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Comparisons of Metropolitan-Nonmetropolitan Poverty During the 1990s

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Abstract

While the greater incidence of poverty in nonmetro relative to metro areas is well documented, there is little research as to whether it is deeper or more severe in nonmetro areas. This report examines metro-nonmetro differences in U.S. poverty rates, using data from Current Population Surveys (1991-2000) and poverty measures that are sensitive to income distribution. The standard practice of examining only the headcount, or incidence, of poverty provides the expected result that poverty is greater in nonmetro areas in all 10 years of the 1990s. The poverty gap index, which measures the depth of poverty, indicates that the difference in this measure of poverty is statistically significant in 6 of the 10 years. When the squared poverty gap index, a measure of severity, is examined, the estimate of nonmetro poverty is greater than the metro measure in only 3 of the 10 years.

Keywords: Poverty, headcount, poverty gap, urban-rural comparison, sample design, CPS

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Contents

Summary

Understanding how poverty is distributed across areas can help to target and improve the efficiency of poverty reduction policies. Although it is well documented that poverty is more prevalent in nonmetro areas, very little research examines whether poverty is more severe in these areas. This report examines differences in poverty between U.S. metropolitan (metro) and nonmetropolitan (nonmetro) areas throughout the 1990s.

There are many indexes of poverty, each providing different insights into its nature. The most common is the share of population living in poverty, often referred to as the headcount index or incidence of poverty. Two other measurements are examined in this report: the poverty gap and squared poverty gap indexes. The poverty gap index is considered to measure the depth of poverty because it is sensitive to changes in the average income of the poor. The squared poverty gap measures the severity of poverty because it is sensitive to changes in the inequality of income distribution of the poor.

The usefulness of these measures can be illustrated by a transfer of money from a rich person to a poor one. If the transfer is insufficient to lift the poor person out of poverty, it has no effect on the headcount index. It has, however, raised the income of the poor person, and this improvement in well-being is reflected in a reduction of both the poverty gap and squared poverty gap indexes. As another example, a transfer of income from a poor person to a poorer person will alter neither the headcount nor the poverty gap index, but it does improve the distribution of income among the poor, and so reduces the squared poverty gap index.

Previous research has shown that the nonmetro headcount index was 2.6 percentage points higher than the metro poverty incidence in the 1990s. Using Current Population Survey (CPS) data from 1991 to 2000, this report confirms that result, and further shows that this difference is highly significant statistically throughout the 1990s.

This study extends the literature on U.S. poverty in two ways. First, to test for statistical significance, it derives estimates of sampling variance for any additively decomposable poverty index. Through incorporating results from the well-established literature on sampling, the estimates of sampling variance for the poverty indexes are corrected for sample design characteristics. In the international literature on poverty measurement, the importance of this methodological issue has been established, but in the U.S. literature, the importance of the correction has not been well recognized. The results of the study show that across the 60 poverty estimates considered (the 3 indexes estimated over 10 years for metro and nonmetro areas), the correction for sample design characteristics more than doubles all standard errors. The implication is that poverty estimates based on unadjusted standard errors will underestimate confidence intervals by more than half the true size.

Second, this study shows that the magnitude and significance of metro-nonmetro differences in poverty are sensitive to the measure of poverty considered. While the nonmetro incidence is larger than the metro rate in all 10 years of the 1990s, the depth of poverty as measured by the poverty gap index is significantly higher statistically in only 6 of the 10 years. In terms of the severity of poverty, the squared poverty gap index is higher in nonmetro areas during only 3 of the 10 years. These results suggest that the observed metro-nonmetro differences in poverty during the 1990s (as measured by the headcount index) are not robust to alternate measures of poverty.

Comparisons of Metropolitan-Nonmetropolitan Poverty During the 1990s

Dean Jolliffe

Introduction

The geographic distribution of poverty is an important input for targeting poverty reduction policies. Throughout the 1980s and 1990s, the proportion of people living in poverty in the United States was significantly greater in nonmetropolitan (nonmetro) than in metropolitan (metro) areas. In the 1980s, the average incidence of poverty was 4.4 percentage points higher in nonmetro areas; in the 1990s, the average difference was 2.6 percentage points.[1]

While it is well documented that the incidence of poverty, also called the headcount index, has been higher in nonmetro areas, there is very little research into whether poverty is deeper or more severe in nonmetro areas. Indeed, most Federal agencies that look at poverty restrict their analysis to its incidence.[2] Zheng et al. (1995) note that the U.S. Government uses the proportion of poor as virtually the only indicator of poverty.[3] Much of the academic research on poverty is similarly focused on the incidence of poverty and does not examine distribution-sensitive measures of poverty.[4] For example, Hanratty and Blank (1992) compare U.S. and Canadian poverty rates from 1970 to 1986 and provide an explanation for why the Canadian poverty rate improved dramatically relative to the U.S. rate. Sawhill (1988) presents a comprehensive review of poverty measurement in the United States and proposes explanations for why poverty changed so little from the mid-1960s to the mid-1980s. Using a consumption-based measure of poverty rather than the official income-based measure, Slesnick (1993) counters that significant progress was made in reducing poverty during this period. In all cases, though, when the authors discuss poverty, they are referring to the incidence of poverty, and never to any sort of index that is sensitive to the income distribution of the poor.

The aim of this report is to provide more information about the nature of metro-nonmetro poverty differences in the 1990s. To this end, we consider three measures of poverty that describe its incidence, depth, and severity. These measures can help to better identify the determinants and effects of metro-nonmetro poverty differences. Similarly, poverty indexes sensitive to the income distribution of the poor can determine whether policymakers should consider different strategies for reducing poverty in different areas.

This report extends the current literature in two ways. First, the analysis considers three different measures of poverty—the headcount, poverty gap, and squared poverty gap indexes. These measures belong to the Foster-Greer-Thorbecke (1984) family of poverty indexes (hereafter referred to as FGT) and have been widely used in international poverty literature.[5] The headcount is the standard index, measuring, as noted,

[1] Nord (1996, 1997), Dagata (2000), and Jolliffe (2002) all show that the incidence of poverty in nonmetro areas has been greater than in metro areas over varying periods during this time.

[2] For example, Ghelfi (2001) shows that the incidence of poverty in poor rural Southern counties has been persistent through the early 1990s. Rogers and Dagata (2000) show that the incidence of children in poverty has been particularly high in nonmetro areas throughout the 1990s. These two reports and those mentioned in the previous note provide important information on the incidence of poverty, but their analysis does not include a measure of poverty that is sensitive to the distribution of income.

[3] A noteworthy exception to this is the Census Bureau P-60 series (for example, Dalaker and Proctor, 2000), which reports the number of persons with income less than various ratios of the poverty line.

[4] There are notable exceptions. Cushing and Zheng (2000) use distribution-sensitive measures to compare area poverty differences using 1990 Census Data. Zheng et al. (1995) consider several distribution-sensitive indexes and test for changes in poverty from 1975 to 1990, and Bishop et al. (1999) examine area differences in Sen's distribution-sensitive index from 1961 to 1996. An important methodological difference between these last two articles and the results in this report is that the statistical tests examined in the report correct for the characteristics of the sample design.

[5] All three measures to describe poverty in various countries: Alwang et al. (1996) examine poverty in Zambia; Boateng et al. (1992) look at Ghana; Jolliffe et al. (forthcoming) look at Egypt; Datt and Ravallion (1992) cover Brazil and India; Howes and Lanjouw (1998) use examples from Pakistan and Ghana; Kakwani (1993) provides estimates for Ivory Coast; World Bank (1996) describes poverty in Ecuador; Foley (1997) looks at poverty in Russia; Ravallion and Bidani (1994) examine Indonesia.

the incidence of poverty. The poverty gap index provides a measure of the depth of poverty, and the squared poverty gap is sensitive to income distribution of the poor and measures the severity of poverty.

The usefulness of these measures can be illustrated by considering a transfer of money from a rich person to a poor one that is insufficient to lift the poor person over the poverty line. This transfer has no effect on the headcount index, but the poor person is better off and this improvement in well-being is reflected in a reduction of both the poverty gap and squared poverty gap indexes. As another example, a transfer of income from a poor person to a poorer one will not alter either the headcount or the poverty gap index, but it improves the distribution of income among the poor and is reflected by a reduction of the squared poverty gap index.[6]

Many social welfare programs aim to reduce poverty, but the policies appropriate to attaining this goal will vary depending on which poverty measure is considered. In particular, if policymakers were interested only in reducing the headcount index, then programs would target the least poor so as to lift them above the poverty line, while ignoring those most in need of assistance. Policymakers concerned about the overall well-being of the poor and not just poverty reduction would do well to consider efforts to reduce the depth and severity of poverty.

Another reason for considering the poverty gap and squared poverty gap indexes in poverty analysis relates to measurement error in estimating the poverty line. There is currently a debate in the United States as to the appropriateness of the current measure of income and the estimated poverty lines. In particular, Citro and Michael (1995) present recommendations from the National Academy of Science's Panel on Poverty and Family Assistance to create a new poverty measure. Several researchers, including Garner et al. (1998), Olsen (1999), Short et al. (1999), and Betson et al. (2000), have shown that the incidence of poverty is sensitive to the recommended changes in the poverty lines and measure of income. An advantage of the poverty gap and squared poverty gap indexes is that they are less sensitive than the headcount index to small changes in income around the poverty line. While the headcount index is discontinuous at the poverty line, changing in value from one to zero at the line, the squared poverty gap is continuous and differentiable at the poverty line. For an elaboration of this point, see Lipton and Ravallion (1995).

This report also extends the literature in that the statistical tests for area differences in poverty are corrected for features of the sample design. Most nationally representative data sets, particularly those from which poverty estimates are formed, are based not on pure random draws from the population but on stratified and multistage sample designs. As one example, the sample used for the Current Population Survey (CPS) is drawn from a census frame using a stratified, multistage design. Howes and Lanjouw (1998) present compelling evidence that estimated standard errors for the FGT poverty indexes can have large biases when erroneous assumptions are made about the nature of the sample design. In particular, they show that if the sample design is multistaged but standard errors are derived from the incorrect assumption of a pure random sample, then the standard errors will significantly underestimate the true sampling variance. Jolliffe et al. (forthcoming) show that in the case of poverty indexes for Egypt, failing to adjust for the characteristics of the sample design would result in an underestimate of the correct standard errors by 187 to 212 percent.

[6]Unlike the Sen (1976) or Kakwani (1980) distribution-sensitive measures of poverty, the squared poverty gap index also satisfies the "subgroup consistency" property, which means that if poverty increases in any subgroup, and does not decrease elsewhere, then aggregate poverty must also increase (Foster and Shorrocks, 1991).

Poverty Measurement

The Data: 1991-2000 CPS and the U.S. Poverty Thresholds

The data used in this report are from the annual March Supplements to the Current Population Survey (CPS) for 1991 through 2000. This survey is conducted by the Census Bureau for the Bureau of Labor Statistics. The CPS data are the basis for the official U.S. poverty estimates and are based on information from approximately 50,000 households each year. The March Supplement, also called the Annual Demographic Survey of the CPS, provides information on income and a variety of demographic characteristics, including age, sex, race, marital status, and educational attainment. The reference period for income-related questions is the preceding calendar year, so the 1991-2000 CPS data provide poverty estimates for 1990 through 1999.

The sample is representative of the civilian, noninstitutional population and members of the Armed Forces either living off base or with their families on base.[7] The sample frame is based on housing units and not individuals, so all individuals who are homeless at the time of the interview are excluded from the sample. Published estimates of the number of homeless people range from a 1990 Census Bureau estimate of 250,000 to a 1987 Urban Institute estimate of up to 600,000 service-using homeless individuals.[8] The exclusion of homeless persons from the sample frame is noteworthy for poverty analysis, since the homeless are almost universally poor. The exclusion may also affect a geographic analysis of poverty because homeless persons are disproportionately located in metro areas.[9] Relative to the number of poor people, however, estimated at 33.6 million in 1990, the homeless population is relatively small and its exclusion may not significantly affect the results presented here.[10]

[7]The excluded institutional population includes, in part, people living in nursing homes, personal care facilities, treatment centers for the mentally ill, and correctional facilities.

[8]For a discussion of measures of homelessness and potential explanations for the rising incidence, see Quigley et al. (2001) and Honig and Filer (1993).

[9]For a discussion of income levels and geographical distribution of homelessness, see Urban Institute (1999, chapters 5 and 13).

[10]Because the homeless are disproportionately located in metro areas, their exclusion from the estimates slightly increases the estimated gap between metro and nonmetro poverty rates. Also, because the homeless are more likely to be extremely poor, their exclusion has a greater impact on the poverty gap and squared poverty gap indexes.

The geographical comparison of poverty rates in this report is between metro and nonmetro areas.[11] The Office of Management and Budget (OMB), which issues Federal standards for defining statistical areas, states that a metro area is any county that contains a city with a population of at least 50,000, a county with an urbanized area as defined by the Census Bureau (an area with a population of at least 100,000 persons), or a fringe county that is economically tied to a metro area.[12] Nonmetro areas are all areas outside the boundaries of metro areas, and contain no cities with populations of over 50,000.

In examining changes over time of metro or nonmetro estimates, it is important to note that the CPS sample frame changes in the middle of each decade. As new decennial census data become available, the Master Address File (MAF) used for the sample frame of the CPS is updated. Due to changing population demographics, the CPS sample becomes less representative of the the population, and the information from the updated MAF is used to draw a new sample.[13] In addition to the changing sample frame, OMB revises its official definitions for metro areas based on census results. Of particular relevance for this report, the 1995 CPS sample is the result of a mixed-sample design, based on both the 1980 and 1990 censuses; in addition, the definition of metro differed within the sample. For these reasons, the U.S. Department of Commerce (1997, User Note 1) urges caution in interpreting changes to metro and nonmetro CPS estimates for 1994.

The definition of income in this report is the same as that used to define Federal poverty rates. It includes all pre-tax income, but excludes capital gains and any

[11]Users of the CPS data use the terms “nonmetro” and “rural” interchangeably, but these terms define different geographic areas. Cromartie (2000) shows that 20.5 percent of the population live in nonmetro areas and 24.8 percent live in rural areas. Rural areas are geographically different areas with fewer than 2,500 residents, but Federal data on the social and economic characteristics of rural residents are available only from the decennial censuses. The population threshold for defining rural is much smaller than it is for defining nonmetro, but the geographic domain for defining this characteristic is also different.

[12]For details of the definitions and enacted changes, see Office of Management and Budget (2000).

[13]The assertion that the sample becomes less representative over time is tempered by noting that the Census Bureau attempts to correct for this problem by collecting information on new housing units built after each decennial census. Newly built units are identified through the Building Permit Survey and are added to the sample to ameliorate the problem of declining ‘representativeness’ over time. (See U.S. Bureau of Census and Bureau of Labor Statistics, 2000, for further discussion on this issue.)

noncash benefit such as public housing, Medicaid, or food stamps.[14] Federal poverty thresholds were developed in 1965, based on the value of a consumption bundle considered adequate for basic consumption needs. Basic needs, in this context, represent a socially determined, normative minimum for avoiding poverty. For more details on this methodology and other methods of drawing poverty lines, see Dalaker and Proctor (2000) and Ravallion (1998). The U.S. poverty line set in 1965 was based on the cost of USDA's economy food plan, a low-cost diet determined to be nutritionally adequate.[15] In addition to the cost of purchasing a minimum food bundle, the poverty line includes an allowance for nonfood expenditures that was twice the food plan's cost.[16]

To account for inflation, the poverty lines set in 1965 are adjusted each year using a price index.[17] Prior to 1969, the index used was the changing cost of the USDA economy food plan; since then, the CPI for all goods and services has been used.[18] The latest poverty line used in this study is from 1999. It is set at $8,667 for an individual under age 65, $11,483 for a two-person family with one child and one adult, and $19,882 for a family with two adults and three children. For a complete listing of 1999 poverty lines for various family sizes, see appendix table 1.

[14]The types of income included in the measure are money wages or salary; net income from self-employment (farm or nonfarm); Social Security or railroad retirement; Supplemental Security Income; public assistance or welfare payments; interest (on savings or bonds); dividends, income from estates or trusts, or net rental income; veterans' payment or unemployment and workmen's compensation; private pensions or government employee pensions; and alimony or child support, regular contributions from persons not living in the household, and other periodic income. Examples of money that is not treated as income include money received from the sale of property, such as stocks, bonds, a house, or a car; withdrawals of bank deposits; borrowed money; tax refunds; gifts; and lump-sum inheritances of insurance payments.

[15]For details on the first U.S. poverty lines, see Orshansky (1965). For a history of poverty lines used prior to the Orshansky lines, see Fisher (1997).

[16]The size of nonfood consumption bundle was based on survey data from 1955 indicating that households with three or more persons spent 35 percent of their after-tax income on food. The nonfood allowance is somewhat larger for households with two or fewer persons.

[17]This adjustment only accounts for price changes over time. The poverty thresholds contain no corrections for price differences across areas or regions. If the cost of living were lower in nonmetro areas and if poverty thresholds accounted for this difference, then one would expect to see smaller differences between the level of poverty in nonmetro and metro areas.

[18]In addition to adjusting the poverty lines to account for changing price levels, there have been a few other adjustments. For example, originally, there were different thresholds for farm households and this distinction was eliminated in 1981. For more details on the official poverty line and a discussion of its strengths and weaknesses, see Ruggles (1990).

Poverty Measures and Standard Errors

The previous section describes the measure of income and the poverty lines used to identify the poor. The next step is to aggregate this information into a scalar measure of poverty. To examine the sensitivity of estimated poverty levels to the choice of a poverty measure, we consider three measures of poverty that belong to the FGT family of measures. The first is the headcount index (P_0), the percentage of the population with income below the poverty line. The second measure is the poverty gap index (P_1), defined as the mean distance below the poverty line (expressed as a proportion of the poverty line), where the mean is formed over the entire population and the nonpoor are counted as having zero poverty gap. The third measure is the squared poverty gap index (P_2), defined as the mean of the squared proportionate poverty gaps. While the headcount index measures the incidence of poverty, the poverty gap index reflects the depth of poverty as well as its incidence. The squared poverty gap index, unlike the poverty gap index, reflects the severity of poverty in that it is sensitive to the distribution of income among the poor.

The FGT class of poverty indexes, also referred to as P_α, can be represented as:

$$P_\alpha = 1/n \sum_i I(y_i < z)[(z - y_i)/z]^\alpha \qquad (1)$$

where n is the sample size, i subscripts the family or individual, y is the relevant measure of income or well-being, z is the poverty line, I is an indicator function which takes the value of one if the statement is true and zero if it is not, and α is a parameter indicating a specific poverty index within the class of indexes. When $\alpha = 0$, the resulting measure is the headcount index, or P_0. When $\alpha = 1$, the FGT index results in the poverty gap index, or P_1; when $\alpha = 2$, the measure is the squared poverty gap index, or P_2.

To determine whether poverty is higher in nonmetro than metro areas, or whether poverty has changed over time or varies over some geographic or demographic characteristic, estimates of the sampling variance for the indexes are required. Indeed, it is hard to think of a poverty-related policy question that does not require an estimate of whether a difference in indexes is statistically significant. Kakwani (1993) provides two formulas to estimate the variance of the FGT class of poverty indexes that are easy to calculate and frequently used. The Kakwani formula for the variance of P_0, the headcount index, is $P_0(1-P_0) / (n-1)$, where n is the sample size. The formula for all other variance estimates of the FGT indexes is $(P_{2\alpha} - P_\alpha^2) / n-1)$, so for example, the variance of the poverty gap is given by $(P_2-P_1^2) / (n-1)$.

The primary disadvantage of the Kakwani estimates is that they assume the sample was drawn using a simple random draw from the population, which is not the case with CPS sample. Using the Kakwani standard errors when the data were collected following a multistage sample design results in a dramatic underestimate of the true sampling variance. The strategy used here to estimate the design-corrected estimates of sampling variance is to first derive exact estimates for the poverty measures and then to address the issue of sample design.

An advantage of using the FGT class of poverty indexes in this context is that they are additively decomposable, a characteristic that greatly simplifies deriving exact estimates of the sampling variance of the poverty measures. To illustrate this, consider any income vector y, broken down into M subgroup income vectors, $y^{(1)}, \ldots, y^{(m)}$. Because P_α is additively decomposable with population share weights, it can be written as:

$$P_\alpha(y;z) = \sum_{j=1}^{M} (n_j / n) \, P_{\alpha,j}(y^j;z) \qquad (2)$$

where n is the sample size, n_j is the size of each subgroup, and z is again the poverty line. By treating each observation as a subgroup, the estimate of poverty becomes the weighted mean of the individual-specific measures of poverty and the sampling variance of the poverty measure is the variance of this mean, or:

$$P_\alpha = \sum_{i=1}^{n} P_{\alpha,i} / n \qquad \text{and}$$
$$V(P_\alpha) = n^{-1}(n-1)^{-1} \sum_{i=1}^{n} (P_{\alpha,i} - P_\alpha)^2 \qquad (3)$$

where i subscripts the individual.[19]

The next step is to incorporate the sample design information into the estimates, which requires access to not only the household record data, but also information on the characteristics of the sample design. In the case of the CPS data, all information on sample design, such as variables marking the strata and primary sampling units (PSUs), has been censored from the data files.[20] To compensate, the U.S. Bureau of Census (2000, appendix C) details how to approximate design-corrected standard errors for a limited set of poverty estimates. The approximations proposed by the Bureau of Census are based on parameters that describe the relationship between a direct estimate of the design-corrected variance and the relevant statistic.

This method unfortunately provides parameter estimates only for the headcount index of poverty. No corrections are provided for any other measures of poverty. Another shortcoming of the Census-recommended method is that corrections are provided only for a very limited set of characteristics. For example, U.S. Bureau of Census (2000, appendix C) provides parameter estimates to adjust the sampling variance for the poverty headcount index by several age categories. If the question under analysis concerns individuals age 15 to 24, the analyst is provided with parameter estimates. If the relevant subsample is, say, working-age adults, then the Census publication does not provide the necessary parameters to estimate standard errors.

Finally, the Census-recommended method for correcting sample design appears significantly less precise for metro-nonmetro comparisons. The proposed correction for all nonmetro statistics (U.S. Bureau of Census, 2000, appendix C) is to multiply the design correction coefficients by 1.5. The implication is that the ratio of the design effects for metro to nonmetro areas is constant for all statistics. Also affecting the accuracy of this nonmetro correction is the fact that it has not been updated in 20 years, while the design correction coefficients for all other characteristics are updated annually.

Given that the Census-recommended method does not provide corrections for the sampling variance of the poverty gap and squared poverty gap indexes, and that the adjustment factor for nonmetro areas appears to be a very rough approximation, we chose to completely abandon this approach. Instead, we followed an approach based on replicating certain aspects of the CPS sample design by creating synthetic variables for the strata and clusters that induce similar design effects. A more detailed description of the approach, with results indicating that it provides useful approximations, is given in Jolliffe (2001).

[19]The variance measures the precision of the poverty estimate and is used to form confidence intervals.

[20]The purpose of censoring is to ensure that individual respondents cannot be identified by using strata and PSU information, thereby maintaining the respondents' confidentiality.

The first step of the synthetic design approach for this analysis of poverty is to sort the data by income.[21] Then each set of four consecutive housing structures (as identified in the CPS data) is assigned to a separate cluster. The purpose of the sorting is to induce a high level of intracluster correlation, and the choice of four matches the average cluster size of the CPS. To capture the geographic aspect of the CPS stratification, we selected as the synthetic strata the four regions of the United States (Northeast, Midwest, South, and West). Appendix table 2 illustrates that the synthetic design approach matches the estimates provided by the Census Bureau for the headcount index.

After selecting the synthetic strata and clusters, one can directly obtain design-corrected estimates of sampling variance based on equation (3). Following Kish (1965), and noting from equation (3) that P_α can be considered a sample mean, the estimated sampling variance of the FGT poverty indexes from a weighted, stratified, clustered sample is given by:

$$\mathrm{V}(\mathrm{P}_{\alpha,w}) = \sum_{h=1}^{L} n_h (n_h - 1)^{-1} \qquad (4)$$
$$\sum_{i=1}^{n_h} \Big(\sum_{j=1}^{m_{h,i}} w_{h,i,j}\ \mathrm{P}_{\alpha,h,i,j} \ - \ \sum_{i=1}^{n_h} \sum_{j=1}^{m_{h,i}} w_{h,i,j}\ \mathrm{P}_{\alpha,h,i,j} \Big)^2$$

where the h subscripts each of the L strata, i subscripts the cluster or primary sampling unit (PSU) in each stratum, and j subscripts the ultimate sampling unit (USU), so that w_{hij} denotes the weight for element j in PSU i and stratum h. The number of PSUs in stratum h is denoted by n_h and the number of USUs in PSU (h,i) is denoted by m_h.[22]

[21] The methodology requires sorting the data on the variable most relevant to the analysis.

[22] The poverty and sampling variance estimates are documented in more detail in Jolliffe and Semykina (1999), which also provides a program to estimate (4) in the *Stata* software.

Results

Before reporting results of the three poverty indexes for nonmetro and metro areas, examination of the distribution and average level of income of the poor will help shed light on the relative well-being of the poor in these areas. For all persons, average income levels were lower in nonmetro areas during all years in the 1990s (table 1). This difference is qualitatively large, with nonmetro income approximately 25 percent lower than average metro income, and the difference is statistically significant. In contrast, average nonmetro income is not significantly different from metro income when the sample is restricted to poor people.

Table 2 reports the Theil index of inequality for the nonmetro and metro poor. The Theil measure of inequality, also known as the entropy index, is defined as:

$$I = 1/n \sum_{i=1}^{n} \left(Y_i / \overline{Y}\right) \log \left(Y_i / \overline{Y}\right) \qquad (5)$$

where $\overline{Y}$ is average income, i subscripts the individual, and n is the sample size. When income is distributed equally, the index takes the value of zero. Higher values of the Theil index indicate greater inequality in the distribution of income.

In general the Theil index, along with the larger family of generalized Theil indexes, has many desirable properties, as described in Foster (1983).[23] In examining inequality among the poor, the Theil index exhibits

[23] Foster shows that an inequality index satisfies the axioms of symmetry, replication invariance, income-scale independence, decomposability, and the principle of transfers only if it is a positive multiple of the Theil entropy index.

Table 1—Average family income for U.S. families, 1990-99: Nonmetro-metro comparison

	All families				Poor families			
Year	Nonmetro	Metro	Difference		Nonmetro	Metro	Difference	
	----------Dollars----------		*Dollars*	*Percent*[1]	*----------Dollars----------*		*Dollars*	*Percent*[1]
1990	31,591	41,699	-10,108	-24	7,229	6,896	333	5
	(270)	(234)	(357)		(153)	(97)	(181)	
1991	32,450	42,109	-9,659	-23	7,243	6,995	248	4
	(266)	(239)	(358)		(150)	(91)	(175)	
1992	33,172	43,313	-10,141	-23	7,316	7,113	203	3
	(280)	(250)	(376)		(153)	(92)	(178)	
1993	34,053	44,381	-10,328	-23	7,608	7,428	181	2
	(288)	(270)	(395)		(145)	(105)	(179)	
1994	37,117	46,191	-9,074	-20	7,630	7,617	13	0
	(338)	(276)	(437)		(163)	(106)	(194)	
1995	37,922	51,084	-13,162	-26	8,231	8,031	200	2
	(481)	(428)	(643)		(212)	(117)	(242)	
1996	38,926	53,482	-14,556	-27	8,104	8,121	-17	0
	(513)	(430)	(670)		(202)	(123)	(237)	
1997	41,219	56,446	-15,227	-27	7,952	8,100	-149	-2
	(491)	(455)	(669)		(187)	(130)	(228)	
1998	43,187	58,905	-15,718	-27	8,395	8,104	291	4
	(462)	(470)	(659)		(224)	(123)	(255)	
1999	45,690	60,664	-14,974	-25	8,517	8,372	145	2
	(516)	(435)	(675)		(237)	(145)	(278)	

Notes: Income is in nominal terms. Standard errors, in parentheses, are corrected for sample design effects following the synthetic-design approach described in Jolliffe (2001).

[1] This column lists the percentage difference between nonmetro and metro average income, using metro as the base; or, {Income(nonmetro) - Income(metro)} / Income(metro).

Table 2—Income inequality of poor persons: Nonmetro-metro comparison, 1990-99

Year	Theil index of inequality		Nonmetro-metro difference in Theil index of inequality		
	Nonmetro	Metro	Difference	Standard error	t-statistic
1990	0.221	0.247	-0.026	(0.013)	2.00
1991	0.218	0.252	-0.034	(0.013)	2.61
1992	0.233	0.260	-0.028	(0.014)	1.96
1993	0.226	0.278	-0.051	(0.013)	3.85
1994	0.237	0.271	-0.034	(0.015)	2.20
1995	0.232	0.278	-0.045	(0.017)	2.71
1996	0.226	0.285	-0.059	(0.016)	3.58
1997	0.272	0.314	-0.042	(0.019)	2.17
1998	0.270	0.332	-0.063	(0.020)	3.08
1999	0.281	0.336	-0.055	(0.021)	2.61

Notes: The Theil index of income inequality is estimated for the poor nonmetro and metro samples. Standard errors are bootstrap estimates based on 1,000 bootstrap samples and a resampling method that replicates the two-stage nature of the sample design. For details, see Jolliffe and Krushelnytskyy (1999).

greater sensitivity to changes in the tails of the income distribution than the more commonly used Gini index of inequality. The Gini index ranges from 0 to 1, with 0 also indicating equality. The primary difference between the two indexes can be illustrated as follows. Consider the transfer of a dollar from one person to another. The resulting change in inequality, as measured by the Gini index, is determined by the relative rankings of the two individuals, and it will therefore be more sensitive to changes that occur around the central tendency of the data. The change to the Theil index resulting from this transfer is determined by the relative income of the two people, and is thus more sensitive to changes in the tails of the distribution.

The inequality levels of the metro poor are higher than those for the nonmetro poor for all years during the 1990s (table 2). The difference between nonmetro and metro inequality of the poor ranges from 11 percent in 1990 and 1992 to 21 percent in 1996. To determine whether these differences are statistically significant, estimates of the sampling variance of the indexes are found through a bootstrap method that replicates the two-stage nature of the sample design.[24] The bootstrap standard errors indicate that the observed differences in nonmetro and metro inequality of the poor are statistically significant in all years.

So while the average income of nonmetro poor persons is about the same as for metro poor persons (table 1), the level of inequality for the metro poor is higher than for the nonmetro poor (table 2). Therefore, poverty measures that are sensitive to the depth and severity of poverty may indicate a less stark nonmetro-metro difference in poverty than does the headcount index.

The headcount index for nonmetro areas ranges from 0.14 in 1999 (representing 7.4 million poor people) to 0.17 in 1993 (9.7 million poor people). For metro areas, it ranges from 0.11 in 1999 (24.8 million poor people) to 0.15 in 1993 (29.5 million poor people) (table 3). Variation in the poverty gap and squared poverty gap indexes is fairly similar. Across both these measures, for metro and nonmetro areas alike, poverty was lowest in 1999. The severity of poverty, as measured by the squared poverty gap index, was highest in 1997 for nonmetro areas and in 1993 for metro areas. In terms of the poverty gap index, the greatest poverty depth for both nonmetro and metro areas was in 1993.

One interpretation of the poverty gap index is that it is equal to the product of the headcount index and the income gap, where the income gap is the average shortfall of the poor as a fraction of the poverty line. This implies that in 1990 the average shortfall of the income of the poor as a fraction of the poverty line was equal to 40 percent in nonmetro and 44 percent in metro areas. In 1999, the average shortfall was equal to 42 percent of the poverty line in nonmetro and 46 percent in metro areas. During all 10 years, the average shortfall was greater in metro than nonmetro areas.

Table 4 reports nonmetro-metro differences in the three poverty measures, both in terms of level and percent. This table indicates that for all years, and for the three considered poverty measures, poverty is higher in nonmetro than in metro areas. The estimates in this table also clearly indicate that the largest difference in

[24]The bootstrap estimates are based on 1,000 replications. For details on the bootstrap methodology and the program used, see Jolliffe and Krushelnytskyy (1999).

Table 3—Incidence, depth, and severity of poverty: Nonmetro-metro comparison, 1990-99

	Headcount, P_o index		Poverty gap, P_1 index		Squared poverty gap, P_2 index	
Year	Nonmetro	Metro	Nonmetro	Metro	Nonmetro	Metro
1990	0.163	0.127	0.066	0.056	0.039	0.035
	(0.0042)	(0.0022)	(0.0021)	(0.0012)	(0.0015)	(0.0009)
1991	0.160	0.137	0.067	0.061	0.041	0.039
	(0.0042)	(0.0023)	(0.0022)	(0.0013)	(0.0016)	(0.0010)
1992	0.167	0.139	0.071	0.063	0.044	0.040
	(0.0042)	(0.0023)	(0.0022)	(0.0013)	(0.0017)	(0.0010)
1993	0.171	0.146	0.072	0.067	0.044	0.043
	(0.0043)	(0.0025)	(0.0022)	(0.0014)	(0.0017)	(0.0011)
1994	0.159	0.141	0.068	0.065	0.043	0.042
	(0.0043)	(0.0025)	(0.0023)	(0.0014)	(0.0017)	(0.0011)
1995	0.156	0.134	0.064	0.060	0.039	0.039
	(0.0049)	(0.0024)	(0.0026)	(0.0013)	(0.0020)	(0.0010)
1996	0.159	0.132	0.067	0.059	0.041	0.038
	(0.0048)	(0.0023)	(0.0025)	(0.0013)	(0.0019)	(0.0010)
1997	0.158	0.126	0.070	0.058	0.046	0.038
	(0.0048)	(0.0023)	(0.0027)	(0.0013)	(0.0021)	(0.0010)
1998	0.143	0.123	0.061	0.057	0.039	0.039
	(0.0046)	(0.0023)	(0.0024)	(0.0013)	(0.0019)	(0.0010)
1999	0.142	0.112	0.060	0.052	0.039	0.035
	(0.0046)	(0.0022)	(0.0025)	(0.0012)	(0.0020)	(0.0010)

Notes: Poverty indexes are the Foster-Greer-Thorbecke P_α indexes. The incidence of poverty is measured by P_0, the depth by P_1 and the severity by P_2. Standard errors, in parentheses, are estimated following equation (4), using the program described in Jolliffe and Semykina (1999).

poverty measurement occurs for the headcount index. The incidence of poverty (P_0) in nonmetro areas ranges from 16 to 28 percent higher than in metro areas. This nonmetro-metro difference in poverty is lower when we consider the depth of poverty (P_1), and diminishes even further when we consider its severity (P_2). The poverty gap index for nonmetro areas ranges from 5 to 21 percent greater than in metro areas, and the squared poverty gap is 1 to 19 percent higher in nonmetro than metro areas. Figure 1 plots the relative difference for each index over the 10 years.[25] The relative difference in nonmetro to metro poverty follows a clear ranking for all years, with the headcount index having the largest difference and the squared poverty gap the smallest percentage difference.

The diminishing percentage difference between nonmetro and metro poverty rates is associated with declining statistical significance of the differences in the depth and severity of poverty (table 4). The poverty incidence is greater in nonmetro areas, a difference is statistically significant in all 10 years of the 1990s.

When considering the poverty gap index, only during 5 of the 10 years is the nonmetro-metro difference in poverty statistically significant, where significance is based on a p-value of less than 0.01. If the level of statistical significance is based on a p-value of less than 0.05 (or the 95-percent confidence level), then the poverty gap index is higher in nonmetro areas in 6 of the 10 years. The statistical significance of nonmetro-metro differences in poverty declines dramatically when considering the squared poverty gap index. When significance is based on a p-value of less than 0.01, the data indicate that only in 1997 is the severity

[25]The relative difference in poverty uses the metro poverty level as the base and can be expressed as {P_0,nonmetro - P_1,metro)/ P_2,metro).

Table 4—Nonmetro-metro differences in poverty: Tests of statistical significance, 1990-99

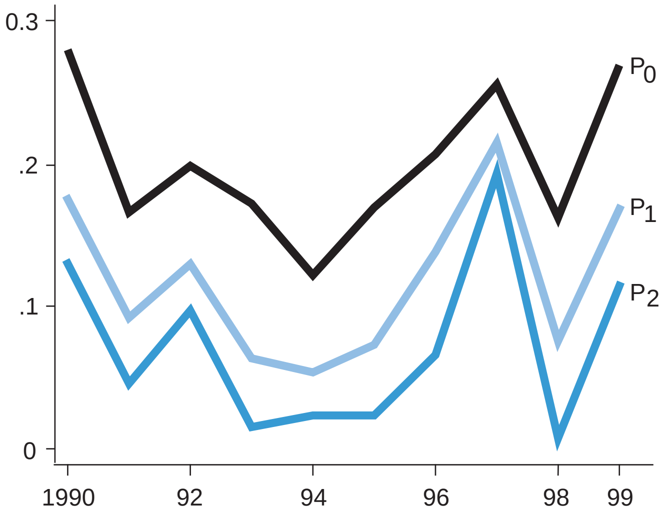
	Difference in P_0 index		Difference in P_1 index		Difference in P_2 index	
Year	Level	Percent	Level	Percent	Level	Percent
1990	0.036*** [0.0000]	28	0.010*** [0.0000]	18	0.005** [0.0108]	13
1991	0.023*** [0.0000]	17	0.006** [0.0264]	9	0.002 [0.3488]	5
1992	0.028*** [0.0000]	20	0.008*** [0.0016]	13	0.004** [0.0462]	10
1993	0.025 [0.0000]	17	0.004 [0.1051]	6	0.001 [0.7393]	2
1994	0.017*** [0.0005]	12	0.003 [0.1950]	5	0.001 [0.6302]	2
1995	0.023*** [0.0000]	17	0.004 [0.1321]	7	0.001 [0.6905]	2
1996	0.027*** [0.0000]	21	0.008*** [0.0040]	14	0.003 [0.2393]	7
1997	0.032*** [0.0000]	26	0.012*** [0.0000]	21	0.007*** [0.0017]	19
1998	0.020*** [0.0001]	16	0.004 [0.1166]	8	0.000 [0.8976]	1
1999	0.030*** [0.0000]	27	0.009*** [0.0016]	17	0.004* [0.0770]	11

Notes: The difference in poverty levels is P_α(Nonmetro) - P_α(Metro), and the p-values for whether each difference is significantly different from zero are in square brackets. The difference is superscripted with ***, **, or * if the p-value is less than 0.01, 0.05, or 0.1, respectively. The difference in percentage terms is 100*{P_α(Nonmetro) - P_α(Metro)} / P_α(metro).

of poverty higher in nonmetro areas. If the criteria for statistical significance is relaxed and based on a p-value of less than 0.05, then the squared poverty gap index is greater in 3 of the 10 years in nonmetro areas.

Figure 2 plots the t-statistics for tests of the null hypothesis that nonmetro and metro poverty rates are the same. The line marking a t-statistic of 1.96 is approximately the same as indicating a p-value of 0.05, and the figure shows that the nonmetro-metro differences in P_0 have t-statistics that are much greater than 1.96 for all 10 years. The figure illustrates again that there is a clear ranking of declining statistical significance for each year as one considers P_0, then P_1, and finally P_2 as measures of poverty.

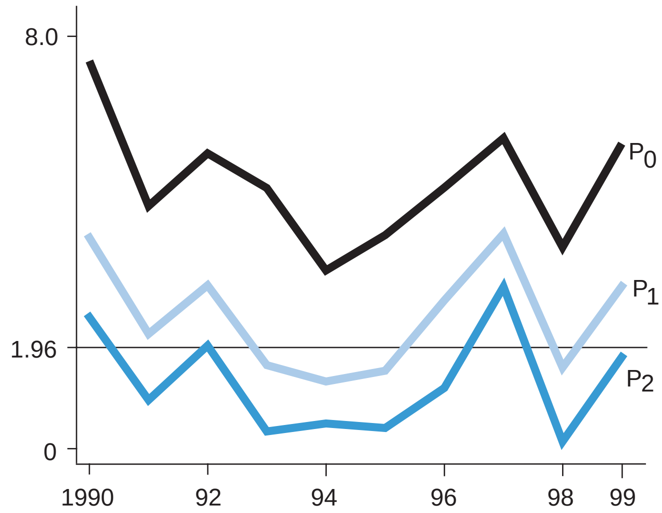
Figure 1
Metro-nonmetro relative differences in poverty levels, 1990-99



Notes: The 'P_α' lines plot the difference between nonmetro and metro poverty levels as measured by P_0, P_1, and P_2 (FGT poverty indexes) using the metro poverty level as a base, or [(P_α, nonmetro - P_α, metro)/ P_α, nonmetro].

Source: Author's calculations using the Current Population Survey, March Supplement.

Figure 2
Metro-nonmetro differences in poverty: t-statistics, 1990-99



Notes: The 'P_α' lines are t-statistics from testing the null hypothesis that there is no statistical difference between the metro and nonmetro level of poverty as measured by P_0, P_1, and P_2 (FGT poverty indexes) over the years 1990-99.

Source: Author's calculations using the Current Population Survey, March Supplement.

Demographic Exploration and Policy Implications

To better understand the results and draw some policy implications, it will help to explore some of the economic and demographic differences between nonmetro and metro poor. For this purpose, we focus on the poor in 1999. Previous results indicate that metro-nonmetro differences in the depth and severity of poverty are much less pronounced than the difference in its incidence. This suggests there are important metro-nonmetro differences in the well-being of the poor.

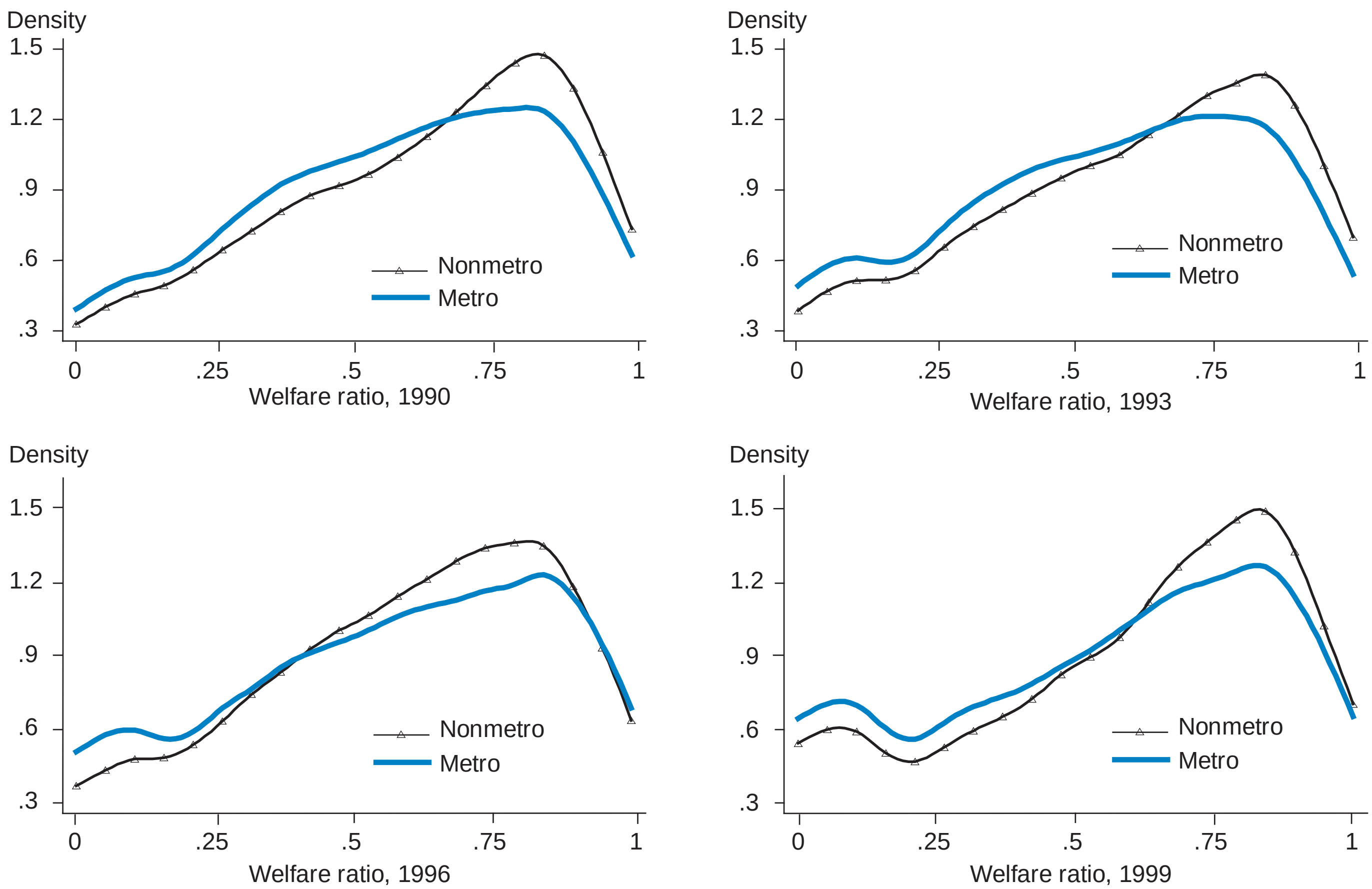
One way to look for distributional differences in well-being is to examine metro and nonmetro welfare ratios (that is, ratio of family income to the poverty line).[26] The advantage of examining welfare ratios rather than income is that they provide measures of well-being that control for the important demographic differences across metro and nonmetro areas. For example, the average age of a poor person living in metro areas is 28 years, compared with 32 years for the nonmetro poor. In terms of family size (treating unrelated individuals as one-person families), the average values are the same in metro and nonmetro areas (2.1 persons), but the distributions differ. In 1999, 16 percent of the metro poor lived in two-person families, compared with 20 percent of the nonmetro poor.[27]

Figure 3 provides estimates of metro and nonmetro welfare ratios for 1990, 1993, 1996, and 1999. Across all years, there is a striking similarity in the relative nonmetro-metro differences in the distribution of welfare ratios. In all cases,

[26]Blackorby and Donaldson (1987), using this terminology, provide an analysis of welfare ratios as an index of well-being in cost-benefit analysis.

[27]Age and family composition estimates are from the 1999 CPS March Supplement. Family members include persons in related subfamilies.

Figure 3
Welfare ratios of the metro and nonmetro poor, 1990-99



Notes: Kernal density estimates of metro and nonmetro welfare ratios (income divided by the poverty line) are for 1990 (upper left panel), 1993 (upper right panel), 1996 (lower left panel), and 1999 (lower right panel). The nonmetro density estimate is marked with triangles. The density of the welfare ratio is measured in terms of the reciprocal of the welfare ratio (not measured on a probability scale), and thus can exceed 1. The Epanechnikov kernal is used for all estimates with a smoothing parameter set to 0.08. For more details on kernal density estimation, see Pagan and Ullah (1999).
Source: Author's calculations using the Current Population Survey, March Supplement.

the nonmetro welfare ratio is much more peaked near the poverty line, indicating that larger proportions of the nonmetro poor have higher welfare ratios and are relatively better off. Similarly, the nonmetro welfare ratio lies below the metro distribution on the left side of the distribution, indicating that a larger proportion of the metro poor live in extreme poverty.

To explain this difference in the distribution of the welfare ratio of poor persons in metro and nonmetro areas, it is useful to examine some labor-related characteristics of the poor. One possible explanation for the difference in welfare ratios is that a larger number of the nonmetro poor are working, but are employed in low-wage jobs. The CPS data do not provide much evidence to support this hypothesis. When considering the sample of all adults not in the Armed Forces, the percentage of the metro poor that are not in the labor force (58 percent) is the same as the nonmetro proportion. Similarly, 22 percent of both the metro and nonmetro poor work full time, and the remaining 20 percent (again, the same proportion for both metro and nonmetro) work part time or are unemployed.

The results show a modest difference when the sample of all civilians age 15 and older is considered. For this sample, 42 percent of the nonmetro poor did some work during 1999, compared with 40 percent of the metro poor. For those persons who worked in the week prior to the survey, the average hours worked during the past 7 days by both the metro and nonmetro poor was the same, at 34 hours. Similarly, both the metro and nonmetro working poor reported working an average of 35 hours per week, for an average of 34 weeks, during 1999.

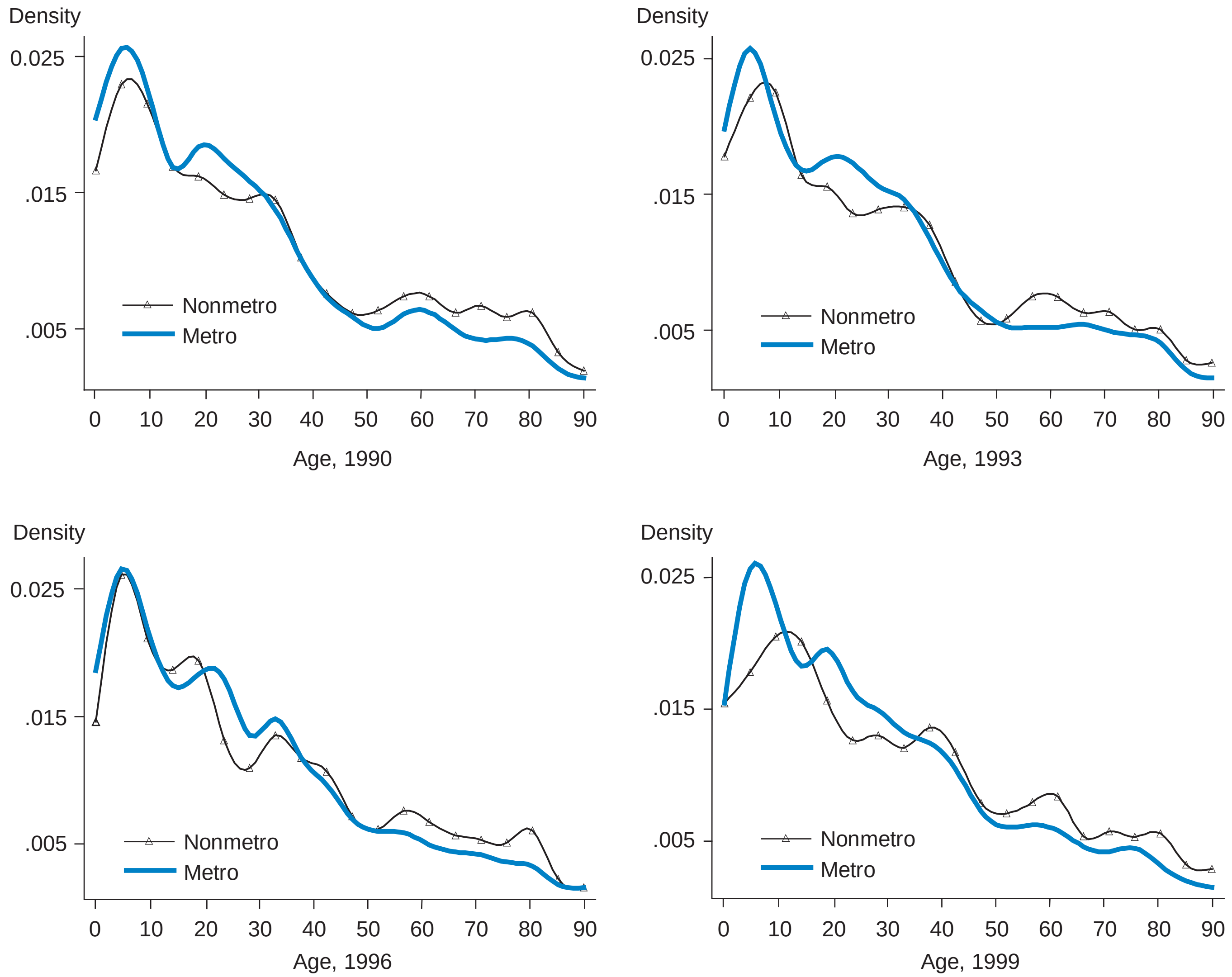
The data, while not indicating significant differences in the proportion of the poor who worked or the hours they spent working, do reveal some important differences in the characteristics of the poor not in the labor force. Of the nonmetro poor who did not work during 1999, 31 percent reported they did not work because they were ill or disabled and 28 percent reported that they were retired. These proportions for the metro poor are much lower, with 26 percent stating that they were ill or disabled and 23 percent that they were retired. In contrast, 22 percent of the metro poor reported that they did not work because they were going to school, while only 16 percent of the nonmetro poor gave this as a reason.

The contrasting explanations for not working are consistent with the result reported above that on average the nonmetro poor are older than the metro poor. Figure 4 sheds more light on this difference by comparing the metro-nonmetro age distributions for poor persons from 1990 to 1999. During the 4 years examined (1990, 1993, 1996, and 1999), the nonmetro age distribution lies above the metro distribution for higher ages and below for lower ages. Figure 4 indicates that the nonmetro poor include relatively more people between the ages of 50 and 90, while the metro poor include more people from 15 to 40.

Not surprisingly, when income sources are examined, there are similar indications of the metro-nonmetro differences in the age composition of the poor. Twenty-two percent of the nonmetro poor received Social Security payments in 1999, while only 16 percent of the metro poor did. Twelve percent of the nonmetro poor received Supplemental Security Income payments, compared with 9 percent of the metro poor.

The data suggest that there are important area differences in the characteristics of the poor who are not working. In particular, the nonmetro poor who are not employed are older and are more likely to be ill or disabled. The nonworking metro poor are younger and more likely to be in school. To the extent that poverty reduction strategies might be tailored for metro and nonmetro areas, these results indicate that policies aimed at enhancing schooling opportunities and job training programs, or at increasing work opportunities—though always helpful—will be of more value when implemented in metro areas. Programs aimed at providing income assistance to the elderly, disabled, or those living on fixed incomes will be of greater benefit in nonmetro areas.

Figure 4
Age distribution of poor persons by metro and nonmetro, 1990-99



Notes: Kernal density estimates of age in years for metro and nonmetro welfare residents are for 1990 (upper left panel), 1993 (upper right panel) 1996 (lower left panel), and 1999 (lower right panel). The nonmetro density estimate is marked with triangles. The Epanechnikov kernal is used for all estimates with a smoothing parameter set to 1. For more details on kernal density estimation, see Pagan and Ullah (1999).
Source: Author's calculations using the Current Population Survey, March Supplement.

Conclusions

It is well documented that the incidence of poverty is higher in nonmetro than in metro areas. Previous research has shown that the poverty headcount index, a measure of incidence, was approximately 2.6 percentage points higher for nonmetro than metro areas during the 1990s. Using CPS data from 1991 to 2000, this study confirms that finding, and further shows that this difference was highly statistically significant throughout the 1990s.

This study expands on the earlier results in two ways. First, to test for statistical significance, it derives estimates of sampling variance for any additively decomposable poverty index. By incorporating results from the well-established literature on sampling, the estimates of sampling variance for the poverty indexes are corrected for sample-design characteristics. In the U.S. literature on measuring poverty, the importance of this correction has not been well recognized. Design-corrected estimates of sampling variance are often reported for the U.S. headcount index, but design-corrected standard errors for any other poverty measure are seldom reported in the U.S. literature.

One important reason for this absence in the literature is that U.S. studies rarely consider measures of poverty other than the headcount index. The primary purpose of this report is to examine whether the large and statistically significant differences in nonmetro-metro poverty rates are robust to measures of poverty that are sensitive to the distribution of income of the poor.

Using three measures of poverty from the Foster-Greer-Thorbecke family of poverty indexes, this report further extends the poverty literature by showing that the size and significance of the nonmetro-metro difference in poverty declines as one examines the depth and severity of poverty. While the nonmetro incidence of poverty was much larger than the metro rate in all 10 years of the 1990s, the depth of poverty as measured by the poverty gap index was statistically higher in nonmetro areas during only 6 of the 10 years. In terms of the severity of poverty, the squared poverty gap index was higher in nonmetro areas during only 3 of the 10 years at the 95-percent confidence level. These results suggest that the nonmetro-metro differences in poverty during the 1990s (as measured by the headcount index) are not robust when poverty is assessed by measures sensitive to income distribution.

Further, the ratio of the poverty gap to the headcount index indicates that the average shortfall of the poor as a fraction of the poverty line is greater in metro areas for all 10 years of the 1990s. Important area differences exist in the income distribution of poor people; income inequality of the poor is higher in metro areas. Similarly, the distribution of the welfare ratio (income divided by the poverty line) indicates the nonmetro poor are relatively better off than the metro poor.

An exploration of economic differences reveals that approximately the same proportion of the metro and nonmetro poor are active in the labor force and appear to work about the same number of hours per year. A comparison of the poor who are not in the labor force indicates that nonworking nonmetro persons are more likely to be disabled and retired, while the nonworking metro poor are more likely to be going to school. This distinction is further supported by the fact that the proportion of people between the ages of 50 and 90 is greater in nonmetro areas, while the metro poor include relatively more people between the ages of 15 and 40. These differences are consistent with the supposition that costs of living are lower in nonmetro areas and are more attractive to poor people on fixed incomes. Attracting more jobs to these areas, or providing job training programs, will help many of the poor, but such programs will be of less value to the retired and disabled.

Results on the incidence of poverty strongly indicate that poverty reduction policies need to include components to target nonmetro areas, while results on income distribution suggest that different policies may be appropriate for each area. One type of poverty reduction strategy could focus on helping younger poor people get the skills necessary to enhance their opportunities in the job market. Another type of antipoverty program could provide income assistance to ease the burden of poverty for those who are retired or unable to work. Many of these people live on fixed incomes, and a modest supplement could elevate their income above the poverty line. The poor in metro and nonmetro areas share many similarities and need both types of programs. Policies aimed at metro areas, though, would be of more value if they focused on mitigating extreme poverty and on job training, while nonmetro areas might benefit more from a focus on supplemental income assistance for the elderly and disabled.

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APPENDIX

Appendix table 1—1999 Annual income poverty thresholds, by size of family and number of related children under 18 years

	Related children under 18								
Size of family unit	None	One	Two	Three	Four	Five	Six	Seven	Eight or more
One individual under 65	8,667								
One individual 65 and over	7,990								
Two-person family:									
Householder under 65	11,156	11,483							
Householder 65 and over	10,070	11,440							
Three people	13,032	13,410	13,423						
Four people	17,184	17,465	16,895	16,954					
Five people	20,723	21,024	20,380	19,882	19,578				
Six people	23,835	23,930	23,436	22,964	22,261	21,845			
Seven people	27,425	27,596	27,006	26,595	25,828	24,934	23,953		
Eight people	30,673	30,944	30,387	29,899	29,206	28,327	27,412	27,180	
Nine people or more	36,897	37,076	36,583	36,169	35,489	34,554	33,708	33,499	32,208

Source: U. S. Bureau of the Census, Current Population Survey. [online] http://www.census.gov/hhes/poverty/threshld/thresh99.html [14 January, 2003].

Appendix table 2—90-Percent confidence intervals resulting from synthetic-design and from Census-recommended correction—1999 CPS headcount poverty indexes

Characteristics	Ratio or percent poor	Estimated 90% confidence intervals (CI) from P-60 Report: Reported table A	Implied by levels	a,b Percentage	a,b Ratio	**90% CI from synthetic design**	90% CI assuming random sample
Persons	11.8	0.3	0.33	*0.33*	*	**0.33**	0.16
Persons in families	10.2	0.3	0.34	0.34	*	**0.36**	0.17
White	9.8	0.3	0.34	*0.33*	*	**0.31**	0.16
Black	23.6	1.2	1.20	*1.20*	*	**1.24**	0.66
Under 18	16.9	0.7	0.65	*0.65*	0.66	**0.64**	0.37
18-64 years	10.0	0.3	0.39	*0.39*	*	**0.30**	0.20
65 years +	9.7	0.5	0.53	*0.53*	0.53	**0.53**	0.43
Families, total	9.3	0.3	0.33	0.28	*0.34*	**0.32**	0.29
Total	9.3	0.3	0.33	0.28	*0.34*	**0.32**	0.29

Notes: Confidence intervals are listed in percentage points, and the asterisk denotes that the number is undefined (square root of a negative number). The first four columns of confidence intervals are derived from the Dalaker and Proctor (2000) P-60 report on poverty. The italics estimate marks whether Census considers the estimate a percentage or ratio. The bold estimates are from the synthetic cluster approach described in Jolliffe (2001), and these are followed by the confidence intervals from assuming that the data are from a weighted, simple random sample.
Source: Jolliffe (2001).