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Poverty in the United States is not evenly distributed across the landscape. Poverty rates are highest in the most remote rural counties and in central cities, and persistent poverty is geographically concentrated in isolated rural regions. The decline in poverty, however, that occurred nationwide between 1990 and 2000 (from 13.1% of the population to 12.4%) made large inroads in persistent poverty areas (Miller, Crandall, and Weber). Previous research on these county-level changes in poverty has left some important questions about spatial dynamics unanswered, however (Rupasingha and Goetz; Weinberg). Were the tract-level poverty dynamics of the 1990's affected by spatial concentrations of poverty? And does the effect of improved economic conditions depend on what happens in neighboring areas?

There is a relatively rich literature on the determinants of poverty and changes of poverty in urban and rural areas (see Weber and Jensen for a review of this literature). Almost all of these studies use county-level data and model poverty rates or changes in poverty rates as functions of demographic characteristics and local economic conditions. Some studies have examined changes in tract-level poverty, but only for urban areas (Jargowsky; Kingsley and Pettit). Recently, economists have begun to examine spatial

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externalities in poverty research. Rupasingha and Goetz, for example, develop a spatial econometric model of changes in county poverty rates during the 1990s, in which they find that changes in poverty are in fact affected by the poverty of neighboring counties.

While counties are useful and convenient geographic units for poverty analysis, they are quite heterogeneous. Studies using county data are likely to be subject to considerable spatial aggregation bias. Since both the 1990 and 2000 Census contain tract-level data for the entire country, it is now possible for the first time to analyze changes in poverty rates at the tract level for both rural and urban areas. To our knowledge, our study is the first to use tract-level data to study nationwide changes in poverty rates, to analyze the strength of spatial externalities in poverty reduction at the tract level, and to examine how the effect of job growth on poverty reduction is mediated by initial poverty conditions and local social capital in one's own and neighboring areas.

We address four questions:

(1) How do county-level job growth and social capital affect tract poverty rates?

(2) How are changes in tract poverty rates affected by initial poverty conditions and adjacency to high poverty tracts?

(3) How is the effect of job growth on poverty reduction mediated by social capital, initial poverty conditions and adjacency to high poverty?

(4) How strong are the spatial spillovers of poverty changes in neighboring tracts?

A Model of Changes in Tract Poverty Rates

In this section of the paper, we develop the basic empirical model without considering spatial dependence or spatial error. In the next section, we outline the rationale for, and specification of, our spatial econometric model. Our conceptual model of tract-level poverty change builds on a framework developed by Blank. Blank identifies five sets of characteristics that affect area poverty rates: demographics, social norms, public and community institutions, natural environment/location, and economic structure. Most previous poverty research has included demographic and economic structure variables, but few studies have attempted to model social norms or community institutions or spatial dimensions.

Our model focuses on employment growth, social capital, and poverty pocket locations as determinants of changes in poverty rates during the 1990s, while controlling for demographics and family structure:

(1) $\mathbf{Y} = f(\mathbf{X}, \mathbf{Z})$

where **X** represents the focus variables and **Z** the control variables used to explain tract-level poverty change (Y). The dependent variable Y, percentage point change in poverty rate, was calculated as the difference between tract level poverty rates in 2000 and 1990. Tracts are geographic areas of 2500 – 8000 people, relatively homogeneous with respect to population characteristics, economic status, and living conditions. In urban areas, tracts are often "neighborhoods", comprising geographically integrated units of residents. In rural areas, tracts are less likely to be functional equivalents of neighborhoods (Jargowsky). This analysis relies on the projection of 1990 data into the 2000 boundaries as developed by GeoLytics, Inc. All tract level data reported for 1990 are the projected data re-aggregated from the block groups into 2000 tract boundaries by GeoLytics. Data for 2000, along with any county data, are the official census long form results for that year. Unless otherwise stated, the explanatory variables are from 1990.

Employment Growth. It is expected that recent employment growth from 1990 to 2000 should affect the incentives for human capital investment, the actual jobs available, and the prevailing wage, and thus employment growth should increase local opportunities to move out of poverty. However, tracts are defined based on the characteristics of residents, whose work opportunities arise from a larger labor market area. Therefore county employment growth rate between 1990 and 2000 was used to better capture area labor market conditions.

Social Capital. Public and community institutions are the organizations that operate within a community to help it function, such as police, courts, schools, churches, and fraternal organizations (Blank). They create networks of connections, both social and economic relationships, for all participants. Social norms (learned behavioral preferences) are shaped to a large extent by peer pressure effects and role models, as these are some of the primary transmitters of future expectations to children. Integrated social networks in an area will therefore provide greater access to role models and peers outside one's class or ethnic group. There have been many recent attempts to construct measures of social capital and test their significance in models of regional success. For example, Rupasingha, Goetz, and Freshwater assessed the impact of social capital on county economic growth, with economic growth measured as per capita income growth. The vector representing social capital included a measure for associational activity or "good" social capital (total number of bowling centers, public golf courses, membership sports and recreation clubs, civic and social associations, religious organizations, labor organizations, business associations, professional organizations, and political organizations per 10,000 persons), “bad” social capital (criminal activity), charitable giving, and voter participation rates in federal elections. Their results indicated that associational activity had a positive, significant effect on economic growth and concluded “social capital or civic engagement is an important determinant of economic growth in US counties” (571). The social capital variable used in this study is a county-level index that was developed by Rupasingha and Goetz based on that research. They used a principal component analysis to combine significant positive social capital variables into one index.

Poverty Pockets. Significance of location has been shown in county level studies of poverty pocket effects (Weinberg). An adjacency variable was developed for this analysis using ArcGIS. It measures, for each tract, the proportion of adjacent tracts that were high poverty (poverty rates greater than or equal to 30%) in 1990 - in other words, the degree to which a given tract began the period in a pocket of poverty[1]. It uses a first-order queen definition of contiguity for this measure[2].

Mediating Effects. Interactions between employment growth rate and adjacency, and employment growth and social capital are included to capture whether the returns to job growth are affected by either of these. It may be that areas of higher social capital are better able to turn job growth into poverty reduction, or that location in a pocket of poverty dampens employment growth effects.

Initial Poverty Condidtion as Mediator. To assess whether the effects of job growth or social capital, for example, depended on a tract's initial poverty condition, tracts were separated into three subgroups. A tract was low poverty if it began the period with less than 10% of the population in poverty, medium poverty if the 1990 poverty rate was 10% to 29.99%, and high poverty if 30% or greater of the population was poor. To model the difference in effects by initial condition, interaction terms were used, multiplying each dependent variable (except for the college tract and regional dummies) by the dummy variables for the medium and high poverty categories (the low poverty category is the base category).

Demographic control variables. Control variables include the percents of tract population identified as African-American, Native American, Hispanic origin, and all other races. Both percent of population under age 17 and the percent over age 64 are included to control for the amount of the population out of the labor force. Single female-headed households as a proportion of all households controls for the very high poverty rates found in this group, while the percent of adults over 25 with at least a high school diploma or 4-year college degree controls for populations likely to have higher earnings or employability. Tract population density in thousands is included to capture any returns to scale that may be present in high-density areas and can be thought of as a continuous measure of an urban – rural scale[3]. Since the changes in poverty in a given tract may depend on how high the poverty rate is initially, we included the poverty rate in 1990 as a control. This variable should capture aspects of a tract's prior history affecting poverty (including natural environment) not otherwise controlled for. Dummy variables are included for each of four census-defined regions to adjust for regional effects over the period and are also used to control for potential tract-based poverty related to high student populations[4].

Empirical Model

The ordinary least squares (OLS) estimator is the best, linear unbiased estimator for the classical linear regression model in equation 1 as long as key assumptions are upheld (Greene). OLS is often used to assess determinants of poverty in studies dealing with aggregate data and either levels of poverty or changes in poverty as the dependent variable; however, due to the spatial and aggregate nature of the data, a commonly violated assumption is that of spherical disturbances.

Spatial dependence has two roots: measurement error and structural dependence. First, when using area data, measurement error associated with the spatial boundaries themselves may occur if the aggregation level is not the same as the level at which the process under study acts. The result of this mismatch is spatial dependence in the error terms. This dependence can be thought of as “nuisance” dependence (Anselin). Second, the spatial dimension of the study may be an important aspect of the underlying model. Regional science and economics both emphasize that location – in terms of natural resources, distances to or from markets, and infrastructure - plays a role in determining the success or failure of an area (LeSage). Spatial lag models deal with “questions of how the interaction between economic agents can lead to emergent collective behavior and aggregate patterns” (Anselin, p. 248).

Our empirical model incorporates both types of spatial dependence by using a combined spatial model (SAC):

$$\text{(2)} \qquad \mathbf{Y} = \alpha + \rho\mathbf{W}_1\mathbf{Y} + \beta\mathbf{X} + \boldsymbol{\upsilon}$$

$$\boldsymbol{\upsilon} = \lambda\mathbf{W}_2\,\boldsymbol{\upsilon} + \boldsymbol{\varepsilon}$$

$$\varepsilon \sim N(0, \sigma^2\mathbf{I_n})$$

where $\mathbf{Y}$ is the vector of changes in tract poverty rate between 1990 and 2000. $\mathbf{W}_1$ and $\mathbf{W}_2$ represent known, row-standardized spatial weight matrices that contain first-order contiguity data for each observation[5] (LeSage). The spatial lag operator, $\rho\mathbf{W}_1\mathbf{Y}$, uses the average neighboring value of the dependent variable for each tract as an explanatory variable; the parameter ρ thus reflects the spatial dependence inherent in the sample data (LeSage). The vector $\mathbf{X}$ represents all aggregate explanatory data included in the regression. Importantly, the dependent variable $\mathbf{Y}$ is now determined by the error terms at all locations in the system, making the spatially lagged $\rho\mathbf{W}_1\mathbf{Y}$ variable endogenous (Anselin). The case where both λ and ρ equal zero is the trivial one where there is no spatial dependence, and the model can be estimated through OLS. The presence of either significant spatial term results in a model that can only be efficiently estimated using maximum likelihood techniques. The two spatial weight matrices $\mathbf{W}_1$ and $\mathbf{W}_2$ can be equivalent or can be different, reflecting levels at which the interactions are believed to occur; in our model, they are equal.

Our model attempts to explore the role that neighboring tracts play in determining the success or failure of poverty reduction in any given tract. Reductions in poverty in one tract are expected to be influenced by the poverty changes in its neighbors. Use of a spatial lag operator $\rho \mathbf{W}_1 \mathbf{Y}$ allows us to determine this dependence between tracts. Significant spatial autocorrelation in the error terms is also expected. Poverty depends to a large extent on the operations of an area's labor market, which is a geographic area much larger than the tract-level aggregation used for the dependent variable. For these reasons our empirical model is estimated using the SAC model[6].

The spatial weight matrix was created with spatial modeling software using a first-order queen contiguity definition of neighbors. Due to the very large number of observations (64367), the full matrix would be at least 4.143 gigabytes in size, even though most of the matrix is zeros. The large size of this data set and spatial weight matrix presented computational problems. Regressions were run in Matlab to take advantage of both its special 'sparse' feature that allows large, mostly zero matrices to be stored in a way that minimizes their size, and the Econometrics Toolkit developed by LeSage and others for economic modeling.

Results

Our results suggest that job growth does reduce poverty rates, and is more effective in reducing poverty in high poverty neighborhoods (table 1). They also suggest that stronger social capital speeds poverty reduction in high poverty tracts, and that being in a pocket of poverty can retard poverty reduction in low poverty neighborhoods.[7]

Job growth and social capital

Employment growth was a significant force for poverty reduction, with dramatic differences by initial poverty condition, and the largest effects in the poorest tracts. A one percentage point increase in employment growth rates increased poverty decline by .011

percentage points in low poverty tracts, while increasing poverty decline by .046 percentage points in medium poverty tracts and by .088 percentage points in high poverty tracts. Social capital also provided more poverty-reducing benefit to tracts that began the period with high poverty rates. A one-unit increase in the social capital index reduced poverty by about an additional one percentage-point for high poverty tracts.

Initial poverty rate and adjacency to high poverty

Other things being equal, the higher the initial poverty rate in a tract, the greater the decline in poverty over the 1990s. Being in a poverty pocket, however, slows the decline. Most tracts are not surrounded by high poverty tracts. The average value for the adjacency variable was 10.5%. A typical tract had six neighbors, so on average, roughly one neighbor was high poverty in 1990 for half the tracts. The tendency of high poverty tracts to group together is shown by the wide disparity in adjacency values by initial condition. For low poverty tracts the average adjacency value was 1.7%. This rises to close to the national average, 10.7%, for medium poverty tracts. High poverty tracts, however, were likely to be half surrounded by other high poverty tracts, with an average adjacency value of 50.2%. To some extent this may reflect the dominance of processes that operate at a larger-than-tract scale that greatly influence poverty, but it also reflects the prevalence of pockets of poverty.

The negative effect of poor neighbors seems to be greatest on low-poverty tracts. For low-poverty tracts, a one percentage-point increase in the proportion of poor neighbors reduced the decline in poverty by .056 percentage points. This effect declined as initial poverty rate increased, and in high poverty tracts, the effect of being in a poverty pocket almost disappears.

Mediating effects of social capital and adjacency on job growth effect

The interaction between social capital and employment growth was not significant. The interaction between adjacency and employment growth was, however. For low poverty tracts, adjacency enhanced the effect of job growth. The more a particular tract was surrounded by high poverty tracts, the larger the effect of job growth in reducing poverty in that tract. For high poverty tracts, however, being surrounded by other high poverty tracts hampered the effectiveness of job growth in reducing poverty.

Spatial spillovers

The two spatial parameters are highly significant. The spatial lag parameter rho (ρ) is relatively large, indicating that neighboring changes in poverty are affecting each tract's expected declines, above and beyond any negative effect felt due to the presence of high poverty neighbors. The highly significant parameter lambda (λ) indicates that significant spatial dependence in the error terms also was present and needed to be accounted for to provide efficient results for this model.

Conclusion

Poverty declines between 1990 and 2000 in the United States represented a change in many ways from previous patterns. Poverty decreased nationwide, concentration of poverty decreased, and significant declines were made in the poorest tracts of the poorest areas of the United States.

This study is the first attempt at using tract-level data across the U.S. over two census observations to model determinants of poverty change. New variables were introduced to capture the effects of social capital, poverty pockets, and spillovers on poverty change. Use of a spatial econometric model allowed us to correct for spatial dependence while taking advantage of the homogeneity of the tract level aggregations.

Our results suggest that job growth does have a poverty-reducing effect, and that this effect is larger in high poverty tracts. The negative effect of being located in a poverty pocket is most pronounced in low poverty tracts, but the poverty-reducing effect of job growth is also greatest for low poverty tracts surrounded by high poverty. Social capital appears to be most important in contributing to poverty decline in high poverty areas. It also enhances the impact of job growth in medium poverty areas.

These results suggest three things for antipoverty policy. First, both job growth and social capital development appear to have poverty-reducing effects, and these effects are strongest in high poverty neighborhoods. Second, geographically targeted policies can enhance the efficiency of anti-poverty policies. Strengthening social capital is more likely to be effective in high poverty neighborhoods than in low poverty neighborhoods, and job growth is most effective in reducing poverty in low poverty tracts in high poverty pockets. And third, the poverty of a neighborhood is tied to the fortunes of neighboring areas: there are geographic spillovers in poverty reduction. Reducing poverty in particular neighborhoods affects the poverty of neighboring tracts.

[1] Urban researchers have primarily used a 40% threshold to classify distressed tracts (e.g. Jargowsky). Rural researchers have often adopted a 20% poverty rate as a threshold for distressed areas, based in large part on the persistently poor county designation developed by the USDA-ERS. Since our analysis uses a geographical aggregation that is more homogeneous than a county-based measure and less homogeneous than urban tracts alone, a rate in between these two seems appropriate.

[2] Spatial relationships are often categorized using terms developed from chess. Rook contiguity includes only neighbors with shared sides, while bishop contiguity includes only those with shared vertices. Queen contiguity counts any area with a shared vertex or side as a neighbor.

[3] Earlier versions of this paper included the tract population change as a variable to proxy migration. That variable was eliminated from the final paper due to endogenaity concerns. The results were not materially affected.

[4] Student tracts are those with a tract-level baccalaureate graduation rate in excess of 42% (greater than 1.5 standard deviations above the mean tract rate for 1990). A total of 6437 tracts were designated as potentially student dominated tracts (10% of the total tracts in the analysis). Of the 6963 high poverty tracts, 287 (4.1%) are likely student tracts.

[5] In a first-order contiguity spatial weight matrix, each element of W_1 and W_2 indicate whether tract *i* is or is not immediately adjacent to tract *j* by a value of 1 or 0, respectively. Row standardization divides each element in that row by the row total.

[6] Preliminary runs verified the appropriateness of the full spatial model by comparing model estimations from OLS, SAR (a model with a spatial lag operator only), and SEM (a model with a spatial error term only) as well as results from a likelihood ratio test for spatial dependence in the error terms. Results were not materially affected by the different model specifications.

[7] Since the expected change in the dependent variable is negative, negative parameter estimates indicate that the variable increased poverty decline; a positive coefficient indicates a variable hinders poverty reduction.

Table 1. Regression Results: Determinants of Changes in Tract Poverty Rates

	Base (Low Poverty)		Medium poverty		High Poverty	
Variable	Estimate	Asy. T-Stat	Estimate	Asy. T-Stat	Estimate	Asy. T-Stat
Intercept	16.617	15.29	-0.899	-1.00	1.447	1.19
Black (%)	0.052	15.81	-0.018	-4.85	-0.034	-7.65
Native Amer. (%)	0.156	7.35	-0.105	-4.64	-0.115	-5.23
Hispanic (%)	0.069	11.32	-0.034	-5.96	-0.075	-10.75
Other Races (%)	0.044	5.50	0.032	3.17	0.038	2.83
Single Mothers (%)	0.171	12.73	0.122	7.50	0.049	2.97
High School Grads (%)	-0.104	-11.06	0.008	0.86	0.016	1.38
College Grads (%)	-0.029	-5.87	0.022	3.59	0.122	12.12
Under age 17 (%)	-0.118	-12.31	-0.049	-4.04	0.001	0.04
Over age 64 (%)	-0.042	-4.93	0.013	1.35	0.035	2.57
Poverty in 1990 (%)	-0.605	-44.98	0.132	8.68	0.075	5.00
Adjacency	0.056	8.70	-0.021	-3.54	-0.051	-7.78
Population Density	0.053	10.55	-0.006	-1.03	0.010	1.56
Employment Growth	-0.011	-3.09	-0.035	-8.84	-0.077	-7.97
Social Capital (SC)	-0.140	-1.17	-0.191	-1.61	-0.835	-4.49
Emp. Growth & SC	-0.001	-0.21	-0.010	-1.84	0.004	0.39
Adjacency & SC	-0.001	-4.63	0.001	2.75	0.002	6.93

rho (spatial lag)	-0.377	-17.32
lambda (spatial error)	0.592	36.32

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