Did a Strong Economy in the 1990s Affect Poverty in U.S. Metro Areas? Exploring Changes in Poverty in Metropolitan Areas Over the Last U.S. Business Cycle, 1992-2003

Ross Gittell and Edinaldo Tebaldi

Economic Development Quarterly 2007; 21; 354
DOI: 10.1177/0891242407310079

Did a Strong Economy in the 1990s Affect Poverty in U.S. Metro Areas? Exploring Changes in Poverty in Metropolitan Areas Over the Last U.S. Business Cycle, 1992-2003

Ross Gittell
University of New Hampshire

Edinaldo Tebaldi
Bryant University

Ross Gittell is James R. Carter Professor at the University of New Hampshire's Whittemore School of Business and Economics. He is the author of Renewing Cities and Community Organizing: Building Social Capital as Development Strategy *and more than 40 academic articles.*

Edinaldo Tebaldi is an assistant professor of economics at Bryant University. His research interests include economic growth and poverty issues with a focus on the impacts of institutions and international trade on individuals' well-being and economic performance.

This article considers whether the economic transformation in the United States during the 1990s included the reduction of poverty in metropolitan (metro) areas. The authors investigate poverty change over the last business cycle, a period of overall strong economic growth. Their analysis identifies evidence of both poverty reduction and persistence. Findings show a general decline in poverty, with decline greatest in the metro areas with the highest poverty rates at the beginning of the last business cycle. Yet the relatively strong economy did not move the metro areas with the highest poverty from their relative position. The article documents that the underlying factors affecting metro-area poverty will have to be changed to fundamentally address poverty in high-poverty-rate metro areas. Reliance on changes in the macro economy will not be sufficient.

Keywords: *poverty; business cycle; metropolitan area economics*

This article considers whether the economic transformation in the United States during the 1990s included the reduction of poverty in metropolitan (metro) areas. The last U.S. business cycle included a boom period, the middle to late 1990s, when there were high expectations regarding a so-called new economy.[1] Starting in the mid-1990s, the United States experienced an unprecedented upsurge in economic productivity (Jorgenson, 2002). At the time, some analysts claimed that a change in the economic structure of the United States had created a state of steady growth and low unemployment and opportunity to fundamentally transform the economy. To many observers, U.S. metro areas[2] were a central point of these changes (Berube, Katz, & Lang, 2006).

The determinants of economic growth in U.S. metro areas have been investigated by many scholars (Fisman & Love, 2004; Glaeser, 1998; Glaeser, Scheinkman, & Shleifer, 1995; Rajan

AUTHORS' NOTE: We would like to thank the participants of the 37th annual meeting of the Urban Affairs Association in Seattle and the anonymous referees for their helpful and insightful comments.

ECONOMIC DEVELOPMENT QUARTERLY, Vol. 21 No. 4, November 2007 354-368
DOI: 10.1177/0891242407310079

& Zingales, 1998; Rappaport, 2003; Sedgley & Elmslie, 2005). A premise of many of these studies is that economic growth will have a positive impact and benefit a significant majority of persons (Kraay, 2004; Ravallion & Chen, 2003). The experience over the past half century in the United States, however, is mixed with regard to the relationship between economic growth and poverty. The economic expansion during the 1960s was associated with a reduction in poverty rates in the United States (Aaron, 1967; Formby, Hoover, & Kim, 2002). However, the beneficent relationship between poverty and economic growth disappeared in the 1970s and 1980s. The economic expansion that the United States experienced during this period benefited the top two quintiles of the population (Bishop, Formby, & Thistle, 1994) while poverty rates increased (Blank, 1991; Blank & Card, 1993; Levernier & White, 1998).

There was poverty reduction in the 1990s (Haveman & Schawabish, 2000), but it was not as significant a reduction as in the 1960s. Blank (1991) attributes this to increasing globalization and stagnant real wages for low-wage workers. LeBlanc (2000) found that output growth had an impact on poverty rates, but output growth alone did not have a significant and lasting influence on poverty rates.

The experience over the past four decades suggests that the impact of economic expansion on poverty rates depends on factors other than macroeconomic ones, such as labor market structure, industrial composition, geography, and social and demographic factors. This study focuses on poverty rates in metro areas over the last U.S. business cycle, 1992 to 2003. It investigates how growth-related variables affected poverty rates and what happened to poverty rates of metro areas during a period of overall strong economic growth followed by a mild recession and the subsequent beginning period of economic recovery. In particular, we examine how key factors affecting overall growth in U.S. metropolitan areas (e.g., growth factors identified by Glaeser et al., 1995) influenced poverty rates in U.S. metro areas from 1992 to 2003. Changes in poverty over the full business cycle are considered to avoid problems associated with analysis that focuses on a boom period or recession that might fail to capture important economic dynamics.

The experience over the past four decades suggests that the impact of economic expansion on poverty rates depends on factors other than macroeconomic ones, such as labor market structure, industrial composition, geography, and social and demographics factors.

The rest of the article is organized as follows: The next section briefly reviews the literature related to the subject matter, followed by an overview of metropolitan area performance over the last business cycle data. Subsequently, the empirical model is introduced, followed by a discussion of the results and a summary of the article's conclusions.

LITERATURE REVIEW

Most studies of urban poverty and economic distress have focused on central cities or the inner-city neighborhoods of central cities or both. For example, Furdell, Wolman, and Hill (2005) examined the performance of 60 U.S. cities during the 1980s and 1990s to determine whether they became more or less distressed. They created an index of urban distress with poverty and unemployment rates, changes in population, and median household income and calculated index scores for the cities in 1980 and 2000. They then compared the cities they classified as distressed in 1980 to the same cities in 2000 and compared the distressed cities (and the changes in their distress index score and component measures of the index) to nondistressed cities. They found that distressed cities were slightly worse off in 2000 than they were in 1980. The population of distressed cities contracted by an average of 8.5%, real median household income fell by an average of 6%, and the national poverty rate remained fairly constant, whereas the average poverty rate rose for cities by 2% primarily because of the weak performance of distressed cities.

However, if one looks beyond the index components, distressed cities fared better. Real per capita income rose by an average of 9.9%, and the number of jobs in the metro areas in which the distressed cities were located rose by an average of 31.7%. Yet compared to nondistressed cities, these gains do not look as good. Although distressed cities made some progress on improving the economic well-being of their residents, nondistressed cities far outpaced them. The average increase in per capita income in nondistressed cities was twice as large as the increase in distressed cities, as was the average rate of employment growth. A similar conclusion can be reached by comparing distressed cities to the nation as a whole. The national poverty rate remained fairly constant at 12.4% over the two decades, whereas the average poverty rate rose for cities by 2% primarily because of the poor performance of distressed cities.

Furdell et al. (2005) used regression analysis to consider how economic and social structural factors contributed to city distress. The variables determined to affect distress most significantly were the percentages of the labor force in manufacturing, finance, insurance, and real estate and the percentage of the population with at least some college education. Although these variables were good predictors of income and the labor force participation rate, they were not good predictors of poverty rates.

Furdell et al.'s (2005) main finding relevant to our inquiry here was that distress in 1980 was a good predictor of distress in 2000, meaning it was difficult for cities to overcome economic liabilities. The best predictor of change in distress uncovered in their analysis was change in the city's dependent population (i.e., the percentage of the population not of working age)—as the percentage of dependent population rose, so did the poverty rate. The change in a city's population with some college was also a strong predictor of change in distress. As this percentage increased, distress declined. The combination of some college with decline in dependency had the greatest poverty rate reduction effect.

Jargowsky (2003) identified some decline in the geographic concentration of poverty in the 1990s. In an analysis of high-poverty neighborhoods nationally in 1990 and 2000, he found that the number of people living in high-poverty neighborhoods, where the poverty rate was 40% or higher, declined by 24%, or 2.5 million people, in the 1990s. This improvement marked a significant turnaround from the 1970 to 1990 period, during which the population in high-poverty neighborhoods doubled. Part of the differences between Furdell et al.'s (2005) findings and Jargowsky's might be explained by the inclusion of the 1980s in Furdell et al.'s analysis. Neither study, however, reviewed the data over a full business cycle period, and neither focused on metropolitan areas.

[M]etropolitan area performance over the last business cycle shows that economic growth (employment growth, per capita income growth, and changes in unemployment) and poverty rates are related, but poverty rates seem to be persistent.

ECONOMIC PERFORMANCE AND POVERTY RATES IN U.S. METRO AREAS OVER THE LAST BUSINESS CYCLE, 1992-2003

Our review of metropolitan area performance over the last business cycle shows that economic growth (employment growth, per capita income growth, and changes in unemployment) and poverty rates are related, but poverty rates seem to be persistent; the pace at which poverty changed did not have a significant impact on poverty ranks across metro areas during the 1990s and the early 2000s.

A variety of data and sources are used in our analysis, including poverty data from the U.S. Census Bureau Small Area Estimates Branch (2005),[3] data on income distribution from the U.S. Census Bureau's (1990, 2000) Public Use Microdata (PUMs), data on employment and unemployment from the U.S. Bureau of Labor Statistics (n.d. [several years]), and data on income per capita from the U.S. Bureau of Economic Analysis (n.d. [several years]). As much as possible, the business cycle is decomposed into four (generally acknowledged) periods—boom (1992-2000), bust (2000-2002), recovery (2002-2003), and the full business cycle (1992-2003). We had available full business cycle data on poverty, employment, income, and unemployment for 206 metropolitan areas.

Overall, the last business cycle was a period of significant growth and positive economic change (see descriptive statistics in Table 1). During the full business cycle, national employment grew by just under 20%. Nearly all (201 of the 206) metropolitan areas in the United States experienced employment growth, with the average metropolitan area employment growth just above the U.S. average. Real per capita personal income increased nationally by 14.9% and in metro areas by approximately the same percentage from 1992 to 2003. Per capita income increased in 204 of the 206 metro areas, increasing by just under 15% in the median metropolitan area.

TABLE 1
Descriptive Statistics, United States and U.S. Metro Areas

			Metro Areas		
Change in	*Period*	*U.S. Average (%)*	*Metro Areas (%)*	*Non–Tech Poles (%)*	*Tech Poles (%)*
Employment	Boom	21.2	21.7	21.26	27.35
	Bust	–1.1	–0.1	–0.02	–0.82
	Recovery	–0.3	0.3	0.36	–0.45
	Full cycle	19.6	22.1	21.90	25.79
Unemployment	Boom	–3.5	–3.2	–3.24	–3.10
	Bust	1.8	1.6	1.58	2.21
	Recovery	0.2	0.2	0.17	0.13
	Full cycle	–1.5	–1.4	–1.49	–0.76
Per capita income	Boom	16.4	14.36	13.37	21.59
	Bust	–1.2	0.17	0.26	–1.97
	Recovery	–0.1	0.23	0.35	–0.76
	Full cycle	14.9	14.70	14.02	18.14
Poverty rates	Boom	–3.8	–3.13	–3.13	–3.18
	Bust	0.8	0.58	0.57	0.67
	Recovery	0.4	0.21	0.19	0.41
	Full cycle	–2.6	–2.35	–2.37	–2.09

SOURCE: Authors' calculations and U.S. Bureau of Economic Analysis (n.d. [several years]); U.S. Census Bureau (1990, 2000); U.S. Census Bureau Small Area Estimates Branch (2005).

Growth in personal income was not evenly distributed across the population in metro or nonmetro areas. Household income inequality, as measured by Gini coefficients, increased nationally and in nearly all (98%) of the metro areas.[4] The increase in household income disparity was more pronounced in metro than in nonmetro areas. The Gini coefficient for household income increased from .427 to .442 in nonmetro areas and from .429 to .461 in metro areas in the United States.

Poverty rates were lower in metro areas than the national average both before and after the last business cycle. Poverty rates nationally declined by 2.6% (from 15.1% to 12.5%) and in 196 of the 206 metro areas. Over the business cycle, poverty rates declined slightly less in metro areas than outside metro areas. The declines in poverty were greatest in the metro areas, with the highest poverty rates at the beginning of the business cycle. However, the poverty rate rankings among the 206 metro areas did not change significantly. Very few metro areas significantly changed their poverty conditions relative to other metro areas and the national average, which suggests that poverty is persistent (see Table 2).

Less than one half of the metro areas had changes in rank of more than 10 positions (out of 206), and very few high-poverty areas had significant change in their poverty rank. This is highlighted by the experience of McAllen, Texas, which had the highest poverty rate of any metro area in the nation in 1993 and also in 2003 (see Table 2). Including McAllen, of the 10 metro areas with the highest poverty rates in 1993, 6 ranked among the top 10 in percentage point reduction in poverty from 1992 to 2003. Although poverty declined significantly in these metro areas, all top 5 ranked in poverty rates in 1993 retained their inglorious *high* rank in 2003, and none of the 5 reduced their poverty rate below twice the national average. At the other end of the poverty spectrum, none of the metro areas in the bottom half rank in change in poverty rates over the last business cycle had poverty rates above the U.S. average in 1993.

The San Diego metro area stands out as an exception, experiencing a decline in poverty rate of nearly 5% (about twice the U.S. average) and dropping from above the U.S. average poverty rate to below with a significant improvement in rank (45 places). Duluth, Minnesota; Fargo, North Dakota; and Naples, Florida, experienced similar but not quite as significant declines in poverty as San Diego.

[I]n the economic boom period (1993-2000), virtually all . . . metro areas had a poverty rate decline.

Of note, in the economic boom period (1993-2000), virtually all (205 of the 206, with the exception of Honolulu) metro areas had a poverty rate decline. The Detroit metro area experienced the

TABLE 2
Poverty Rates, U.S. Metropolitan Areas, 1993-2003

	Poverty Rate, 1993		*Poverty Rate, 2003*		*Poverty Change, 1993-2003*		
Metropolitan Area	*%*	*Rank*	*%*	*Rank*	*%*	*Rank*	*Rank Change, 1993-2003*
Ten highest poverty rates in 1993							
McAllen-Edinburgh-Pharr, TX	41.10	206	31.00	206	–10.10	1	0
Brownsville-Harlingen, TX	38.50	205	29.50	205	–9.00	3	0
Laredo, TX	36.10	204	27.10	204	–9.00	4	0
El Paso, TX	30.20	203	25.70	203	–4.50	27	0
Las Cruces, NM	30.00	202	24.50	202	–5.50	19	0
Tuscaloosa, AL	29.83	201	20.67	200	–9.17	2	–1
Visalia-Porterville, CA	28.20	200	21.50	201	–6.70	10	1
Fresno, CA	28.10	199	20.60	199	–7.50	8	0
Charleston, WV	25.34	198	17.44	185	–7.90	7	–13
Lubbock, TX	25.10	197	20.20	198	–4.90	23	1
Ten lowest poverty rates in 1993							
Appleton, WI	5.70	1	5.20	1	–0.50	186	0
Sheboygan, WI	7.30	2	6.60	4	–0.70	179	2
Milwaukee-Waukesha-West Allis, WI	7.35	3	7.13	8	–0.23	195	5
Minneapolis-St. Paul-Bloomington, MN-WI	7.45	4	5.71	2	–1.74	127	–2
Rochester, MN	8.13	5	6.23	3	–1.90	119	–2
Indianapolis, IN	8.16	6	7.21	10	–0.95	167	4
Fort Wayne, IN	8.20	7	7.73	18	–0.47	188	11
York-Hanover, PA	8.20	8	7.50	13	–0.70	178	5
Denver-Aurora, CO	8.39	9	7.29	11	–1.10	160	2
Wausau, WI	8.40	10	7.20	9	–1.20	153	–1

SOURCE: Authors' calculations using data from the U.S. Census Bureau Small Area Estimates Branch (2005).

greatest decline in poverty rate, from 24.6% to 14.4%, and Memphis experienced the second greatest decline, from 24.8% to 15%. In contrast, during the economic "bust" (from 2000 to 2002), 176 of the 206 metro areas experienced an increase in poverty. Detroit had the second biggest increase in poverty (14.4% to 16.7%) and Pine Bluff, Arkansas, the greatest (19% to 21.4%) during this period.

There was some turnaround in metro area poverty rates during the initial stages of recovery from the early 2000s recession. From 2002 to 2003 (the period for which complete data were available for this inquiry), nearly one quarter (53 of the 206) of metro areas had a decline in poverty. McAllen, Texas, once again, experienced the greatest percentage point decline.

During the last business cycle, metro areas overall experienced greater employment growth, about the same per capita income growth, greater increase in inequality, and less poverty reduction than nonmetro areas and the national average (see descriptive statistics in Table 1). So what explains the duality of poverty in U.S. metro areas over the last business cycle with both changes and persistence in poverty? Why did poverty decline and persist at the same time? The next section investigates the determinants of poverty change of metro areas during the last business cycle.

REGRESSION ANALYSIS

Regression analysis is used to gain insight into the factors that had the greatest influence on the poverty rate in U.S. metro areas over the last business cycle. An econometric model based on the economic literature is specified (Barro, 1991; Barro & Sala-i-Martin, 1995; Formby et al.,

TABLE 3
Milken Tech Poles, 1999

Rank	*MSA[a]—Tech Pole*	*Composite Index*	*Rank*	*MSA[a]—Tech Pole*	*Composite Index*
1	San Jose, CA	23.69	14	Oakland, CA	2.21
2	Dallas, TX	7.06	15	Philadelphia, PA	2.19
3	Los Angeles–Long Beach, CA	6.91	16	Rochester, MN	1.95
4	Boston, MA	6.31	17	San Diego, CA	1.93
5	Seattle-Bellevue-Everett, WA	5.19	18	Raleigh-Durham-Chapel Hill, NC	1.89
6	Washington, DC-MD-VA-WV	5.08	19	Denver, CO	1.81
7	Albuquerque, NM	4.98	20	Newark, NJ	1.80
8	Chicago, IL	3.75	21	Austin-San Marcos, TX	1.78
9	New York, NY (NWY)	3.67	22	San Francisco, CA	1.62
10	Atlanta, GA (ATL)	3.46	23	Houston, TX	1.62
11	Middlesex-Somerset, NJ	3.40	24	Boise City, ID	1.43
12	Phoenix-Mesa, AZ	2.60	25	New Haven-Stamford, CT	1.33
13	Orange County, CA	2.59			

SOURCE: DeVol and Wong (1999).
a. Metropolitan statistical area.

2001; Glaeser et al., 1995; Glaeser, Kallal, Scheinkman, & Shleifer, 1992; Hoover, Formby, & Kim, 2004). More specifically, change in poverty over the business cycle is regressed on explanatory variables measured at the start of the period. This approach is taken because it minimizes endogeneity difficulties and allows us to use standard econometric techniques to obtain parameter estimates. Moreover, we combine the data from the boom (1992-2000) and bust (2000-2002) periods of the last U.S. business cycle, which allows for specification of a panel data model. This method deals with a potential omitted variable bias that plagues cross-sectional regressions by combining time series and cross-sectional data and estimating a random effects panel data model. This also controls for time-invariant state unobserved characteristics. The panel data model is specified as follows:

$$\Delta p_{i,t} = \alpha + \beta x_{i,t-1} + \gamma tech_i + \mu_i + \varepsilon_{i,t}, \quad (1)$$

where i indexes metro areas; t indexes time; Δp measures change in poverty rates; *tech* is a dummy variable equal to one if the metro area is a *tech pole*[5] and zero otherwise; α, β, and γ are parameters to be estimated; ε is the error term; and μ is a time-invariant unobserved characteristic. The unobserved component is treated as "random effects" because a "fixed-effects" model prevents the addition of dummy variables in the model, such as the *tech pole* dummy variable. Equation 1 is estimated using the feasible generalized least squares (GLS) estimator (or random effects estimator), which is a simple, yet widely used, estimator.

Tables 4 and 5 present the results of the regression analysis considering change in poverty rates as a function of initial conditions. Table 4 reports the panel data estimates (random effects) for the boom and bust periods. Table 5 reports estimates of an alternative model that considers *changes* in the industry employment composition rather than the industry employment composition level. All regressions of poverty rates change are regressed against initial poverty rates, a dummy variable for high-technology-based economies, educational attainment, the share of manufacturing employment, and geographical dummies.

The reliability of the estimates was examined by testing several other controls (e.g., percentage of foreigners, Hispanics, and Blacks; cost of living; and share of employment in finance, among other covariates). For robustness purposes, we also use the ordinary least squared (OLS) estimates for the full cycle growth. Almost all coefficients obtained using OLS (to save space, the OLS estimates are not reported in this article) have the same sign of those reported in Tables 4 and 5. However, several coefficients that are significant in Tables 4 and 5 (random effects) turn insignificant in the OLS cross-sectional model. There are also significant differences in the size

TABLE 4
Results of Regression Analysis (Random Effects)—Dependent Variable: Percentage Change in Poverty Rates (Yearly Average)

Explanatory Variable	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*	*Model 7*	*Model 8*	*Model 9*
Logarithm of initial poverty rates	–0.059***	–0.057***	–0.036***	–0.036***	–0.043***	–0.032***	–0.037***	–0.033***	–0.037***
	(–10.7)	(–9.99)	(–6.19)	(–6.04)	(–7.16)	(–5.94)	(–6.21)	(–5.28)	(–6.19)
Tech poles	–0.180**	–0.183**	–0.150**	–0.153**	–0.182***	–0.246***	–0.138	–0.250***	–0.151**
	(–2.42)	(–2.42)	(–2.13)	(–2.16)	(–2.61)	(–3.68)	(–1.92)	(–3.61)	(–2.04)
Percentage of population with BA	–0.282	0.217	–2.298***	–2.221***	–1.284	–0.132	–2.243***	–0.132	–2.285***
	(–0.33)	(0.25)	(–2.69)	(–2.56)	(–1.46)	(–0.16)	(–2.6)	(–0.15)	(–2.63)
Percentage of population with high school	–1.605***	–1.696***	–2.207***	–2.237***	–1.012	0.533	–2.198***	0.520	–2.156***
	(–2.52)	(–2.66)	(–3.7)	(–3.73)	(–1.52)	(0.81)	(–3.65)	(0.75)	(–3.53)
Percentage of employment in manufacturing	0.145	–0.514	–0.527*	–0.553*	–0.380	–0.174	–0.471	–0.192	–0.648**
	(0.52)	(–1.59)	(–1.75)	(–1.81)	(–1.28)	(–0.61)	(–1.53)	(–0.66)	(–2.09)
Percentage of employment in finance		–4.448***	–3.299***	–3.364***	–3.469***	–3.703***	–3.195***	–3.769***	–3.479***
		(–3.63)	(–2.87)	(–2.9)	(–3.07)	(–3.45)	(–2.73)	(–3.44)	(–2.96)
Percentage of employment in government		–1.012***	–1.222***	–1.183***	–0.995***	–0.773**	–1.121***	–0.791**	–1.268***
		(–2.53)	(–3.27)	(–3.09)	(–2.68)	(–2.19)	(–2.91)	(–2.18)	(–3.3)
Unemployment rates			–0.078***	–0.078***	–0.079***	–0.083***	–0.078***	–0.083***	–0.079***
			(–8.42)	(–8.25)	(–8.6)	(–9.52)	(–8.41)	(–9.49)	(–8.43)
Rent as a proportion of personal income				–0.005					
				(–0.54)					
Percentage of Hispanics					0.518***			–0.021	
					(3.75)			(–0.12)	
Percentage of foreigners						2.783***		2.842***	
						(7.6)		(6.47)	
Percentage of African Americans							–0.258	0.005	
							(–1.5)	(0.03)	
Minimum wage differential									0.087
									(1.55)
West	–0.158***	–0.161***	–0.002	0.003	–0.039	–0.061	–0.047	–0.061	–0.047
	(–2.8)	(–2.87)	(–0.04)	(0.04)	(–0.71)	(–1.17)	(–0.74)	(–1.03)	(–0.76)
Northeast	–0.153*	–0.113	–0.011	–0.002	–0.073	–0.126*	–0.045	–0.126*	–0.062
	(–1.96)	(–1.44)	(–0.15)	(–0.03)	(–0.98)	(–1.79)	(–0.58)	(–1.71)	(–0.76)
Midwest	–0.218***	–0.180***	–0.103*	–0.101*	–0.156***	–0.161***	–0.133**	–0.160***	–0.148**
	(–3.96)	(–3.26)	(–1.95)	(–1.91)	(–2.91)	(–3.25)	(–2.35)	(–3.03)	(–2.48)
Constant	1.303***	1.727***	2.312***	2.437***	1.823***	0.936***	2.325***	0.950***	2.316***
	(3.85)	(4.87)	(6.88)	(6.01)	(5.16)	(2.59)	(6.86)	(2.58)	(6.74)
R^2—within	.86	.86	.71	.71	.73	.71	.71	.71	.71
Number of metro areas	204	204	204	204	204	204	204	204	204
Number of observations	408	408	408	408	408	408	408	408	408

NOTE: Data are coefficients with *t* ratios in parentheses. Estimation method: Random effects with standard errors robust to arbitrary heteroskedasticity—generalized least squares (GLS).
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

of the coefficients. A possible explanation for this is that the unobserved characteristics are relevant and the failure to take them into account generates biased coefficient estimates. The Breusch and Pagan Lagrangian multiplier test of significance of the random effects suggests evidence that at the 1% level, the random effects are jointly significant. This result implies that the OLS estimates are biased so for this reason, the discussion below is focused on the results of the random effects model (Tables 4 and 5).

The R^2 of all regressions of Table 4 is greater than .7. This indicates that a significant portion of the variations in changes of poverty rates in metro areas is explained by the model and shows that adding controls makes little difference to the overall fit of the model.

Did the metro areas with the highest poverty rates at the start of the business cycle reduce poverty more than the other metro areas? According to our estimates (Tables 4 and 5),

TABLE 5
Results of Regression Analysis (Random Effects)—Dependent Variable: Percentage Change in Poverty Rates (Yearly Average)

Explanatory Variable	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*	*Model 7*	*Model 8*	*Model 9*
Logarithm of initial poverty rates	–0.060	–0.046	–0.032	–0.031	–0.037	–0.029	–0.032	–0.029	–0.032
	(10.87)***	(9.78)***	(6.60)***	(6.24)***	(7.33)***	(6.25)***	(6.54)***	(5.52)***	(6.50)***
Tech poles	–0.176	–0.090	–0.073	–0.079	–0.104	–0.157	–0.064	–0.154	–0.074
	(2.38)**	(1.44)	(1.23)	(1.32)	(1.76)*	(2.68)***	(1.08)	(2.58)***	(1.23)
Percentage of population with BA	–0.404	0.200	–1.519	–1.420	–0.895	–0.343	–1.473	–0.355	–1.523
	(0.48)	(0.28)	(2.15)**	(1.97)**	(1.23)	(0.48)	(2.09)**	(0.49)	(2.15)**
Percentage of population with high school	–1.589	–0.948	–1.326	–1.378	–0.529	0.398	–1.320	0.374	–1.306
	(2.50)**	(1.78)*	(2.63)***	(2.71)***	(0.95)	(0.70)	(2.63)***	(0.64)	(2.58)***
Change in the share of employment in manufacturing	–0.001	0.028	0.016	0.017	0.014	0.008	0.016	0.008	0.016
	(0.08)	(2.54)**	(1.51)	(1.57)	(1.35)	(0.82)	(1.49)	(0.82)	(1.53)
Change in the share of employment in finance		0.058	0.001	–0.000	0.002	0.004	–0.003	0.003	0.002
		(1.86)*	(0.03)	(0.00)	(0.07)	(0.12)	(0.09)	(0.10)	(0.06)
Change in the share of employment in the government sector		0.133	0.121	0.121	0.118	0.108	0.120	0.108	0.123
		(12.94)***	(12.34)***	(12.32)***	(12.04)***	(11.10)***	(12.19)***	(11.06)***	(12.24)***
Unemployment rates			–0.061	–0.061	–0.063	–0.068	–0.061	–0.068	–0.062
			(7.35)***	(7.24)***	(7.60)***	(8.42)***	(7.36)***	(8.38)***	(7.35)***
Rent as a proportion of personal income				–0.006					
				(0.72)					
Percentage of Hispanics					0.374			–0.009	
					(3.17)***			(0.06)	
Percentage of foreigners						1.902		1.896	
						(5.86)***		(4.86)***	
Percentage of African Americans							–0.223	–0.036	
							(1.55)	(0.23)	
Minimum wage differential									0.014
									(0.30)
West	–0.159	–0.166	–0.045	–0.038	–0.067	–0.071	–0.081	–0.077	–0.050
	(2.79)***	(3.47)***	(0.94)	(0.79)	(1.40)	(1.54)	(1.53)	(1.48)	(0.95)
Northeast	–0.151	–0.172	–0.101	–0.091	–0.140	–0.168	–0.127	–0.171	–0.109
	(1.92)*	(2.62)***	(1.62)	(1.41)	(2.23)**	(2.75)***	(1.96)**	(2.72)***	(1.61)
Midwest	–0.211	–0.207	–0.146	–0.145	–0.178	–0.171	–0.167	–0.173	–0.153
	(3.84)***	(4.49)***	(3.32)***	(3.29)***	(3.99)***	(4.02)***	(3.63)***	(3.89)***	(3.05)***
Constant	1.338	0.984	1.418	1.555	1.135	0.634	1.446	0.648	1.406
	(3.99)***	(3.49)***	(5.22)***	(4.68)***	(4.01)***	(2.16)**	(5.32)***	(2.15)**	(5.11)***
R^2—within	.857	.696	.724	.726	.737	.744	.726	.743	.727
Number of metro areas	204	204	204	204	204	204	204	204	203
Number of observations	408	408	408	408	408	408	408	408	406

NOTE: Data are coefficients with *t* ratios in parentheses. Estimation method: Random effects with standard errors robust to arbitrary heteroskedasticity—generalized least squares (GLS).
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

metropolitan areas with the highest rates of poverty in 1993 experienced greater reduction in poverty rates than did other metro areas. The model suggests that the gap in poverty rates among U.S. metro areas has decreased during the last business cycle. More precisely, the coefficient on initial poverty rates is negative and statistically significant, which indicates that on average, metro areas with high initial poverty rates were the ones that experienced the largest reductions in poverty (Figure 1 shows the unconditional correlation between poverty rates and changes in poverty rates). This indicates a tendency for poverty rates to converge toward the mean across metro areas. However, the degree of convergence is relatively small and the "half-life," which

[T]he gap in poverty rates among U.S. metro areas has decreased during the last business cycle.

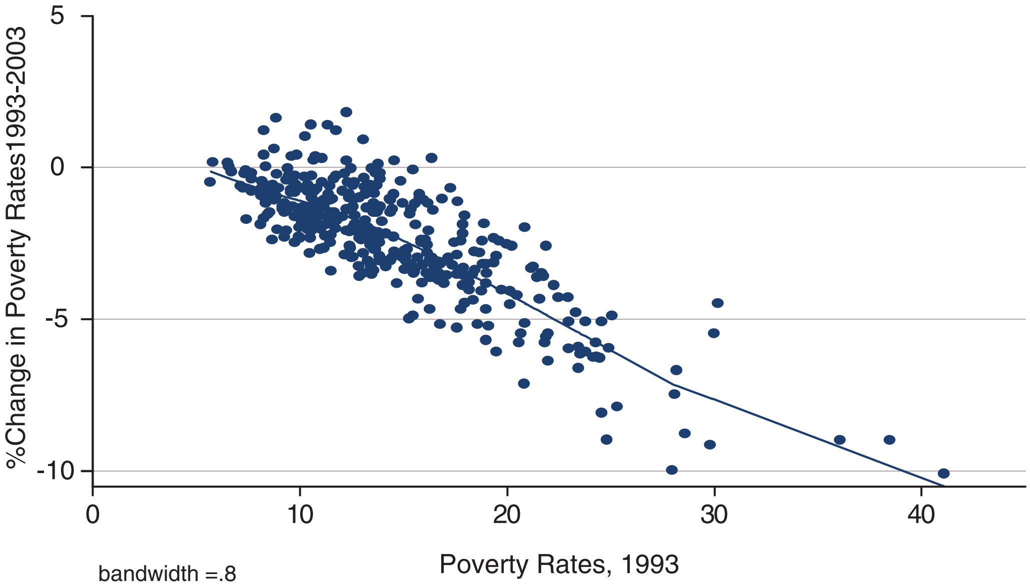

Figure 1: Convergence in Poverty Rates, U.S. Metro Areas

measures the time for which the poverty gap is reduced by half, is estimated to range from 12 to 23 years.[6]

Economic growth over the last business cycle was concentrated in metro areas with technology specialization. The Milken Institute (DeVol & Wong, 1999) documented how growth in high-technology goods and services explained about two thirds of the difference between metro areas with the fastest growing economies and average growth in the United States. They also identified the 25 leading technology centers in the nation during this period and called them *tech poles*.[7]

We tested the influence of metro technology specialization and development on poverty using the Milken tech pole definition. The regression analysis provides evidence that metro areas with specialization in high technology, as indicated by the metro area designation as a tech pole by the Milken Institute, performed better in terms of reducing poverty rates over the last business cycle than did other metro areas. The coefficient on the tech poles dummy is statistically significant at the 5% level of significance. Regression 1 of Table 4 suggests that over the boom and bust periods, the reduction in poverty rates in tech pole metro areas was, on yearly average, 0.18% higher than that in other metro areas. Adding other controls neither changes the sign of the coefficient on tech poles nor affects its size significantly. This finding suggests that the economic dynamics of technology-based metro areas generates economic growth, which reduces poverty rates.[8]

Educational attainment, measured as the percentages of persons with high school and bachelor's degrees, is found to be negatively correlated with growth in poverty rates. Specifically, Regression 1 of Table 4 indicates that a 1% increase in the population with high school diplomas is associated with a yearly average reduction of about .016% in poverty rates over the boom and bust periods. The negative relationship between the change in poverty rates and the percentage of population with high school diplomas is robust to a wide number of controls, as shown in

Table 4. In addition, the coefficients on higher education (bachelor's degree attainment) are negative in all regressions except for Regression 2 in Table 4. However, the significance of the coefficient on percentage of people with bachelor's degrees is sensitive to the set of variables included in the model. Overall, the results suggest that given initial poverty rates and controlling for other covariates, metro areas with a more highly educated population reduced poverty more than metro areas with a less well-educated population over the last business cycle. This result is consistent with the findings of Levernier and White (1998) and Schiller (1989).

Regressions 2 through 9 of Table 4 show that metro area industry employment composition also affected poverty rates over the last business cycle. The percentage of total metro area employment in financial services is negatively correlated with changes in poverty rates.[9] More specifically, metro areas with a higher percentage of employment in financial services experienced larger reductions in poverty rates. Regression 2 of Table 4 shows that a 1% increase in the percentage of employment in financial services is associated with a .044% yearly average reduction in poverty rates over the last business cycle (adding other controls does not change this result significantly). The employment share of the government sector is also negatively correlated with changes in poverty rates over the business cycle.

Regression 1 of Table 4 shows that the coefficient on the relative size of the manufacturing sector is statistically equal to zero. Adding other controls such as unemployment rates affects the size as well as the significance of this coefficient. The coefficient on the share of manufacturing employment is unstable and only marginally significant in Models 3, 4, and 9. This provides evidence that the size of the manufacturing sector did not affect poverty rates significantly during the last business cycle. This result is consistent with the findings of Levernier and White (1998).

We also examined whether the *changes* in the industry employment share variables, rather than the *levels*, help to predict poverty. Table 5 reports the estimates of this alternative model and shows that neither the change in the share of manufacturing nor the change in the share of finance employment affected poverty rates over the period under consideration. However, we find that changes in the size of the government sector are positively correlated with poverty rates over the last business cycle. This result must be carefully interpreted because of potential endogeneity difficulties. More precisely, local governments that operate in metro areas with high levels of poverty might have tried to address poverty by expanding their services (and employment) at rates greater than that of the rest of the economy. If so, poverty would be motivating the employment changes in the government sector rather than the other way around.[10]

In Regression 3 of Table 4, the initial unemployment rate is included as an explanatory variable (see Hirsch, 1980), and a negative relationship between initial unemployment and changes in poverty rates is identified. This relationship is robust to a wide number of controls and contradicts Hoover et al. (2004). The connection between change in poverty rates and unemployment, however, is not simple. Theoretically, some unemployment can contribute to overall economic growth through labor mobility and employment expansion. Initial period unemployment may contribute to growth over a business cycle and may affect the extent of the decline in poverty over a period of time. In addition, unemployment may also be understood as a proxy for omitted human capital variables (or development), so high rates of unemployment may indicate the lack of skilled labor force necessary for boosting economic growth (Glaeser et al., 1995) and reducing poverty.

The finding that initial unemployment rates is negatively correlated with subsequent growth in poverty rates is consistent with the view that metro areas with high initial unemployment rates and available labor supply are better able to benefit from growth opportunities and reduce poverty than are metro areas with lower initial unemployment rates.

The regression modeling also included a set of dummy variables to control for the four U.S. Census regions (i.e., the Northeast, Midwest, South, and West). Regression 1 of Table 4 shows that region matters (Freeman & Mathur, 2003). When we controlled for initial poverty rates and other factors, the reduction in poverty rates in the West, Northeast, and Midwest regions was, on yearly average, about .16%, .15%, and .22%, respectively, larger than that observed in the South region (omitted category) over the last business cycle. Adding other controls does not change the sign of the coefficients on the regional dummies but does affect their sizes and significances. More specifically, the coefficients on the West and Northeast regions were found to be insignificant as we controlled for initial unemployment rates (Regressions 3-9).

Regressions 5 through 8 of Table 4 add controls to examine the correlation among racial and ethnical compositions—the percentage of population African American, foreign-born, and Hispanic—and changes in poverty rates. Regression 5 shows that the coefficient on the percentage of the population that is Hispanic is positive and statistically significant at the 1% level and suggests that, ceteris paribus, a 1% increase in the share of the Hispanic population is associated with an increase, on yearly average, of .05% in poverty rates. However, this effect disappears when education reaches certain levels. More specifically, the coefficient on an interaction term between the percentage of population with a bachelor's degree and the percentage of the Hispanic population is found to be negative and statistically significant at the 5% level, which indicates that the higher the proportion of population with a bachelor's degree, the lower the potential adverse impact of the share of Hispanic population on poverty rates.[11] In Regression 8, the coefficient on the share of Hispanics also becomes insignificant as we add controls for the percentage of the population that are foreign born and African American.

Consistent with Clark (1998), Regressions 6 and 8 provide evidence that the share of foreign born is positively correlated to increases in poverty. When the percentage of the foreign-born population in the metro areas increased by 1%, poverty rates increased by a yearly average of .03% over the business cycle.

We find that there is a very weak correlation between the percentage of African American population and changes in poverty rates over the last business cycle. The coefficient on the percentage of African Americans is negative and marginally significant in Model 7 of Table 4. However, this relationship is weak, and its significance is sensitive to other controls. In particular, Model 8 of Table 4 shows that when we control for other characteristics such as geographical area, education, ethnical origin, and unemployment, the change in poverty rates in metro areas is not influenced by the share of the African American population.[12]

Finally, the effect of a state minimum wage above the federal standard is considered. The regression modeling findings (Model 9 of Table 4) suggest that that there is a counterintuitive positive and marginally significant correlation between minimum wage differentials and poverty rates. In other words, metro areas in states with higher minimum wages tended to experience relatively small reductions in poverty rates over the last business cycle. This result must be interpreted with caution because the significance of the coefficient on minimum wage differentials is sensitive to model specification.

Several variables often thought to affect poverty rates did not have statistically significant coefficients. These included cost of living proxies such as rent as a proportion of personal income, median rent, and median real estate value. The finding that there was no significant statistical relationship between poverty rate and living costs suggests that the poverty rate reductions observed in metro areas most likely reflect real increases in income. However, the relationship between poverty rate change and living costs needs to be further investigated.

DISCUSSION OF FINDINGS

The factors that have contributed to the reduction of poverty in U.S. metro areas over the last business cycle are similar to the factors affecting overall growth in U.S. metropolitan areas (Glaeser et al., 1995). This suggests that economic development efforts that focus on growth in general in metro areas can help to reduce poverty. We identify the key factors reducing poverty rates in metro areas as technological specialization, the percentage of the population with a 4-year college degree and with a high school education, and the concentration of employment in finance and government sectors. We also find that there is a positive correlation between Hispanic and foreign-born population percentages and poverty rates.

[E]conomic development efforts that focus on growth in general in metro areas can help to reduce poverty.

The findings contrast in part with the findings of Furdell et al. (2005). The regression modeling and the simple descriptive review of the metro area poverty data stated above suggest that the gap in poverty rates among U.S. metro areas has decreased over the last business cycle. More specifically, the coefficient on initial poverty rates in the regression modeling is negative and statistically significant, which indicates that on average, metro areas with high initial poverty rates were the ones that experienced the largest reductions in poverty. Yet similar to the findings of Furdell et al. on distressed cities, we found that poverty persisted at high levels in the metro areas that had the highest poverty rates at the beginning of the last business cycle and that the movement toward U.S. metro area convergence in poverty rates was very modest over the last business cycle. This is consistent with a study by Freeman and Mathur (2003) that finds that "poverty can become quite entrenched in locations" (p. 3). This phenomenon reflects that many of the key factors that affect poverty rates identified in the regression analysis, such as educational attainment, employment or industry base, and the concentration of Hispanic and foreign-born populations, showed significant change over the last business cycle in very few metro areas.

We find evidence that metro areas with high educational levels experienced the largest reductions in poverty rates. Metro areas with a more highly educated population reduce poverty faster than do metro areas with a less well-educated population. We also found that a high percentage of Hispanics and foreign born increases metro area poverty rates. However, we find that the effect with Hispanics disappears when education reaches certain levels. More specifically, the coefficient on an interaction term between the percentage of population with 4-year college degrees and the percentage of Hispanics is found to be negative and statistically significant. This suggests that high attainment in education among the residents of metro areas can help reduce the influence of a high percentage of Hispanic residents on poverty.

Additionally, we find that metro areas with a high concentration of employment in financial services and government tended to reduce poverty more than other metro areas over the last business cycle. This might reflect employment opportunities in these sectors that were available to a broad cross section of metro area residents. The strong positive effect of the concentration of employment in these sectors on the reduction of poverty may also reflect enhanced availability of government and financial services to the residents of these cities, which may help residents to advance economically. These factors require further study and empirical testing.

The results of the regression analysis also indicate that technology-intensive metro areas reduced poverty more than did other metro areas over the last business cycle. This finding suggests that the economic dynamics of technology centers may be favorable to populations in poverty: The benefits of technology-based economic growth might reach the poor, promoting an increase in personal income, which can reduce poverty rates. However, the reduction in the poverty rate could also result from significant in-migration of higher income residents into tech poles. The nature and relative contribution to the reduction in poverty rate in technology centers of these two factors should be further investigated.

Finally, it is important to recognize that the findings discussed in this article should be considered in a particular context and time period (the last business cycle studied here was 1992 to 2003). The relation between poverty rates and factors such as racial and ethnic population composition and educational attainment may not be fixed over other periods of time (e.g., Freeman & Mathur, 2003).[13]

CONCLUSION

Our inquiry revealed evidence of both poverty reduction and persistence across U.S metro areas. It also identified some of factors affecting poverty in U.S. metro areas. Over the last business cycle in the United States, there was significant decline in poverty rates in metro areas across the nation. The decline in poverty was broad and was greatest in the metro areas with the highest poverty rates at the beginning of the business cycle.

[T]he relatively strong economy that prevailed in the last business cycle did not move the metro areas with the highest poverty from their position.

Yet the relatively strong economy that prevailed in the last business cycle did not move the metro areas with the highest poverty from their position. The underlying factors affecting metro-area poverty will have to be changed to more fundamentally address poverty in high-poverty-rate metro areas. Reliance on changes in the macro economy will not be sufficient.

This inquiry has been narrowly focused on changes in poverty in U.S. metro areas over the last business cycle. More research is needed to explore poverty and its sources within and among metro areas in the United States and elsewhere. It would be beneficial to explore further why high poverty rates persisted in some metro areas even in very good economic times. It would also be helpful to better understand why and how a select few metro areas (e.g., San Diego, Duluth, Fargo, and Naples) were able to significantly reduce poverty and poverty rank over the last business cycle. Case studies of these metro areas could be useful to uncover what happened and to explore whether poverty was reduced because of significant in-migration of well-educated workers, out-migration of dependent low-income residents, changes in public policy, and/or growth of a particular industrial sector.

NOTES

1. The term *new economy* was used to describe the changes in the 1990s in the United States and other developed countries from an industrial and manufacturing base into information, technology, and knowledge-based economies.

2. In the United States, metro areas are defined by the U.S. Census Bureau as a collection of contiguous counties that exceed a certain threshold of commuting to the closest central city. A metro area is for the most part a single labor market, with a 1- to 2-hour commute from end to end. Specialized job skills needed by specific industries, such as tourism and hospitality industry workers in Miami or New Orleans or software companies in Seattle or San Jose (Silicon Valley), are accessed within a metro area but are difficult to move between metro areas. Metro areas share not only a workforce and industries in common but also educational institutions, housing, transportation, and other critical economic and social infrastructure.

3. The poverty estimates provided by the U.S. Census Bureau, Small Area Estimates Branch (2005) were released on November 29, 2005, and constructed using data from the Current Population Survey.

4. To measure the distribution of income, we use a standard and widely accepted measure: the Gini coefficient. The Gini is calculated as the difference between an area's income distribution and a reference distribution in which income is uniformly distributed across all households (or full equity). The Gini ranges from 0 to 1. As the Gini approaches 1, the greater is the income disparity among households in a geographic area. The primary data source we use to calculate the household income Gini coefficients is the U.S. Census of 1990 and 2000 Public Use Microdata (PUMs; U.S. Census Bureau 1990, 2000). We rely on the detailed data of the decennial census to calculate the Gini coefficients, so we do not have measures at different phases of the last business cycle. The measure of income we use is comprehensive; it includes all household income from wages, business profits, earnings, interest, dividends, and real estate investment.

5. The Milken Institute identified the 25 leading technology centers in the nation and called them *tech poles* (DeVol & Wong, 1999). See Table 3 for a list of the 25 tech poles.

6. The time for which the poverty gap is reduced by half is know as "half-life" and, given the model's specification (see Barro & Sala-i-Martin [1995, p. 37] for more detail), can be calculated as follows: $\text{Half} - \text{Life} = \frac{\ln(2)}{\beta}$, where β is the coefficient on the log of initial poverty rates reported on Tables 4 and 5.

7. The ranking used by Milken (DeVol & Wong, 1999) was a composite index for each metro area. The index was calculated as each metro area's percentage of national high-technology real output multiplied by its high-technology real output location quotient. (The location quotient is the percentage output of high technology in each metropolitan area divided by the percentage of output in high technology in the United States.)

8. An anonymous referee pointed out that that the tech pole dummy variable might be picking effects other than increased income for the poor living in tech poles. For instance, tech poles might have attracted more high-income people into the metropolitan area, which would decrease poverty rates while leaving unchanged the number of people in poverty. Although this may be the case, our focus here is *relative* poverty, and the results show that tech poles reduced poverty rates faster than non–tech poles did over the last business cycle. Our results are robust to several controls. In addition, we control for changes in population over time by including population density as an additional explanatory variable, and the results (not reported in the article) on tech poles did not change.

9. The percentage of employment in services and the percentage of employment in retail trade were also tested as explanatory variables. The coefficients on these two variables were found to be insignificant so were not included in the model.

10. The estimates reported in Table 4 are supposedly free from this *endogeneity* problem because all explanatory variables included in the model are measured at the start of the period. However, the coefficients reported in Table 5 may be biased because of eventual endogeneity resulting from adding the industry share variables in terms of *changes*.

11. The estimates of the model including the interaction term are not reported in this article. However, based on the results, we obtain the following relation:

$$\frac{\partial E[\Delta p]}{\partial h} = 1.64019 - 9.9695 * BA,$$

where E denotes the expectancy operator, Δp indicates change in poverty rates, h is the percentage of Hispanics, and BA denotes the percentage of the population with bachelor's degrees. The estimates imply that when the percentage of the population with bachelor's degrees reaches about 16%, the share of Hispanics would have no influence on poverty rates.

12. This result does not imply that the size of the African American population is unassociated with poverty, as widely reported (e.g., Cautley & Slesinger, 1998); rather, it does suggest that given initial poverty levels and controlling for other characteristics such as geographical area, educational attainment, ethnical origin, and unemployment rates, change in poverty is weakly correlated with the size of the African American population across U.S. metro areas.

13. "Here we find that the coefficients for the regressors are unstable over the three decades of changes in the sample period. Most notable, coefficients for black, Hispanic, and even single parents can be positive, negative, or zero, depending on the decade. Only the manufacturing, education, and immigration variables are consistent in sign, but not in significance level, over the entire sample" (Freeman & Mathur, 2003, p. 20).

REFERENCES

Aaron, H. (1967). The foundations of the War on Poverty reexamined. *American Economic Review*, *57*, 1229-1243.

Barro, R. (1991). Economic growth in a cross section of countries. *Quarterly Journal of Economics*, *106*(2), 407-443.

Barro, R., & Sala-i-Martin, X. (1995). *Economic growth*. Cambridge, MA: MIT Press.

Berube, A., Katz, B., & Lang, R. E. (Eds.). (2006). *Redefining urban and suburban America evidence from Census 2000*. Washington, DC: Brookings Institution Press.

Bishop, J. A., Formby, J. P., & Thistle, P. D. (1994). Convergence of the south and non-south income distributions, 1969-1979. *American Economic Review*, *82*(1), 262-272.

Blank, R. M. (1991). *Why were poverty rates so high in the 1980s?* (NBER Working Paper No. 3878). Cambridge, MA: National Bureau of Economic Research.

Blank, R. M., & Card, D. (1993). Poverty, income and growth: Are they still connected? *Brookings Papers on Economic Activity*, *2*, 285-325.

Cautley, E., & Slesinger, D. P. (1998). Labor force participation and poverty status among rural and urban women who head families. *Policy Studies Review*, *74*(4), 795-809.

Clark, W. A. V. (1998). Mass migration and local international migration to the United States creating a new urban underclass? *Urban Studies*, *35*(3), 371-383.

DeVol, R., & Wong, P. (1999). *America's high-tech economy: Growth, development, and risks for metropolitan areas*. Santa Monica, CA: Milken Institute.

Fisman, R., & Love, I. (2004). *Financial development and growth in the short and long run* (NBER Working Paper No. 10236). Cambridge, MA: National Bureau of Economic Research.

Formby, J., Hoover, G., & Kim, H. (2002). Economic growth and poverty in the United States. *Journal of Income Distribution*, *10*(3-4), 6-22.

Freeman, D. G., & Mathur, V. K. (2003). *Poverty in metropolitan areas of the U.S.: Causes and consequences* (Sam Houston State University Economics and International Business Working Paper No. WP03-02). Huntsville, TX: Sam Houston State University.

Furdell, K., Wolman, H., & Hill, E. W. (2005). Did central cities come back? Which ones, how far, and why? *Journal of Urban Affairs*, *27*(3), 283–305.

Glaeser, E. (1998). Are cities dying? *Journal of Economic Perspectives*, *12*(2), 139-160.

Glaeser, E., Kallal, H., Scheinkman, J., & Shleifer, A. (1992). Growth in cities. *Journal of Political Economy*, *100*(6), 1126-1152.

Glaeser, E., Scheinkman, J., & Shleifer, A. (1995). Economic growth in a cross section of cities. *Journal of Monetary Economics*, *36*, 117-143.

Haveman, R., & Schawabish, J. (2000). Has macroeconomic performance regained its antipoverty bite? *Contemporary Economic Policy*, *18*, 415-427.

Hirsch, B. T. (1980). Poverty and income growth: Has trickle down petered out? *Economic Inquiry*, *18*, 151-158.

Hoover, G., Formby, J., & Kim, H. (2004). Poverty, non-White, and the Sen index. *Review of Income and Wealth*, *50*(4), 543-559.

Jargowsky, P. A. (2003). Stunning progress, hidden problems: The dramatic decline of concentrated poverty in the 1990s. Washington, DC: Brookings Institution.

Jorgenson, D. W. (2002). *Economic growth in the information age*. Cambridge, MA: MIT Press.

Kraay, A. (2004). *When is growth pro-poor? Evidence from a panel of countries* (World Bank Policy Research Working Paper No. 3225). Washington, DC: World Bank.

LeBlanc, M. (2000). *Poverty, policy, and the macroeconomy* (Economic Research Service Technical Bulletin No. 1889). Washington, DC: U.S. Department of Agriculture.

Levernier, W., & White, J. B. (1998). The determinants of poverty in Georgia's plantation belt: Explaining the differences in measured poverty rates. *American Journal of Economics and Sociology*, *57*(1), 47-68.

Rajan, R., & Zingales, L. (1998). Financial dependence and growth. *American Economic Review*, *88*(3), 559-586.

Rappaport, J. (2003). U.S. urban decline and growth, 1950 to 2000. *Economic Review*, 3rd Quarter, pp. 15-44. Kansas City, MO: Federal Reserve Bank of Kansas City.

Ravallion, M., & Chen, S. (2003). Measuring pro-poor growth. *Economics Letters*, *8*, 93-99.

Schiller, B. (1989). *The economics of poverty and discrimination*. Englewood Cliffs, NJ: Prentice Hall.

Sedgley, N., & Elmslie, B. (2005). Do we still need cities? Evidence on rates of innovation from count data models of metropolitan statistical area patents. Unpublished manuscript.

U.S. Bureau of Economic Analysis. (n.d. [several years]). *Local area personal income*. Washington, DC: U.S. Department of Commerce.

U.S. Bureau of Labor Statistics. (n.d. [several years]). *Current employment survey*. Washington, DC: U.S. Department of Labor.

U.S. Census Bureau. (1990). *Public use microdata (PUMs)*. Washington, DC: U.S. Department of Commerce.

U.S. Census Bureau. (2000). *Public use microdata (PUMs)*. Washington, DC: U.S. Department of Commerce.

U.S. Census Bureau Small Area Estimates Branch. (2005). *Poverty and median income estimates—Counties*. Washington, DC: U.S. Department of Commerce.