro areas and based on whether or not they have their "own town" of at least 2,500 residents (Weber et al., 2005). Studies have shown that the higher the portion of the population in rural areas, the lower the level of economic activity (Lichter and Johnson, 2007; Weber et al., 2005). The Urban Influence Code variable is introduced in order to examine the effect of urbanization on prosperity. This variable is measured on a scale from 1 to 12, indicating increasing rurality. In a spatial study such as this, it is important to know the role of rurality in determining prosperity in a county.

2.4. Agricultural

Percent population in farming

This variable is used to see the effect on prosperity of the percentage of the farming population. Generally, agriculture-based counties have lower levels of economic activity, hence fewer employment opportunities for people (Walzer and Siegan, 2003). As the U.S. has witnessed a rapid decline of the farming population, it is important to see whether the percentage of the population in farming activities has any relation to a county's prosperity.

2.5. Human and Social Capital

Social capital index

Social capital has been seen as an important missing link in understanding societal prosperity (Crandall and Weber, 2004; Putnam, 2000; Rupasingha et al., 2007). This is seen as an important determinant of economic growth in U.S. counties (Crandall and Weber, 2004; Rupasingha et al., 2000). The social capital variable used in this study is a county-level index for 1997 that Rupasingha et al. (2000) developed. It was developed using county-level civic organizations, sport clubs, religious organizations, labor organizations, business associations, and voting patterns.

Percent population with bachelor's degree

Education, as an indicator of human capital, is widely recognized as a good indicator of prosperity (Alesina et al., 2004; Fuentes et al., 2013). The proportion of the population with higher educational levels is associated with higher-level employment and, generally, increased income (Irwin et al., 2002). Studies from different scholars conclude that higher education rates in a county increase prosperity.

Percent change in population with bachelor's degree between 1990 and 2000

This lag variable is introduced in order to determine the overall effect of the percent change in the population with bachelor's degrees. It is assumed that an increased percentage of the population with bachelor's degrees in a county (e.g., higher education itself) positively contributes to higher prosperity levels.

3. The eclectic conceptual model

Based on the above definition and conceptual idea, an eclectic conceptual model can be developed. Let us assume prosperity is measured by Y. Prosperity can be measured using different variables such as poverty (y_1), unemployment (y_2), high school dropout (y_3), and housing characteristics (y_4). Given the fact that a composite index of these variables is better than an individual variable, an index of these variables can be: $\mathrm{Y} = \sum_{i=1}^{4} \beta_i \, y_i$. Here, β is a vector of weights created using a suitable weighting scale such as principal components. Explanatory variables that are representative of demography (x_1), economy (x_2), geography (x_3), agriculture (x_4), and human and social capital (x_5) generally affect the prosperity index of a given location. This can be written as:

$$Y = \sum_{i}^{4} \beta_i y_i = f(x_1, x_2, x_3, x_4, x_5). \tag{1}$$

3.1. A spatial model

As this study seeks to understand the spatial extent of prosperity across U.S. counties, it is helpful to conduct a polygon pattern analysis. Because counties are non-overlapping geographical units that resemble polygons, we can use spatial methods for analysis (Monchuk and Miranowski, 2010). The spatial analysis of county-level prosperity helps to understand whether the pattern is clustered, dispersed, or random. If phenomena are related to each other, an attractive relationship might form a cluster of counties that have higher or lower prosperity levels. If the phenomena are "repulsive," this may form a dispersed structure. If the spatial pattern appears to be neither clustered nor dispersed, we can say that a random pattern shows that place has no effect on prosperity.

The use of a measure such as Moran's I helps with understanding these phenomena. This test is important for spatial pattern analysis, as it provides a weighted correlation coefficient used to detect departures from spatial randomness (Anselin, 1999). A null hypothesis of no spatial autocorrelation can be tested against an alternative of positive or negative spatial autocorrelation of prosperity and place. If a certain pattern appears, how do we describe this phenomenon, and what are the factors that shape this relationship? In order to confirm this pattern, a spatial error model can be used to investigate the relationship between various county-level socioeconomic indicators and prosperity (Voss et al., 2006).

For the analysis, ArcGIS and GeoDa software have been used. The boundary file of U.S. counties is derived from the U.S. Census Bureau website. Later, socio-economic data were joined using ArcGIS in the boundary file (Mitchell, 1999). ArcGIS software is also used to create the map of the prosperity distribution among counties (Figure 1). GeoDa has been used for Moran's I analysis, which produces a scatter plot (Figure 2) and clustered map (Figure 3).

Moran's I statistics indicate that each variable in the analysis exhibits a significant degree of spatial clustering (correlation among values of neighboring units) unlikely to have occurred by chance. The global Moran's I can be decomposed into local indicators of spatial association (LISA), which identify local clusters of units with similar values (Anselin, 1999; Khatiwada, 2010).

Spatial autocorrelation occurs when the value at any one point in space is dependent on values at the surrounding points. That is, the arrangement of values is not just random. Positive spatial correlation means that similar values tend to be near each other (Wang, 2006). Negative spatial correlation means that different values tend to be near each other.

The spatial regression method is used to estimate the effect of various socio-economic and spatial variables on the prosperity dependent variable. If autocorrelation is present, the spatial error model should be used to avoid violation of basic assumptions in the regression model (Doreian, 1981; Khatiwada, 2010).

The spatial error model considers the error term as autoregressive. The conceptual model is:

$$\mathrm{Y} = \mathrm{X}\beta + \mathrm{u}, \tag{2}$$

where $\boldsymbol{X}$={x_1,x_2,x_3,x_4,x_5), the explanatory variables, and u is related to its spatial lag, such that

$$\mathrm{u} = \lambda \mathrm{W}\mathrm{u} + \varepsilon \tag{3}$$

and

$$\varepsilon = N(o, \sigma^2 I), \tag{4}$$

where λ is a spatial autoregressive coefficient, $\boldsymbol{W}$ is the spatial weight, and $\boldsymbol{\varepsilon}$ is normally distributed with zero mean and variance $\sigma^2 I$.

Solving the above equation for u and substituting yields the reduced form (Wang, 2006)

$$\mathrm{Y} = \mathrm{X}\beta + (\mathrm{I} - \lambda \mathrm{W})^{-1} \varepsilon. \tag{5}$$

This shows that the value of y_i at each location i is affected by the stochastic error ε at all other locations via the spatial multiplier $(I-\lambda W)^{-1}$. Estimation of the spatial error model for the prosperity index dependent variable is implemented by the maximum likelihood method (Wang, 2006; Anselin, 1999).

3.2. Data sources and procedure

The data used in this study were prepared using multiple data sources. Initially, data related to income, race, population, education, age, poverty rate, and employment were downloaded from the Missouri Census Data Center (MCDC) website (Census, 2000). Other data were obtained from the following sources:

- data related to county rates for high school dropouts, unemployment, poverty, and housing problems were obtained from Isserman et al. (2007);
- data for the computation of the Gini coefficient were obtained directly from the Census Bureau;
- data related to the social capital index were obtained from the Northeast Regional Center for Rural Development; and
- data related to the number and type of manufacturing establishments were obtained from the County Business Pattern report (CBP) from the Bureau of the Census.

Descriptive statistics are presented in Table 1.

Table 1. Descriptive statistics.

Variables	N	Mean	SD	Min	Max
Demography					
Percent Minority Population, 2000	3108	18.38	18.71	0.00	98.40
Median Age, 2000	3108	37.37	3.96	20.60	54.30
Economy					
Median Household Income, 2000	3108	35,262	8837	12,692	82,929
Gini Coefficient, 2000	3108	43.45	3.88	31.52	60.85
Gini Change, 1990-2000	3108	1.00	2.46	-14.64	15.17
Poverty Change, 1990-2000	3108	-2.46	3.04	-23.70	14.10
Percent in Manufacturing Jobs, 2000	3108	15.92	9.08	0.00	48.60
Percent in Service Jobs, 2000	3108	15.69	3.02	2.00	31.90
Percent Employed Female, 2000	3108	46.07	2.23	34.15	59.78
Percent Small Manufacturing Estab., 2005	3108	54.68	19.17	0.00	100
Geography					
Person Per Square Mile, 2000	3108	244	1675	0.30	66,940
Urban Influence Code, 2003	3108	5.41	3.45	1	12
Agriculture					
Percent in Farming, 2000	3108	2.23	2.50	0.00	27.00
Human and Social Capital					
Social Capital Index, 1997	3108	.00	0.64	-1.94	3.54
Percent with Bachelor's Degree, 2000	3108	10.96	4.92	2.50	40.00
Percent Change with Bachelor's Degree, 1990-2000	3108	1.95	1.59	-6.10	15.00
Prosperity Index	3108	.00	1.00	-8.53	2.15

After obtaining these data, they were merged into a single data set using SAS software. The merged data were imported into ArcGIS 9.2 (Environmental Systems Research Institute). The data set was joined to the boundary file using a common field as designated by the Federal Information Processing Standards (FIPS) Codes.

Data were exported as a "shapefile" for working on GeoDa software. The reason for using GeoDa is twofold: this software provides techniques for measuring the presence of autocorrelation (Global and Local Moran's I) and for developing models using regression analysis. According to Anselin et al. (2006), GeoDa is a collection of software tools designed to implement techniques for exploratory spatial data analysis (ESDA). It has a wide range of options for using different spatial analyses, with facilities for importing, joining, and exporting files.

4. Empirical results and discussion

A prosperity index for contiguous U.S. counties has been created using principal components analysis. Before running the PCA, the dependent variable was redefined by taking the negative of the current measures of unemployment, high school dropouts, poverty, and housing problem rates, which helps to interpret the results as higher values correspond to greater prosperity. The four measures of prosperity, the negative values of unemployment, high school dropouts, poverty, and housing problems, were loaded in a single-dimensional component that explained 58 percent variation in the model. This single-dimensional component, which had an Eigenvalue of 2.33, was retained as a county prosperity index. The standardized index value has a mean of zero and a standard deviation of one. It runs from -8.53 to 2.15, indicating that the higher the score, the more prosperous is the county.

Mapping this prosperity index in ArcMap reveals a clear pattern. The spatial concentrations of prosperous counties are seen in the Northeast and Midwest states, whereas the counties of the U.S.-Mexico border, Mississippi Delta, Appalachia, and Black Belt regions have a lower prosperity index (Figure 1). This finding is consistent with that of other studies, such as Isserman et al. (2007) and Rupasingha and Goetz (2007). The highest levels of prosperity appear to be found in the North Central and Upper Midwest regions. This implies that prosperity is not independent of location and is not random. Rather, it is a function of regional spatial effects. These phenomena can be tested using the global and localized version of Moran's I. While the global Moran's I provides understanding as a global set of data, the local version gives an understanding of the extent and nature of spatial clustering in a dataset (Voss et al., 2006).

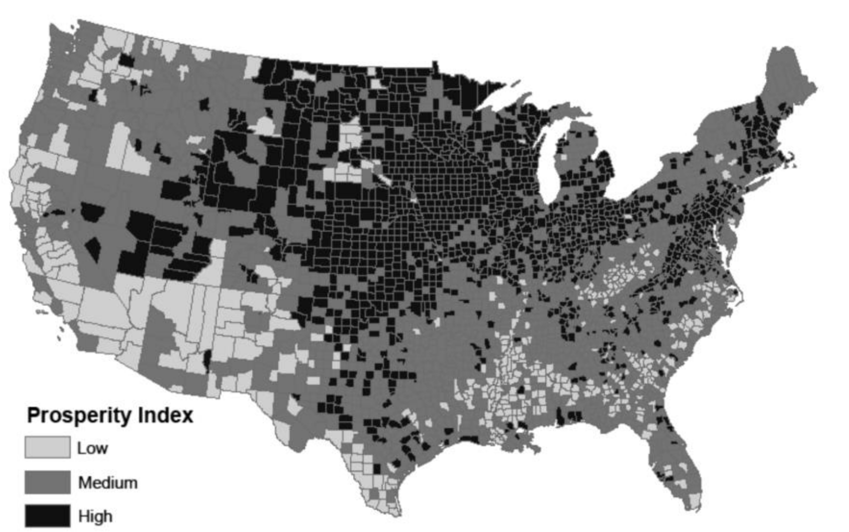

Figure 1. Spatial concentration of prosperity in U.S. counties.

4.1. Moran's I result

The Moran's I scatter plot gives a significant value of 0.536, indicating autocorrelation of the dependent variable (Figure 2). Spatial autocorrelation refers to value association between observations that are geographically near to each other (Green and Sanchez, 2007). The Moran's I value of 0.536 indicates a strong positive spatial autocorrelation.

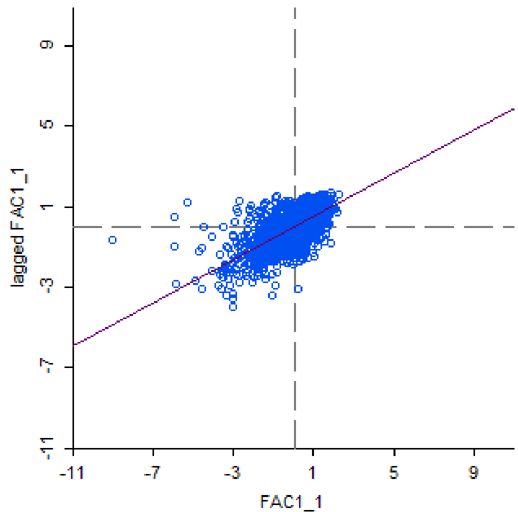

Figure 2. Scatter plot of Moran's I for all counties.

The horizontal axis shows the average value of prosperity for that county's neighbors as defined by the weight matrix. Because the higher the index score, the higher the prosperity, the upper right quadrant of the Moran's scatter plot shows those counties with above-average prosperity index values that also share boundaries with neighboring counties that have above-average scores for the dependent variable. They are termed "high-high" counties (Khatiwada, 2010; Voss et al., 2006). The lower left quadrant shows counties with lower average values and neighbors who also have lower average values (low-low). The lower right quadrant displays counties with higher average values surrounded by counties with below-average values of prosperity (low-high). Similarly, the upper left quadrant contains low average values surrounded by counties with higher average values (high-low).

The Moran's map (Figure 3) shows how these higher and lower prosperous counties are grouped together, telling us that the prosperous counties are not randomly distributed, but rather follow a systematic pattern (Rupasingha and Goetz, 2007; Voss et al., 2006). The hot spots of high-high counties are in the West-North-Central, East-North-Central, Middle Atlantic, and New England regions (Figure 3). The cold spots with lower prosperity values are in the U.S.-Mexico border regions, lower Black Belt, southern parts of the Mountain States, and rural counties of North and South Dakota.

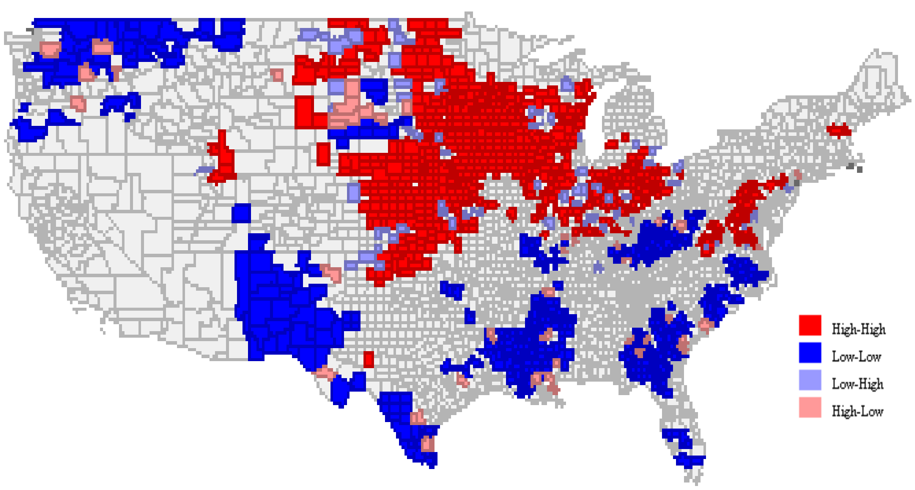

Figure 3. Moran's Map for Low and High Prosperity

4.2. Comparison: high-high vs. low-low counties

Before using a regression model, comparing the means of all socioeconomic indicators could provide some ideas about whether the two extreme groups of counties, high-high vs. low-low, are really different (Table 2).

Comparing the two groups of counties — high-high vs. low-low — shows some interesting results. The result shows that 599 counties belong to the high-prosperity group, while the number of low-prosperity counties is 407 across the contiguous U.S. Some of the observed differences are: percent minority population (6.24 percent for high-high vs. 36.88 percent for low-low), median household income ($38,558 vs. $27,938), Gini coefficient (40.38 vs. 47.30), percent in manufacturing jobs (17.15 percent vs. 15.04 percent), persons per square mile (110 vs. 226), percent with bachelor's degree (12.22 percent vs. 8.37 percent), and social capital index (0.77 vs. -0.61).

Table 2. Comparing high-high vs. low-low counties.

Characteristics	Low-low	High-high
Demography		
Percent Minority Population, 2000	36.88	6.24
Median Age, 2000	35.50	38.47
Economy		
Median Household Income, 2000	$27,938	$38,558
Gini Coefficient, 2000	47.38	40.38
Gini Change, 1990-2000	0.94	0.50
Poverty Change, 1990-2000	-3.76	-2.19
Percent in Manufacturing Jobs, 2000	15.04	17.00
Percent in Service Jobs, 2000	16.64	14.79
Percent Employed Population, 2000	91.54	96.18
Percent Employed Female, 2000	46.46	46.27
Percent Small Manufacturing Establishment, 2005	53.08	53.11
Geography		
Person Per Square Mile, 2000	226.16	110.65
Urban Influence Code, 2003	6.33	5.99
Agriculture		
Percent in Farming, 2000	2.76	2.34
Human and Social Capital		
Social Capital Index, 1997	-0.61	0.77
Percent with Bachelor's Degree, 2000	8.37	12.22
Percent Change with Bachelor's Degree, 1990-2000	1.21	2.53
Prosperity Index	0.98	-1.28
No. of Counties	407	599

This comparison shows that the highly prosperous counties are different from the counties with low prosperity levels. Those counties that are prosperous have lower minority populations, higher median household incomes, lower inequality, higher percentages of people who are employed in manufacturing jobs, lower numbers of people per square mile, lower percentages of people who work in farming, higher percentages of people with bachelor's degrees, and higher social capital index.

The Moran's I analysis gives an exploratory view of the data. It suggests that prosperity is a highly regional and clustered phenomenon and tells us to go further to test socio-economic factors that might play roles in dividing counties into higher and lower prosperity levels (Voss et al., 2006). The modeling of different social, economic, geographical, and demographic factors can best explain why some counties enjoy prosperity while others do not.

4.3. Spatial regression analysis

As the dependent variable (prosperity) is spatially distributed, it is appropriate to use the spatial error model (Anselin, 1996; Voss et al., 2006). The spatial error model considers the error term as autoregressive. The result of using the spatial error model is a much higher R^2, with more than 83 percent of the variation in the prosperity index explained and a significant lambda (Table 3).

The result shows that the spatial patterning of prosperity is highly associated with the spatial patterning of demographic, economic, geographic, agriculture, and human and social capital variables. This further implies that prosperity depends, to a large extent, on the operation of an area's labor market (as shown by highly significant economic indicators), which is a geographic area that is much larger than the county level used for the dependent variable (Crandall and Weber, 2004). The percentage of the minority population, median age of the population, educated population, household income, and lower income inequality all are important for a county's prosperity.

Table 3. Maximum likelihood estimation models predicting prosperity in U.S. counties.

Independent variables	Coeff	Sd. Err.
Constant	-0.007	0.050
Percent Minority Population, 2000	-0.022***	0.008
Median Age, 2000	0.063***	0.002
Median Household Income, 2000	0.000***	0.000
Gini Coefficient, 2000	-0.070***	0.003
Gini Change, 1990–2000	0.023***	0.003
Poverty Change, 1990–2000	-0.021***	0.003
Percent in Manufacturing Jobs, 2000	0.001	0.001
Percent in Service Jobs, 2000	-0.013***	0.003
Percent Employed Female, 2000	-0.002	0.003
Percent Small Manufacturing Establishment, 2005	-0.001***	0.000
Person Per Square Mile, 2000	0.000	0.000
Urban Influence Code, 2003	-0.012**	0.003
Percent in Farming, 2000	0.013**	0.004
Social Capital Index, 1997	0.005	0.003
Percent with Bachelor's Degree, 2000	0.032***	0.006
Percent Change with Bachelor's Degree, 1990–2000	-0.003	0.016
R^2	0.83	
Log Likelihood	-1651.84	
AIC	3337.69	
Lambda	0.67***	0.016

*p < 0.05; ** p < 0.01; *** p< 0.001.

The results show that the two demographic variables, percentage of the minority population and median age, are both significant. The positive coefficient value for median age suggests that an increasing median age may be positively associated with prosperity, which is consistent with Isserman et al.'s (2007) finding. The negative coefficient value of the minority population in a county is associated with decreasing prosperity in the county. This is consistent with the work of other researchers (Crandall and Weber, 2004; Isserman et al., 2009; Rupasingha and Goetz, 2007). The researchers have found that minority populations of the counties are associated with higher levels of poverty, a component of lower levels of prosperity. According to Holzer (2007), minorities are more likely to be in poverty than are Whites. The report mentions that African Americans (24.9 percent poor in 2005), Hispanics (21.8 percent), and Native Americans (25.3 percent) all have poverty rates that are far greater than those of Whites (8.3 percent). When the entire population is considered, 45 percent of all poor people are non-Hispanic Whites.

The coefficient for median household income suggests that it is a strong predictor of prosperity in the counties. The coefficient for the Gini index is negative, indicating that the higher the inequality in the counties, the lower the prosperity. Isserman et al.'s works (2007, 2009) also note this fact. The changes in the poverty rate between 1999 and 2000 also show a significant result. Those counties that are successful in lowering the poverty rate obviously have a greater chance to enjoy prosperity. The coefficient for the urban influence code is negative for the model. This tells us that rurality increases the probability of being a less-prosperous county. Many findings confirm that distance is a major factor that plays a role in economic activities. Increasing the distance from the city core decreases the chance of being economically active. This is consistent with Isserman et al. (2009), as the authors found prosperous counties on average are closer to urban areas. As discussed earlier, rural areas have severely limited options for economic activities, so for the prosperity of rural areas, renewed attempts should be made to increase economic activities by reducing obstacles created by distance, such as improving roadways and Internet access. The result shows that a higher percentage of people employed in the service sector is negatively associated with prosperity. Low-paying jobs in the service sector are probably not enough for enjoying a prosperous life.

Another strong variable is the percentage of the county population with bachelor's degrees. Higher education is associated with success in life, helping to achieve prosperity. This finding is consistent with the finding of Isserman et al. (2007), as the authors found that counties with more college educated people are more likely to prosper.

5. Conclusion

The spatial approach helps to identify the pockets of high- and low-prosperity counties *and* the factors associated with them. One important observation is that prosperity is not distributed randomly across physical space. The spatial clustering of counties with high prosperity rates (and low prosperity rates) may mean that observed prosperity rates are not independent of one another. The prosperity of neighboring counties appears to be linked. Why this is the case requires a different sort of research in order to identify the various economic, social, cultural, natural amenity, and political linkages among these counties. The results also imply that prosperity depends, to a large extent, on the operation of the area's labor market (as shown by highly significant economic indicators), which is a geographic area that is much larger than the county level used for the dependent variable here (Voss et al., 2006). Further, this implies that the labor market is one of the factors that determines prosperity, and studying county-level poverty and prosperity needs to take into consideration the spatial effect of neighboring counties. Also, because we know that workers are highly mobile, often living in different counties than where they may be employed, the transportation and telecommunication infrastructure also is a likely factor to target for further research.

Spatial analysis additionally confirms that counties exhibit strong spatial dependence, and spatial (location) parameters are found to be significant determinants of prosperity in U.S. counties. One county may depend on another county for various reasons: for employment, health care, business services, or agricultural products. People may commute for work from one county to another if a good transportation network is available. These processes develop spatial dependence (Khatiwada, 2010).

The results show that a prosperous county has a lower percentage of minority population, a higher median household income, lower income inequality, a lower percentage of people who work in low-paying service sectors, a relatively urban nature, few people working in agriculture, and higher human and social capital. Prosperous counties are often spatially contiguous to other prosperous counties (Khatiwada, 2010), meaning that prosperity is not restricted by jurisdictional boundaries but rather has more of a relationship to structural factors, such as labor markets, and is representative of social processes such as those that Brasier (2005) delineated. We therefore can argue that these findings should guide policies, which can more effectively address the problem of poverty in rural counties.

A prosperous county is likely to be part of a cluster of prosperous counties, forming a prosperous region. This suggests that we use a regional approach while planning for economic development programs (Partridge and Rickman, 2005). One of the obvious questions is what happens to those counties that are not a part of any cluster? The spatial autocorrelation effect on prosperity does not intervene in the social and economic processes in these counties in the way it does in other locations. We probably need a different sort of developmental approach in these counties. Maybe those counties are not ready for a regional approach (Khatiwada, 2010).

This paper uses only some factors that affect county-level prosperity. Other factors may be equally important in explaining county-level prosperity. Particularly, it is worthwhile to see the relationship between natural amenities and prosperity. Further, factors such as personal income variables, interest, dividends, rents, and transfer payments may predict county-level prosperity. Therefore, a future work needs to investigate the relationship between prosperity and personal income variables from the U.S. Bureau of Economic Analysis Personal Income data.

Acknowledgements

I would like to express my deepest appreciation to Dr. Ken Pigg for his helpful comments and suggestion while preparing the manuscript. I would also like to thank the late Dr. Andrew Isserman for sharing data. This research article was supported in part by a grant from the USDA/CSREES/NRI under Project No. 2003-35401-13769.

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