



The Causes of Enduring Poverty
An Expanded Spatial Analysis of the
Structural Determinants of Poverty in the US

by Anil Rupasingha and Stephan J. Goetz
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“Contributing to the well-being of small towns and rural communities.”

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Executive Summary

Persistent rural poverty is one of the most stubborn social problems facing policy makers. Despite decades of intervention, and the spending of billions of public dollars, many rural communities remain mired in poverty. The economic boom of the 1990s not only failed to reduce poverty in all counties, but it was also associated with rising poverty rates in certain counties. This in turn presents an opportunity to discover the factors that perpetuate or ameliorate poverty.

This report expands knowledge of the determinants of poverty by focusing on two sets of structural causes that have not been considered in econometric analyses of poverty: social capital and so-called political power or democratic governance variables. Like human capital or education, social capital is increasingly recognized as essential to community well-being and economic growth. Further, recent case study research reveals that some community leaders may deliberately prevent local development to maintain their position of power.

We also incorporate variables that have previously been excluded from county-level analyses, including self-employment as a pathway out of poverty, and the importance of Big-box (as opposed to “mom-and-pop”) stores to measure the industrial organization of a county’s retail sector. This is also the first county-level study of poverty that explicitly accounts for the geographic clustering of poverty, which has implications for the statistical modeling. Finally, we use all of the variables that have been used in previous county-level studies to control for structural and individual-level determinants of poverty.

Systematic and consistent measurement of the effects of political power and social capital on poverty in settings that involve a large statistical population has been problematic. We were able to incorporate these effects by making innovative use of existing and new secondary data sets. The political influence variables include the degree of political competition in a county, per capita federal grants, income inequality and ethnic polarization, and the ratio of current local government expenditure to total expenditure in a county.

Our results show that greater political competition in a county is associated with lower poverty rates. Political competition is measured as the absolute value of the deviation between local and national shares of votes received by the Democratic presidential candidate; it is therefore not a measure of voter participation, which could itself depend on poverty rates. Instead, political competition measures the degree to which a candidate faces competition in the election from a candidate representing the other party.

Social capital levels, measured in the form of civic participation and presence of membership organizations (including social and clubs as well as bowling alleys), are unequivocally and positively associated with lower poverty rates and greater reductions in poverty over the decade. Two other key findings include the fact that self-employment is associated with lower poverty rates, while the presence of Big-box retailers is associated with higher poverty rates when we include all US counties (this effect is not statistically significant when only rural counties are included). This latter finding has profound implications for public policy, but the causal paths are not fully understood.

One implication of these results is that certain communities – those with low levels of political competition – will not be able to reduce poverty on their own, even with the injection of external resources. Our analytical framework and data allow us to identify these specific counties, as well as the degree of vulnerability of all counties to the different causes of enduring poverty.

Introduction

Few problems have proven more intractable for social scientists and policymakers than that of poverty. Although the overall family poverty rate declined slightly between 1989 and 1999, poverty persists in many areas. Geographic concentration of poverty remains a major aspect of the poverty problem. A total of 566 counties (18 %) had family poverty rates¹ in excess of 15 percent in 1999 according to the US Census Bureau, following the unprecedented national growth of the 1990s. Most (510) of these high-poverty counties are non-metropolitan (rural),² and many have been persistently poor since at least the 1960s. Although public attention has focused mainly on suburban or urban areas, and their inner city neighborhoods, the data show that poverty is more persistent in rural than in urban areas, and it may also be more severe in those areas. The rural South had the highest shares of families living under the poverty line in 1999 while metro counties in the Great Plains and Great Lakes regions reported the lowest shares.

This study contributes to basic knowledge of the structural determinants of poverty by analyzing an expanded set of determinants of poverty, namely factors related to social capital and political influence. Evidence is mounting that the level of social capital influences the path of development in communities. In particular, Robert Putnam argues that the same factors that he found to contribute to civic engagement and high levels of social capital also foster economic and community development. Recent case study research suggests that some community leaders may deliberately retard local economic development to maintain their position of power, and promote only the well-being of those who are aligned with them politically or otherwise (Duncan 1999). Duncan contends that poverty is inseparable from class and race relations in a community. Other researchers have argued that income and ethnic polarization in a society may impede economic progress (Alesina et al. 1999; Ngarambe et al. 1998; Alesina and Rodrik 1996). New data sets, and creative use of existing data sets, make it possible to measure these county-wide social and political factors that have previously been excluded from studies of poverty, or included only anecdotally, and to quantify the complete set of forces determining poverty within counties.

It is well-known that poverty in the US occurs in clusters or geographic pockets. Counties in Appalachia, the Mississippi Delta, Rio Grande Valley, and the southern “black belt,” for example, had above-average poverty rates in 1990 (Friedman and Lichter 1998). Yet prior research fails to account for the statistical implications of this clustering. If this bias is ignored, econometric results may be incorrect and produce policy recommendations that are counterproductive. We use spatial data analysis methods in this study to explore the spatial clustering of poverty, and spatial econometric methods to incorporate the spatial bias formally into the econometric models.

¹ Although the poverty rate is often criticized as arbitrary, it is widely used in the poverty literature, and it is used to define eligibility for public assistance programs such as food stamps.

² We use *non-metro* and *rural* interchangeably in the text to refer to counties that have rural-urban continuum codes 4 through 9 (ERS).

Conceptual Framework and Previous Literature

The traditional conceptualization and measurement of poverty by economists has focused mainly on income and employment growth. Economists have argued since the 1950s that poorer regions should grow more rapidly than richer regions because diminishing returns to physical capital would cause more-advanced regions to grow more slowly than less advanced ones. However, the persistence, and even growth of the gap between rich and poor areas contradicts this argument. It has become clear that while economic and demographic factors explain a large amount of variation in poverty across counties (e.g., Levernier et al. 2000), they alone are not sufficient to explain, let alone reduce poverty. While scholars generally agree that raising educational attainment levels is one means of moving people out of poverty (see Jensen and McLaughlin, 1995), for example, investments in human capital do not occur automatically if other complementary factors are not also in place.

Sociological research presents two broad sets of theories to explain poverty: one stresses culture, the other structural or external causes (Albrecht et al., 2000 and Cotter, 2002 provide an overview). Culture-based explanations are centered on the argument that people are poor for reasons of their own making. Structural causes are those that are beyond the control of the individuals living in poverty. One major complaint is that economists have neglected the role of social and institutional structure in the process of economic development (Rural Sociological Society (RSS) Task Force on Persistent Rural Poverty 1993; Robinson 2000). Writers in the sociological, political science and regional science literatures argue that certain community attributes are empirical correlates of successful communities (Batten 1993; Glahe and Vorhies 1989; Granato, Inglehart, and Leblang 1996; Green et al. 1990; McDowell 1995; Robinson 2000; RSS Task Force on Persistent Rural Poverty 1993; Rupasingha et al. 1999; Rupasingha et al. 2002).

This literature suggests that many factors influence the level of community and economic development of a place. Farmer et al. (1989), for example, view poverty as a condition of the local social structure. They write that “income is only one of the salient parameters of a complex latent concept of poverty” (p. 492). Lloyd and Wilkinson (1985) found that community actions, in the form of concerted efforts to achieve common local goals, and solidarity have historically influenced manufacturing development in rural Pennsylvania. Duncan (1999) points out that poverty persists when communities lack civic participation and are rigidly divided by class and race. The idea that institutions matter for economic development has received attention in the economics literature as well. Cole et al. (1992) write that “the interaction between the organization of a society and its economic performance was once considered perhaps the fundamental question of political economy” (p. 1095). Abramovitz and David (1996) maintain that the attributes and qualities of people and organizations which originate from social and political institutions influence the responses of people to economic prospects.

The concept of social capital gained prominence with the much-publicized work of Putnam (1993; also see Coleman, 1988; Fukuyama 1995). The social capital literature emphasizes indicators of trust and civic participation. More effective local civic organizations, or higher levels of social capital, create economic development options that markets and political institutions alone cannot provide (Galston and Baehler 1995). Flora et al. (1997) found that social capital is associated with successful collective development action in the non-metropolitan US, while

Temple and Johnson (1998) and others found that various social capital indices perform well in predicting economic growth across countries. Using social capital indicators from the World Values Survey, Knack and Keefer (1997) determined that trust and civic norms are stronger in nations with higher and more equal incomes. Narayan and Prichett (1999) found for a sample of Tanzanian villages that membership levels in various associations were positively related with income. Helliwell and Putnam (1995) found significant evidence that per capita GDP convergence is faster, and equilibrium levels of income are higher in regions with higher levels of social capital. Rupasingha, Goetz and Freshwater (2000; 2002) examined the independent effect of social capital on economic growth using U.S. county-level data and found that social capital has a significant positive effect on the rate of per capita income growth.

Another strand of the growth literature focuses on the impact of ethnic diversity or heterogeneity on economic outcomes. The RSS Task Force on Persistent Rural Poverty (1993) pointed out that minorities “have endured the most intense forms of economic deprivation and its consequences” (p. 173). Slack and Jensen (2002) find minorities are positively associated with underemployment in the nonmetropolitan USA. Easterly and Levine (1997, p. 1204) argue that “[e]thnic diversity may increase polarization and thereby impede agreement about the provision of public goods and create positive incentives for growth reducing policies.” As a result, economic development is stifled. Easterly and Levine show that ethnic diversity helps to explain cross-country differences in public policies and other economic indicators. They seek a better understanding of cross-country differences by examining the direct effect of ethnic diversity on economic growth, and by evaluating the indirect effect of ethnic diversity on public policy choices that in turn influence long-run growth rates. Indirectly, ethnic diversity encourages poor policies, poor education, inadequate infrastructure and, consequently, it discourages economic development. Similarly, Alesina et al. (1999) maintain that the provision of most public goods, such as education, roads, libraries, and sewer systems is inversely related to ethnic fragmentation in localities.

Some authors argue that income inequality increases income growth rates, while others claim the opposite. The hypothesized effect depends upon the assumptions made about the nature of the society. Inequality is typically seen as beneficial in those societies where it allows resources to be concentrated in the hands of those who invest in activities that stimulate growth. This is the assumption of standard growth theory (Aghion et al. 1999, pp. 1620-1621). Li and Zou (1998) find that income inequality has a positive relationship with per capita income growth, while Barro (1999) shows that inequality has a negative relationship with growth in poor countries, but a positive relationship in rich countries. Conversely, in economies with high levels of inequality the political process may lead to the implementation of income redistribution policies, which in turn hamper economic growth because of distortions (Alesina and Rodrik 1996). Barro (1999) argues that transfer payments and the associated tax financing distort economic decisions, and a greater amount of redistribution creates more distortions and tends to reduce investment (Barro 1999, p. 3). Kuznets (1955) first synthesized these conflicting theories into a model that suggests that inequality may speed growth in the early stages of development but slow it later on. This leads to an inverted U-shaped relationship between income inequality and per capita GDP. Aghion et al. (1999) recently showed that inequality may be harmful at all stages of development, if capital market imperfections are significant. Ngaramb , Goetz and Debertin (1998) find that more rapid increases in inequality were associated with a reduced income growth rate in the

1970s, but that the opposite was true in the 1980s. Rupasingha et al. (2002) find that income inequality has a negative relationship with per capita income growth in US counties.

Duncan (1999) demonstrated using rural case studies that subtle factors and processes are at work within communities according to which individuals in positions of power deliberately hold back other members of their communities. This is illustrated anecdotally in the following quote from a rural Pennsylvania newspaper (*The Daily News*, Aug. 26, 2000, p. 1):

Local residents say poor roads and small businesses' fear of large commercial chains have greatly stagnated Huntingdon County's economic development. ... A [resident] said local merchants' fear of ... competition has impacted the county's growth and variety. "Anytime someone wants to come in here, [local merchants] complain that we don't have the support facilities for bigger and better business. They're afraid they'd lose what little business they get."

The fact that economic development can hurt existing businesses by driving up local wages or reducing prices has long been recognized, but has for the most part not been confirmed by careful and rigorous study. At first glance the subtle forces identified by Duncan may appear to be impossible to measure empirically at the county-level. However, on further reflection, it is clear that the social capital network in place in a community, and the relative power of local governments, are critical in determining whether these "political" factors are able to come into play.

The influence of political characteristics of countries or localities on economic well-being has received considerable attention in the growth and development literature (Adelman and Morris 1965; Baron 1994; Frey and Schneider 1978; Rauch 1995; Grossman and Helpman 1999; Keefer and Knack 1997; LaFerrara and Bates 2001; and Levitt and Poterba 1999). Adelman and Morris (1965) listed "political" variables thought to affect economic development in the developing world. Virtually all of these studies are based on comparisons of nations (i.e., cross-country studies), with different political systems. We hypothesize that many of these variables, such as degree of centralization of political power, degree of commitment of leadership to economic development, extent of government participation in economic activity, and strength of the labor movement also play a significant role in poverty alleviation or perpetuation in rural America.

Prior studies of distributive politics use state-level data and focus, for example, on the geographic allocation of federal dollars. Congressional representation has been linked to the distribution of government-controlled economic benefits (Gilligan and Matsusaka 1995, 2000; Levitt and Poterba 1999; Matsusaka 1995). This strand of literature contends that seniority and membership on house committee, as well as per capita senatorial representation, and political competition between parties are positively associated with federal spending across states. Levitt and Poterba (1999) find that states in which two major political parties are competitive experienced faster income growth than states with less competition. Atlas et al. (1995) find that policy outcomes are tilted because political parties give in to the needs of special interests groups. Most of these studies look at federal spending or employment data over time or across states as policy indicators. Roberts (1990) examines the theoretical and empirical relationship between committee seniority and distributive politics using changes in securities prices in response to political events (e.g., Washington State Senator Jackson's death).

Rauch (1995) argues that elected officials' desire to stay in power may lead them to allocate available public funds to the delivery of current local consumption services instead of using them for long-term infrastructure development or investments. In this manner, elected officials gain currency with local voters but fail to address long-term poverty problems.

The regional variation of poverty has been the subject of several studies but as far as we know, none formally incorporates spatial effects in the estimated models. Beale (1993, in Nord, 1998, p. 330) identified four regions that are clustered in terms of persistent poverty: (1) areas of black poverty in the heart of the old agricultural South, (2) areas of high Hispanic poverty in the Rio Grande Valley and High Plains of the Central Southwest, (3) areas of Native American Poverty in the Southwest, and (4) areas of high White poverty in the Appalachian Highlands and the Ozark-Ouachita Plateau. Triest (1997) attributed much of the regional variation in poverty rates to the differences in the distribution of potential family earnings. More recently, Levernier et al. (2000) explore potential explanations for the regional variation in poverty across US counties. Studies that ignore spatial dependence bias can produce biased results (coefficient estimates) and lead to ineffective – and possibly counterproductive – recommendations for policies targeted at poverty alleviation.

Based on above conceptual framework, we formulate as the major hypotheses of this study that economic, social, political and other institutional factors, along with individual-level factors, independently affect poverty rates in the US. A general conceptual model for a given time period is:

$$(1) \quad \text{POV} = f(\mathbf{EF}, \mathbf{IF}, \mathbf{SF}, \mathbf{PF})$$

where POV is the family poverty rate, **EF** is a vector of economic factors affecting poverty, **IF** individual-level factors, **SF** social, and **PF** “political” factors. We estimate the above model alternatively using levels of and rates of change in family poverty rates as dependent variables.

Empirical Model and Selection of Variables

Based on the conceptual model we estimate a regression model of the following form:

$$(2) \quad \text{POV} = a + b\mathbf{EF} + c\mathbf{IF} + d\mathbf{SF} + e\mathbf{PF} + \varepsilon$$

where letters *a* through *e* denote parameters or parameter vectors to be estimated, and ε is an error term. We include all counties in the contiguous United States in the analysis, and conduct separate analyses using metro (urban-rural continuum codes 0-3) and non-metro counties (urban-rural continuum codes 4-9) to identify differences between rural and urban counties. We also estimate a separate model for counties in the rural South only, since this region has experienced some of the nation's highest poverty rates over time. This allows us to investigate whether the factors that affect poverty nationally also affect poverty in the rural south. The family poverty rate used here is from the 2000 Census and is measured for 1999. Except where noted, the explanatory variables are measured in 1990 as starting conditions for the later year (1999) in which the poverty rate is measured (to reduce endogeneity bias).

Below we list the different variables hypothesized to influence poverty rates and their expected relationships to poverty. The definitions of all variables and their summary statistics are given in Tables 2 and 3 respectively. To some extent the distinction between economic, individual, social and political factors is arbitrary. For example, human capital has been used by economists as an aggregate macroeconomic “cause” of growth and by sociologists as an individual-level factor to “explain” poverty; here we classify this variable among the individual-level explanations of poverty.

Economic Factors [EF]

A sizeable literature exists on economic and demographic (individual) determinants of poverty, and because of space limitations we only outline the regressors. Additional details can be found in Cotter, 2002; Albrecht, 2000; Levernier et al. 2000; or Madden, 1996. Conventional wisdom holds that stronger labor demand reduces poverty. Following Levernier et al. (2000) we use employment growth over a two year period in a the county to measure the effects of labor market performance on the poverty rate, and hypothesize that higher growth rates reduce poverty. *Labor force participation rates* have also been linked to county poverty rates (Levernier et al. 2000). Other studies have used the *total labor force* to measure urban spillover effects and availability of local inputs (Henry and Drabenstott 1996). We also include *labor force participation by gender* to test for their effects on poverty rates.

Albrecht et al. (2000) argue that the *changing industrial structure* of rural America has led to increases in poverty in some communities. This is mainly due to the adjustment costs facing workers forced to change between sectors (see also Levernier et al. 2000). This variable is calculated as a dissimilarity index based on the sum of absolute changes in the share of one-digit industry employment between two periods, divided by two (Allen and Freeman, 1995, as cited in Levernier et al. 2000). In addition, we use a static measure to reflect the degree of *specialization of the county by industry*. Another variable that has not been used in previous studies is the number of non-farm proprietors in a locality. This variable is used to measure the relationship between poverty and the availability of a pool of investors in a locality. Historically, the *entrepreneurial class* was seen as a driving force in the growth of business enterprise in a community. Attraction of big box retailers into a locality has been touted as an economic development strategy by some observers. Others have argued that jobs created by big box retailers are mostly low-paying jobs that do not allow families to escape from poverty, and that these nationally-owned establishments do not reinvest locally the profits they extract from communities. Therefore the relationship between big box retailers and poverty is indeterminate *a priori*. We use the number of retail stores that employ 20 or more workers per 10,000 people in the model to measure Big boxes. These stores include general merchandise stores, department stores, discount and mass merchandising stores, and warehouse clubs and superstores.³

We also include dummy variables based on urban-rural continuum codes to measure *urban influence* on poverty. These are: (1) central counties of metro areas of 1 million population or more, (2) fringe counties of metro areas of 1 million population or more, (3) counties in metro areas of 250,000 to 1 million population, and (4) counties in metro areas of fewer than 250,000 population. Non-metro counties are the excluded category.

³ The specific SIC codes are 5210, 5230, 5250, 5260, 5310, 5390, 5700, 5910, 5941, 5942, 5943, and 5949.

Individual-level Factors [IF]

Much has been written about the contribution of *human capital* to poverty alleviation and economic growth. Varying education and training levels among localities result in differing opportunities for economic advancement. Raising human capital levels is clearly one means of moving people out of poverty and investments in human capital are frequently encouraged at the policy prescription level. A change in the economic structure of a community from a primary industry to a service- or a high-tech industry changes requirements in the educational and training sphere. Communities with more low-skilled workers in general are more likely to experience higher rates of poverty. We use educational attainment to measure the quality of human capital. Poverty rates are also higher for female-headed families (RSS Task Force on Persistent Rural Poverty 1993; Farmer et al. 1985; Levernier et al 2000), for most minority groups and families with higher numbers of children (Levernier et al, 2000). We incorporate these variables,⁴ several age cohort variables and percent of foreign-born population in county to test whether they have a relationship with county poverty rates. Foreign-born population has not been used in previous poverty studies of this nature. Another important variable is county-level mobility. We include the percent of people who stayed in the same county during the past five years as a measure of county-level mobility (or immobility). Migration is known to concentrate poverty because those who are not poor tend to leave if a community falls into economic decline, and those who are poor tend to migrate to persistent-poverty counties (Nord, 1998).

Social (Capital) Factors [SF]

Social capital consists of multiple components and demands a broad measurement strategy; it is a theoretical construct that is not directly observable and therefore not measurable. However, social capital is a structural condition expected to influence the covariance of a set of observed variables or indicators. This premise allows the development of a measurement model that employs proxies of social capital. We develop several proxies used in the previous literature to create a comprehensive index of social capital.

For example, associational density has been used previously as a proxy for social capital (Putnam 1993; Narayan and Prichett 1996; Rupasingha, Goetz, and Freshwater 2000, 2002). Using County Business Patterns (CBP) data compiled by the Census Bureau we are able to identify an extensive and comprehensive set of variables representing membership establishments in each county on a per capita basis: *a.* bowling centers; *b.* public golf courses; *c.* membership sports and recreation clubs; *d.* fitness centers; *e.* civic and social associations; *f.* religious organizations; *g.* labor organizations; *h.* business associations; *i.* professional organizations; and *j.* political organizations. Several additional measures along with the associational density variables are used to create a separate index of social capital. These other measures are percent of eligible voters who voted in presidential elections (Alesina and La Ferrara, 2000), the county-level response rate to the Census Bureau's decennial census (Knack, 2002), and the number of tax-exempt non-profit organizations from the National Center for Charitable Statistics. We extract principal components of these four variables, and retain the first principal component (which explained about 46% of variation) as our index of social capital.

⁴ Some of these variables are highly correlated and could not be used in the analysis. Details of these correlations are given in the estimation section of the paper.

Political factors [PF]

The interrelationship between political characteristics of communities and poverty rates has not received much attention in the poverty literature in the US, at least not in statistical analyses covering all counties. According to Duncan (1999), not all members of a community are necessarily interested in reducing poverty. Greater inequality in a community helps maintain the *status quo* that benefits the wealthy and powerful class. We use the ratio of mean household income to median household income (see Alesina et al. 1999; Persson and Tabellini 1994) to measure income inequality.

Ethnic diversity may increase polarization, thereby impeding agreement about the provision of public goods, and creating incentives to implement policies that stifle economic growth and perpetuate poverty (Alesina et al. 1999). We use the ethnic fractionalization index as a measure of ethnic diversity in counties (see Alesina et al., 1999). It measures the probability that two randomly drawn people from a county belong to different ethnic groups and is calculated as:

$$(3) \quad Ethnic = 1 - \sum_i (Race_i)^2$$

where $Race_i$ denotes the share of population self-identified as of race $i \in I = \{\text{White, Black, Asian and Pacific Islander, American Indian, and Other}\}$. We also use the percent of different minority groups in a community as a supplementary measure of race.

Another political variable is the extent of the *political leadership's commitment* to poverty reduction and economic development. Lobbying for federal funding, as well as state and federal jobs, are measures of commitment explored in this study using readily available county-level data over time. We use per capita federal grants (designed as an injection of federal funds from the outside), which is hypothesized to be negatively associated with poverty. We employ the method used by Levitt and Poterba (1999) to measure *political competition* in a county. This involves constructing the absolute value difference between the county vote for the Democratic presidential candidate and the average for that candidate in national elections over time. Counties with vote outcomes equal to the national average are more highly competitive politically. The ratio of various maintenance expenditures (police and fire protection, health, parks and recreation, utilities, filling potholes, etc.) to total local government expenditures (available in the Census of Governments, Bureau of Census, data set) is used to measure the preference of elected official over whether to stay in power or to serve the long-term interest of the community. A positive association of this variable with poverty is expected. The Census of Governments divides these expenditures into the categories of current operation, construction, and other capital outlay, making it feasible to sort out maintenance expenditures from capital investments.

Descriptive Evidence

Table 1 presents changes in poverty rates over the last three decades. These changes are presented separately for various regions and their rural and urban counties. The family poverty rate for all counties in the US was 11 percent in 1999, the lowest since 1979. The overall poverty rate has declined from 1989 to 1999 in all regions and their rural and urban counties, except

for the metro counties in the Mideast and Farwest regions. These two sub-regions have experienced slight increases over past decade. Although, rural poverty rates have in general improved over time, rural areas still lag behind their urban counterparts. In 1999, the metro poverty rate was around 8 percent, compared with a nonmetro rate of about 12 percent. While rural poverty is higher than metro poverty in all regions, the difference is most noticeable in the rural South and rural West. The historical fact that the rural southeast and southwest have been marked by high poverty rates compared to the regions in the rest of the country has not changed over the last three decades. The nonmetro (adjacent and nonadjacent) southeast and southwest counties had the highest poverty rates in the nation over these three decades. The poverty rate for nonmetro counties in the Rocky Mountain and Farwest regions, at around 10%, was lower than that of the nonmetro South. Poverty rates in New England, the Mideast, and Great Lakes regions are the lowest and have remained that way for the last three decades. Also, differences in the poverty rate between metro and nonmetro counties in these regions are less pronounced.

Definitions of variables used in the analysis are given in Table 2 and their descriptive statistics are given in Table 3. Column 1 of Table 3 presents means and standard deviations of variables for all counties while columns 2 and 3 present these statistics for metro and nonmetro counties. A comparison of the columns shows that, relative to nonmetro counties, metro counties had higher employment growth between 1988 and 1990, a higher employment rate in 1990, higher female labor force participation, higher population shares between 18 and 24 years of age, more high school and college graduates, larger shares of foreign-born population, more ethnic diversity and slightly more local political competition (as measured here). Compared to nonmetro counties, metro counties also had higher shares of jobs in trade, transportation, service, and finance, insurance, and real estate sectors.

On the other hand, a number of other variables had higher means for non-metro counties compared to metro counties. The variable that measures the structural changes in a county between 1988 and 1990, the ISC, was higher in non-metro counties, indicating that these counties have undergone more structural changes than their metro counterparts. Non-metropolitan counties also had higher employment shares in the agricultural and goods-producing sectors, more non-farm proprietor shares, and higher proportions of younger and older populations. Fewer people in non-metro counties decided to move during 1985-90 compared to metro counties. Compared to metro counties, non-metro counties also were wealthier in social capital and received more federal grants per capita. Local governments in non-metro counties spent more on consumption activities compared to infrastructure development.

We compare the South in terms of our explanatory variables compared to all non-metro counties in the nation. Non-metro counties in the South had less job growth between 1988 and 1990, slightly higher unemployment rates, smaller female labor force participation rates, slower structural changes in industry, lower shares of high school and college graduates, very low stocks of social capital, and slightly lower self-employment rates. On the other hand, non-metro South counties had proportionally more manufacturing jobs, larger shares of people between 18 and 24 years old, more foreign-born people, and these counties also received more money per capita in the form of federal grants.

Estimation Issues

Endogeneity

Endogeneity is a potential concern that we address by using starting or initial conditions at a point in time (around 1990, given the availability of data on exogenous variables in only certain years), that precedes the year in which the poverty rate is calculated (1999). This lag is one key difference between our work and that of Levernier et al. (2000). In addition, we created instruments from two auxiliary regressions for two particularly sensitive variables, namely income inequality and mobility. Based on previous literature (Rupasingha and Goetz, 2003; Ritsilä and Ovaskainen, 2001; Meyer et al., 2001; Saltz, 1998; Mueser and Graves, 1995), a migration (mobility) equation was constructed using the cancer risk rate, whether or not the location has a superfund site, natural and other amenities (including the incidence of serious crime), population density, whether the county is urban or rural, expected income, age, local taxes and expenditures, and industrial structure as independent variables. We employ empirical equations used in Braun (1988) and Bishop et al. (1992) to obtain instruments for income inequality, such that inequality is determined by mean family income, per capita health expenditure, years of schooling, per capita educational expenditure, percent of labor in manufacturing, and population density.

Spatial Effects

The distribution of poverty in 1999 across counties is shown in Figure 1. A high concentration of poverty occurs in Appalachia, the southern black belt, the Mississippi Delta, Native American areas in the Southwest, *colonias* along the US-Mexico border region, and a cluster of upper Midwest counties. Figure 1 also reveals that poverty is not independently distributed over space. This spatial association can be quantified using a global Moran's I , which measures similarity or dissimilarity in a variable across neighboring spatial units. A higher value of the statistic indicates a greater degree of positive correlation in the variable over the study area, and hence greater clustering of values by geographical unit. Moran's I is calculated as (Anselin 1992, p. 132):

$$(4) \quad I = (n/\sum_i \sum_j w_{ij}) ((\sum_i \sum_j w_{ij}(y_i - \mu)(y_j - \mu))/\sum_i (y_i - \mu)^2)$$

where n is the number of observations, w_{ij} is the element in the spatial weight matrix corresponding to spatial units i, j , y_i and y_j are observations for respective locations and μ is the mean of y . We calculate I for poverty rates across all continental US counties, using a contiguity-based spatial weights matrix and find that these variables exhibit statistically significant clustering. The Moran's I value of 0.63 (see Figure 2) is considerably higher than the theoretical mean of zero for the case of an absence of spatial dependence.

As a global statistic, Moran's I captures the existence of a homogeneous pattern of spatial association over the entire study area (Anselin, 1995). It is less helpful when clusters are unevenly distributed over space, as in the case of varying levels of autocorrelation across regions of the study area; this non-stationarity can arise in the form of local "hot spots." To detect such spatial instabilities, local indicators of spatial association (LISA) are more appropriate (Figure 3). Anselin's (1995) "Moran scatter plot" plots Wy against y , where y is the variable of interest.

This measure permits a more disaggregated view of the type of spatial autocorrelation that exists in the data.

Figure 2 shows the nature of the spatial clustering of poverty using the Moran scatterplot suggested by Anselin (1995). The quadrants of a scatter plot correspond to four types of local spatial association between a county and its neighbors:⁵ (a) *high autocorrelation* – a county with a high poverty rate has neighboring counties with high poverty rates; (b) *low autocorrelation* – a county with low poverty is next to counties with low poverty; and (c) *negative autocorrelation* – a county with a low poverty rate is surrounded by counties with high poverty rates, or a county with a high poverty rate is surrounded by counties with low poverty rates.

The apparent clustering of poverty rates indicates that the data are not randomly distributed, but instead follow a systematic pattern. The spatial clustering of variables, and the possibility of omitted variables that relate to the connectivity of neighboring localities, raise model specification issues. In this section we review spatial econometric methods that account for the observed clustering of poverty rates. We employ two alternative specifications to correct for spatial dependence. One is the spatial auto-regressive model. This specification is relevant when the spatial dependence works through a spatial lag of the dependent variable:

$$(5) \quad \begin{aligned} POV &= \rho W(POV) + X\beta + \varepsilon \\ \varepsilon &\sim N(0, \sigma^2 I_n), \end{aligned}$$

where POV denotes an $n \times 1$ vector of the dependent variable, X represents an $n \times k$ matrix containing the determinants of poverty (**EF**, **SF**, **PF**, **IF**), and W is a spatial weights as explained above. Scalar ρ is a spatial autoregressive parameter and β denotes the k parameters to be estimated for the explanatory variables. The other specification is the spatial error model. This specification is relevant when the spatial dependence works through the disturbance term:

$$(6) \quad \begin{aligned} POV &= X\beta + u \\ u &= \lambda Wu + \varepsilon \\ \varepsilon &\sim N(0, \sigma^2 I_n) \end{aligned}$$

where λ is a scalar spatial error coefficient.

If evidence exists that spatial dependence is present in both forms, through both a spatial lag and error terms, the general spatial model (SAC) is appropriate. The SAC model includes both the spatial lag term as well as the spatial error structure:

$$(7) \quad \begin{aligned} POV &= \rho W(POV) + X\beta + u \\ u &= \lambda Wu + \varepsilon \\ \varepsilon &\sim N(0, \sigma^2 I_n) \end{aligned}$$

LeSage (1999) suggests that we rely on this model if there is evidence of spatial dependence in the error structure from a SAR estimation.

⁵ Neighbors are typically defined in terms of their physical proximity to the local geographic unit.

Spatial data analysis requires calculating $n \times n$ relations among n observations and it employs determinants, eigenvalues and matrix inverses. Until fairly recently, it was impossible to carry out these calculations using data on all 3,047 contiguous US counties. Recent developments have led to procedures that allow corrections for spatial dependence bias even in large models (Pace and Barry 1997; LeSage 1999). In particular, LeSage's Spatial Econometrics Toolbox for MATLAB™ allows such large spatial models to be estimated. The spatial contiguity matrix is set up using each county's latitude and longitude coordinates. Finally, Figures 4 and 5 show poverty rates in 1979 and 1989, while Figure 6 shows the change in the poverty rate over the last decade.

Results

OLS Results

Table 3 presents ordinary least squares (OLS) estimates of equation (2) corrected for heteroskedasticity.⁶ We estimated a base model for all counties patterned after previous studies of the determinants of US poverty rates (Albrecht et al., 2000; Levenier et al., 2000; Madden, 1996), excluding the new variables proposed in the present study. We were unable to use some of the variables employed in previous studies because of multicollinearity (initial estimations revealed parameter instability when these correlated variables were included in the model). In particular, female and male labor force participation rates were highly correlated (0.71), and we elected to keep only female labor force participation rate. Average child per family was correlated (0.91) with the age group 0-17, and we retained the latter in the model with other age groups for comparison purposes. The percent of African Americans was correlated with female-headed households shares (0.81) and both of these variables were correlated with the ethnic heterogeneity index (0.78 and 0.74, respectively) included in our expanded model. Because of our interest in the ethnicity index, we excluded both percent of blacks and percent of female-headed households from the model. The effects of these two variables on poverty rates are well established in the literature.

Column 1 of Table 3 shows the results of the base model using all counties. Negative and significant coefficients for URBAN902 and URBAN903 show that these counties (fringe counties of metro areas of one million population or more and counties in metro areas of 250,000 to one million population) have significantly lower poverty rates than their non-metro counterparts. The effect of 1988-90 employment growth is not statistically significant in this specification. The coefficient on the employment rate is negative and highly significant, indicating that employment reduces poverty rates, all else equal. As also found by Levenier et al. (2000), the effect of industrial structural change is positive and significant, confirming that short-term shocks destabilize local job markets. Female labor force participation has a negative and statistically significant effect. Most of the industrial composition variables have negative effects on

⁶ Following Levenier et al. (2000), all models in this study, including the spatial models, control for state fixed-effects to account for missing state-specific variables.

poverty compared to the excluded category of public administration.⁷ Service sector employment shares do not have a statistically significant effect on poverty rates in this specification.

Larger shares of children (aged 0 to 17) and residents between the ages of 18 and 24 years are associated with higher poverty rates, as are shares of non-African-American minorities. As expected, both educational attainment variables (high school plus some college, and 4 or more years of college) are associated with significantly lower poverty rates, *ceteris paribus*. Prospects for reducing poverty by raising educational attainment differ significantly between high school plus some college, and a college degree or more, with high school plus some college exerting a stronger effect on the margin (note that virtually all of those with college degrees also hold a high school degree). Furthermore, a high school degree or more reduces family poverty rates to a greater degree in metro than in non-metro areas, and the same is true *a fortiori* for a college degree or more. This also means that the additional effect of a high school degree plus some college in terms of reducing poverty rates is considerably greater in metro than in non-metro areas. The effect of geographic mobility is positive and significant, indicating that counties with more long-term or permanent residents also have more poverty. Alternatively, mobility or out-migration in pursuit of opportunities elsewhere, is one path to reducing poverty.

Next we turn to the main focus of this study, which is the expanded regression specification. This specification includes foreign-born population shares, ethnic heterogeneity, income inequality, per capita federal grants, political competition, social capital, big box retailers per 10,000 capita, the ratio of current (consumption) expenditure to total local expenditure, and the percent of non-farm proprietors. We again estimate one model for all 3,047 counties, and separate regressions for metro and non-metro counties as well as non-metro counties in the South (column 2-5, Table 3). The main results reported in the base model for all counties remain largely unchanged and robust to the inclusion of social and political variables for all of the estimates, with the exception of the industrial structural change variable and the shares of agricultural and trade sector employment variables. In the expanded model, these variables are no longer statistically different from zero. The coefficient on the share of service sector employment, which was not statistically significant in the base model, is significant and positive in the expanded model.

The *F*-statistic of 228, significant at the zero probability level, confirms the significance and relevance of the new variables entered as a vector in a model of family poverty rates. Among the new variables, foreign-born population, ethnic heterogeneity, income inequality, per capita federal grants, political competition, social capital and percent of non-farm proprietors are each statistically significant and have the expected association with county-level family poverty rates, with the exception of per capita federal grants. This variable has an unexpected positive sign. Contrary to expectation, higher federal grant funding per capita tends to exacerbate rather than ameliorate poverty rates in a locality.⁸ Our measures of ethnic inequality and economic

⁷ Levenier et al. (2000) found a positive association between the share of agriculture sector employment in 1990 and family poverty rate in 1989.

⁸ This suggests the possibility of reverse causality – that federal grants are directed more to poorer places. However, another set of regressions that uses the change in poverty rates between 1989 and 1999 as the dependent variable yields the same result, even when we control for initial poverty rates (in the same year as that in which federal grants are measured).

inequality (operationalized as income inequality and entered as an instrument) exhibit positive and highly significant effects, indicating that ethnic and income polarization hampers poverty reduction efforts. The expanded equation includes a political competition variable that is based on the Democratic share of local votes in the 1988 presidential election relative to the nation's. As indicated earlier, higher levels of this variable (more deviation from national preferences) mean lower levels of political competition. This variable is statistically significant and positive, indicating that the lack of political competition among parties in a locality exacerbates poverty. Our results also confirm a common hypothesis in the literature, that social capital reduces assorted social and economic problems. The coefficient on the social capital index is negative and significant, implying that counties rich in social capital have lower poverty rates, all else equal. The per capita "big boxes" variable is not statistically significant in this formulation.

Column 3 of Table 3 shows results of the expanded model for metro counties. Some of the statistically significant variables in the full model are no longer significant in the metro model. These are industry share variables for agriculture, transportation, and the finance and real estate sectors, and social capital. The effect of non-African American minority shares, which was positive in the full model, is reversed in the metro model (associated with lower poverty rates). In contrast, higher foreign-born population shares are linked to higher poverty rates in metro areas. The industry structural change variable, which had a positive but only weakly significant effect in the full model, had a negative and highly significant in the metro model, indicating that these short term industry-level changes are beneficial to metro counties in terms of reducing poverty rates.

Results of the expanded non-metro specification are remarkably similar to those of the full model, except that college-age (age between 18 and 24) and foreign-born population shares are not statistically significant in the non-metro model (column 4, Table 3). There are several notable differences in the results for the rural South and rural counties taken together. Agricultural jobs and non-black minorities help reduce poverty, but transport sector employment has no effect on poverty in the rural South. While the population shares aged 18 to 24 and 65 years and older were not significant in the non-metro model, they were positive and significant for the rural South. Also, non-farm proprietor shares had no statistical effect on poverty in the rural South.

Spatial Results

LeSage (1999) presents several methods for choosing appropriate specifications of the spatial model. Since the general spatial model (SAC) nests both the spatial lag (SAR) and the spatial error model (SEM), we first estimated the SAC model. If both spatial parameters (ρ and λ) are positive and significant, then the SAC model should be chosen. If only ρ (λ) is positive and significant, then the SAR (the SEM) should be selected as the appropriate spatial model. The SAC estimation for all specifications showed both spatial parameters to be positive and statistically significant, except in the case of the metro specification. The spatial error parameter (λ) in the metro model estimation was not statistically significant and therefore the most appropriate specification for metro areas is the spatial lag model (SAR). The significant spatial parameters further indicate that OLS is not appropriate for modeling poverty data for 1999. The following inference is based on the spatial model estimation, with results reported in Table 4.

The significant spatial parameters have interesting implications. A positive and significant spatial dependence in the dependent variable (poverty rate) indicates that the poverty rate in a particular county is associated with (not independent of) poverty rates in surrounding counties. The value of the spatial autocorrelation coefficient ($\rho = 0.21$ in the model for all counties) indicates that a 10 percentage point increase in the poverty rate in a county results in a 2 percent increase in the poverty rate in a neighboring county. This is strong evidence that spillover effects exist between counties with respect to poverty. The highly significant spatial error coefficients suggest that a random shock in a spatially significant omitted variable that affects poverty in a particular county triggers a change in the poverty rate not only in that county but also in its neighboring counties.

Differences exist in the results obtained for the OLS and spatial models based on all counties. The performance of most variables is enhanced when spatial effects are incorporated. The coefficients that improved from the OLS specification are: 1988-90 employment growth, industrial structural change, agriculture and trade sector employment, and per 10,000 capita big boxes. Growth in employment is positive and statistically significant in the spatial model indicating that employment growth in a county increases poverty rates, perhaps in part due to in-migration⁹, but also due to changes in labor force participation (which we measure here only for females and only for 1990). The spatial model results also show that short-term industrial structural change reduces a localities' ability to lower poverty rates. Contrary to the popular belief that big box retailers such as WalMart and K-Mart stores can help local communities reduce poverty by providing employment opportunities, the results suggest that these types of retailers in fact raise family poverty rates. The coefficient for URBAN02 becomes insignificant with the incorporation of spatial effects.

As is true for the OLS specification, differences arise in the spatially-corrected full model, as well as in the models for metro and non-metro counties. Initial estimation of a general spatial model showed that no spatial error effects are present in metro counties. Non-metro counties exhibited significance in both types of spatial effects. The industrial structural variable was negative and significant in the metro model, indicating that these short-term adjustments lead to lower poverty rates in metro areas; in non-metro areas this variable was positive but only weakly significant (at below the 20 percent level). As in the OLS model, several industry composition variables, namely, agriculture, transportation, trade, and finance and real estate sectors were not significant in the metro model whereas sectors were significant and tended to reduce poverty in non-metro areas. While higher shares of non-African American minorities are associated with lower rates of poverty in metro counties, they are associated with higher poverty rates in non-metro counties. The opposite is true for shares of foreign-born residents. As was observed in the OLS model, social capital is not significant in the metro model, but it is highly significant with a negative effect in the non-metro model. Density of big box retailers has a significant and positive effect on the poverty rate in the metro model, but not in the non-metro model.

A number of differences arise in the non-metro South spatial model compared to non-metro areas in general. As in the full model, the employment growth variable is positive and sta-

⁹ Levenier et al., 2000 point out that the poverty-reducing effects of employment growth are offset by in-migration in response to job opportunities.

tistically significant. Unlike the result for non-metro areas in general, however, the structural change variable in the non-metro South model is negative and significant, indicating that short-term structural change in the industrial sector leads to poverty reduction in non-metro south. Trade sector employment and non-farm proprietor variables have no impact on poverty in the rural South. Also, unlike what is observed in non-metro areas in general, higher shares of foreign-born populations are associated with higher rates of family poverty in the non-metro South.

Social and Political Variables

The major focus of this study was to examine the impacts of social and political variables on poverty in a locality. As mentioned earlier, social capital, race and class relations, and political influence directly affect a community's well-being. And, the impact of these variables has not been formally addressed in previous studies of poverty involving thousands of counties. The statistical analysis shows the relative and independent significance of most of these social and political factors, holding constant the effects of conventional determinants of poverty. The argument made at the beginning of the paper that ethnic and economic polarization is positively associated with poverty is confirmed by the empirical results. The coefficient estimates for ethnic heterogeneity and income inequality are both positive and highly significant in the model for all counties, as well as in the models for the metro, non-metro and rural South counties.

Numerous studies have found a positive association between economic development and social capital. Here we investigated the independent effect of social capital on poverty rates, and find that counties rich in social capital have lower family poverty rates, with the exception of metro areas where the effect of social capital was not statistically distinguishable from zero.

Variables measuring political participation have been tied to the economic performance of communities. We incorporate political competition and per capita federal grants and find both variables to be statistically significant. Our results show that the political competition variable is positive and significant across all the models, so that counties that are politically less competitive (vote outcomes skewed in a direction that are at odds with national trends) also have higher family poverty rates. The initial postulate that federal grants help alleviate poverty is not supported by our results. This variable is positive and highly significant across all models, indicating, in fact, that federal grants exacerbate poverty in communities (the possibility of reverse causality, of course, arises, as discussed above). The ratio of maintenance expenditures (police and fire protection, health, parks and recreation, utilities, filling potholes, etc.) to total local government expenditures (curexp87) is not statistically significant.

Interactions

Important clues about the determinants of poverty can be obtained by interacting right hand side variables in equation (2), especially those variables that had unexpected signs, with other variables. Interaction terms show the effect of different variables on poverty through other important variables. Levenier et al. (2000) examine interactions of employment growth, education and structural change variables with some of the demographic and county-type variables. We carry out several interactions of employment growth, education and structural change variables with our new variables (Table 5).

Panel *a* of Table 5 presents the interactions of employment growth with mobility, ethnic heterogeneity, income inequality, federal grants, political competition, social capital, big box retailers, and consumption expenditure of local governments. The independent effect of employment growth becomes insignificant in the new regression (not shown). However, employment growth has a significant negative effect on poverty rates in counties that are more ethnically diverse, less politically competitive, richer in social capital, and in counties that have larger shares of permanent populations and big box retailers per capita. On the contrary, counties that had more unequal income distributions were unable to reduce poverty rates through employment growth.

The industrial structural change variable was similarly interacted with mobility, ethnic heterogeneity, income inequality, federal grants, political competition, social capital, big box retailers, and consumption expenditure of local governments; results are shown in Panel *b*. The results suggest that structural change helps to lower family poverty levels in counties that have higher ethnic and income polarization, more Big box retailers per capita, and lower federal grant funding.

The interactions of ethnic heterogeneity with both education variables show that counties that are more ethnically diversified, and have higher educational attainment levels, also have lower poverty rates (Panel *c*). This is counter to the general result obtained earlier that ethnic diversity exacerbates poverty. The positive effects of ethnic diversity on poverty outweigh the negative effects of social capital on poverty. Also, higher ethnic diversity is associated with higher poverty rates in counties that have more per capita big box retailers and that receive more federal grants.

Panel *d* of Table 5 presents the interactions of income inequality with education and other social and political variables. As with ethnic polarization, counties that have higher income inequality and higher educational attainment also have lower poverty rates. Local government consumption expenditure failed to exhibit statistical significance in any of the specifications presented thus far. A striking result of this regression is that higher local government consumption expenditures are positively associated with poverty but the interaction effect between this variable and income inequality is negative and statistically significant, signifying that a higher level of income inequality is associated with a lower poverty rate in counties that have higher government consumption expenditures. Income inequality is associated with higher poverty rates in counties that receive more federal grants. Less convincing is the result that income inequality is positively associated with poverty in counties that have higher levels of social capital.

Panel *e* of Table 5 shows the interaction results of federal grants per capita with political competition, social capital and local government consumption expenditure. Earlier findings related to the direction of the effects of several independent variables changed with the new specification. The impact of federal grants on poverty, which was positive and significant in the specification without interactions is now negative (and significant statistically). Government consumption expenditure, which was not significant in the original model, is negative and significant in the new specification. Also, the political competition and social capital variables are no longer significant. As for the interaction variables, federal grants are positively associated

with family poverty rates in counties that are politically less competitive and spend more on consumption items. Most notably, federal grants are effective in reducing poverty rates in counties that have higher levels of social capital, according to these results.

Panel Estimation

We next estimate a panel model for two time periods to control for unobserved heterogeneity and also to investigate inter-temporal changes. With panel data, the sample size is increased, allowing for more robust estimates. A random effects model is used to estimate the panel. The primary reason for using a random effects model is that several variables are time invariant and therefore fixed effects are not appropriate. Random effects estimation also allows for possible correlations of disturbances between two time periods, thus minimizing potential biases in the estimates [Moulton, 1986]. Table 7 presents results of the panel estimation. Social capital and big-box retailer variables have to be removed from the panel estimation because they were unavailable for 1980-90 period.

Most of the results obtained in the cross-section regression for the 1990-99 time-period are confirmed and become even stronger in the panel estimation. For the sake of brevity, only the differences in the results between the one-time period and panel models are discussed here. Several variables that were not statistically significant in the cross-section model became significant in the panel model. They are urban1, urban4, change in employment, and trade sector employment. While service sector employment variable was positive and significant in the cross-section model, it became insignificant in the panel model. The most markedly different result was obtained with regard to self-employment. This variable was negative and highly significant in the cross-section model but became positive and highly significant in the panel model.

Change in Poverty Results

In addition to the poverty levels models, we estimated equations with the change in poverty over the decade as the dependent variable. Summary statistics for these regressors are shown in Table 8, along with definitions of each variable and their data sources (we essentially use the same regressors in the change and levels equations, since we have no prior information to do otherwise). Initial regressions revealed the presence of spatial dependence bias, which we corrected for using techniques described above. Selection of an appropriate spatial model for our data was based on the procedures outlined in Lesage (1999). We first estimated the SAC model and then selected the appropriate model by considering the significance and sign of the spatial parameters. Accordingly, the SEM model was estimated for all counties, non-metro counties only, and rural counties in the South, and the SAR model was estimated for metro counties.

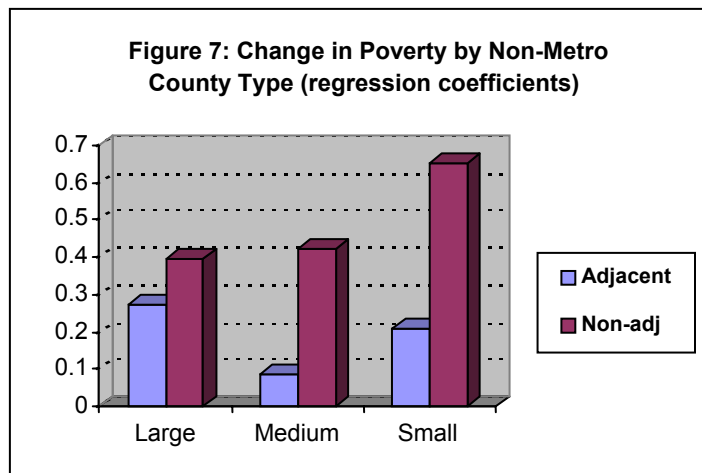
OLS results and results corrected for spatial dependence are shown in Table 9. The average value of the dependent variable (Δpov_i) is -2.36 percentage points. This means that a negative coefficient estimate resulted in a *larger*-than-average reduction in the poverty rate as the value of the regressor increased, while a positive coefficient estimate means that the variable in questions led to a *smaller*-than-average decline in the poverty rate. In other words, higher values of a variable with a positive coefficient estimate had the effect of maintaining poverty in the county at a higher rate than it would have been otherwise. A coefficient estimate that is not dis-

tinguishable from zero indicates that the variable in question neither raised nor lowered the change in the poverty rate relative to the sample average decline of -2.36 percentage points.

Among the economic structural characteristics, coefficient estimates are for the most part statistically significant and have the expected signs. In particular, counties with higher initial rates of poverty and with more initial employment (agglomeration economies), less industrial structural adjustment, fewer jobs in agriculture or services, more jobs in manufacturing or transportation and public utilities, and fewer big boxes per 10,000 experienced faster declines in poverty rates, *ceteris paribus*. The results for the employment shares generally parallel those of previous studies (especially Albrecht et al. 2000).

In terms of the individual-level factors there are, similarly, few surprises in the results. Counties with a larger share of young residents had significantly smaller declines in poverty rates, as did counties with smaller shares of graduates with a high school degree or more (shares of college graduates had no effect), larger shares of non-black minorities, larger shares of residents who were immobile and fewer self-employed workers. The foreign-born population had a statistically significant effect only in the Metro and Rural South equations, where the effect was to reduce the rate of poverty reduction.

Rural areas that are adjacent to a metro area had a clear disadvantage relative to their urban counterparts in terms of reducing poverty rates in the 1990s, and that disadvantage grew as population size fell (see the adjacent figure 7). The graphic starkly illustrates that the economic disadvantage of non-adjacent counties increases as population size falls: each of these coefficient estimates is statistically different from zero, and the larger number for small non-adjacent non-metros shows that poverty rates there declined by the least amount (recall that a larger value means that the poverty rate did not decline as much as the average for all counties).



Finally, we turn to the political influence-type variables. The political competition variable shows a clear impact on poverty rate changes in that greater competition leads unequivocally to greater declines in poverty rates, while no statistically significant effect emerged for consumption spending (political patronage). For federal grants, we have the unexpected result that more spending leads to a smaller decline in the poverty rate, implying that federal spending is counterproductive in terms of poverty reduction efforts. Higher income inequality had a statistically significant effect of reducing the amount of decline in poverty, whereas public consumption spending had no effect statistically. A higher degree of ethnic fractionalization was associated with lower rates of poverty reduction, as expected. Also as expected, higher levels of social capital were associated with a greater reduction in poverty rates, all else equal, suggesting that this variable reduces local political influence that seeks to hinder poverty reduction efforts.

To explore further the interrelationships that exist among the political influence variables, we estimated equations with various interactions. In one such equation we obtained the following parameter estimates, each of which was statistically significant at below the one percent level:

$$\Delta pov_i = -0.170 RAUCH90 - 0.00170 FEDGNT90 + 0.000022 Interact$$

Thus, higher consumption spending leads to greater reductions in poverty rates, but the effectiveness of such spending increases with the size of federal grants received. Likewise, the effectiveness of federal grant spending in *reducing* poverty (note that the sign on the non-interacted variable has changed) is attenuated as local consumption spending increases. Thus, when these two types of spending increase, they tend to counteract each other in terms of their effectiveness in reducing poverty rates over time. We caution that these parameter estimates are not very stable, and that further research on the interaction effects is warranted.

Concluding Comments

Despite decades of poverty alleviation efforts, poverty persists in many parts of the US. While federal programs such as the New Markets Initiative or the Enterprise Zones and Enterprise Community programs may reduce poverty rates, only the targeted communities are impacted. In the long-run, more cost effective approaches may be found only by probing within persistently poor communities and counties for the forces that are holding them back.

The internal political workings of communities, and the social capital that does or does not exist within them, have not been examined systematically at the level of all counties. In this study, the analysis of poverty is expanded to a wider set of factors, including social capital and political influence. Most importantly, this expanded approach shifts attention away from a narrow economic conceptualization and solutions to an emphasis on the complex, non-economic and difficult-to-measure processes that occur within communities. The results have important implications for public policy regarding community development in general and poverty alleviation in particular. Finding effective solutions to long-term poverty enhances the vitality of communities, and allows them to contribute to rather than detract from GDP. Furthermore, testing the hypothesis that ethnic diversity is associated with less economic growth or greater poverty is timely in a period of relative labor scarcity in agriculture, in which numerous rural communities have experienced substantial increases in the number of Hispanic workers in low-skill food industry jobs. This hypothesis is at odds with the idea that incomes in the US are high precisely because the nation is a “melting pot.” Our study finds no evidence in support of this hypothesis.

In addition, this study provides insights into spatial dimensions of poverty and the effect of spatial dependence in formal econometric models of poverty. To our knowledge, this is the first study to explicitly test and correct for spatial effects in US poverty rates. The application of spatial data analysis methods revealed strong evidence of spatial interaction across county boundaries.

One conclusion from this study is that policy makers should not leave poverty reduction efforts to local communities themselves. Further, the effects of social and political forces on poverty must be viewed in combination with other significant economic, demographic and structural determinants of poverty. While the results on social and political forces are strong and quite unequivocal, we do not want to overstate their significance until further confirmation is carried out.

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Table 1. Regional Variation in Family Poverty Rate

Area	FAMPOV79	FAMPOV89	FAMPOV99	No. of Obs.
All counties	12.47	13.06	10.73	3108
Metro	8.96	9.16	7.98	833
Nonmetro adjacent	13.05	13.69	11.03	999
Nonmetro nonadjacent	14.33	15.12	12.30	1276
New England	8.41	6.76	6.60	67
Metro	7.27	6.03	6.08	30
Nonmetro adjacent	8.55	6.88	6.61	20
Nonmetro nonadjacent	10.25	7.93	7.48	17
Mideast	8.07	7.76	7.68	178
Metro	7.49	6.92	7.17	110
Nonmetro adjacent	8.86	8.77	8.23	50
Nonmetro nonadjacent	9.40	10.10	9.26	18
Great Lakes	8.19	9.49	6.96	437
Metro	6.59	7.64	6.03	149
Nonmetro adjacent	8.26	9.35	6.77	165
Nonmetro nonadjacent	10.05	11.91	8.34	123
Southeast	16.06	16.04	13.40	1064
Metro	11.13	10.50	9.12	311
Nonmetro adjacent	16.87	16.70	13.82	387
Nonmetro nonadjacent	19.39	20.05	16.60	366
Southwest	14.14	17.12	13.78	379
Metro	10.55	12.89	10.57	83
Nonmetro adjacent	14.60	17.76	14.13	150
Nonmetro nonadjacent	15.72	18.87	15.25	146
Plains	11.57	11.43	8.83	618
Metro	6.75	7.47	5.77	72
Nonmetro adjacent	10.55	10.43	7.57	144
Nonmetro nonadjacent	12.80	12.50	9.83	402
Rocky Mountain	10.48	11.57	9.85	215
Metro	6.94	8.35	6.59	20
Nonmetro adjacent	10.85	11.85	9.43	39
Nonmetro nonadjacent	10.86	11.99	10.37	156
Farwest	8.89	10.00	9.69	150
Metro	8.15	8.80	8.89	58
Nonmetro adjacent	8.91	10.52	9.87	44
Nonmetro nonadjacent	9.77	10.95	10.49	48

Table 2. Variables Considered as Determinants of Poverty

Variable	Description
FAMPOV99 ¹	Dependent Variable: family poverty rate 1999
URBAN901 ²	Central counties of metro areas of 1 million population or more
URBAN902 ²	Fringe counties of metro areas of 1 million population or more
URBAN903 ²	Counties in metro areas of 250,000 to 1 million population
URBAN904 ²	Counties in metro areas of fewer than 250,000 population
CHPVEM590 ³	Growth of private employment between 1988-1990
EMP90 ³	Civilian employed labor force/total civilian labor force 1990
MALLAB90 ⁴	% male labor force participation in 1990 (total male labor force/males 16 years and over*100)
FEMLAB90 ⁴	% female labor force participation in 1990 (total female labor force/females 16 years and over*100)
ISC8890 ³	Industrial dissimilarity index 1988-1990: the sum of absolute changes in the share of one-digit industry employment between 1988 and 1990, divided by two
AGR90 ⁴	% Agriculture, forestry, and fisheries employment 1990
GOODS90 ⁴	% Manufacturing, mining, construction employment 1990
TRANS90 ⁴	% Transportation and public utilities employment 1990
WHRET90 ⁴	% Wholesale and retail trade employment 1990
FIRE90 ⁴	% Finance, insurance, and real estate employment 1990
SERVIC90 ⁴	% Services employment 1990
A017A90	% 18-24 years old persons 1990
A1824A90 ⁴	% 18-24 years old persons 1990
A65OV90 ⁴	% 65 years and over persons 1990
BLACK90 ⁴	% African Americans 1990
NONBLK90 ⁴	% Non-African Americans minorities 1990
FEMHH90 ⁴	% Female-headed households 1990
CHILD90 ⁴	Average children per family 1990
HISSOM90 ⁴	% High school plus some college 1990
COLL90 ⁴	% 4-year college or more 1990
STAY90 ⁵	% of persons in 1990 who lived in the same county in 1985-1990
FBPOP90 ⁴	% Foreign-born population in a county 1990
ETHNIC90 ⁴	Ethnic fractionalization index 1990
INEQ89 ⁴	Family mean income/Family median income 1989
FEDGNT90 ⁴	Per capita Direct federal expenditures or obligations - grant awards 1990
POLCOM92 ⁴	Index of political competition (see text) in a county 1988
SKI90PCM ^{1,6,7}	Index of social capital (see text) 1990
PCBGBX90	Big box retailers, number of establishments per 10,000 capita, 1990
CONEXP87	Ratio of current (consumption) local government expenditure to total expenditure in a county in 1987
SELEMP90	% of nonfarm proprietors in a county in 1990

Data Sources: 1. US Bureau of the Census. 2. Based on Beale codes. 3. Regional Economics Information System (BEA). 4. USA Counties. 5. County-to-County Migration Files. 6. County Business Patterns. 7. National Center for Charitable Statistics.

Table 3. Descriptive Statistics

	All Counties		Metro		Non-metro		Non-metro South	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
FAMPOV99	10.76	5.79	7.99	4.05	11.75	6.00	15.15	5.82
URBAN901	0.054	0.226	0.205	0.404				
URBAN902	0.043	0.204	0.165	0.371				
URBAN903	0.102	0.303	0.388	0.488				
URBAN904	0.064	0.244	0.242	0.429				
CHGEMP90	0.035	0.055	0.051	0.048	0.029	0.057	0.026	0.062
EMP90	93.33	3.06	94.00	2.01	93.09	3.33	92.15	3.28
FLF90	51.89	7.09	56.89	6.15	50.11	6.53	47.79	6.32
ISC8890	0.629	5.286	0.040	0.169	0.839	6.143	0.592	4.158
AG90	10.56	9.60	3.62	3.04	13.04	9.92	10.73	8.08
GOODS90	27.17	10.28	26.58	7.95	27.38	10.98	32.11	10.72
TRANS90	6.537	2.088	7.141	2.060	6.322	2.055	6.447	1.958
WHRET90	19.59	3.50	21.42	2.53	18.94	3.56	18.32	3.45
FIRE90	4.356	1.803	5.942	2.142	3.791	1.249	3.594	1.151
SERVIC90	28.76	5.73	31.05	5.58	27.95	5.55	26.67	5.44
A017A90	26.88	3.44	26.23	3.11	27.12	3.52	27.07	3.45
A1824A90	9.310	3.379	10.686	3.229	8.819	3.296	9.580	2.743
A65OV90	14.98	4.33	12.11	3.53	16.00	4.12	15.28	3.75
NONBLK90	3.884	7.575	3.978	5.506	3.851	8.189	4.359	8.278
HISSOM90	56.18	7.536	57.01	5.944	55.88	8.008	49.40	5.863
COLL90	13.37	6.393	17.94	7.864	11.74	4.828	10.18	3.789
STAY90	0.749	0.071	0.720	0.079	0.760	0.065	0.770	0.060
FBPOP90	2.180	3.464	3.721	4.762	1.630	2.656	1.722	3.303
ETHNIC90	0.175	0.168	0.213	0.157	0.162	0.169	0.271	0.176
INEQ89	1.460	0.138	1.453	0.166	1.463	0.126	1.479	0.139
FEDGNT90	476.7	511.8	447.1	604.4	487.2	474.1	527.2	455.7
POLCOM88	8.501	6.120	8.762	6.024	8.407	6.153	8.679	6.449
SKI90PCM	0.011	1.350	-0.304	1.093	0.123	1.414	-0.840	0.923
PCBGBX90	0.953	0.901						
CONEXP87	88.57	7.020	86.39	7.341	89.35	6.734	89.11	6.871
SELEMP90	17.26	5.339	16.29	5.461	17.60	5.253	16.68	5.584
N	3047		801		2246		1022	

Table 4. OLS Results for the Base and Expanded Models

	Base Model				Expanded Model					
	Column 1		Column 2		Column 3		Col. 4 Non-		Column 5	
	All counties		All Counties		Metro Counties		Metro Counties		Rural South	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
Constant	72.17	0.000	34.11	0.000	48.71	0.000	27.27	0.000	13.34	0.070
URBAN901	0.130	0.563	-0.241	0.251						
URBAN902	-1.046	0.000	-0.522	0.005						
URBAN903	-0.569	0.000	-0.528	0.000						
URBAN904	-0.060	0.693	-0.149	0.263						
CHGEMP90	1.198	0.355	1.666	0.146	2.169	0.149	1.412	0.282	2.467	0.226
EMP90	-0.543	0.000	-0.367	0.000	-0.512	0.000	-0.342	0.000	-0.218	0.000
FLF90	-0.152	0.000	-0.162	0.000	-0.120	0.000	-0.171	0.000	-0.208	0.000
ISC8890	0.056	0.006	0.025	0.155	-1.071	0.004	0.017	0.308	-0.027	0.547
AG90	-0.025	0.093	-0.013	0.374	-0.028	0.348	-0.017	0.300	-0.066	0.003
GOODS90	-0.147	0.000	-0.084	0.000	-0.049	0.050	-0.086	0.000	-0.090	0.000
TRANS90	-0.166	0.000	-0.116	0.000	-0.036	0.366	-0.127	0.000	-0.072	0.265
WHRET90	-0.088	0.000	-0.038	0.130	0.028	0.429	-0.033	0.238	-0.011	0.789
FIRE90	-0.098	0.018	-0.100	0.011	0.018	0.646	-0.173	0.002	-0.361	0.000
SERVIC90	-0.030	0.191	0.048	0.027	0.098	0.003	0.051	0.051	0.075	0.054
A017A90	0.440	0.000	0.471	0.000	0.427	0.000	0.464	0.000	0.737	0.000
A1824A90	0.188	0.000	0.055	0.021	0.104	0.000	0.032	0.283	0.106	0.036
A65OV90	0.022	0.503	-0.026	0.440	-0.0001	0.998	-0.049	0.239	0.121	0.022
NONBLK90	0.069	0.000	0.052	0.004	-0.056	0.097	0.065	0.000	-0.031	0.066
HISSOM90	-0.267	0.000	-0.226	0.000	-0.222	0.000	-0.209	0.000	-0.269	0.000
COLL90	-0.087	0.000	-0.098	0.000	-0.173	0.000	-0.063	0.032	-0.081	0.073
STAY90	10.78	0.000								
PRDSTY90			19.83	0.000	13.74	0.000	22.508	0.000	20.66	0.000
FBPOP90			-0.064	0.084	0.074	0.011	-0.065	0.298	0.046	0.464
ETHNIC90			3.305	0.000	3.779	0.000	3.019	0.000	2.869	0.000
PRINEQ89			6.083	0.000	3.679	0.000	7.725	0.000	6.633	0.000
FEDGNT90			0.0005	0.000	0.0003	0.004	0.0005	0.009	0.001	0.009
POLCOM88			0.042	0.000	0.024	0.016	0.048	0.000	0.063	0.000
SKI90PCM			-0.187	0.043	0.108	0.288	-0.229	0.032	-0.388	0.015
PCBGBX90			0.096	0.208	0.349	0.001	0.001	0.986	-0.004	0.972
CONEXP87			0.0002	0.970	0.006	0.435	-0.002	0.846	0.001	0.925
SELEMP90			-0.046	0.001	-0.048	0.004	-0.040	0.026	-0.036	0.119
Adjusted R ²	0.83		0.86		0.89		0.84		0.83	
Log-L	-6943		-6697		-1318		-5097		-2338	
					801.00					
N	3047		3047		0		2246		1022	

Table 5. Spatial Results for the Expanded Model

Variable	Column 1 All Counties (SAC)		Column 2 Metro Counties (SAR)		Column 3 Non-Metro Counties (SAC)		Column 4 Rural South (SAC)	
	Coeff.	P-Value	Coeff.	P-Value	Coeff.	P-Value	Coeff.	P-Value
cons	27.71	0.000	46.73	0.000	21.27	0.000	7.393	0.116
URBAN901	0.043	0.861						
URBAN902	-0.201	0.351						
URBAN903	-0.413	0.008						
URBAN904	-0.118	0.501						
chgemp90	1.348	0.091	1.789	0.147	1.330	0.165	2.693	0.037
emp90	-0.337	0.000	-0.506	0.000	-0.312	0.000	-0.201	0.000
flf90	-0.130	0.000	-0.104	0.000	-0.141	0.000	-0.169	0.000
isc8890	0.022	0.009	-1.095	0.000	0.013	0.150	-0.055	0.009
ag90	-0.021	0.038	-0.032	0.200	-0.027	0.019	-0.073	0.000
goods90	-0.078	0.000	-0.049	0.002	-0.080	0.000	-0.086	0.000
trans90	-0.118	0.000	-0.028	0.356	-0.141	0.000	-0.082	0.077
whret90	-0.057	0.001	0.019	0.516	-0.051	0.010	-0.029	0.354
fire90	-0.075	0.033	0.017	0.658	-0.159	0.002	-0.350	0.000
servic90	0.037	0.011	0.093	0.000	0.033	0.068	0.052	0.069
a017a90	0.440	0.000	0.427	0.000	0.447	0.000	0.701	0.000
a1824a90	0.078	0.000	0.112	0.000	0.064	0.013	0.130	0.005
a65ov90	0.014	0.540	0.020	0.539	0.007	0.798	0.164	0.000
nonblk90	0.068	0.000	-0.054	0.012	0.083	0.000	-0.016	0.285
hissom90	-0.200	0.000	-0.223	0.000	-0.178	0.000	-0.232	0.000
coll90	-0.094	0.000	-0.172	0.000	-0.058	0.009	-0.079	0.025
prstay90	19.65	0.000	13.60	0.000	21.75	0.000	20.95	0.000
fbpop90	-0.066	0.000	0.062	0.007	-0.044	0.080	0.070	0.028
ethnic90	2.911	0.000	3.837	0.000	2.119	0.000	2.156	0.003
prineq89	5.426	0.000	3.724	0.000	6.550	0.000	5.471	0.000
fedgnt90	0.0004	0.000	0.0003	0.000	0.0004	0.001	0.001	0.000
polcom88	0.040	0.000	0.025	0.003	0.041	0.000	0.055	0.000
ski90pcm	-0.188	0.001	0.083	0.385	-0.237	0.000	-0.368	0.002
pcbgbx90	0.111	0.062	0.369	0.000	0.023	0.739	0.003	0.982
CONEXP87	0.0004	0.946	0.005	0.462	-0.001	0.864	0.001	0.895
selemp90	-0.043	0.000	-0.047	0.001	-0.036	0.004	-0.021	0.261
rho	0.205	0.000	0.090	0.024	0.221	0.000	0.206	0.000
lambda	0.056	0.000			0.028	0.000	0.028	0.001
Adjusted R ²	0.87		0.89		0.86		0.84	
Log-L	-2249		-1035		-1830		-854	
N	3047		801		2246		1022	

Table 6. Results of Interactions (Spatial)

Interaction Term	Coefficient	P-Value
<i>Panel a</i>		
Change in employment × mobility	-41.5628	0.004
Change in employment × ethnic diversity	-20.3689	0.000
Change in employment × income inequality	13.5952	0.004
Change in employment × federal grants	-0.0002	0.852
Change in employment × political competition	-0.3245	0.002
Change in employment × social capital	-1.1811	0.036
Change in employment × big box retailers	-2.5846	0.003
Change in employment × local government consumption expenditure	0.0727	0.406
<i>Panel b</i>		
Industrial structural change × mobility	0.0432	0.841
Industrial structural change × ethnic diversity	-0.1916	0.058
Industrial structural change × income inequality	-0.4532	0.000
Industrial structural change × federal grants	0.00002	0.073
Industrial structural change × political competition	0.0012	0.447
Industrial structural change × social capital	-0.0082	0.287
Industrial structural change × big box retailers	-0.0402	0.023
Industrial structural change × local government consumption expenditure	0.0011	0.432
<i>Panel c</i>		
Ethnic diversity × % high school graduates	-0.1880	0.000
Ethnic diversity × % college graduates	-0.3389	0.000
Ethnic diversity × % income inequality	-1.4122	0.438
Ethnic diversity × % federal grants	0.0021	0.000
Ethnic diversity × % political competition	0.0621	0.119
Ethnic diversity × % social capital	0.8528	0.001
Ethnic diversity × % big box retailers	1.1210	0.001
Ethnic diversity × % local government consumption expenditure	0.0444	0.191
<i>Panel d</i>		
Income inequality × % high school graduates	-0.1933	0.000
Income inequality × % college graduates	-0.2337	0.000
Income inequality × federal grants	0.0016	0.002
Income inequality × political competition	0.0015	0.969
Income inequality × social capital	0.4822	0.050
Income inequality × % local government consumption expenditure	-0.0767	0.000
<i>Panel e</i>		
Federal grants × political competition	0.0001	0.000
Federal grants × social capital	-0.0003	0.000
Federal grants × % local government consumption expenditure	0.00004	0.000

Table 7. Panel Estimation Results (poverty levels)

Variable	Coeff.	t-ratio	P-value
Constant	54.642	17.83	0.000
URBAN1	-1.019	3.17	0.002
URBAN2	-0.676	2.61	0.009
URBAN3	-0.443	2.06	0.039
URBAN4	-0.569	2.32	0.021
CHGEMP	2.239	3.66	0.000
EMP	-0.410	22.26	0.000
ISC	-0.012	1.17	0.240
AG	0.002	0.16	0.869
GOODS	-0.196	15.86	0.000
TRANS	-0.142	5.41	0.000
WHRET	-0.069	3.39	0.001
FIRE	-0.246	5.70	0.000
SERVIC	-0.019	0.99	0.322
A017	0.311	11.42	0.000
A1824	0.190	6.76	0.000
A65OV	-0.030	1.10	0.272
NONBLK	0.027	2.21	0.027
HISSOM	-0.272	29.15	0.000
COLL	-0.445	24.54	0.000
STAY	2.631	3.38	0.001
FBPOP	-0.195	7.73	0.000
ETHNIC	6.526	10.95	0.000
INEQ	7.920	18.30	0.000
FEDGNT	0.0001	2.28	0.023
POLCOM	0.037	6.03	0.000
CONEXP	0.001	0.22	0.827
SELEMP	0.048	4.01	0.000

Table 8. Descriptive Statistics, Poverty Change Model

Variable	Description	Mean	Std.Dev.
CHGFMPOV ¹	Change in family poverty rate between 1989 and 1999	-2.359	2.805
FAMPOV99 ¹	Family poverty rate 1989	13.12	6.97
NONMET4 ²	Urban population of 20,000 or more, adjacent to a metro area	0.0423	0.201
NONMET5 ²	Urban population of 20,000 or more, not adjacent to a metro area	0.0348	0.183
NONMET6 ²	Urban population of 2,500 to 19,999, adjacent to a metro area	0.197	0.398
NONMET7 ²	Urban population of 2,500 to 19,999, not adjacent to a metro area	0.210	0.408
NONMET8 ²	Completely rural or less than 2,500 urban population, adjacent to a metro area	0.081	0.274
NONMET9 ²	Completely rural or less than 2,500 urban population, not adjacent to a metro area	0.171	0.377
CHPVEM590 ³	Growth of private employment between 1988-1990	0.035	0.0554
EMP90 ³	Civilian employed labor force/total civilian labor force 1990	93.33	3.062
FEMLAB90 ⁴	% female labor force participation in 1990 (total female labor force/females 16 years and over*100)	51.89	7.09
ISC8890 ³	Industrial dissimilarity index 1988-1990: the sum of absolute changes in the share of one-digit industry employment between 1988 and 1990, divided by two	0.629	5.286
AGR90 ⁴	% Agriculture, forestry, and fisheries employment 1990	10.56	9.604
GOODS90 ⁴	% Manufacturing, mining, construction employment 1990	27.17	10.28
TRANS90 ⁴	% Transportation and public utilities employment 1990	6.54	2.09
WHRET90 ⁴	% Wholesale and retail trade employment 1990	19.59	3.50
FIRE90 ⁴	% Finance, insurance, and real estate employment 1990	4.36	1.80
SERVIC90 ⁴	% Services employment 1990	28.76	5.73
A017A90	% 18-24 years old persons 1990	26.89	3.44
A1824A90 ⁴	% 18-24 years old persons 1990	9.31	3.38
A65OV90 ⁴	% 65 years and over persons 1990	14.98	4.32
NONBLK90 ⁴	% Non-African Americans minorities 1990	3.88	7.58
HISSOM90 ⁴	% High school plus some college 1990	56.18	7.54
COLL90 ⁴	% 4-year college or more 1990	13.37	6.39
STAY90 ⁵	% of persons in 1990 who lived in the same county in 1985-1990	0.749	0.071
FBPOP90 ⁴	% Foreign-born population in a county 1990	2.18	3.46
ETHNIC90 ⁴	Ethnic fractionalization index 1990	0.175	0.168
INEQ89 ⁴	Family mean income/Family median income 1989	1.46	0.138
FEDGNT90 ⁴	Per capita Direct federal expenditures or obligations - grant awards 1990	476.7	511.8
POLCOM92 ⁴	Index of political competition (see text) in a county 1988	8.50	6.12
SKI90PCM ^{1,6,7}	Index of social capital (see text) 1990	0.0110	1.340
PCBGBX90 ⁶	Big-box retailers per 10,000 people 1990	0.953	0.901
CONEXP87 ¹	Ratio of current (consumption) local government expenditure to total expenditure in a county in 1987	88.57	7.02
SELEMP90 ³	% of nonfarm proprietors in a county in 1990	17.26	5.34

Data Sources: 1. US Bureau of the Census. 2. Based on Beale codes. 3. Regional Economics Information System (BEA). 4. USA Counties. 5. County-to-County Migration Files. 6. County Business Patterns. 7. National Center for Charitable Statistics.

Table 9. Estimation Results, Poverty Change Model

	Column 1		Column 2		Column 3		Column 4		Column 5	
	OLS – All Counties		SEM - All Counties		SAR - Metro		SEM - Non-Metro		SEM - Rural South	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Constant	5.294	1.34	12.69	4.82	5.745	1.25	9.474	2.60	-2.106	0.52
<i>Economic and Structural Conditions</i>										
FAMPOV89	-0.512	21.13	-0.526	30.97	-0.412	15.45	-0.553	27.72	-0.600	17.88
CHGEMP90	0.781	0.73	0.933	1.31	-0.449	0.46	1.185	1.36	1.599	1.32
EMP90	-0.103	3.07	-0.135	4.78	-0.115	5.30	-0.115	3.82	-0.056	1.61
FLF90	-0.063	4.07	-0.061	5.59	-0.010	0.65	-0.083	6.22	-0.113	4.86
ISC8890	0.008	0.44	0.014	1.84	-0.373	1.55	0.005	0.66	0.031	1.52
AG90	0.027	2.10	0.022	2.35	0.0003	0.02	0.020	1.83	-0.007	0.38
GOODS90	-0.0001	0.009	-0.012	1.34	-0.015	1.09	-0.017	1.64	-0.001	0.06
TRANS90	-0.037	1.43	-0.041	2.12	-0.005	0.19	-0.066	2.68	0.022	0.48
WHRET90	0.007	0.31	-0.012	0.75	-0.0004	0.02	-0.003	0.17	0.038	1.26
FIRE90	-0.022	0.70	-0.028	0.89	0.033	1.10	-0.080	1.73	-0.205	2.58
SERVIC90	0.046	2.60	0.017	1.28	0.051	2.59	0.026	1.60	0.060	2.20
PCBGBX90	0.100	1.50	0.102	1.91	0.319	3.72	0.052	0.838	0.057	0.47
<i>Individual-Level Characteristics</i>										
A017A90	0.196	5.94	0.185	7.66	0.145	4.14	0.223	7.30	0.469	10.01
A1824A90	0.002	0.11	0.035	1.91	0.039	1.81	-0.016	0.66	0.060	1.43
A65OV90	-0.011	0.41	0.015	0.75	0.032	1.10	-0.009	0.32	0.126	2.86
NONBLK90	0.030	1.77	0.031	3.93	-0.055	3.14	0.050	5.19	-0.034	2.35
HISSOM90	-0.062	4.87	-0.063	6.22	-0.045	3.12	-0.075	5.90	-0.115	5.17
COLL90	-0.018	1.19	-0.016	1.18	-0.066	4.38	0.024	1.17	0.018	0.53
PRDSTY90	7.765	4.34	4.579	5.00	5.843	3.81	8.265	3.23	8.656	2.53
SELEMP90	-0.061	5.34	-0.059	6.43	-0.057	4.95	-0.059	5.13	-0.061	3.48
FBPOP90	0.014	0.53	0.005	0.29	0.108	6.05	-0.020	0.83	0.056	1.80
<i>Rural Status (disadvantage)</i>										
NONMET4	0.311	2.53	0.272	1.48						
NONMET5	0.353	1.95	0.396	1.88						
NONMET6	0.081	0.75	0.085	0.67						
NONMET7	0.430	3.31	0.422	3.06						
NONMET8	0.154	0.84	0.206	1.20						
NONMET9	0.635	3.36	0.650	3.71						
<i>Political Influence Variables</i>										
POLCOM88	0.027	3.52	0.026	4.10	0.024	3.53	0.031	3.79	0.045	3.78
RAUCH90	0.001	0.25	-0.002	0.40	0.003	0.56	-0.002	0.26	-0.003	0.26
FEDGNT90	0.0002	2.77	0.0002	2.40	0.0002	2.33	0.0002	1.43	0.0005	2.57
PRINEQ89	2.161	4.20	1.891	5.08	1.044	2.81	2.228	3.69	1.764	1.66
ETHNIC90	2.581	4.59	2.656	6.13	1.456	2.85	2.176	3.85	2.089	3.00
SKI90PCM	-0.187	3.15	-0.248	4.76	-0.075	0.96	-0.223	3.61	-0.381	3.44
Rho					0.091	1.53				
Lambda			0.200	11.61			0.194	11.07	0.165	6.05
Adjusted R2	0.54		0.55		0.65		0.52		0.56	
Log-L	-6226		-6208		-867		-4786		-2230	

Figure 1. Family Poverty Rate, 1999

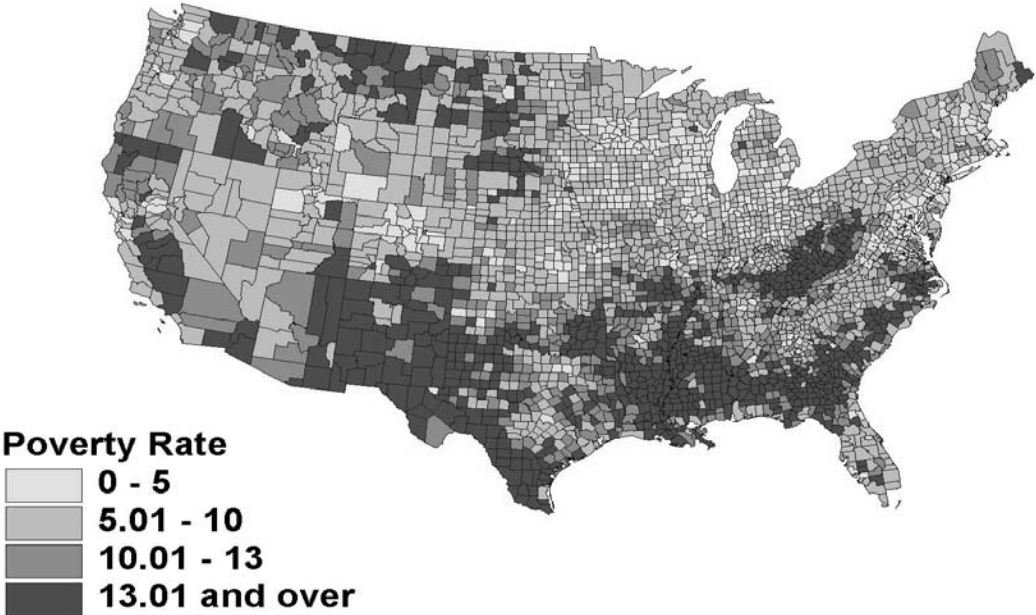


Figure 2. Moran Scatter plot for Poverty Rate 1999

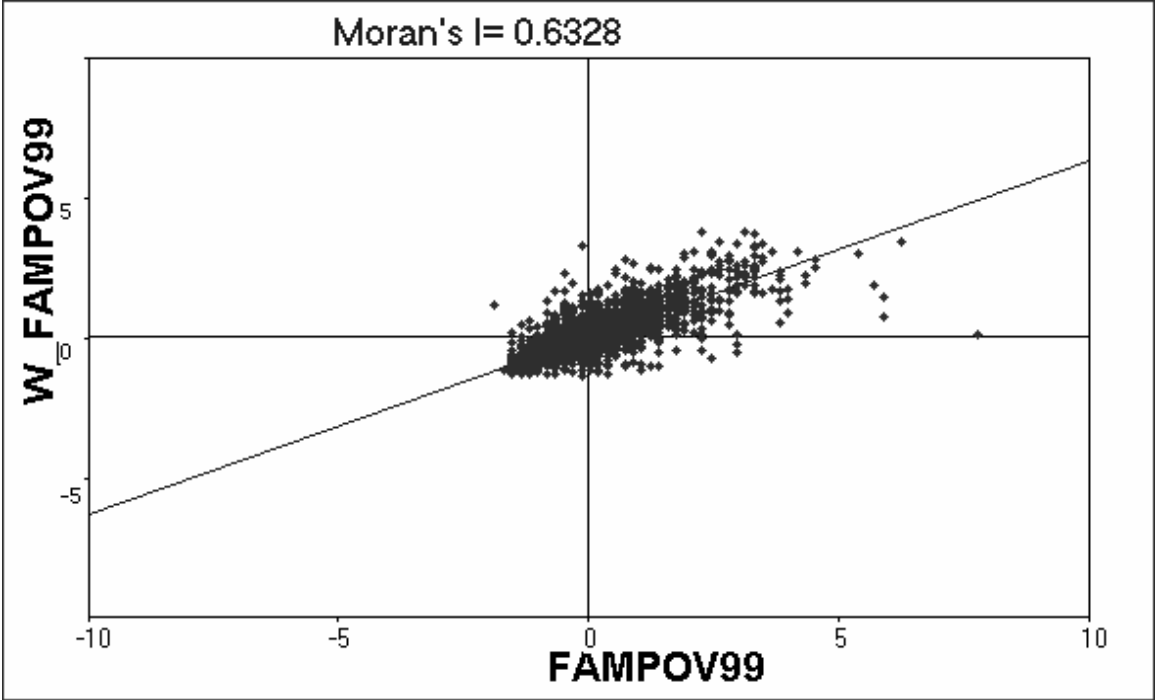


Figure 3. LISA Cluster Map for Family Poverty 1999.

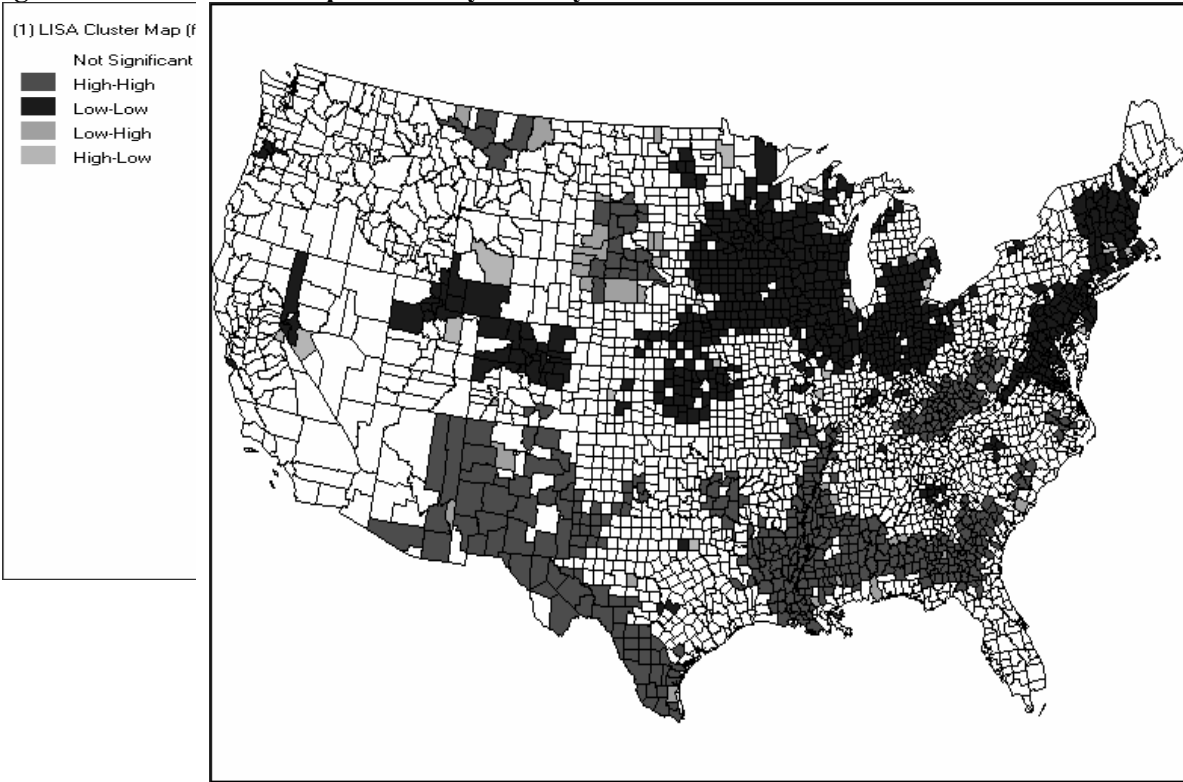


Figure 4. Family Poverty Rate, 1979

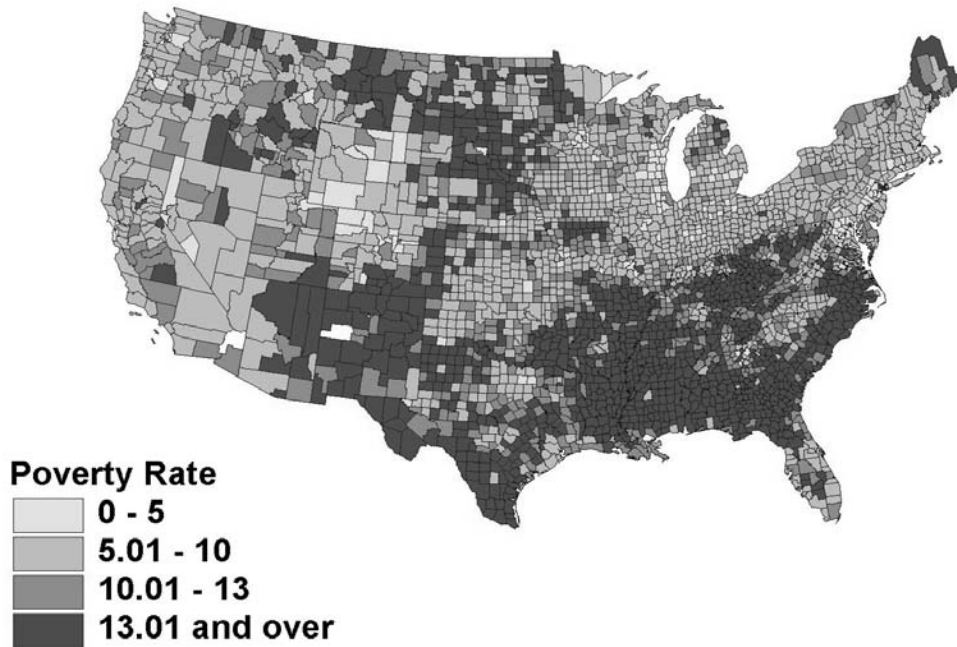


Figure 5. Family Poverty Rate, 1989

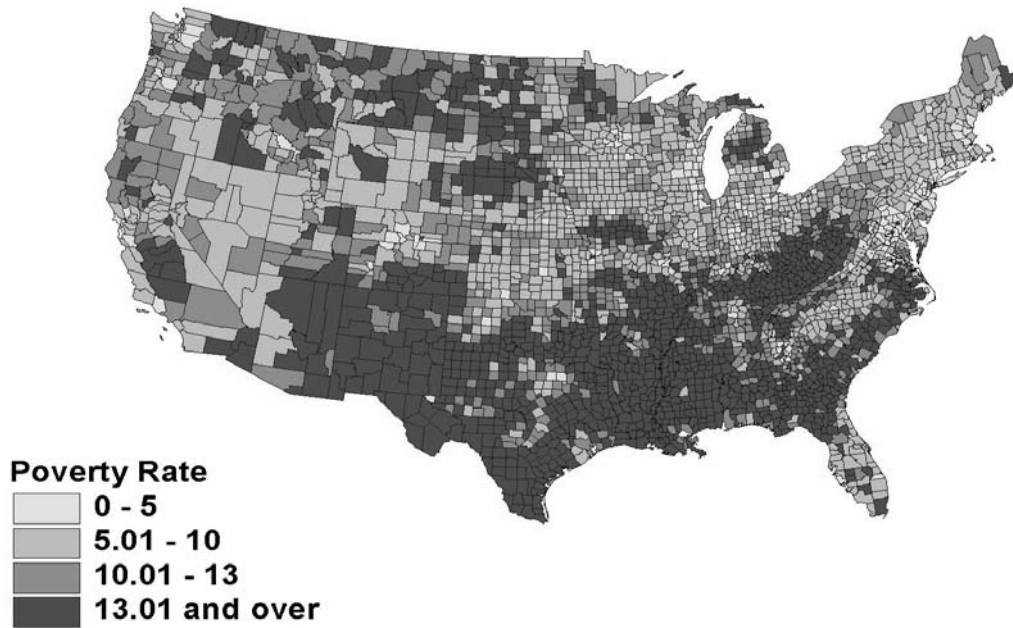


Figure 6. Change in Poverty Rate, 1989-1999

