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WORKING PAPER SERIES

Trickling Down:
Does Local Job Growth Reduce Poverty?

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Trickling Down: Does Local Job Growth Reduce Poverty?

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Abstract

Was local job growth a significant determinant of poverty reduction between 1990 and 2000? This research takes advantage of newly available data and techniques to explore the job growth on tract-level poverty reduction. Spatial corrections to the model allow for more accurate identification of the significant determinants of poverty reduction across the United States. Results indicate that job growth is a highly significant predictor of poverty reduction, though its effect is modest. While spatial models didn't materially affect the regression coefficients, significant gains in model explanatory power were seen when using a spatial model as compared to OLS.

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I. Introduction

It has long been affirmed that poverty is inextricably linked to both the characteristics of the individual or family who is poor as well as the characteristics of the overall economic environment. The higher incidence of poverty among certain populations in the U.S. (such as minority groups or those with less education) is well documented (see e.g. Schiller 1998 for a discussion), as is the logical link between overall labor market performance and changes in poverty. Many studies have discussed possible reasons why economic growth during the period from the 1950s to the 1970s was correlated with large declines in poverty, or why similar economic growth during the 1980s was not as strongly related to poverty declines (Anderson 1964; Blank 1996). In particular, much recent poverty research has focused on what possible changes in the structure and function of the large economy have resulted in smaller benefits for the poor and near poor as the economy grows in recent decades (discussed in Iceland 1997) or why there is so much regional variation in poverty rates in the US (Levernier et al 2000).

Research has also recently explored to what extent poverty is related to an area's neighbors, social history, or geographic location. These ideas have been incorporated in many ways: through the use of newer spatial modeling techniques or social capital measures, or through more traditional means such as regional or metropolitan dummy variables. Including these variables reflects a growing awareness that poverty existence and poverty change are best viewed not as occurring in a vacuum, but as an interaction of the individual, labor market, and government effects, occurring in a specific location, that may carry with it its own negative or positive benefits (Blank 2004).

Between 1990 and 2000, there was a large, nationwide economic expansion, along with an overall reduction in both the amount of and concentration of poverty. This study takes

advantage of newly available, more finely grained data to explore the relationship between the change in poverty at the census tract level and economic changes. In addition, spatial modeling techniques are explored to see if model function improves after properly correcting for spatial autocorrelation.

II. Recent Literature and Conceptual Model

Most recent work exploring the relationship between poverty change and labor market conditions has occurred at the county level. For example, Levernier, Partridge, and Rickman (2000) explored the regional variations in poverty rate levels by regressing county poverty rates in 1989 on aggregate geographic, demographic, and economic performance variables. In this study, industrial structural change led to short-term increases in poverty, while county employment growth was insignificant. The standard demographic controls led to predicted effects on poverty, and state fixed effects, along with county type specifications (i.e., whether metropolitan, suburban, or non-metropolitan), were significant. A county level study by Rupasingha and Goetz (2003) explored similar variables' effects on both the 1999 level of poverty, as well as changes in poverty between 1989 and 1999, while also incorporating social capital and using a spatial model. They found strong evidence of spatial interactions, along with significant effects related to employment change, some individual characteristics, and non-adjacent, non-metropolitan location.

Despite a recent possible weakening of the historically strong job growth and poverty reduction relationship (Blank 1996; Levernier et al 2000), these studies – along with studies looking at the relationship between individual poverty or probability of employment and local labor markets (Cotter 2002, Davis and Weber 2002) – suggest that improvements in local labor

market conditions still have the potential to change poverty through changes in both earnings and probability of employment. Theoretically, earnings and probability of employment are directly related to an area's poverty level, because the majority of income for US households comes from wages and salaries (Schiller 1998), and areas with better job growth are likely to provide more job offers or better wage offers (Hoynes 2000). Job growth can increase wages and employment of disadvantaged workers – who are also likely to be at or near the poverty level – by reducing unemployment and increasing upward mobility (Bartik 1996). In addition, research has shown that employment and earnings improve for the poor during periods of economic growth (as discussed in Davis and Weber 2002).

III. Data

Most previous studies of determinants of poverty change have relied on county-level aggregations of data. Counties have many advantages: before 1990, this was the only level of geographic aggregation available for the entire U.S.; county boundaries rarely change, and models can use historical data sets; and the wide usage of counties as a data aggregation unit means that combining data from several data sources is relatively easy. However, counties also may suffer from aggregation bias. Because of their large geographic size and large range of population sizes, county aggregate data may be combining values for central city minorities, suburban families, and remote rural residents. If there are significant differences between these populations with regard to poverty and the relationship between job growth and poverty change, the effect may be more difficult to detect because of the nature of the data aggregation.

In 1990 the U.S. Census delineated tracts for the entire country, and the 2000 census is the first time that two consecutive censuses have utilized this geographic aggregation

nationwide. Tracts represent a large improvement econometrically over counties, as they are delineated to capture relatively homogeneous aggregations of 2,000 – 8,000 people with respect to ethnicity and economic class, two key variables in studies of poverty change. Econometric best practices would dictate choosing the level of aggregation closest to that which theory predicts the interaction between poverty and the variable to occur. Since the demographic variables affect poverty at the individual level, and are much more homogeneous in value at the tract level, we chose census tracts as the level of aggregation for those variables. However, the nature of tract definitions means that the number and actual boundaries of tracts change following each census. In 1990, there were over 59,000 tracts with population; in 2000, that number increased to over 65,000. Using tracts as an aggregation unit is difficult between two censuses and may be impossible for any longer term studies, but this research takes advantage of a product by GeoLytics, Inc, that re-aggregates the 1990 census data from the block group level to the tract boundaries in 2000, making comparisons and models of changes between the two censuses possible. The dependent variable is calculated as a simple percentage-point change in poverty rate between the two censuses. Figure 1 maps the geographic distribution of poverty change. The average tract change in poverty was -0.43, while the standard deviation was 6.30 (table 1). Lighter areas of the map saw declines above average over the period, while darker areas experienced smaller declines than average or even increases in poverty over the period.

While tracts may provide more homogeneous units for estimating poverty change than counties, they are clearly not appropriate for representing local labor market conditions. Most people travel outside their tract of residence for work; increasingly, people travel outside their county of residence to work. Research in the South has shown that most new jobs in a county are filled by in-commuters from neighboring counties, suggesting that the functional labor market is

larger even than the county level (Renkow 2003). Using counties as the labor market equivalent, as has been done in many other studies (e.g., Crandall and Weber 2004, Crandall 2004, Rupasingha and Goetz 2003, Levernier et al 2003) may therefore incorrectly state the impact of job growth. Instead, this study uses commuting zones as the labor market area. Commuting zones are county aggregates based on actual commuting data that cover the entire U.S. and have been used in other studies as labor market equivalents (e.g., Davis, Connolly, and Weber, 2003). Whether counties or commuting zones are used, use of a larger level of geographic aggregation for this variable eliminates endogeneity problems between poverty change and employment change (it is unlikely that tract level poverty change has any effect on commuting zone employment change, when there are potentially thousands of tracts in one commuting zone).

There are several possible key changes in the local labor market area that may affect poverty rates. Previous studies have used the area's unemployment rates, predicted employment growth, changes in wage premiums, and employment growth (for a good discussion, see Davis, Connolly, Weber, 2003). Studies have found employment growth to have significant, positive effects on real earnings of males in metropolitan areas, and predicted employment growth to lead to better labor market outcomes for metropolitan residents. Studies have found job growth associated with greater likelihood of employment for low-income adults and employment growth to be significant in studies of county poverty levels and county poverty changes (Davis et al. 2003; Levernier et al. 2000; Rupasingha and Goetz 2003). Employment growth is probably less endogenous that unemployment, so this study uses commuting zone area employment growth between 1990 and 2000 as a primary determinant of poverty changes. In addition, the size of the total commuting zone labor force is used to control for urban spillovers and availability of local

labor (Rupasingha and Goetz 2003). We expect that larger values of both of these labor market variables will result in larger declines in poverty.

Other characteristics of an area will impact possible changes in poverty over the period by influencing labor force participation decisions and outcomes of residents. As alluded to earlier, individuals of racial or ethnic minority groups earn, on average, lower wages than their white counterparts, while households with children headed by single mothers face multiple labor market constraints that lead to a very high likelihood of poverty for these families. Individuals with less human capital (formal higher education) will earn less. Large families are at a higher risk for poverty. High rates of poverty among elderly have to a large extent been mitigated by social security programs, but by virtue of being out of the labor market, they may also be at higher risk for poverty. Larger proportions of any of these household types or residents in an area will therefore lower the average income and raise the poverty rate. Tract-level variables control for differences in populations of those at higher risk for poverty. The tract proportion of African-Americans, Native Americans[1], Hispanics, and all other races are each included as variables, with an expected positive sign. Tract-level proportions of those with high school diplomas or GEDs, some college or a two-year degree, and at least a four-year degree are each separate control variables and are measures of human capital. Larger proportions of residents with higher levels of education can be expected to accelerate poverty decline. Two age categories are used to control for larger proportions of a tract's population that are out of the labor market and thus possibly at higher risk for poverty: the proportion of the population under 17, and the proportion over 64. The first measure is also a gauge of average family size, and we expect that larger families are at a higher risk for poverty. The proportion of single-mother households out of all

[1] Native Americans and other racial groups were included in this study because individual tracts may be dominated by a group that comprises relatively little of the overall U.S. population.

households is also used as a control variable, and is expected to act as a drag on area poverty declines[2].

History clearly plays a role in determining what areas of the U.S. are poor, as pockets of persistent poverty have been noted in several studies (Duncan 1999; Miller et al 2002). In these pockets, poverty remains high and entrenched, despite nationwide increases in job availability or other positive factors. It could be that this resistance to poverty declines is due to ingrained systems of negative social capital; if this is the case, measures of social capital may be correlated with poverty declines as well. However, there has been little agreement on how to appropriately measure social capital, particularly in a quantitative way. Instead, poverty at the beginning of the period is included to control for all previous conditions in the tract. In essence, it controls for history, in that the poverty rate at the beginning of the period is a function of all prior conditions in the tract (ethnic composition, social history, previous labor market conditions, etc). Poverty change is not likely to be unrelated to beginning levels of poverty; neo-classical theory would lead us to expect prior poverty to be positively associated with poverty change if, in fact, areas of cheaper labor and underdevelopment grow at a faster rate than more developed areas.

Changes in the actual households in an area over the period may also change the poverty rate, if the movement of poor and non-poor households into and out of an area is not equal, and there is evidence that both the poor and nonpoor migrate preferentially to poor and nonpoor areas, respectively (Nord 1998). Migration could matter in a poverty change study if it is assumed that migration *other than that related to job growth* changes the poverty rate. However,

[2] Previous studies (e.g., Rupasingha and Goetz 2003) have found multicollinearity problems at the county level between variables measuring the proportion of African-Americans and the proportion of single-mother households, but there were no statistics indicating this was a problem at the tract level, so both were used in the final regression analysis.

limitations in data available at the tract and commuting zone level make it impossible to include a meaningful migration variable in this analysis.

Dummy variables control for two other possible influences on tract-level poverty change. Because tracts are defined for small, homogeneous populations, it is possible that some tracts will be dominated by student populations (Jargowsky 1997). Although nominally poor, they are clearly not people at risk for life long poverty and its attendant disadvantages; in these areas, changes in poverty are less likely to be related to changes in labor market conditions (with the possible exception of overall increases and decreases in population related to declines and improvements in job prospects). In this study, we denote tracts with a baccalaureate attainment rate greater than 42% in 1990 (greater than one and a half standard deviations above the mean rate) as student tracts. In addition, regional dummy variables control for broad differences seen in poverty changes between the four census-defined regions, with the western states dummy variable the excluded category in the regression analysis.

IV. Empirical Model

The empirical model assumes a direct, linear relationship between the change in tract poverty and changes in employment growth in the local labor market over the period, after correcting for racial, ethnicity, household structure, and human capital differences between tracts:

$$(1) \qquad \mathbf{Y} = \alpha + \mathbf{X}\beta + \mathbf{Z}\gamma + \boldsymbol{\varepsilon}$$

where $\mathbf{Y}$ is the vector of tract level percentage point changes in poverty between 1990 and 2000 for all tracts 1 – n, $\mathbf{X}$ is a matrix of tract-level demographic and human capital controls for all tracts, $\mathbf{Z}$ is a matrix of the job growth and labor force size variables for the commuting zone that each tract is in, and $\boldsymbol{\varepsilon}$ is a vector of error terms. If the error terms are spherical, ordinary least-

squares (OLS) can be used to estimate the regression parameters β and γ. If there is evidence of spatial dependence, a spatial model must be estimated using a maximum likelihood or method-of-moments estimator.

Spatial dependence can take two possible forms: that present as a spatial lag, and that present in the error term. The former model, known as the spatial lag or SAR model, is:

(2) $$\mathbf{Y} = \alpha + \rho\mathbf{WY} + \mathbf{X}\beta + \mathbf{Z}\gamma + \boldsymbol{\varepsilon}$$

$$\boldsymbol{\varepsilon} \sim N(0, \sigma^2\mathbf{I}_n)$$

where **Y, X,** and **Z** represent the same vector and matrices previously described, $\rho\mathbf{WY}$ calculates a spatial lag variable, and **W** represents a known spatial weight matrix, defined by the analyst to reflect the geographic level at which the spatial dependence is thought to occur.

The latter model referred to above is the spatial error or SEM model:

(3) $$\mathbf{Y} = \alpha + \mathbf{X}\beta + \mathbf{Z}\gamma + \boldsymbol{\upsilon}$$

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

$$\boldsymbol{\varepsilon} \sim N(0, \sigma^2\mathbf{I}_n)$$

where $\boldsymbol{\upsilon}$ is an error term corrected for spatial dependence through the $\lambda\mathbf{W}\boldsymbol{\upsilon}$ variable that adjusts the spherical, normally distributed error term$\boldsymbol{\varepsilon}$.

Several tests exist to diagnose spatial dependence between observations. In general, a spatial lag variable is included when there is theoretical reason to expect the value of Y in one tract to be related to the values of Y in neighboring tracts, or when the value from the diagnostic test indicates that spatial lag dependence is of greater magnitude than that in the error terms (Florax et al 2003). Since the spatial lag operator uses the average neighboring value of the dependent variable for each tract as an explanatory variable, the parameter ρ reflects the spatial dependence inherent in the sample data (LeSage 1999). Spatial error dependence often arises

when the geographical level of aggregation does not match the geographic level at which the process under study occurs and can be thought of as "nuisance" dependence (Anselin 2002). The spatial error parameter λ corrects for this dependence that occurs between neighboring tracts that shows in adjacent error terms.

The row-standardized spatial weight matrix used in this study was created with the free spatial modeling software and statistics program GeoDa, using a first-order queen contiguity definition of neighbors[3]. Regressions were also run in GeoDa (Anselin 2003). GeoDa includes a 'sparse' feature that allows large, mostly zero matrices to be stored in a way that minimizes their size, which is critical for modeling very large spatial data sets of this nature.

V. Results

One measure of spatial correlation among observations is Moran's *I* statistic, an indicator of global spatial dependence. However, global indicators, with their assumption of structural stability over space, may be unrealistic (Anselin 1995). A local indicator of spatial association (LISA) such as the local Moran's *I* statistic can identify local spatial clusters that may exist and may or may not be identified through a global indicator (Anselin 1995). Local Moran's *I* statistics indicate the presence of values that are significantly related to neighboring ones in any direction – i.e., whether a high value in deviations from the mean of the variable in question is adjacent to another high value or low value, and the same for a low value of the variable, resulting in four possible significant values: low-low, low-high, high-low, and high-high. The values are often graphed as locations in a quadrant, where the axes are 0. For this data set, both

[3] Spatial relationships are often categorized using terms developed from chess. Queen contiguity counts any area with a shared vertex or side as a neighbor. In a first-order contiguity spatial weight matrix, each element of W indicates 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.

the global Moran's *I* (Moran's *I* = 0.202, p-value of 0.0010) and many local Moran's *I* statistics (figure 2) were highly significant, indicating the presence of spatial autocorrelation to correct for. This is expected since much spatial error can arise from inconsistencies between the level of aggregation used and the level at which the process under study occurs. Since our poverty data is measured at the tract level, while the key influence is anticipated to be labor market-level employment growth, there is a direct reason to expect 'nuisance' spatial autocorrelation in the error terms. In examining figure 2, the map of significant local Moran's *I* values overlaid with commuting zone level employment growth, it is reasonable to expect there to be spatial autocorrelation even after commuting zone level employment growth is accounted for. Significant clusters of values occur in areas of both positive and negative employment growth, indicating that there are spatial interactions between adjacent tracts above and beyond the effects felt through commuting zone employment change.

The first model considered was estimated using ordinary least squares, which has been commonly used in studies of this nature (table 2). Using OLS, the overall model fit was 0.277, not uncommon for cross-sectional models of this type with change variables as dependent, and low enough that no significant gain is seen using tract geography relative to county aggregations, despite being better theoretically. Since the mean value of the dependent variable is negative, positive coefficients indicate determinants that led to a smaller than average reduction, or even an increase, in poverty over the period, while negative coefficients indicate determinants that led to accelerations in poverty decline over the period. In general, best practices in spatial modeling dictates that the OLS residuals be checked for spatial dependence through two Lagrange Multiplier tests (LM_λ and LM_ρ), which test the null hypothesis of no spatial dependence against alternatives of spatial error and spatial lag dependence, respectively (Florax et al 2003). The

results from the two tests are compared and, if both are significant, the larger value is used to indicate which dependence to control for.

The difficulty in calculating some of these statistics for very large data sets has been noted (LeSage 1999), and indeed we were unable to calculate the LM_ρ statistic, which involves as a step calculating the product of the X and W matrices – resulting in a non-sparse matrix of 64,367 by 64,367 elements. However, the results from the LM_λ test did indicate strong evidence of spatial error (LM_λ = 4977.4; chi-squared critical value of 17.6110). Since the results from the Moran's *I* as well as the LM_λ test indicated spatial dependence, the spatial lag and spatial error models were then estimated in turn. Of these three specifications, the spatial error model provided the best fit and had the most significant spatial parameter and was adopted in the final specification. However, there is little change between the actual parameter estimates using OLS as compared to the SAR or SEM models. This is consistent with theory, which states that in the presence of spatial error correlation, OLS is unbiased but not as efficient. Using the spatial model in the presence of spatial error autocorrelation is necessary theoretically and results in better overall model fit, but to use OLS in this instance did not result in materially different or incorrectly signed parameter estimates.

As anticipated, higher proportion of minority populations led to slower poverty declines over the period (column 5, table 2). This held true for each of the minority groups included (African-American, Native American, Hispanic origin, and other races). Higher proportions of female-headed households were also a significant drag on poverty reduction. Larger populations of people with higher levels of education, measured at three different thresholds, led to larger declines in poverty. One unexpected result is the negative sign for proportion of population under 17. As a proxy for larger family size, which is clearly associated with higher probability of

poverty (simply due to the nature of the poverty, in that larger families essentially must divide income from generally one or two workers among more family members), it is hard to imagine a scenario where increased family size results in larger reductions in poverty. Conversely, it's not too surprising that higher proportions of elderly also results in larger declines, because of their insulation from poverty risk factors associated with not participating in the labor market due to programs like social security.

Prior poverty was a highly significant determinant of poverty change, and the negative coefficient indicates that areas of high poverty in 1990 had larger declines in poverty over the decade. This provides some support for the idea of convergence in poverty rates around the country between the 1990 and 2000 censuses and indeed matches other data analysis that has indicated a decline in poverty concentration in urban areas over this period (Jargowsky 2003; Kingsley & Pettit 2003). It is clear that expected poverty change cannot be viewed in isolation from initial poverty, at any rate.

The dummy variables for possible college tracts and two of the three census defined regions used were also significant and of expected sign. As anticipated, college dominated areas are more resistant to poverty change than areas more dependent on prevailing labor markets, and the South and Midwest saw greater poverty declines compared to the West (the excluded category), with tracts in New England not statistically different.

The change in employment in each tract's commuting zone was significant and negative. In this recent decade, with poverty measured at the tract level, the relationship between employment growth and poverty decline still holds. This relationship has even been controlled for differences in overall labor market size through the total labor force variable, and the

negative coefficient on the total labor force variable indicates that areas with a larger labor force (generally more urban areas) experienced greater declines in poverty.

To address our initial concern that using county employment growth would incorrectly state the effect of employment change on tract level poverty change, we compare the results of this model with a very similar spatial error model that used county employment change as the measure of labor market conditions (Crandall 2004). Although the county model used in Crandall (2004) did include three other insignificant variables not included here as well as a different measure of overall labor force size and so is not exactly comparable in every way, there is surprisingly little difference – both in sign and in absolute coefficient – between the two specifications. The model using county employment growth had a coefficient estimate of -0.020 and an asymptotic T-stat of -8.46, along with an overall adjusted R2 of 0.355, compared to our results here of -0.022, -6.34, and 0.342, respectively.

VI. Conclusion

Local employment growth does appear to trickle down to the poor. If one controls for demographics, initial poverty rates and major Census region, local job growth speeds tract-level poverty reduction. Our study is the first to use national tract-level poverty change data to examine the job growth/poverty reduction relationship. The fact that our results confirm previous research conducted with county level data increases confidence that the relationship is robust. Yet an additional one percentage point increase in local job growth over the decade of the 1990s was associated with only a 0.02 percentage point decline in tract level poverty, holding demographics and historical factors constant. The effect is significant, but not large, considering how difficult it is to effect local job growth.

Our study is one of only a few to correct for spatial autocorrelation. Corrections for spatial lag and spatial error appear to improve the explanatory power of the model somewhat, but do not change the conclusions in any significant way. If one controls for spatial error, the estimated effects of demographic characteristics appear to increase slightly: with spatial controls, minority status had a slightly larger retarding effect on poverty decline and additional formal education slightly speeds poverty reduction. But the effect of job growth on poverty reduction – our primary interest – does not change when one adds spatial corrections.

The good news from this study is that job growth does appear to help the poor and reduce local poverty rates. The bad news is that the effect is not large. Job growth benefits communities in a number of ways, including reducing poverty, and can be part of a local poverty reduction strategy. However, subsidies for local job creation, if done in isolation from complementary programs and only to reduce poverty, would appear to be an expensive way to reduce local poverty rates.

Table 1: descriptive statistics

Tract-Level Statistics (N=64367)				
Variable	Minimum	Maximum	Mean	St. Dev.
Change in Poverty	-100.00	100.00	-0.44	6.30
% African-American	0.00	100.00	12.32	23.27
% Native American	0.00	100.00	0.85	4.82
% Hispanic Origin	0.00	100.00	8.33	16.46
% Other Races	0.00	100.00	2.47	5.36
% Female Headed Households	0.00	100.00	6.59	6.07
% High School Grads	0.00	100.00	30.01	9.45
% Some College	0.00	100.00	24.59	8.12
% College Grads	0.00	100.00	19.61	15.05
% Under 17	0.00	85.71	22.76	6.47
% Over 64	0.00	100.00	12.94	7.47
% Poverty, 1990	0.00	100.00	13.92	12.67
% Growth Rate Employment	-27.96	96.36	12.58	11.78
CZ Labor Force (1,000s)	0.64	7484.80	1466.77	1943.36
Commuting Zone Statistics (N=723)				
Variable	Minimum	Maximum	Mean	St. Dev.
% Growth Rate Employment	-27.96	96.36	12.97	13.12
CZ Labor Force (1,000s)	0.64	7484.80	173.35	492.14

Table 2: regression results

	OLS		SAR		SEM	
Variable	Estimate	T-Stat	Estimate	Z-Value	Estimate	Z-Value
Intercept	15.402	48.68	14.987	47.88	17.161	47.44
% African-American	0.034	24.80	0.034	24.79	0.047	27.76
% Native American	0.048	10.52	0.053	22.72	0.067	12.26
% Hispanic Origin	0.038	20.31	0.036	19.66	0.046	18.77
% Other Races	0.062	13.63	0.053	11.94	0.083	14.82
% Female Headed Households	0.207	34.38	0.184	30.78	0.205	32.48
% High School Grads	-0.126	-27.86	-0.124	-27.80	-0.134	-27.14
% Some College	-0.050	-13.35	-0.058	-15.46	-0.074	-17.31
% College Grads	-0.115	-33.68	-0.112	-33.32	-0.125	-33.87
% Under 17	-0.184	-39.15	-0.170	-36.54	-0.180	-35.06
% Over 64	-0.043	-11.68	-0.039	-10.74	-0.046	-11.45
% Poverty, 1990	-0.371	-123.77	-0.348	-110.30	-0.437	-130.76
College tract dummy	0.625	5.38	0.591	5.18	0.625	5.36
NE region dummy	-0.026	-0.29	-0.114	-1.31	-0.145	-1.13
MW region dummy	-1.249	-16.07	-0.957	-12.44	-1.254	-10.82
S region dummy	-0.792	-10.68	-0.691	-9.45	-0.793	-7.19
% Growth Rate Employment	-0.023	-9.80	-0.018	-7.75	-0.022	-6.34
CZ Labor Force (1,000s)	0.000	-6.09	0.000	-9.34	0.000	-7.10
rho (lag)			0.211	38.49		
lambda (error)					0.392	72.05
Adjusted R2	0.277		0.299		0.342	

* Shaded cells indicate variable not significant at 5%.

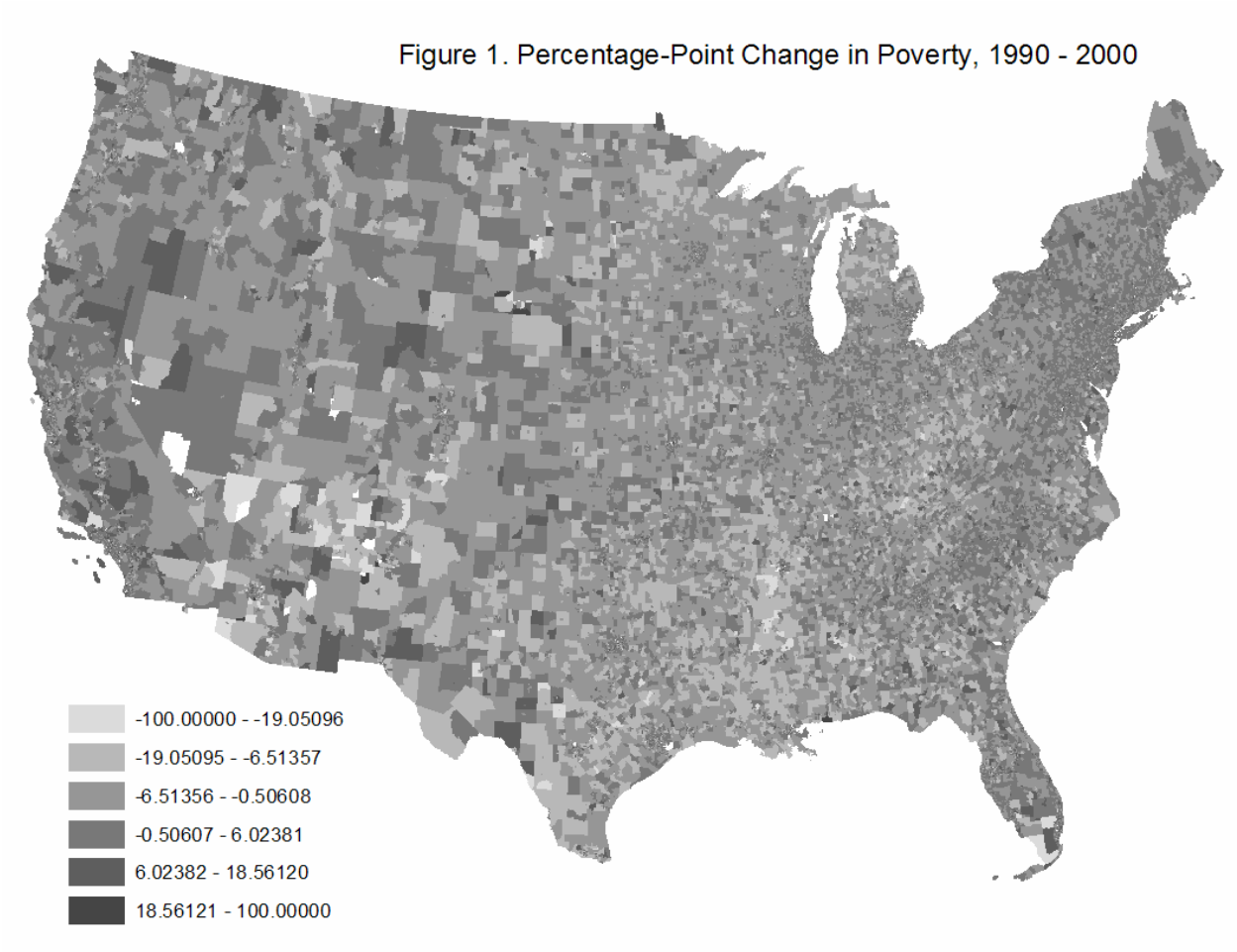
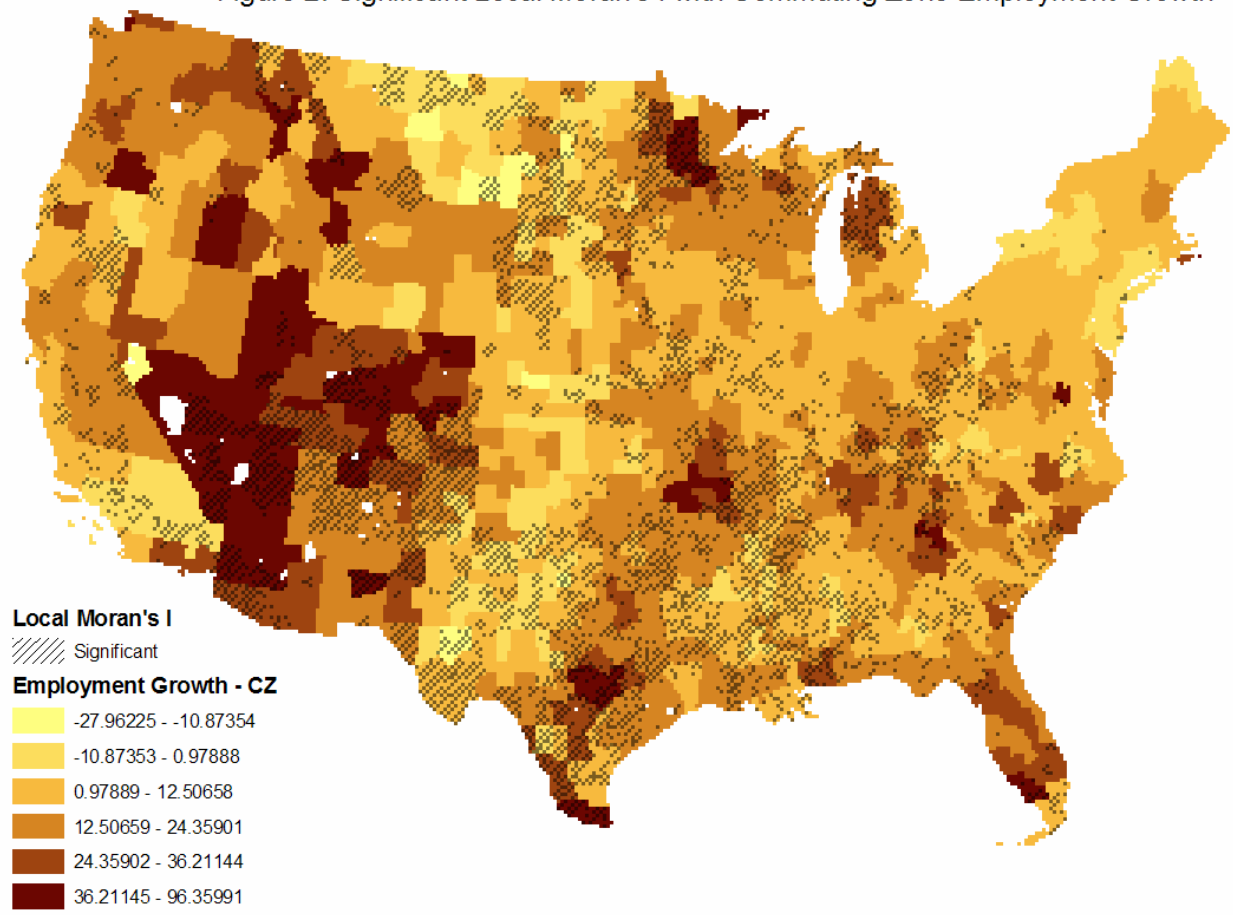


Figure 1. Percentage-Point Change in Poverty, 1990 - 2000
-100.00000 - -19.05096
-19.05095 - -6.51357
-6.51356 - -0.50608
-0.50607 - 6.02381
6.02382 - 18.56120
18.56121 - 100.00000

Figure 2. Significant Local Moran's I with Commuting Zone Employment Growth



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