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ABSTRACT

This paper focuses on why metropolitan areas vary in their capacity to translate generally high employment rates into economic opportunity for the disadvantaged. Data come from the Urban Institute's Urban Underclass Database, which includes poverty and employment data for 1980 and 1990 for the 100 largest metropolitan areas down to the Census tract level. Despite unprecedented economic growth since 1993, large segments of the population remain poor, and many cities have unacceptably high rates of poverty and economic disadvantage. The first section of this paper illustrates the wide divergence among metro areas along two dimensions: (1) the proportion of residents employed, compared with the proportion who are poor and (2) the relationship between 1980-90 employment change in a metro area and the 1980-90 change in that area's poverty rate. The second section uses multiple regression to distill the systematic influence of structural factors on the ability of a metro area to convert employment and employment growth into poverty reduction. Among these factors are the quality of education, industrial structure, and forms of business ownership in a given metro area. The third section identifies metro areas whose experiences are exceptions to the patterns predicted by those structural factors. The final section discusses potential implications of the findings and suggests next steps for research. (SM)

METROPOLITAN GROWTH AND ECONOMIC OPPORTUNITY FOR THE POOR: IF YOU'RE POOR DOES PLACE MATTER?

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INTRODUCTION

Despite unprecedented economic growth since 1993, large segments of the population remain poor, and many cities still have unacceptably high rates of poverty and economic disadvantage. According to a 1999 report prepared for the U.S. Department of Housing and Urban Development (HUD),[1] 32 percent of cities continue to have poverty rates above the national average and 14 percent are "doubly" burdened by above-average poverty combined with above-average unemployment.

The goal of this paper is to begin to understand why metropolitan areas vary in their capacity to translate generally high employment rates into economic opportunity for the disadvantaged. The ultimate goal of such understanding is to use the experiences of particularly successful and particularly unsuccessful metro areas to help design more effective workforce development and other strategies to bring economic opportunity to the urban poor. The Urban Institute's Urban Underclass Database is a uniquely valuable body of data for this purpose. It includes employment and poverty data for 1980 and 1990 for the 100 largest metropolitan areas, down to the Census tract level. In addition to estimating the poverty rate as traditionally measured, it provides metropolitan-wide measures of the degree to which poverty is concentrated in particular Census tracts in the metro area. Concentrated poverty, other things equal, is likely to be harder to tackle than dispersed poverty of the same overall magnitude.

The first section of the paper illustrates the wide divergence among metro areas along two dimensions: (1) the proportion of residents employed, compared with the proportion who are poor, and (2) the relationship between 1980–1990 employment change in a metro area and the 1980–1990 change in that area's poverty rate. The second section uses multiple regression to distill the systematic influence of structural factors on the ability of a metro area to convert employment and employment growth into poverty reduction. The third section identifies metro areas whose experiences are exceptions to the patterns predicted by those structural factors. The final section discusses potential implications of the findings and suggests next steps for research.

[1] *Now is the Time: Places Left Behind in the New Economy*, 1999 for the U.S. Department of Housing and Urban Development.

Converting Employment and Economic Growth into Economic Opportunity for the Poor

Most research into the relationship between economic activity and poverty at the metro area level contrasts the degree of deprivation in the area's central city with that in its suburbs.[2] Such studies provide insight into how badly off central city residents are compared with their fellow residents in the surrounding areas. But they shed no light on why some metro areas seem to do much better than others in converting their overall levels of economic activity into opportunity for their poorer residents.[3] Poverty indicators—such as the general poverty rate, the spatial poverty rate, or changes in those rates—provide valuable information on the relative prevalence of and trends in poverty across metropolitan areas. But they also give no insight into the factors that help explain divergences between areas in how poverty compares with overall employment.

This section uses a new type of measure (which the authors call conversion ratios) to look directly at the relationship between employment and poverty rates across metropolitan areas. The first column of table 1 shows the number of people employed relative to the number of poor people in 1990. The ratio is calculated by dividing the employment-to-population ratio by the poverty rate in a metro area. The ratio shows the relationship between employment and poverty in a metro area, and gives a sense of how well a metro area converts its employment base into economic opportunity. For example, the larger the number, the more effective a metro area was in converting employment into lower poverty. On the other hand, a low number implies less capacity to reduce poverty. The ratio allows you to compare metro areas and determine whether places with the same (or similar) employment base were able to reduce poverty by the same amount. Of the 100 largest metropolitan statistical areas (MSAs) in the Urban Institute's Underclass Database, table 1 shows 15 metro areas with the best and 15 metro areas with the worst employment conversion ratio ranking. The conversion ratio for the top entry in the table (Washington, D.C.), for example, indicates that for every 1 person in poverty there were 9 people employed in 1990. For the bottom entry in the table (El Paso, Texas), in contrast, for every 1 person in poverty only slightly more than 1 person was employed.

[2] Gottlieb, Paul. *The Effects of Poverty on Metropolitan Area Economic Performance: A Policy-Oriented Research Review*, June 1998 for the National League of Cities. David Rusk also highlights the disparity between cities and suburbs in *Cities without Suburbs*, 1993.

[3] The 1999 HUD study provides a descriptive analysis of the relationships between poverty and economic growth in different metro areas. However, it does not claim to address the extent to which structural factors in the demographic, social, or economic environment might explain why the cities mentioned in the report are doing so poorly despite general economic prosperity.

TABLE 1. METROPOLITAN AREAS RANKED BY EMPLOYMENT TO POVERTY CONVERSION RATIO		
MSA	EMPLOYMENT-TO-POVERTY CONVERSION RATIO	1990 EMPLOY-TO-POPULATION INDICATOR
	Top 15	
Washington, DC	8.9	0.56
Bergen	8.7	0.52
San Jose	7.3	0.54
Seattle	7.1	0.53
Hartford	7.1	0.52
Oxnard	7.1	0.50
Allentown	6.9	0.48
Minneapolis	6.8	0.54
Harrisburg	6.7	0.51
Wilmington	6.7	0.51
Honolulu	6.6	0.47
Boston	6.6	0.53
Bridgeport	6.5	0.50
New Haven	6.5	0.51
Vallejo	6.4	0.45
	Bottom 15	
Birmingham	3.0	0.45
Johnson	3.7	0.45
Stockton	2.6	0.41
New York	3.9	0.45
Miami	3.9	0.47
Tucson	2.2	0.43
Flint	2.0	0.42
Memphis	3.5	0.45
Baton Rouge	3.1	0.44
Bakersfield	2.6	0.39
San Antonio	2.1	0.42
Mobile	2.7	0.42
New Orleans	1.9	0.42
Fresno	2.4	0.40
El Paso	1.4	0.37

The second column of table 1 shows the 1990 employment-to-population ratios for the same metro areas, to highlight metro-area differences in the relationship between their conversion ratios and their employment-to-population ratios. Take Allentown, Pennsylvania, and Miami, Florida, for example: Both had roughly the same employment-to-population ratios (.48 and .47 respectively) in 1990. However, Allentown had an employment-to-poverty conversion ratio of 6.9 while Miami had a ratio of only 3.9. We are left with the important question of why Allentown, with the same employment base, had less poverty than Miami.

TABLE 2. METRO AREAS RANKED BY EMPLOYMENT BASE AND CAPACITY TO CONVERT 1990 EMPLOYMENT INTO REDUCED SPATIAL POVERTY RATES

MSA	EMPLOYMENT-TO-SPATIAL-POVERTY CONVERSION	1990 EMPLOY-TO-POPULATION INDICATOR
	Top 15	
Vallejo	65.2	0.45
Oxnard	52.8	0.50
San Jose	34.5	0.54
Honolulu	32.5	0.47
Seattle	30.9	0.53
Allentown	27.0	0.48
Washington, DC	27.0	0.56
Bergen	26.4	0.52
Minneapolis	21.5	0.54
Greensboro	20.3	0.53
Scranton	20.0	0.45
Portland	19.3	0.51
Providence	19.1	0.49
Charlotte	18.9	0.53
Albany	18.6	0.49
	Bottom 15	
Mobile	5.0	0.42
Flint	5.0	0.42
Johnson	5.0	0.45
New York	5.0	0.45
Albuquerque	4.9	0.47
Los Angeles	4.6	0.47
Tucson	4.6	0.43
Miami	4.6	0.47
Stockton	4.2	0.41
Baton Rouge	4.1	0.44
San Antonio	3.7	0.42
New Orleans	3.5	0.42
Bakersfield	3.3	0.39
Fresno	2.8	0.40
El Paso	1.9	0.37

Table 2 shows employment conversion ratios for a different measure of poverty—spatial poverty. The spatial poverty rate allows metro areas to be compared according to how concentrated their poverty populations are.[4] The higher the spatial poverty rate, the more concentrated the poor are in particular parts of the metro region. As can be seen, using the 1990 spatial poverty rate as the denominator and the 1990 employment-to-population ratio as the numerator in the conversion ratio, there was considerable variation between metro areas with the same or similar employment bases. Look at Allentown and Miami again. Allentown had an employment-to-spatial poverty ratio in 1990 of 27.0, while Miami's was 4.6. This means that for every spatially concentrated poor person in Allentown, there were 27 people employed. However, in Miami, there were only 4.6 people employed for every spatially concentrated poor person. This suggests that the employment base in Allentown seems to be more effective at reducing spatial poverty than the same employment base in Miami.

Table 3. Top 15 and Bottom 15 Metropolitan Areas Ranked by % Change in Employment-to-Poverty Conversion Ratio, 1980–1990

MSA	ANNUALIZED % CHANGE IN EMPLOYMENT-TO-POVERTY RATIO 1980–1990	AVERAGE EMPLOYMENT TO POPULATION 1980–1990
Top 15		
Wilmington	4.8%	0.53
Jacksonville	3.7%	0.52
Washington, DC	3.6%	0.53
New Haven	3.5%	0.52
Honolulu	3.5%	0.52
Newark	3.4%	0.52
Vallejo	3.4%	0.51
Atlanta	3.3%	0.51
Orlando	3.3%	0.50
Bridgeport	3.1%	0.51
Norfolk	2.9%	0.50
Baltimore	2.8%	0.51
Raleigh	2.8%	0.52
Philadelphia	2.6%	0.51
Jersey City	2.6%	0.50
Bottom 15		
El Paso	-1.6%	0.36
Wichita	-1.7%	0.49
Akron	-1.7%	0.45
New Orleans	-1.9%	0.42
Baton Rouge	-1.9%	0.43
Pittsburgh	-2.0%	0.42

[4] See appendix for a full definition of the spatial poverty rate and the spatial poverty rates for the 100 metro areas in the study.

Table 3. Top 15 and Bottom 15 Metropolitan Areas Ranked by % Change in Employment-to-Poverty Conversion Ratio, 1980–1990		
MSA	ANNUALIZED % CHANGE IN EMPLOYMENT-TO-POVERTY RATIO 1980–1990	AVERAGE EMPLOYMENT TO POPULATION 1980–1990
Tucson	-2.2%	0.42
Tulsa	-2.5%	0.47
Oklahoma	-2.6%	0.47
Youngstown	-2.9%	0.41
Bakersfield	-3.0%	0.40
Milwaukee	-3.1%	0.48
Flint	-3.4%	0.40
Houston	-4.1%	0.49
Fresno	-4.1%	0.41

Table 4. Metro Areas Ranked by % Change in Employment-to-Spatial Poverty Conversion Ratio, 1980–1990		
MSA	ANNUALIZED % CHANGE IN EMPLOYMENT-TO-SPATIAL-POVERTY CONVERSION RATIO	AVERAGE EMPLOYMENT-TO-EMPLOYMENT 1980- 1990
Top 15		
Columbia	8.8%	0.48
Norfolk	7.6%	0.41
Orlando	7.6%	0.49
Jersey City	7.0%	0.46
Vallejo	6.8%	0.43
Memphis	6.5%	0.43
Honolulu	5.9%	0.45
Washington, DC	5.8%	0.53
Greenville	5.6%	0.48
Greensboro	5.3%	0.51
Jacksonville	5.3%	0.44
Baltimore	4.5%	0.47
New Haven	4.2%	0.49
Albany	3.9%	0.46
Bergen	3.6%	0.50
Bottom 15		
San Jose	-4.7%	0.52
Portland	-4.7%	0.49
Gary	-4.8%	0.43
Fort Worth	-4.9%	0.50

Table 4. Metro Areas Ranked by % Change in Employment-to-Spatial Poverty Conversion Ratio, 1980–1990		
MSA	ANNUALIZED % CHANGE IN EMPLOYMENT-TO-SPATIAL-POVERTY CONVERSION RATIO	AVERAGE EMPLOYMENT-TO-EMPLOYMENT 1980- 1990
Tulsa	-5.1%	0.47
Stockton	-5.4%	0.40
Salt Lake	-5.4%	0.44
Oklahoma	-5.4%	0.47
Pittsburgh	-5.6%	0.42
Las Vegas	-6.8%	0.49
Flint	-7.3%	0.40
Houston	-7.9%	0.49
Anaheim	-8.2%	0.52
Bakersfield	-8.2%	0.40
Scranton	-11.5%	0.42

A more dynamic version of the conversion ratio concept (the percentage change in the employment-to-poverty conversion ratio) is shown in tables 3 and 4. This ratio relates the annualized change in the employment-to-poverty ratios from 1980 to 1990. (Table 3 shows the conversion ratio for overall poverty; and table 4 shows the conversion ratio for spatial poverty.) Thus, table 3 shows that the top metro area (Wilmington, Delaware) over the 10-year period, increased its capacity to lower poverty through employment by 4.8 percent per year on an annualized basis. On the other hand, the bottom metro area (Fresno, California), saw its capacity to reduce poverty through employment decline by 4.1 percent per year on an annualized basis. Comparing Wichita, Kansas, and New Haven, Connecticut, demonstrates once again the divergence in the conversion capacities of different metro areas with similar employment bases. Both had average employment-to-population ratios of .49. However, New Haven improved its conversion ratio by 3.5 percent per year on an annualized basis, while Wichita's ratio declined by 1.7 percent per year on an annualized basis.

Table 4 relates the annualized 1980–1990 change in employment-to-spatial-poverty conversion ratio. The top three metro areas were in the South. Each of these metro areas gained substantially in their capacity to reduce poverty through employment. On the other hand, the bottom three—Scranton, Pennsylvania; Bakersfield, California; and Anaheim, California—saw their capacity to reduce poverty through employment decline substantially over the period.

Tables 1 through 4 indicate that several metro areas (Washington, D.C. Wilmington, Delaware; and New Haven, Connecticut) did consistently well in converting their employment into lower poverty. On the other hand, others (Flint, Pittsburgh, Miami) were consistent poor performers.

What factors might explain the difference in capacity to convert employment and economic growth into economic opportunity?

Explaining Differences in Conversion Capacity

The conversion ratios presented above confirm that metropolitan areas have different capacities to transform employment and employment growth into economic opportunity for the poor. This section addresses the crucial question of what leads to these differences. The appropriate statistical technique for this purpose is multiple regression, which reveals the separate contributions of each of a set of employment, population, and regional factors that can be expected to lead to differences in "conversion" success, holding other influences constant.[5] A single basic model is used, with five separate measures of the dependent variable (indicator of metro-area poverty).[6] The sample used to test the model consisted of the 100 largest metropolitan areas, with observations for 1980 and 1990, from the Urban Institute's Underclass Database.

The structural factors chosen as independent (explanatory) variables in the model—all of which directly or indirectly reflect the workings of the labor market—along with the rationale for their inclusion are as follows:

- *Metro-area employment growth between 1980 and 1990.* The hypothesis is that employment growth leads to reduced poverty, other things equal. That is, rising employment will enable more low-income people to find jobs that will pay increasingly higher wages as the labor market tightens. This increase in employment and, presumably, wages should result in lower poverty—making the expected sign on the coefficient of this variable negative.
- *Metro-area population change.* The hypothesis is that population growth increases poverty, other things equal. While rapid growth in population often leads to economic vitality, it also means increased labor market competition, as the growing population increases the supply of low-skilled workers competing for employment. Given the low skills and marginal labor market connections of poor individuals, this increased competition can be expected to limit their opportunities to find the type of work that improves their economic status—making the expected sign on the coefficient of this variable positive.

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[5] See Gottlieb 1998 and Adelman and Jaret 1999 for recent research looking at the relationship between poverty and economic factors.

[6] See appendix A for the functional form of the regression model and full definitions of the independent variables and different versions of the dependent variable.

- The metro-area poverty rate at the start of the period (1980). The hypothesis here is twofold. On the one hand, metropolitan areas with higher-than-average initial poverty rates will have to reduce poverty at much higher rates than average to have low poverty at the end. On the other hand, high poverty rates at the beginning of a period may be an indicator of two factors that could hasten poverty reduction: (a) low-income workers willing to reduce the wage at which they will take a job (their reservation wages) because of the large number of individuals with similar characteristics searching for work; and/or (b) high initial poverty, indicating a large number of low-income people ready to enter the labor market, if economic growth is strong and in-migration of low-income people into the area low. Thus, the expected sign of the coefficient on this variable is unclear.
- The ratio of the number employed at the start of the period to the population at the start of the period. The hypothesis is that tight labor markets at the beginning of a period result in higher demand for low-income workers during periods of growth, other things equal. This is based on the assumption that most low-income workers will be at the end of most job queues. The expected sign of the coefficient on this variable is negative.
- Geographic region. The hypothesis is that region is important in explaining differences in economic performance, because it reflects (is a proxy for) differences among metro areas in social or institutional factors that affect the way the metro-area labor market functions, such as industrial structure, quality of education, and forms of business ownership. Geographic region is represented by a set of binary or dummy (0, 1) variables, the expected signs on the coefficients of which are unclear.
- *Population size at the end of the period (1990).* The hypothesis is that the scale of poverty in a metropolitan area is influenced by population size, independent of other factors. This is based on the assumption that large metropolitan areas have different economic, social, and social institutional capacity compared with small ones and that these differences will lead to different degrees of poverty. The expected sign of the coefficient on this variable is unclear.

Table 5 Regression Results

VARIABLES	COEFFICIENT	COEFFICIENT	COEFFICIENT	COEFFICIENT	COEFFICIENT
DEPENDENT VARIABLE	CPR90	POV90	PGR90	SP90	CSP
Intercept	1.76	0.17	1.57	0.08	4.31
South	-0.03*	0.00*	-0.05*	-0.01*	-0.09*
Southwest	0.13	0.01	0.12	0.01	0.16*
Northeast	-0.13	-0.01	-0.13	0.00*	-0.23*

Table 5 Regression Results					
VARIABLES	COEFFICIENT	COEFFICIENT	COEFFICIENT	COEFFICIENT	COEFFICIENT
DEPENDENT VARIABLE	CPR90	POV90	PGR90	SP90	CSP
Central	0.07	0.01*	0.04*	0.01	-0.17*
TPPR	2.84	0.32	3.94	0.31	4.46
ECGROW1	-2.90	-0.31	-2.93	-0.29	-4.26
Pov80	-3.07	0.84	-1.57	0.70	-9.10
MPOP80	-2.17	-0.25	-2.40	-0.16	-6.17
Totper90	0.00*	0.00*	0.00*	0.00*	0.00*
Adjusted R Square	0.73	0.92	0.82	0.81	0.30
Standard Error	0.11	0.01	0.10	0.01	0.42
Observations	100.00	100.00	100	100.00	100.00
* Not Significant					

Table 5 shows the results of the analysis. The table presents the coefficient values for each of the regression models. (An asterisk next to a number indicates the results were not statistically significant. All *p*-values of .10 and below are statistically significant.) The following are the dependent variables depicted in each column in table 5:

- Column 1 is the results for the change in poverty rates between 1980 and 1990.
- Column 2 uses the 1990 poverty rate as the dependent variable.
- Column 3 shows the results for the percent change in the number of poor people between 1980 and 1990.
- Column 4 presents the findings for the 1990 spatial poverty rate.
- Column 5 shows the results for change in spatial poverty between 1980 and 1990.

Of the six explanatory variables, employment growth, labor market tightness, and population change prove to be the most powerful predictors. All three are statistically significant for each of the five poverty indicators.

As classic economic theory would predict, employment growth contributes to lower poverty rates and lower trends in poverty. A vigorous economy increases demand for workers, including low-income workers. This increased labor market demand results in greater opportunities for employment and in higher wages. The outcome is lower poverty. Because low-skilled, low-income workers are typically the last to be hired, other things equal, it makes sense that a tighter labor market, as measured by the employment-to-population ratio, improves a metro area's chances of turning employment growth into lower poverty. That population growth increases poverty in metropolitan areas indicates that the boost to economic activity from increases in the population is outweighed by the negative impact of increased labor supply on the labor market facing the poor.

The impact of the initial poverty rate is more complex. On the one hand, it is negative for the three dependent variable formulations that measure trends in poverty—change in conventional poverty rate, change in number of poor people, and change in spatial poverty rate—indicating that higher initial poverty is associated with faster reductions in poverty. This supports the view that places with high initial poverty rates have a larger supply of poor people willing to enter the labor market during periods of economic growth, and that their lower reservation wage as a result of the high poverty makes them more attractive in the labor market. These factors together might improve labor market participation by the poor and therefore lead to reduced poverty. On the other hand, the impact of the initial poverty rate was positive for the two measures of area-wide poverty at the end of the period. This suggests that areas with high initial poverty rates, although they can see relatively rapid reductions in poverty over time, require employment growth well above average in order for this to happen.

What about the set of regional dummy variables that is intended to reflect social or institutional factors that may be unique to particular areas? The results are mixed. Metropolitan areas located in the West and Southwest are likely to have higher poverty on all five definitions of the dependent variable, other things equal. None of the other regions have statistically significant impacts for all five measures of poverty. Poverty as measured by the spatial poverty rate for 1990 and the change in the overall poverty rate is higher for metro areas located in the Midwest (the Central region), relative to those located in the West. Metro areas located in the South had higher spatial poverty rates, relative to metro areas in the West. Poverty, as measured by the level and change in the traditional poverty rate and the change in the number of poor people,[7] was lower in the Northeast relative to metro areas in the West.

These regional variations are likely to be due, at least in part, to differences in the quality of employment available for low-skilled workers. For example, the industrial structure in the Northeast may provide better opportunities for quality work. Workers in the West and Southwest, in contrast, may be overly concentrated in low-wage industries and industrial sectors. This means that people may be working but earning wages that are not high enough to keep them out of poverty—especially if they have a family. Another factor is likely to be the quality and quantity of education in different regions of the country, with a more educated workforce resulting in greater employment and lower poverty. Finally, regional differences in the

[7] The Northeast variable is almost statistically significant at the 10 percent level for the change in spatial poverty. Metropolitan areas located in the Northeast have greater reductions in spatial poverty than metropolitan areas located in other parts of the country.

spatial concentration of low-income people on the basis of race and class may also create barriers to labor-market participation (and therefore less employment and lower wages) for the disadvantaged in some areas.

Population size at the end of the period, the final independent variable in the model, has no statistically significant effect on any of the five poverty indicators.[8]

In sum, the most important impacts on poverty in metropolitan areas of the six factors tested are from relative labor market tightness and population growth. Metropolitan areas with tight labor markets do better at converting employment growth into economic opportunity for low-income individuals, other things equal. Population growth reduces the success of an area in reducing poverty, other things equal. But other things are not always equal, of course. The next section identifies metro areas that are exceptions to the systematic pattern identified by the regression analysis just described.

Metropolitan Areas That Did Better or Worse than Predicted

The regression analysis presented in the previous section identifies several systematic features that make some metro areas more successful than others in converting employment and employment growth into economic opportunity for low-income people. However, some metropolitan areas did significantly better than the structural factors captured in the model would predict, and some did worse. This section identifies the exceptions by comparing the regression-predicted poverty scores with their actual values for each metropolitan area.[9]

The distribution of metro area exceptions is shown in figure 1, by number of poverty measures on which they are outliers. Of the 100 largest metro areas, 21 are outliers on at least one poverty measure. Of these, 2 did better and 3 did worse on three or more of the five poverty measures; 12 did better and 9 did worse on one or two measures.

Differences between the actual and predicted values for each poverty measure on which a metro area is an outlier are shown in table 5. (Negative numbers mean that a metropolitan area did worse than predicted; positive numbers indicate it did better than predicted.) Of the six metropolitan areas that are outliers on three or more poverty measures, Norfolk, Honolulu, West Palm Beach, and Bridgeport did consistently better than predicted. Flint and Anaheim did consistently worse. Of the 20 metro areas that are outliers on a single poverty measure, Jacksonville, Las Vegas, Memphis, Mobile, St. Louis, Salt Lake City, San Antonio, Scranton,

[8] The 1980 population size was also used a control variable, but was not statistically significant.

[9] A 90 percent confidence interval, constructed using the standard error of the regression for each dependent variable, was used to identify the outliers.

Springfield, Tulsa, and Vallejo, California did better than predicted. Baton Rouge, El Paso, Fresno, Fort Lauderdale, Lansing, Louisville, Pittsburgh, San Diego, and Tulsa did worse.

Figure 1. MSAs with Significant Deviations from A

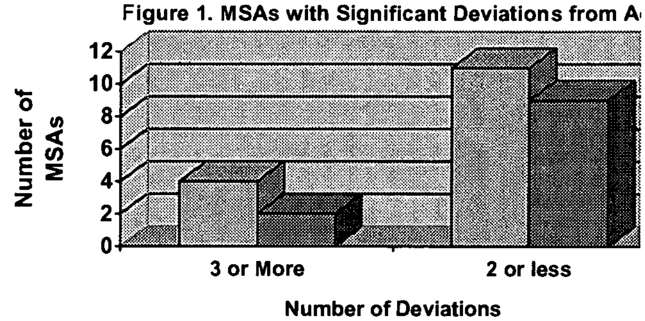

Table 5 Significant Deviations in Actual Poverty Outcomes Compared to Predicted Outcomes					
MSA	SPATIAL POVERTY RATE	POVERTY RATE	CHANGE IN POVERTY RATE	PERCENT CHANGE IN NUMBER POOR	CHANGE IN SPATIAL POVERTY
Anaheim	0	0	-0.18	-0.16	-1.11
Baton Rouge	-0.02	-0.02	0	0	0
Bridgeport	0	0.02	0.21	0.21	0
El Paso	-0.02	0	0	0	0
Flint	0	-0.03	-0.28	-0.23	-0.78
Fort Lauderdale	0	0	0	-0.19	0
Fresno	-0.02	-0.02	0	0	0
Honolulu	0	0.03	0.32	0.28	0.79
Jacksonville	0	0.02	0	0	0
Lansing	0	-0.02	0	-0.17	0
Las Vegas	0.02				
Louisville	-0.02	0	0	0	0
Memphis	0.03				
Milwaukee	0	0	-0.22	-0.18	0
Mobile	0.03				
Norfolk	0.03	0.03	0.23	0.23	0
Pittsburgh	0	0	-0.19	0	0
Salt Lake City			0.22		
San Antonio	0.09	0	0	0	0

Table 5 Significant Deviations in Actual Poverty Outcomes Compared to Predicted Outcomes					
MSA	SPATIAL POVERTY RATE	POVERTY RATE	CHANGE IN POVERTY RATE	PERCENT CHANGE IN NUMBER POOR	CHANGE IN SPATIAL POVERTY
San Diego	-0.07				
Scranton	0.03	0	0	0	-2.38
Springfield	0.04				
St Louis	0.02	0	0	0	0
Tucson	0	-0.02	0	-0.19	0
Tulsa	0.02				
Vallejo	0	0	0	0.22	0.85
West Palm Beach	0	0.02	0.20	0.20	0
Total Deviations in Category	14	10	9	2	9
Note: Negative = Actual greater than predicted					
Positive = Actual Less than predicted					

How do the outliers differ from metro areas with similar employment growth rates that were not outliers? This is an important question because it can potentially provide insight into how programs might be designed to help the low performers improve. Table 6 shows the types of differences that exist, by focusing on two pairs of metro areas, each in a pair having the same 1980–1990 employment growth rates, and comparing their actual values for each of the five poverty indicators and the deviations of these from the predicted values.

Table 6 Comparison of Poverty Indicators for Four Metropolitan Areas with Similar Job Growth								
MSA	JOB GROWTH 1980–1990	EMPLOY-TO-POP.	POPULATION GROWTH	SPATIAL POVERTY 1990	OVERALL POVERTY RATE 1990	PGR90	SP90	CPR90
Norfolk	0.33	0.38	0.20	0.04^	0.11^	0.00^	0.47	-0.10^
Charleston	0.34	0.39	0.18	0.08	0.15	0.09	0.00	-0.03
Flint	0.04	0.38	0.10	0.08	0.16*	0.48*	0.33*	0.74*
Springfield	0.04	0.45	0.15	0.03^	0.12	0.09	-0.19	0.26
Note:								
* Actual Poverty Indicators Statistically Worse than Predicted								
^ Actual Poverty Indicator Statistically Better than Predicted								

Look first at the top pair, Norfolk and Charleston. They both have similar 10-year employment growth rates, .33 and .34 respectively (about the middle of the range for the 100 largest metro areas). All Norfolk's poverty indicators are better than predicted except for change in spatial poverty. All Charleston's poverty indicators, in contrast, are as predicted. While Norfolk's actual spatial and overall poverty rates were lower than Charleston's, the predicted rates for both metro areas were roughly the same. This suggests that although Norfolk and Charleston had similar values on the structural factors in the regression model, Norfolk did a better job of reducing poverty.

The second pair highlights similar differences between two areas with relatively low employment growth rates. Both Flint and Springfield had employment growth rates of only .04 over the 1980–1990 period. But Flint's record on poverty indicators is considerably worse than predicted for all except the spatial poverty rate, whereas, except for spatial poverty, Springfield's record is as predicted. Most of Flint's poverty measures are not only worse than Springfield's, they are considerably worse than would have been predicted given the structural characteristics captured in the model.

Discussion and Suggestions for Further Research

Several factors not captured well in the model developed here might plausibly explain why particular metro areas did not follow the pattern predicted. Regression models that include richer and more precise demographic and socioeconomic variables than those available in the data set used for this paper can test some of these. Others require the type of rich institutional detail that can only be collected by comparative case studies.

First, differences in industrial structure may simply provide better opportunities for obtaining family-supporting employment (i.e., employment with enough hours and high enough wages to support dependents) for low-skilled, low-income individuals. The set of variables capturing regional variations in the model developed in this paper represents only a very crude attempt at getting at such variation and may well be capturing something quite other than industrial structure. Casual inspection of the high performers identified in this paper certainly reveals no general link to industrial structure. Bridgeport, Honolulu, Norfolk, and West Palm Beach, for example, all have poverty indicators better than predicted. But it is hard to see a common industrial link between, say, Bridgeport and Honolulu.

Second, regardless of industrial structure, jobs available to low-skilled workers in the high-performing metropolitan areas may pay better wages than those in the more poorly performing areas. Other research on the availability of full-time employment with wages high enough to keep a family out of poverty, for example, suggests that some metropolitan areas are much more successful on two relevant labor-market fronts.[10] First, some areas have better-than-average opportunities for low-skilled workers to gain and hold family-supporting employment. Second, some areas have smaller racial disparities in labor market outcomes. Research shows, for example, that Bridgeport, Las Vegas, Grand Rapids, and Denver are unlike many metro areas. Each of these metro areas not only had higher-than-average opportunities for low-skilled workers to hold living wage employment, they also had much smaller than average gaps in labor market outcomes between African-American and European-American low-skilled prime-age males.[11] The better-wage hypothesis is testable within a multiple regression framework using metro-level wage and/or earnings data.

Third, while the quality of employment for low-skilled, low-income workers may not be particularly high in some areas, the absolute availability of work in those areas may still keep metro-area poverty lower than expected. West Palm Beach, for example, has an economy that is strongly driven by population growth and tourism. As a result, it tends to produce low-skill, low-wage jobs in abundance. During the 1980s, overall employment growth in the West Palm Beach metro region was well above the national average, leading to labor shortages there in many occupations and industries.[12] This increase in labor market opportunities generally might well explain why the area's poverty indicators were better than their predicted values. This hypothesis can also be tested within a multiple regression framework with metro-area data on the distribution of industry and occupation.

Fourth, spatial mismatch between the residential concentration of low-income people on the basis of class and race and the location of low-skilled, entry-level jobs is also plausible as a factor explaining lower-than-average labor market opportunities for disadvantaged groups in some metro areas. High spatial concentration can restrict physical or social mobility for low-income and minority individuals, which in turn can limit their access to labor-market opportunities. Several measures might be used to discover whether spatial mismatch helps to explain the variations among metro areas in the poverty measures used in this study. A promising research strategy would be to include appropriate measures of racial and class spatial concentration relative to the spatial concentration of jobs as explanatory variables in a regression framework. This might also provide valuable information on outlier/non-outlier

[10] The Urban Institute's Program on Regional Economic Opportunities is documenting differences in living-wage employment rates by race, gender, and metro area in the Living-Wage Employment Project. Several research papers are expected from this research project.

[11] The Urban Institute's Program on Regional Economic Opportunities—The Living-Wage Employment Project.

[12] See Foster-Bey, Rosenfeld, Pryde, and Gragg 1999.

performance to see whether there are major differences in the level of spatial mismatch between pairs of otherwise similar areas with different poverty indicator profiles.

Fifth, the race and immigration makeup of a metro area's population may be a major influence. Much of the literature, for example, indicates that large African-American and Latino populations may contribute to higher poverty rates. However, there appears to be no consistent demographic pattern across the metropolitan areas identified as outliers in this paper. The demographic makeup of Bridgeport shares little in common with that of Honolulu, for example, although both are high performers. The demographic makeup of Anaheim and Lansing are similarly disparate, yet both have proportional changes in absolute poverty greater than their predicted values. The number of foreign-born residents is a potential part of this demographic puzzle. The theory here is that low-skilled immigrants will have low incomes and, thus, compete with native born low-skilled workers for limited employment opportunities. This competition will, in turn, put pressure on wages and employment opportunities, leading to increases in poverty. The empirical literature does not clearly support or reject this theoretical relationship. In the analysis presented in this paper, immigration again is only crudely captured (through population growth and the regional variables). This group of hypotheses could be fruitfully explored through multiple regression using metro-area statistics on the racial/ethnic distribution of the population and percent foreign-born.

Finally, specific institutional or contextual factors may be important determinants of an area's outlier status, for example, by mitigating or exacerbating the negative aspects of population growth. High-performing areas may have better policies and programs intended to move people out of poverty. Or they may have school systems that are better than average at allowing low-income people to take advantage of higher-skilled, higher-wage opportunities when the economy is doing well. This is the type of question that is best suited for—and indeed requires—comparative case studies for insight. Once again, the indicated strategy would be to select a set of metro areas paired along known dimensions and do a detailed on-site investigation of the major institutional dimensions on which they differ.

The most promising overall research strategy to make progress in this area may be to do the richer and more refined types of regression analysis sketched here first, and then use their results as the basis for a comparative case study. In such a study, pairs of metro areas would be selected that are alike on a variety of dimensions captured in the richer regression modeling but still substantially different in their poverty indicator profiles.

An important final observation: This paper looks at data from 1980 and 1990. The overall economy has been booming since then. It is possible that this boom may have substantially changed the underlying patterns revealed here, although the HUD (1999) report cited earlier makes it clear that many of the places experiencing difficulties in 1990 are still facing challenges today. In any case, these results provide, at a minimum, a baseline for assessing how well metropolitan areas have done during the 1990s. It is especially important to search for additional structural patterns that may have differentiated among metro areas during the 1980s and to see whether and how the underlying structural relationships between poverty and economic growth have changed since then. This, of course, demands more recent metro-area data. An update of the Urban Underclass Database would allow replication of the analysis reported here and limited additions to the explanatory variables used in that analysis. But most of the suggested analytic extensions would require data that are not now included in this data set. As already emphasized, the statistical analysis would need to be augmented by case studies designed to get at the qualitative institutional information that is also crucial to designing effective strategies to help lagging metro areas improve their poverty-employment conversion efforts.

REFERENCES

Adelman, Robert M., and Charles Jaret. 1999. “Race and U.S. Metropolitan Social and Economic Structure.” *Journal of Urban Affairs* 21 (1): 35–56.

Foster-Bey, John, Stuart Rosenfeld, Paul Pryde, and Vance Gragg. 1999. *Linking Low-Income People to Economic Opportunity in Palm Beach County*. Report to the Community Foundation for Palm Beach and Martin Counties and the MacArthur Foundation.

Gottlieb, Paul. 1998. *The Effects of Poverty on Metropolitan Area Economic Performance: A Policy Oriented Research Review.* Report for the National League of Cities.

Jargowsky, Paul A. 1997. *Poverty and Place: Ghettoes, Barrios, and the American City.* New York: Russell Sage Foundation.

U.S. Department of Housing and Urban Development. 1999. *Now is the Time: Places Left Behind in the New Economy.* Washington, D.C.: Government Printing Office.

APPENDIX A

The functional form of the regression model is as follows:

The independent variables are:

ECGROW1 = Change in number of individuals employed in metropolitan areas between 1980 and 1990;

MPOP = 1980 ratio of number employed in metro area, divided by metro labor pool;

POV80 = Number of poor people, divided by total population in metro area in 1980;

TPPR = Change in metro-area population between 1980 and 1990;

Totper90 = Total metro area population in 1990;

South = one if South region, zero otherwise;

Southwest = one if Southwest region, zero otherwise;

Northwest = one if Northwest region, zero otherwise;

Midwest = one if Central region, zero otherwise;

Intercept = West region;

The dependent variable, POVERTY, has five alternative definitions:

PGR = 1980–1990 percent change in the number of poor people in metro area;

CPR = 1980–1990 change in number of poor people in metro area, divided by total metro-area population—i.e., change in metro-area overall poverty rate;

Pov90 = Number of poor people in metro area in 1990, divided by total metro-area population in 1990;

SP90 = Spatial poverty rate—defined as number of poor people residing in high-poverty areas (areas with poverty rates 20 percent or higher), divided by the total metro population for 1990;

CSP = Percent change in spatial poverty between 1980 and 1990;

APPENDIX B

TABLE B-1 EMPLOYMENT CONVERSION RATIOS, 100 LARGEST METROPOLITAN AREAS, 1990

MSA	1990 EMPLOYMENT-TO-POPULATION RATIO	CONVERSION RATIO (OVERALL POVERTY)	CONVERSION RATIO (SPATIAL POVERTY)
Akron	0.46	3.9	9.8
Albany	0.49	5.8	18.6
Albuquerque	0.47	3.3	4.9
Allentown	0.48	6.9	27.0
Anaheim	0.54	6.4	15.5
Atlanta	0.53	5.4	12.7
Austin	0.52	3.5	5.2
Bakersfield	0.39	2.4	3.3
Baltimore	0.50	5.1	11.9
Baton Rouge	0.44	2.4	4.1
Bergen	0.52	8.7	26.4
Birmingham	0.45	3.0	5.6
Boston	0.53	6.6	14.4
Bridgeport	0.50	6.5	12.4
Buffalo	0.46	3.8	7.7
Charleston	0.44	3.0	5.8
Charlotte	0.53	5.6	18.9
Chattanooga	0.47	3.5	9.1
Chicago	0.48	4.0	7.7
Cincinnati	0.48	4.2	11.5
Cleveland	0.46	3.9	6.6
Columbia	0.50	4.6	17.0
Columbus	0.50	4.4	11.9
Dallas	0.52	4.4	9.2
Dayton	0.46	4.0	8.1
Denver	0.52	5.5	11.6
Detroit	0.45	3.5	8.5
El Paso	0.37	1.4	1.9
Flint	0.42	2.6	5.0
Fort Lauderdale	0.48	4.7	12.7
Fort Worth	0.51	4.7	10.1
Fresno	0.40	1.9	2.8
Gary	0.44	3.7	5.7
Grand Rapids	0.50	6.2	12.0
Greensboro	0.53	5.5	20.3
Greenville	0.50	4.6	15.6
Harrisburg	0.51	6.7	17.9

TABLE B-1 EMPLOYMENT CONVERSION RATIOS, 100 LARGEST METROPOLITAN AREAS, 1990			
MSA	1990 EMPLOYMENT-TO-POPULATION RATIO	CONVERSION RATIO (OVERALL POVERTY)	CONVERSION RATIO (SPATIAL POVERTY)
Hartford	0.52	7.1	15.3
Honolulu	0.47	6.6	32.5
Houston	0.49	3.3	5.1
Indianapolis	0.51	5.4	11.0
Jacksonville	0.47	4.0	9.4
Jersey City	0.49	3.3	6.5
Johnson	0.45	2.9	5.0
Kansas City	0.50	5.2	11.3
Knoxville	0.47	3.4	7.6
Lansing	0.50	4.1	9.1
Las Vegas	0.50	4.8	16.6
Little Rock	0.47	3.6	7.3
Los Angeles	0.47	3.2	4.6
Louisville	0.48	3.8	7.4
Memphis	0.45	2.5	6.1
Miami	0.47	2.6	4.6
Milwaukee	0.49	4.3	12.6
Minneapolis	0.54	6.8	21.5
Mobile	0.42	2.1	5.0
Nashville	0.51	4.6	12.1
New Haven	0.51	6.5	10.7
New Orleans	0.42	2.0	3.5
New York	0.45	2.7	5.0
Newark	0.50	5.7	11.3
Norfolk	0.43	3.9	11.8
Oakland	0.50	5.5	10.5
Oklahoma	0.47	3.5	7.0
Omaha	0.50	5.3	12.0
Orlando	0.52	5.3	18.4
Oxnard	0.50	7.1	52.8
Philadelphia	0.48	4.7	9.8
Phoenix	0.47	3.9	8.4
Pittsburgh	0.44	3.7	8.5
Portland	0.51	5.2	19.3
Providence	0.49	5.3	19.1
Raleigh	0.55	5.7	12.1
Richmond	0.51	5.4	10.6
Riverside	0.42	3.5	8.1
Rochester	0.49	5.2	12.8
Sacramento	0.47	4.0	8.3

TABLE B-1 EMPLOYMENT CONVERSION RATIOS, 100 LARGEST METROPOLITAN AREAS, 1990			
MSA	1990 EMPLOYMENT-TO-POPULATION RATIO	CONVERSION RATIO (OVERALL POVERTY)	CONVERSION RATIO (SPATIAL POVERTY)
St Louis	0.47	4.5	10.2
Salt Lake	0.45	4.8	12.8
San Antonio	0.42	2.2	3.7
San Diego	0.46	4.2	9.6
San Francisco	0.54	6.1	15.8
San Jose	0.54	7.3	34.5
Scranton	0.45	4.4	20.0
Seattle	0.53	7.1	30.9
Springfield	0.47	4.0	14.8
Stockton	0.41	2.7	4.2
Syracuse	0.47	4.7	16.5
Tacoma	0.43	3.9	11.6
Tampa	0.45	4.0	9.3
Toledo	0.45	3.4	6.3
Tucson	0.43	2.6	4.6
Tulsa	0.47	3.7	9.3
Vallejo	0.45	6.4	65.2
Washington, DC	0.56	8.9	27.0
West Palm Beach	0.45	4.9	11.3
Wichita	0.49	4.7	16.1
Wilmington	0.51	6.7	14.3
Worcester	0.49	5.9	11.3
Youngstown	0.42	3.1	7.2

TABLE B-2 ANNUALIZED PERCENT CHANGE IN EMPLOYMENT-TO POVERTY CONVERSION RATIOS, 100 LARGEST METROPOLITAN AREAS, 1980–1990			
MSA	AVERAGE EMPLOYMENT-TO-POPULATION RATIOS 1980–1990	% CHANGE IN OVERALL POVERTY CONVERSION RATIO 1980–1990	% CHANGE IN SPATIAL POVERTY CONVERSION RATIO 1980–1990
Akron	0.45	-1.7%	-1.6%
Albany	0.46	2.4%	3.9%
Albuquerque	0.46	-0.2%	-0.1%
Allentown	0.47	1.0%	0.4%
Anaheim	0.52	-0.9%	-8.2%
Atlanta	0.50	3.3%	1.8%
Austin	0.50	-0.2%	-2.1%
Bakersfield	0.40	-3.0%	-8.2%
Baltimore	0.47	2.8%	4.5%
Baton Rouge	0.43	-1.9%	-1.2%

TABLE B-2 ANNUALIZED PERCENT CHANGE IN EMPLOYMENT-TO POVERTY CONVERSION RATIOS, 100 LARGEST METROPOLITAN AREAS, 1980–1990

MSA	AVERAGE EMPLOYMENT-TO-POPULATION RATIOS 1980–1990	% CHANGE IN OVERALL POVERTY CONVERSION RATIO 1980–1990	% CHANGE IN SPATIAL POVERTY CONVERSION RATIO 1980–1990
Bergen	0.50	2.4%	3.6%
Birmingham	0.43	1.0%	1.2%
Boston	0.50	2.2%	1.2%
Bridgeport	0.48	3.1%	1.7%
Buffalo	0.44	-0.4%	0.0%
Charleston	0.41	2.1%	1.3%
Charlotte	0.51	1.6%	-1.5%
Chattanooga	0.44	1.1%	-1.4%
Chicago	0.47	0.5%	0.3%
Cincinnati	0.45	0.0%	-1.1%
Cleveland	0.45	-1.4%	-2.4%
Columbia	0.48	2.0%	8.8%
Columbus	0.48	0.3%	1.5%
Dallas	0.52	-1.4%	-1.6%
Dayton	0.44	-0.4%	-2.5%
Denver	0.51	-1.3%	-4.7%
Detroit	0.43	-1.4%	1.2%
El Paso	0.36	-1.6%	1.5%
Flint	0.40	-3.4%	-7.3%
Fort Lauderdale	0.45	0.0%	-4.3%
Fort Worth	0.50	-1.3%	-4.9%
Fresno	0.41	-4.1%	-4.5%
Gary	0.43	-1.4%	-4.8%
Grand Rapids	0.48	0.6%	-4.1%
Greensboro	0.51	2.0%	5.3%
Greenville	0.48	1.7%	5.6%
Harrisburg	0.49	1.2%	-2.1%
Hartford	0.51	1.0%	-2.0%
Honolulu	0.45	3.5%	5.9%
Houston	0.49	-4.1%	-7.9%
Indianapolis	0.48	0.7%	-1.6%
Jacksonville	0.44	3.7%	5.3%
Jersey City	0.46	2.6%	7.0%
Johnson City	0.43	0.7%	-0.9%
Kansas City	0.48	-0.3%	-0.6%
Knoxville	0.45	1.6%	-2.3%
Lansing	0.48	-1.1%	-3.3%
Las Vegas	0.49	-1.1%	-6.8%
Little Rock	0.45	0.3%	1.7%

TABLE B-2 ANNUALIZED PERCENT CHANGE IN EMPLOYMENT-TO POVERTY CONVERSION RATIOS, 100 LARGEST METROPOLITAN AREAS, 1980–1990

MSA	AVERAGE EMPLOYMENT-TO-POPULATION RATIOS 1980–1990	% CHANGE IN OVERALL POVERTY CONVERSION RATIO 1980–1990	% CHANGE IN SPATIAL POVERTY CONVERSION RATIO 1980–1990
Los Angeles	0.47	-0.9%	-1.8%
Louisville	0.45	-0.1%	-2.9%
Memphis	0.43	2.0%	6.5%
Miami	0.46	-1.5%	-1.8%
Milwaukee	0.48	-3.1%	0.6%
Minneapolis	0.52	-1.2%	-2.6%
Mobile	0.40	-0.1%	1.3%
Nashville	0.49	1.1%	0.4%
New Haven	0.49	3.5%	4.2%
New Orleans	0.42	-1.9%	-1.5%
New York	0.44	1.1%	1.1%
Newark	0.48	3.4%	2.6%
Norfolk	0.41	2.9%	7.6%
Oakland	0.48	1.3%	1.2%
Oklahoma	0.47	-2.6%	-5.4%
Omaha	0.47	0.4%	-3.1%
Orlando	0.49	3.3%	7.6%
Oxnard	0.47	2.2%	0.2%
Philadelphia	0.45	2.6%	2.4%
Phoenix	0.46	-0.8%	-4.0%
Pittsburgh	0.42	-2.0%	-5.6%
Portland	0.49	-0.5%	-4.7%
Providence	0.47	1.3%	-0.1%
Raleigh	0.52	2.8%	1.6%
Richmond	0.49	2.3%	3.5%
Riverside	0.40	-0.2%	-2.6%
Rochester	0.47	-0.1%	0.9%
Sacramento	0.45	0.3%	-3.4%
Salt Lake	0.45	0.5%	1.0%
San Antonio	0.44	-0.6%	-5.4%
San Diego	0.41	0.0%	1.3%
San Francisco	0.43	1.0%	-1.2%
San Jose	0.53	1.1%	0.5%
Scranton	0.52	0.0%	-4.7%
Seattle	0.42	0.5%	-11.5%
Springfield	0.51	0.8%	0.1%
St Louis	0.46	-0.4%	2.6%
Stockton	0.40	-1.2%	-5.4%
Syracuse	0.45	1.1%	3.4%

TABLE B-2 ANNUALIZED PERCENT CHANGE IN EMPLOYMENT-TO POVERTY CONVERSION RATIOS, 100 LARGEST METROPOLITAN AREAS, 1980–1990

MSA	AVERAGE EMPLOYMENT-TO-POPULATION RATIOS 1980–1990	% CHANGE IN OVERALL POVERTY CONVERSION RATIO 1980–1990	% CHANGE IN SPATIAL POVERTY CONVERSION RATIO 1980–1990
Tacoma	0.40	0.6%	-3.4%
Tampa	0.42	1.7%	-1.4%
Toledo	0.43	-1.3%	-0.8%
Tucson	0.42	-2.2%	-2.0%
Tulsa	0.47	-2.5%	-5.1%
Vallejo	0.43	3.4%	6.8%
Washington, DC	0.53	3.6%	5.8%
West Palm Beach	0.43	1.6%	1.2%
Wichita	0.49	-1.7%	-0.8%
Wilmington	0.48	4.8%	1.8%
Worcester	0.47	1.7%	1.3%
Youngstown	0.41	-2.9%	-2.7%

TABLE B-3. THE ACTUAL VALUES OF DEPENDENT VARIABLES, 100 LARGEST METRO AREAS

MSA	GR	PR	POV90	SP	P90
Akron	0.27	0.49	0.12	0.06	0.10
Albany	-0.07	0.03	0.09	0.03	0.03
Albuquerque	0.26	0.24	0.15	0.06	0.08
Allentown	0.05	0.17	0.07	0.02	0.02
Anaheim	0.45	0.42	0.08	0.01	0.02
Atlanta	0.07	-0.08	0.10	0.07	0.08
Austin	0.58	0.22	0.15	0.06	0.09
Bakersfield	0.79	0.51	0.17	0.04	0.10
Baltimore	0.08	0.04	0.10	0.07	0.07
Baton Rouge	0.35	0.40	0.19	0.09	0.16
Bergen	-0.16	0.03	0.06	0.03	0.02
Birmingham	0.02	0.08	0.15	0.07	0.09
Boston	-0.09	0.03	0.08	0.05	0.05
Bridgeport	0.12	-0.08	0.08	0.07	0.06
Buffalo	0.09	0.31	0.12	0.07	0.09
Charleston	0.09	-0.03	0.15	0.09	0.11
Charlotte	0.09	0.08	0.10	0.04	0.05
Chattanooga	0.00	0.10	0.14	0.07	0.09
Chicago	0.01	0.15	0.12	0.10	0.12
Cincinnati	0.15	0.28	0.11	0.07	0.09
Cleveland	0.14	0.38	0.12	0.08	0.11
Columbia	0.01	0.01	0.12	0.08	0.08

TABLE B-3. THE ACTUAL VALUES OF DEPENDENT VARIABLES, 100 LARGEST METRO AREAS					
MSA	GR	PR	POV90	SP	P90
Columbus	0.18	0.23	0.12	0.06	0.07
Dallas	0.55	0.41	0.12	0.05	0.08
Dayton	0.15	0.31	0.12	0.05	0.08
Denver	0.35	0.43	0.10	0.02	0.04
Detroit	0.25	0.46	0.13	0.05	0.10
El Paso	0.53	0.22	0.27	0.18	0.24
Flint	0.48	0.74	0.16	0.04	0.13
Fort Lauderdale	0.38	0.29	0.10	0.03	0.05
Fort Worth	0.62	0.41	0.11	0.03	0.07
Fresno	0.92	0.64	0.21	0.07	0.15
Gary	0.15	0.42	0.12	0.06	0.13
Grand Rapids	0.18	0.23	0.08	0.03	0.05
Greensboro	0.00	0.05	0.10	0.04	0.04
Greenville	0.02	0.04	0.11	0.06	0.06
Harrisburg	0.03	0.17	0.08	0.03	0.04
Hartford	0.00	0.14	0.08	0.05	0.06
Honolulu	-0.13	-0.10	0.07	0.02	0.03
Houston	0.77	0.77	0.15	0.04	0.11
Indianapolis	0.10	0.20	0.10	0.04	0.06
Jacksonville	-0.02	-0.15	0.12	0.07	0.07
Jersey City	-0.13	-0.06	0.15	0.10	0.06
Johnson	0.04	0.13	0.16	0.07	0.07
Kansas City	0.19	0.28	0.10	0.05	0.07
Knoxville	0.01	0.04	0.14	0.07	0.09
Lansing	0.27	0.42	0.13	0.04	0.08
Las Vegas	0.85	0.38	0.11	0.02	0.04
Little Rock	0.14	0.17	0.14	0.06	0.09
Los Angeles	0.33	0.28	0.15	0.06	0.08
Louisville	0.11	0.27	0.13	0.06	0.08
Memphis	-0.02	-0.05	0.18	0.17	0.17
Miami	0.42	0.32	0.18	0.09	0.13
Milwaukee	0.46	0.70	0.12	0.06	0.11
Minneapolis	0.38	0.45	0.08	0.03	0.05
Mobile	0.16	0.14	0.20	0.12	0.16
Nashville	0.14	0.13	0.11	0.06	0.07
New Have	-0.01	-0.09	0.08	0.06	0.05
New Orleans	0.20	0.31	0.21	0.12	0.18
New York	-0.01	0.02	0.17	0.12	0.11
Newark	-0.23	-0.09	0.09	0.08	0.06
Norfolk	0.00	-0.10	0.11	0.08	0.07
Oakland	0.11	0.10	0.09	0.05	0.05
Oklahoma	0.46	0.53	0.14	0.05	0.09
Omaha	0.11	0.23	0.10	0.05	0.07

TABLE B-3. THE ACTUAL VALUES OF DEPENDENT VARIABLES, 100 LARGEST METRO AREAS					
MSA	GR	PR	POV90	SP	P90
Orlando	0.26	-0.06	0.10	0.05	0.04
Oxnard	0.15	0.08	0.07	0.01	0.01
Philadelphia	-0.10	-0.02	0.10	0.06	0.06
Phoenix	0.64	0.35	0.12	0.04	0.06
Pittsburgh	0.21	0.52	0.12	0.04	0.07
Portland	0.25	0.32	0.10	0.02	0.04
Providence	-0.01	0.10	0.10	0.04	0.05
Raleigh	0.11	-0.04	0.10	0.06	0.07
Richmond	-0.01	0.00	0.10	0.06	0.06
Riverside	0.81	0.22	0.12	0.03	0.06
Rochester	0.14	0.30	0.10	0.06	0.09
Sacramento	0.42	0.20	0.12	0.03	0.05
Salt Lake	0.32	0.31	0.11	0.02	0.05
San Antonio	0.32	0.13	0.09	0.11	0.14
San Diego	0.37	0.13	0.19	0.03	0.04
San Francisco	0.00	0.11	0.11	0.03	0.03
San Jose	0.22	0.29	0.09	0.04	0.01
Scranton	0.06	0.21	0.08	0.01	0.02
Seattle	0.23	0.21	0.11	0.02	0.02
Springfield	0.09	0.26	0.08	0.07	0.08
St Louis	0.07	0.19	0.12	0.07	0.09
Stockton	0.63	0.31	0.16	0.05	0.09
Syracuse	0.03	0.16	0.10	0.05	0.06
Tacoma	0.31	0.21	0.11	0.03	0.06
Tampa	0.24	0.07	0.11	0.04	0.06
Toledo	0.24	0.42	0.14	0.07	0.12
Tucson	0.65	0.47	0.17	0.06	0.13
Tulsa	0.40	0.53	0.13	0.02	0.07
Vallejo	0.10	-0.07	0.07	0.02	0.01
Washington, DC	0.05	0.06	0.06	0.03	0.02
West Palm Beach	0.37	0.05	0.09	0.03	0.04
Wichita	0.30	0.42	0.10	0.03	0.05
Wilmington	0.20	0.17	0.08	0.06	0.04
Worcester	0.05	0.05	0.09	0.03	0.05
Youngstown	0.32	0.63	0.14	0.05	0.12

TABLE B-4.VALUES OF EXPLANATORY VARIABLES						
MSA	TPPR	ECGROW1	POV80	MPOP80	TOTPER80	TOTPER90
Akron	-0.15	0.07	0.08	0.38	752,717	639,547
Albany	-0.10	0.18	0.08	0.39	934,812	843,329
Albuquerque	0.02	0.23	0.12	0.40	464,807	472,908
Allentown	-0.10	0.16	0.06	0.39	741,597	667,464
Anaheim	0.02	0.33	0.06	0.42	2,326,960	2,369,931
Atlanta	0.16	0.48	0.11	0.42	2,405,114	2,784,333
Austin	0.30	0.56	0.13	0.45	581,835	753,757
Bakersfield	0.19	0.32	0.11	0.36	444,623	528,151
Baltimore	-0.05	0.21	0.10	0.40	2,443,318	2,320,359
Baton Rouge	-0.03	0.11	0.13	0.39	531,043	514,525
Bergen	-0.18	0.07	0.06	0.40	1,545,519	1,259,757
Birmingham	-0.06	0.12	0.14	0.38	949,997	890,678
Boston	-0.12	0.13	0.08	0.42	3,145,790	2,768,738
Bridgeport	-0.04	0.20	0.08	0.40	453,950	434,602
Buffalo	-0.16	0.05	0.09	0.37	1,130,555	944,942
Charleston	0.12	0.34	0.16	0.38	435,596	488,192
Charlotte	0.02	0.28	0.09	0.43	1,116,463	1,136,552
Chattanooga	-0.09	0.11	0.12	0.39	464,150	423,846
Chicago	-0.12	0.06	0.11	0.41	6,806,766	5,976,800
Cincinnati	-0.10	0.14	0.09	0.38	1,583,285	1,422,561
Cleveland	-0.17	-0.01	0.09	0.39	2,170,965	1,803,057
Columbia	0.00	0.23	0.12	0.43	425,982	425,735
Columbus	-0.04	0.21	0.10	0.41	1,392,023	1,330,135
Dallas	0.10	0.34	0.09	0.44	2,289,618	2,512,265
Dayton	-0.12	0.11	0.09	0.38	1,049,500	927,259
Denver	-0.06	0.18	0.07	0.42	1,695,131	1,598,630
Detroit	-0.14	0.08	0.09	0.36	5,051,207	4,329,478
El Paso	0.25	0.30	0.22	0.36	462,101	579,395
Flint	-0.15	0.04	0.09	0.34	500,038	425,331
Fort Lauderdale	0.06	0.37	0.08	0.37	1,165,159	1,239,413
Fort Worth	0.15	0.42	0.08	0.42	1,140,981	1,307,831
Fresno	0.17	0.26	0.13	0.38	559,146	655,133
Gary	-0.19	0.01	0.09	0.36	731,453	594,892
Grand Rapids	-0.04	0.25	0.07	0.39	698,230	671,362
Greensboro	-0.05	0.21	0.10	0.43	965,159	916,710
Greenville	-0.02	0.21	0.11	0.42	631,242	618,255
Harrisburg	-0.11	0.16	0.07	0.40	640,764	568,196
Hartford	-0.12	0.11	0.07	0.42	852,146	747,070
Honolulu	-0.03	0.22	0.08	0.39	830,945	803,204
Houston	0.00	0.17	0.09	0.42	3,242,701	3,258,485
Indianapolis	-0.08	0.18	0.08	0.40	1,338,030	1,224,745
Jacksonville	0.15	0.41	0.14	0.39	768,406	883,870

TABLE B-4.VALUES OF EXPLANATORY VARIABLES						
MSA	TPPR	ECGROW1	POV80	MPOP80	TOTPER80	TOTPER90
Jersey City	-0.08	0.12	0.16	0.40	593,631	546,990
Johnson	-0.09	0.11	0.14	0.38	465,641	425,344
Kansas City	-0.08	0.16	0.08	0.41	1,659,225	1,533,600
Knoxville	-0.03	0.18	0.14	0.40	608,368	587,920
Lansing	-0.11	0.14	0.09	0.41	461,228	410,534
Las Vegas	0.34	0.65	0.08	0.41	544,607	728,830
Little Rock	-0.03	0.17	0.12	0.40	515,635	500,619
Los Angeles	0.04	0.21	0.12	0.42	8,333,643	8,682,078
Louisville	-0.13	0.10	0.10	0.39	1,069,221	935,289
Memphis	0.04	0.19	0.19	0.41	920,858	955,314
Miami	0.07	0.21	0.14	0.42	1,770,220	1,902,642
Milwaukee	-0.14	0.06	0.07	0.41	1,627,080	1,399,077
Minneapolis	-0.05	0.23	0.06	0.43	2,544,084	2,414,850
Mobile	0.02	0.15	0.17	0.38	460,200	468,400
Nashville	0.01	0.27	0.10	0.42	948,866	954,874
New Haven	0.09	0.40	0.09	0.41	468,419	510,700
New Orleans	-0.09	-0.01	0.16	0.39	1,330,066	1,215,032
New York	-0.02	0.11	0.17	0.41	8,576,215	8,373,169
Newark	-0.16	0.08	0.10	0.40	2,127,259	1,792,240
Norfolk	0.11	0.33	0.13	0.38	1,190,916	1,324,970
Oakland	0.01	0.27	0.08	0.41	2,018,134	2,035,079
Oklahoma	-0.05	0.12	0.09	0.41	976,650	930,827
Omaha	-0.09	0.16	0.08	0.40	666,720	605,000
Orlando	0.34	0.74	0.11	0.41	778,146	1,044,258
Oxnard	0.06	0.43	0.07	0.38	615,870	655,482
Philadelphia	-0.09	0.16	0.11	0.38	5,194,930	4,730,685
Phoenix	0.22	0.52	0.09	0.39	1,713,349	2,087,745
Pittsburgh	-0.20	-0.01	0.08	0.36	2,522,487	2,011,751
Portland	-0.05	0.19	0.08	0.41	1,287,507	1,217,469
Providence	-0.10	0.12	0.09	0.41	1,232,450	1,104,178
Raleigh	0.15	0.45	0.11	0.46	608,950	701,085
Richmond	-0.01	0.25	0.10	0.42	844,299	837,393
Riverside	0.48	0.77	0.10	0.36	1,709,095	2,521,470
Rochester	-0.12	0.12	0.08	0.40	1,105,475	968,134
Sacramento	0.18	0.46	0.10	0.39	1,222,169	1,445,524
Salt Lake	-0.10	0.12	0.09	0.37	1,050,831	1,058,281
San Antonio	0.01	0.25	0.07	0.38	1,088,499	1,270,831
San Diego	0.17	0.32	0.17	0.38	1,987,688	2,394,227
San Francisco	0.20	0.51	0.10	0.44	1,744,066	1,571,548
San Jose	-0.10	0.12	0.08	0.43	1,551,443	1,462,674
Scranton	-0.06	0.22	0.06	0.36	807,222	709,485
Seattle	-0.12	0.11	0.09	0.41	1,906,445	1,935,821

TABLE B-4.VALUES OF EXPLANATORY VARIABLES						
MSA	TPPR	ECGROW1	POV80	MPOP80	TOTPER80	TOTPER90
Springfield	0.02	0.33	0.06	0.41	585,744	509,430
St Louis	-0.13	0.04	0.10	0.38	2,678,909	2,398,206
Stockton	0.25	0.44	0.12	0.36	373,016	465,134
Syracuse	-0.11	0.15	0.09	0.38	709,174	632,874
Tacoma	0.08	0.38	0.09	0.35	518,898	561,587
Tampa	0.16	0.47	0.11	0.36	1,751,102	2,025,790
Toledo	-0.12	0.09	0.10	0.38	679,366	596,899
Tucson	0.13	0.32	0.12	0.38	577,884	650,384
Tulsa	-0.09	0.09	0.09	0.41	760,176	695,513
Vallejo	0.17	0.53	0.08	0.36	366,981	430,848
Washington, DC	0.01	0.35	0.07	0.43	3,780,718	3,824,803
West Palm Beach	0.31	0.62	0.09	0.37	648,704	848,856
Wichita	-0.08	0.10	0.07	0.42	519,166	476,226
Wilmington	-0.05	0.28	0.09	0.39	587,837	561,115
Worcester	0.00	0.24	0.08	0.41	420,915	420,150
Youngstown	-0.19	-0.02	0.08	0.35	601,409	485,494

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