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The Cost of Living and the Geographic Distribution of Poverty

Dean Jolliffe

Abstract

The prevalence of poverty has been greater in nonmetro areas than in metro areas in every year since the 1960s when poverty rates were first officially recorded. Accordingly, Federal funds for social assistance programs and community development have favored nonmetro areas. This study suggests that adjusting poverty measures to account for cost-of-living differences between metro and nonmetro areas reverses that ranking. Once adjusted for cost-of-living differences using the Fair Market Rents index, metro poverty is greater than nonmetro poverty in terms of prevalence, depth, and severity over the entire 1991-2002 study period.

Keywords: Poverty, cost-of-living adjustments, Fair Market Rents data, urban-rural comparison, sample design, Current Population Survey

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Contents

Summary

The prevalence of poverty has been greater in nonmetro areas than metro areas in every year since the 1960s when poverty rates were first officially recorded. Accordingly, Federal funds for social programs for the needy and community development have favored nonmetro areas.

Poverty estimates figure prominently in determining the distribution of large sums of cash and in-kind benefits from State and Federal Government programs. For example, Federal block grants for community development are typically linked to county-level poverty estimates. Persistently poor rural counties benefit disproportionately from block grants, receiving more than $1,000 per person in 1994. In 1997, per capita distribution of Federal funds for social programs was 8 percent higher in nonmetro areas than in metro areas.

One can argue that distribution of social assistance is well targeted because the prevalence of poverty consistently has been greater in nonmetro areas than in metro areas. However, how poverty is defined plays an important role in the geographic distribution of poverty, and changes to the definition could affect the funding for social programs.

What Is the Issue?

The official poverty measure from the U.S. Census Bureau assumes that the cost of living is the same throughout the United States. The Federal Government is examining experimental poverty measures, however, that adjust poverty rates according to geographic cost-of-living differences. The Government has developed an experimental index that uses Fair Market Rent (FMR) data to adjust for geographic differences in the cost of living. How does the use of an index to adjust for cost-of-living differences affect the distribution of poverty across metro and nonmetro areas and how does it affect the age composition of the poor?

What Did the Study Find?

Adjusting poverty rates with the FMR index completely reverses the nonmetro-metro poverty profile. With no adjustment for cost-of-living differences, poverty over the last 12 years is higher in nonmetro areas than in metro areas. (The depth and severity of poverty also are higher in nonmetro areas, but in about one-half the cases, the differences are not statistically significant.) When the FMR index is used to adjust for cost-of-living differences, the prevalence, depth, and severity of poverty over the last 12 years are higher in metro areas than in nonmetro areas. In 2001, for example, the prevalence of nonmetro poverty was 28 percent higher than in metro areas. Once adjusted for cost-of-living differences, the rate is reversed and the prevalence of poverty in nonmetro areas is 12 percent lower than in metro areas.

Our analysis also examines how adjusting for cost-of-living differences affects the age composition of the poor. The nonmetro poor consist disproportionately of the elderly, many of whom are living on fixed incomes near the poverty line. Using the FMR index to adjust for cost-of-living differences

results in reclassifying many of the elderly poor as nonpoor. To the extent that these elderly people are receiving Federal funds tied to poverty rates, they have the most to lose from this reform. More generally, using the FMR index to adjust poverty rates for cost-of-living differences could have significant adverse affects on funding for nonmetro social programs and developmental block grants.

How Was the Study Conducted?

The spatial (geographic) price index used in this analysis comes from the Census Bureau's research on experimental poverty measures and is based on the FMR data collected by the U.S. Department of Housing and Urban Development. The primary advantages of these data are that they provide full coverage of the United States and reflect spending of lower income households. The FMR data estimate the cost of gross rent (utilities included) at the 40th percentile for standard-quality housing. The primary purpose of the FMR is to determine eligibility of rental housing units for the Section 8 Housing Assistance Payments program.

The poverty estimates come from the 1992-2003 March Supplement of the Current Population Survey (CPS), which is the data base for the official U.S. poverty rates. The sample represents the civilian, noninstitutionalized population and members of the Armed Forces either living off base or with their families on base. The measure of well-being is income as it is defined for Federal poverty rates. This definition includes all pre-tax income but includes neither capital gains nor any noncash benefits, such as public housing, Medicaid, or food stamps. The reference period for income-related questions is the preceding calendar year, and therefore, the 1992-2003 CPS data provide poverty estimates for 1991-2002.

Introduction

Poverty estimates figure prominently in the criteria that determine the geographic distribution of large sums of cash and in-kind benefits from State and Federal Government programs. Citro and Michael (1995, pp. 89-90) note that, in the early 1990s, 27 different Federal assistance programs linked their eligibility criteria in part to poverty lines or area average poverty rates.

For example, one eligibility criterion for the Food Stamp Program is that household income must be equal to or less than 130 percent of the poverty line. In 2003, the Food Stamp Program distributed $21 billion in program benefits. Data from the 2003 Current Population Survey indicate that per capita benefits were 39 percent higher in U.S. nonmetropolitan (nonmetro) areas than in metropolitan (metro) areas.[1]

[1]Per capita benefits are averaged over the entire population (recipients and nonrecipients). This finding is similar to Ghelfi (2003), who uses data from the Bureau of Economic Analysis and documents that per capita food stamp benefits were 32 percent greater in nonmetro areas than in metro areas in 2001.

Another example is Federal block grants for community development, which are typically linked to county-level poverty estimates. Reeder (1996, p. 1) notes that persistently poor rural counties benefit disproportionately from block grants, receiving more than $1,000 per person in 1994. Reeder et al. (2001, p. 4) also show that, in 1997, per capita distribution of Federal funds for social safety net programs was 8 percent higher in nonmetro than in metro areas.

One can argue that this distribution of social assistance is well targeted because the prevalence of poverty has been greater in nonmetro areas than in metro areas in every year since the 1960s when poverty rates were first officially recorded (Jolliffe, 2003b). However, how poverty is defined plays an important role in the geographic distribution of poverty, and any changes to the definition could affect the geographic distribution of funding for social safety nets.

The National Academy of Sciences (NAS) Panel on Poverty and Family Assistance has recommended several changes in how the Federal Government measures poverty, including adjustments for geographic differences in the cost of living (Citro and Michael, 1995). While the NAS Panel recommended several changes, adjusting for cost-of-living differences is the one aspect of reform that would most systematically change the geographic distribution of poverty (Nord and Cook, 1995). The official Federal poverty thresholds currently assume that the cost of living is the same throughout the United States, but the Census Bureau has now developed experimental poverty measures that use Fair Market Rent data to create an index for spatial differences in the cost of living. The purpose of this report is not to advocate for, or against, the use of this index, but rather to examine how the use of the index to adjust for cost-of-living differences affects the distribution of poverty across metro and nonmetro areas.

An adjustment for cost-of-living differences will have the greatest effect on a comparison of metro and nonmetro areas. The study's focus on the two areas is driven largely by this effect and by the strong historical difference in poverty rates across these areas.

Because this study solely examines how spatial price differences affect poverty rates, it provides information on only one of the NAS Panel's suggested changes, and it is important to interpret the results with this caveat in mind. Nonetheless, an advantage to the narrow focus on spatial-price adjustments is that the findings readily highlight the sensitivity of the relative poverty levels of nonmetro and metro areas to this change. The results from this analysis suggest a complete reversal of all three poverty measures considered. Specifically, once adjusted for cost-of-living differences using the Fair Market Rents index, metro poverty is greater than nonmetro poverty in terms of prevalence, depth, and severity over the entire 1991-2002 period considered in this analysis.

This report adds to the current literature on poverty measure reform in primarily two ways. First, it focuses on the impact of change on relative differences in poverty rates between metro and nonmetro areas. This focus is important both in terms of understanding how reform could affect the geographic distribution of benefits from Federal assistance programs and in terms of the potential political economy issues that might develop from such a proposed change.

Second, much of the current analysis of the experimental poverty measures is based on how change will affect the prevalence of poverty. This study considers three different measures of poverty-the headcount, poverty gap, and squared poverty gap measures-that will provide more information on the distributional effects of the proposed change. The three measures belong to the Foster-Greer-Thorbecke (1984, hereafter referred to as FGT) family of poverty measures and have been widely used in the international poverty literature.[2] The headcount is the standard measure used and provides a measure of the prevalence of poverty. The poverty gap measure provides a measure of the depth of poverty. The squared poverty gap is sensitive to the income distribution of the poor and provides a measure of the severity of poverty.

[2]The following all use these three measures: Jolliffe et al. (2004) for Egypt, Datt and Ravallion (1992) for Brazil and India, Howes and Lanjouw (1998) for Pakistan and Ghana, Kakwani (1993) for Côte d'Ivoire, and Ravallion and Bidani (1993) for Indonesia.

Poverty Measurement

This section covers the Fair Market Rents index, data, poverty line, and the FGT poverty measures.[3]

The Fair Market Rents Index

While the data are limited, the evidence suggests that geographic differences in the cost of living are significant. Up until 1982, the Bureau of Labor Statistics collected data from the Family Budget Program (FBP), which provided estimates of the relative cost of a consumption bundle for a family of four living in different areas of the United States. The last sample of FBP data indicates that, in 1981, the spatial variation in the cost of purchasing the fixed bundle of goods was significant. For example, in urban areas of the Northwest, the cost was 113 percent of the national average, and in the nonmetro South, it was 91 percent of the national average (Citro and Michael, 1995, p. 186).

Other sources of data on spatial differences in the cost of living are available, but none of these include full coverage of metro and nonmetro areas. For example, the Bureau of Labor Statistics has been working on using data from the Consumer Price Index (CPI) to develop a spatial price index, but these efforts have focused strictly on urban areas (Aten, 2005; Kokoski, 1991; Moulton, 1995). Perhaps the best known spatial price index is the ACCRA index, which was developed by the American Chamber of Commerce Researchers Association.[4] The index has some shortcomings: It provides an estimate of the cost of living in an area only if a volunteer has reported the data, and it is intended to reflect cost-of-living differences for households in the top quintile of income. For the purposes of poverty analysis, this index is most likely not a useful one.

This study uses the spatial price index for 2001 developed by the Census Bureau in their research on experimental poverty measures (Short, 2001a, 2001b) and is based on the Fair Market Rent (FMR) data collected by the U.S. Department of Housing and Urban Development (HUD).[5] The primary advantages of the FMR data are that they provide full coverage of the United States and reflect spending of lower income households. HUD produces annual estimates of the FMR for 354 metro areas and 2,350 nonmetro counties. The FMR data estimate the cost of gross rent (utilities included) at the 40th percentile for standard-quality housing.[6] The purpose of the FMR is to determine eligibility of rental housing units for the Section 8 Housing Assistance Payments program. Section 8 participants cannot rent a unit if the rent exceeds the FMR. (FMR also serves as the payment standard used to calculate subsidies under the Rental Voucher program.) See U.S. Housing and Urban Development (2003) for more details.

The FMR index used in this analysis was constructed by Short (2001a, 2001b) for the Census Bureau's experimental poverty measures and is based on FMR data from 2001. In using this index to examine poverty differences over many years, we are implicitly assuming that the spatial distribution of prices has not changed significantly over the years.[7] A cursory look at the early FMR data files suggests that the results are not likely to be qualitatively affected by this simplifying assumption. The study tests this suggestion by

[3]The findings in this report along with more technical detail can also be found in Jolliffe (2006).

[4]For an ACCRA example, see Dumond, Hirsch, and MacPherson (1999). See Koo, Phillips, and Sigalla (2000) for a comparison of CPI-based and ACCRA indexes.

[5]For a critique of the FMR as a spatial price index, see Short (2001b, Appendix A). For an alternative examination of spatial price differences based on subjective measures of food security, see Nord (2000) and Nord and Leibtag (2006).

[6]From 1995 to 1999, the FMR is based solely on the 40th percentile. As of 2001, the FMR index is based on the 40th percentile except for 39 MSAs, which are based on the 50th percentile. Between 1983 and 1994, the index was based on the 45th percentile.

[7]While the FMR data are publicly available, for this analysis, they need to be merged with the CPS data using geographic identifiers that are only complete in the private (not for public release) CPS files. The Census Bureau provided the 2001 FMR index for this research to enable participation in a panel on "Adjusting for Geographic Cost-of Living Differences in Federal Statistics" held by the Society of Government Economists.

examining the simple mean FMR for nonmetro counties and mean FMR for Metropolitan Statistical Areas between 1991 and 2004. These estimates will not be comparable to the means for the FMR index because they have not been population weighted, but significant temporal variation in the means would suggest that the findings for years other than 2001 could be sensitive to this assumption. Over the 14 years examined, the nonmetro mean FMR was between 68 percent and 77 percent of the metro mean FMR, which is interpreted as evidence of some stability in the spatial differences in prices over time.

Another caveat in interpreting the findings of this study is that about 4 percent of the counties switched from nonmetro to metro (or vice versa) in 1993, depending on the demographic changes observed in the 1990 Census. Given the changing status of some counties in 1993 and the assumption that the spatial distribution of prices has not changed over time, the findings for the more recent years are viewed as somewhat more accurate. For this reason, the core findings are presented for all years between 1991 and 2002, but the more detailed analysis focuses on the last 2 years from the sample.

The index is constructed as a fixed-weight index consisting of two components—housing and all other goods and services. Following the recommended approach of the National Academy of Sciences report (Citro and Michael, 1995, p. 197), the index assigns a weight of 44 percent for housing expenses and 56 percent on all other goods and services. Further, the index assumes that variation in the FMR data reflects variation in housing prices for the poor and that the prices of all other goods and services do not vary. The focus on housing prices in the index is supported by Moulton (1995, p. 181) who notes that "the cost of shelter is the single most important component of interarea differences in the cost-of-living." By construction then, if the FMR data indicate that rents in a particular area are 10 percent higher than the baseline, then the FMR index used by the Census Bureau reflects a cost of living in this area that is 4.4 percent higher than the baseline.

The primary reason for assuming that prices for nonhousing goods and services do not vary is a lack of credible data sources for spatial price variation in nonhousing prices. The data that do exist suggest that areas where housing costs are high also have somewhat higher prices for other goods (housing and nonhousing prices are positively correlated). This correlation implies that the no-spatial-variation assumption in nonhousing prices will underestimate the magnitude spatial price differences. In other words, the estimates are likely to be lower bound, or conservative, estimates of the effect of adjusting poverty estimates for spatial price differences. The section "The Cost of Housing and All Other Goods" examines the sensitivity of the core findings to the assumption of no correlation.

Finally, the FMR index used in the Census Bureau's experimental poverty measures is aggregated up to 100 different price levels, one for metro areas and one for nonmetro areas of each State and the District of Columbia.[8] This step differs from the approach followed by the National Academy of Sciences (Citro and Michael, 1995, pp. 195-97), which used Census data and disaggregated the index by Census regions and population categories. The National Academy of Sciences report recognizes that the use of Census data is problematic due to the limited frequency of its availability and recommends

[8]New Jersey and the District of Columbia consist of only metro areas, hence, 100 total FMR price levels.

using an index that can be updated more frequently than once every 10 years. They further recommend exploring the potential of using the FMR data (Citro and Michael, 1995, p. 200), as is done in recent reports on the experimental poverty measures, including this report and Short (2001a, 2001b).

For purposes of this analysis, the FMR index is scaled to ensure that the FMR-adjusted poverty estimates match the official U.S. Federal estimates at the national level. With this scaling, any deviation from official estimates at the subnational level will be strictly due to relative price differences in the index. Table 1 lists basic descriptive statistics of the FMR index by metro and nonmetro areas. The index shows that the average cost of living in nonmetro areas is 79 percent of that in metro areas. It is the first indication that using the index to adjust for cost-of-living differences is likely to significantly affect the measurement of metro-nonmetro poverty differences.

The Data: 1992-2003 CPS and U.S. Poverty Thresholds

The data used in this study are from the 1992-2003 March Supplement to the Current Population Survey (CPS) 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 provide information on about 50,000 families in each year (80,000 in the more recent years). The March Supplement, also called the Annual Demographic Survey of the CPS, collects information on income and a variety of demographic characteristics. The reference period for income-related questions is the preceding calendar year, and therefore, the 1992-2003 CPS data provide poverty estimates for 1991 through 2002.

The sample represents the civilian, noninstitutionalized population and members of the Armed Forces either living off base or with their families on base. The sample frame is based on housing structures and not on individuals, so all individuals who are homeless at the time of the interview are excluded from the sample. Because the homeless are disproportionately located in metro areas, their exclusion disproportionately biases the metro poverty estimates downward. A primary finding of this study is that adjusting for cost-of-living differences with the FMR index decreases nonmetro poverty and increases metro poverty to the extent that the nonmetro-metro poverty rankings are completely reversed. If the homeless were included in this analysis, they would further reinforce this finding.

The measure of well-being used in this study is income as defined for Federal poverty rates. This definition includes all pre-tax income but does not include capital gains or any noncash benefits, such as public housing, Medicaid, or food stamps. The poverty thresholds used in this study are the U.S. Federal

Table 1
Scaled Fair Market Rent index, nonmetro-metro comparison

Fair Market Rent index	Average	Median	(Minimum, maximum)
National	1.00	1.00	(0.74, 1.21)
Nonmetropolitan	.82	.81	(.74, 1.21)
Metropolitan	1.04	1.01	(.85, 1.19)

Note: Fair Market Rent index weighted by individual weights to match weights used for poverty estimation.

Government poverty lines, which were developed in 1965 following a cost-of-basic-needs methodology that sets the poverty line at the value of a consumption bundle considered to be 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 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. In addition to the cost of this food plan, the poverty line included an allowance for nonfood expenditures that was twice the value of the cost of the USDA economy food plan.[9] To account for inflation, the poverty lines set in 1965 are adjusted each year using a price index.[10] The latest poverty line used in this study is from 2002, set at $9,359 for an individual younger than 65, $12,400 for a two-person family with one child and one adult, and $21,469 for a family with two adults and three children. For a complete listing of 2002 poverty lines for individuals and families of various sizes, see Proctor and Dalaker (2003, p. 4).

[9]For details on the first poverty lines, see Orshansky (1965). For a history of poverty lines before Orshansky, see Fisher (1997). For a critical discussion of the official poverty line, see Ruggles (1990).

[10]Before 1969, the index used was the changing cost of the USDA economy food plan. Since 1969, the CPI for all goods and services has been used.

The Foster-Greer-Thorbecke Poverty Measures

The previous section describes the measure of well-being and poverty lines used to identify who is 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 that belong to the FGT family. The first is the headcount measure (P_0), which is the percentage of the population that is poor. The second measure, called the poverty gap index (P_1), is found by first measuring the income gap (i.e., the proportionate difference between income and the poverty line) for all poor persons. The poverty gap index is then the average value of the income gaps, where the average is formed over the entire population, counting the nonpoor as having zero income gap. The third measure is the squared poverty gap measure (P_2) and is defined as the mean value of the squared income gaps.

The FGT class of poverty measures, 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 well-being, z is the poverty line, and I is an indicator function that takes the value of one if the statement is true and zero otherwise. When α=0, the resulting measure is the headcount measure, or P_0. When α=1, the FGT measure results in the poverty gap measure, or P_1; and the squared poverty gap measure (P_2), results when α=2.

The usefulness of these measures can be illustrated by considering a transfer of money from a rich person to a poor person that is not large enough to move the poor person over the poverty line. This transfer has no effect on the headcount measure, but the poor person is better off and the improvement in well-being is reflected in a reduction of both the poverty gap and

squared poverty gap. As another example, a transfer of income from a poor person to a poorer person will not alter either the headcount or the poverty gap measure, but it improves the distribution of income of the poor and this change is reflected by a reduction of the squared poverty gap.[11]

These examples point to an important reason to consider the poverty gap and squared poverty gap measures in addition to the commonly reported headcount measure. A frequent goal of many programs is to reduce poverty, but the policies appropriate to attain this goal will vary depending on which poverty measure is considered. If policymakers are focused on the head-count measure, then the most efficient way to reduce poverty is through assistance to the least poor. If, on the other hand, policymakers are concerned about the overall well-being of the poor and not just on reducing the number of people living in poverty, then the appropriate measure is one that captures the depth and severity of poverty.

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

Results

Nonmetro-Metro Poverty Comparisons, The Unadjusted (Official) Estimates

Before answering whether nonmetro-metro poverty comparisons are sensitive to spatial price adjustments, the baseline for comparison must be established. Appendix table 1 lists the headcount (P_0), poverty gap (P_1), and squared poverty gap (P_2) measures for metro and nonmetro areas for each year between 1991 and 2002. The appendix discusses the derivation of the sampling variance of these estimates. The nonmetro headcount measure ranges from a high of 0.17 in 1993, representing 9.7 million poor people, to a low of 0.13 in 2000, 6.8 million poor people. The metro headcount measure ranges from a high of 0.15 in 1993, 29.5 million poor people, to a low of 0.11 in 2000, 24.3 million poor people. The variation in the poverty gap and squared poverty gap measures is similar. Across both of these measures, for metro and nonmetro areas alike, poverty was at its lowest level in 2000. In terms of the poverty gap measure, the year with the highest level of poverty came in 1993. The worst year, as measured by the squared poverty gap measure, came in 1997 for nonmetro areas and 1993 for metro areas.

Appendix table 1 also provides estimates of the design-corrected standard errors for each of the 72 poverty estimates (P_0, P_1, and P_2 for each year from 1991 to 2002 by metro and nonmetro areas). None of the estimates has a design effect of less than 4, which means that the design-corrected standard errors are all more than twice as large as those that would be estimated if one (incorrectly) ignored the complex sample design.[12]

[12]The largest design effect is 6.1 for the 2001 nonmetro P_1 measure, which means that the corrected standard errors are almost $2^{1/2}$ times greater than what one would estimate if ignoring the sample design.

The poverty gap measure is equal to the product of the headcount measure and the income gap, where the income gap is the average shortfall of the poor as a fraction of the poverty line. The poverty gap measure implies that, in 1991, the average shortfall of the poor as a fraction of the poverty line is equal to 42 percent in nonmetro areas and 45 percent in metro areas. In 2002, the average shortfall in nonmetro areas is equal to 44 percent of the poverty line and 47 percent in metro areas. During all 12 years, the average shortfall is greater in metro areas than in nonmetro areas, which indicates that on average the metro poor are worse off than the nonmetro poor.

This difference in the average income shortfall of the poor suggests that the well-being of the poor could differ across areas. Figure 1 explores this issue by graphing density estimates of the income-to-needs ratio, which is the ratio of income to the poverty threshold. The advantage of income-to-needs ratios over income is that they provide measures of well-being that control for demographic differences (and these demographic characteristics may differ across areas).[13] The control for demographic differences occurs because the income-to-needs ratios are a function of the poverty thresholds, which are adjusted to reflect different levels of need for families of various sizes and ages.

[13]For example, in 1999, the average age of a metro poor person is 28 compared with 32 for a nonmetro poor person. In terms of family size, 16 percent of the metro poor live in two-person families compared with 20 percent for the nonmetro poor.

Figure 1 provides kernal density estimates of metro and nonmetro income-to-needs ratios for 1992, 1995, 1998, and 2001. For all years, the nonmetro income-to-needs ratio is more peaked near the poverty line, indicating that a larger share of the nonmetro poor live on greater income-to-needs ratios and are therefore relatively better off. Similarly, the nonmetro income-to-needs

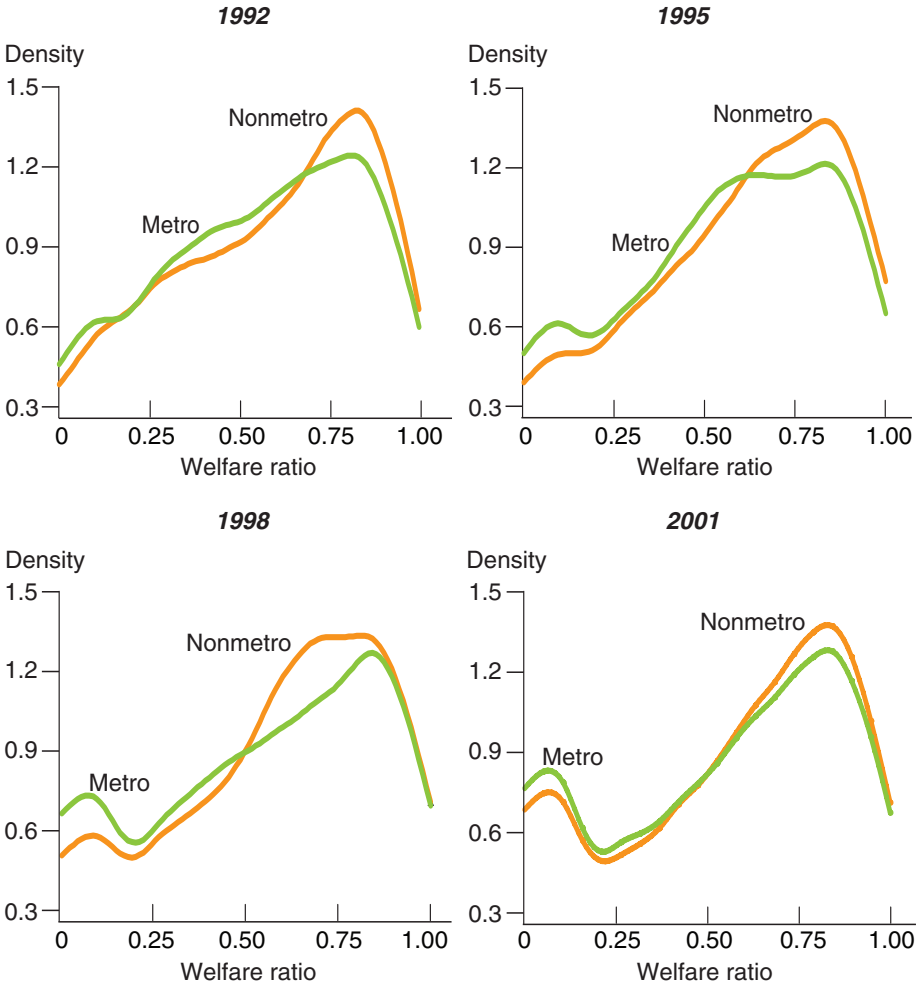
ratio lies below the metro distribution on the left side of the distribution, indicating that a larger share of the metro poor live in extreme poverty.

Another way of interpreting figure 1 is to note that, in 2001, 62 percent of the nonmetro poor lives on income greater than one-half of the poverty line compared with 58 percent of the metro poor. In 1998, the difference is larger; 65 percent of the nonmetro poor have income greater than one-half of the poverty line compared with 58 percent of the metro poor. One implication of this difference is that a small increase in income would move disproportionately more nonmetro poor than metro poor over the poverty line.

Nonmetro-Metro Poverty Comparisons, Adjusted Using the FMR index

Table 2 compares the poverty estimates from appendix table 1 with the estimates for 2001 and 2002 using the FMR index. The unadjusted headcount measure for 2001 shows that 14.2 percent of nonmetro residents are poor

Figure 1
Income-to-needs ratios of the poor (unadjusted) by area, 1991-2001



Notes: The density of the income-to-needs ratio is measured in terms of the reciprocal of the income-to-needs ratio (not measured on a probability scale) and thus can exceed 1.00. The Epanechnikov kernal is used for all estimates with a smoothing parameter set to 0.08.

compared with 11.1 percent of metro residents. In other words, the nonmetro poverty rate is 28 percent greater than the metro rate. This ranking holds for the two other poverty measures. The 2001 poverty gap is 21 percent greater in nonmetro than in metro areas, and similarly, the squared poverty gap is 18 percent higher in nonmetro areas. This pattern continues in 2002 (table 2). Nonmetro poverty is higher than metro poverty across all three measures, although the percentage difference declines as one considers the distribution-sensitive measures, P_1 and P_2.

The estimates listed in the FMR-adjusted columns provide the poverty estimates when each of these measures are calculated based on income levels that have been corrected for spatial-price differences following the FMR index. In 2001, the official nonmetro poverty rate of 14.2 percent drops to 10.5 percent when corrected for spatial-price differences. At the same time, the metro poverty rate increases from 11.1 to 12.0 percent when adjusted using the FMR index. The net effect is that the prevalence of nonmetro poverty is 12 percent lower than the metro poverty rate when both measures are adjusted for cost-of-living differences (as measured by the FMR index). This reversal of the relative ranking of nonmetro and metro poverty holds for the poverty gap and squared poverty gap measures in 2001 and 2002 (table 2).[14]

[14]If metro areas are separated into central city and suburban areas, the rankings do not reverse. Without price adjustment, the lowest poverty rates are in suburban areas and the highest are in the central cities. Nonmetro poverty rates are between the two but significantly closer to those of inner cities. With the price adjustment, the rankings are the same; but nonmetro poverty rates are significantly closer to the suburban rates.

Table 2
Poverty measures, nonmetro-metro comparison, 2001 and 2002

	Headcount		Poverty gap		Squared poverty gap	
Year/area	Actual	FMR-adjusted	Actual	FMR-adjusted	Actual	FMR-adjusted
	---P_0 measure---		*---P_1 measure---*		*---P_2 measure---*	
2001:						
Nonmetro	0.142	0.105	0.063	0.050	0.043	0.036
	(.004)	(.003)	(.002)	(.002)	(.002)	(.002)
Metro	.111	.120	.052	.055	.036	.038
	(.002)	(.002)	(.001)	(.001)	(.001)	(.001)
			Percent			
Nonmetro-metro difference	28	-12	21	-9	18	-5
	(3.80)	(3.01)	(4.71)	(3.97)	(5.64)	(4.97)
	---P_0 measure---		*---P_1 measure---*		*---P_2 measure---*	
2002:						
Nonmetro	.142	.105	.062	.049	.041	.034
	(.004)	(.003)	(.002)	(.002)	(.002)	(.002)
Metro	.116	.125	.055	.058	.038	.040
	(.002)	(.002)	(.001)	(.001)	(.001)	(.001)
			Percent			
Nonmetro-metro difference	22	-15	13	-16	8	-14
	(3.55)	(2.76)	(4.06)	(3.33)	(4.73)	(4.11)

FMR = Fair Market Rent index. Numbers in parentheses are standard errors.

Notes: Poverty measures are the Foster-Greer-Thorbecke P_α measures. FMR-adjusted measures are poverty measures after adjusting for spatial-price variation with the Fair Market Rent index. Nonmetro-metro differences are $[(P_{\alpha_{nonmetro}} - P_{\alpha_{metro}}) / P_{\alpha_{metro}}]$, both using actual levels and FMR-adjusted levels. Standard errors for the poverty measures are estimated following equation (4) and using the program described in Jolliffe and Semykina (1999). Standard errors for the differences are second-order approximations by the delta method.

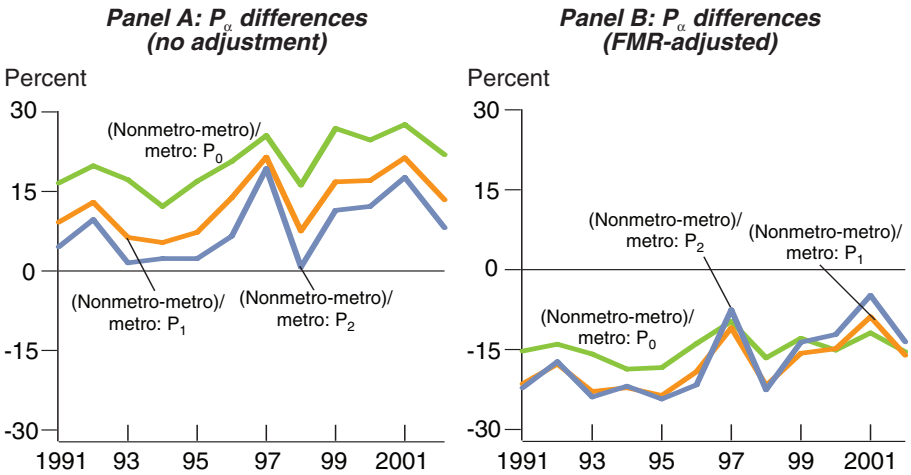
To understand whether the reversal of the poverty rankings is unique to recent events, the study repeats this analysis for all years between 1991 and 2001. Appendix table 2 provides all of the FMR-adjusted poverty estimates for these years. Panel A of figure 2 plots the nonmetro-metro percentage differences for the three poverty measures.[15] Over all years between 1991 and 2001, all three of the poverty measures indicate that nonmetro poverty is greater than metro poverty.[16] Panel B plots these same differences but for poverty measures that have been adjusted with the FMR index. This panel reveals that reversal of the relative rankings holds over all years considered. The spatial-price-adjusted estimate of nonmetro poverty is lower than the adjusted metro estimate for all measures over all years. This panel indicates that most of the price-adjusted nonmetro poverty estimates are 10-25 percent less than the price-adjusted metro estimates.

Age and the FMR-Induced Change in Nonmetro Poverty

Previous research on demographic differences in area poverty rates has indicated that the nonmetro poor are more likely to be elderly and retired while the metro poor are more likely to be younger and going to school. Figure 3 illustrates this difference by graphing the age distribution of the poor in metro and nonmetro areas in 2001 and 2002. For both years, the nonmetro age distribution lies below the metro distribution for younger ages and above for older ages. Relative to the poor in metro areas, disproportionately more of the nonmetro poor are over the age of 40 (which similarly means, disproportionately fewer of the nonmetro poor are under 40).

While Table 2 shows that the FMR-adjusted poverty rates produce a complete reversal of the relative rates of nonmetro and metro poverty, table 3 shows that age is an important correlate of this readjustment. In both 2001 and 2002, the nonmetro poor were about 2 years older than the metro poor on average.

Figure 2
Nonmetro-metro poverty differences, 1991-2002



FMR = Fair Market Rent index.

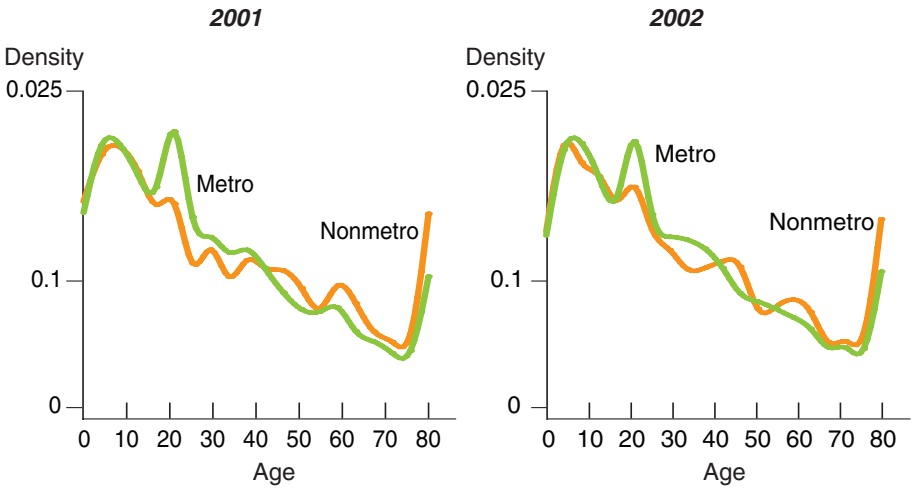
Notes: In panel A, the P_α lines plot the difference between nonmetro and metro poverty as measured by P_0, P_1, and P_2 using metro poverty as the base, or $[(P_{\alpha_{nonmetro}} - P_{\alpha_{metro}})/P_{\alpha_{metro}}]$. In panel B, the P_α lines are adjusted using the FMR index to correct for geographic differences in prices.

[15]The relative difference in poverty uses the metro poverty level as the base and can be expressed as $[(P_{\alpha_{nonmetro}} - P_{\alpha_{metro}}) / P_{\alpha_{metro}}]$.

[16]Panel A also reveals a primary finding of Jolliffe (2003b). Namely, the nonmetro-metro poverty differences diminish as one considers measures that are sensitive to the income distribution of the poor. In other words, P_0 indicates a much greater nonmetro-metro difference in poverty than does P_1 and P_2.

Figure 3

Age distribution of the poor (unadjusted) by area, 2001 and 2002



Notes: The Epanechnikov kernal is used with a smoothing parameter set to 1.

Table 3

Average age of the poor by area

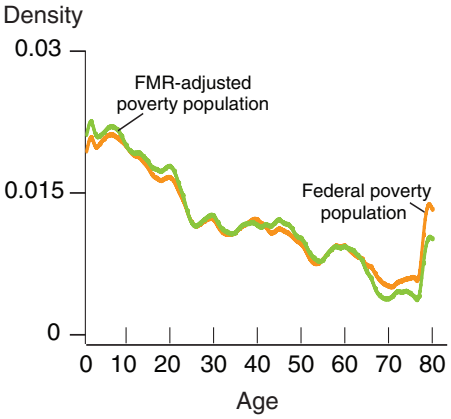
Item	2001 Metro	2001 Nonmetro	2002 Metro	2002 Nonmetro
	Years			
Poor	29.75 (.257)	32.27 (.506)	30.20 (.252)	32.00 (.484)
FMR-adjusted poor	30.08 (.252)	30.59 (.561)	30.40 (.245)	30.25 (.516)

Numbers in parentheses are standard errors. FMR = Fair Market Rent index.

Notes: FMR-adusted poor are those designated as poor after adjusting income with the Fair Market Rent index. Standard errors corrected for complex design following Jolliffe (2003a).

Figure 4

Age distribution of the nonmetro poor: Federal poverty population versus FMR-adjusted poverty population, 2001



FMR = Fair Market Rent index.

Notes: The Epanechnikov kernal is used for both estimates with a smoothing parameter set to 1.2.

Adjusting for cost-of-living differences with the FMR index reduces the average age of the nonmetro poor by almost 2 years, eliminating the difference in average ages. Eliminating the age difference suggests that the nonmetro poor who are being re-classified as nonpoor with the FMR adjustment (those with income closest to the poverty line) are disproportionately older people.

Figure 4 explores this issue in more detail by plotting the age distribution of the nonmetro poor in 2001. The nonmetro age distribution is plotted for those who are considered poor according to the Federal definition and by using the FMR-adjusted rates. In both

years, the FMR-adjusted age distribution lies below the age distribution of the poor at ages older than 60 and above the distribution for ages younger than about 25, confirming that the FMR adjustments reclassify disproportionately more of the nonmetro elderly as not poor. Such a reclassification would have implications for several Federal assistance programs, including Supplemental Security Income, Medicaid, the Child and Adult Care Food Program, and the Commodity Supplemental Food Program.

The Cost of Housing and All Other Goods

The FMR index used by the Census Bureau implicitly assumes that the prices of all goods other than housing costs have no spatial variation. To test the sensitivity of the findings to the assumption, this study examines the case where prices of housing and other goods are correlated. Kurre (2003) examines spatial price differences in all counties of Pennsylvania and finds that prices are about 6 percent higher in urban areas for a broad basket of goods and services. He further finds that, while housing costs are the most important component of the spatial variation in prices, prices for other categories of goods and services are positively correlated with housing costs.

Following this line then, consider a case where the coefficient of correlation between housing and other prices is +0.2, which implies that areas with housing prices 10 percent higher than the baseline are also areas with prices of other goods that are 2 percent higher. With the fixed budget weights, this implies an FMR index that is 5.5 percent higher than the baseline ($10*0.44 + 2*0.56 = 5.5$). Another way of saying this is that the assumption of positive correlation will amplify the spatial variation by approximately 25 percent.[17]

[17]In the example of housing prices 10 percent greater than the baseline, the FMR index (with no correlation in prices) is 4.4. When assuming +0.2 positive correlation in prices of housing and other goods, the FMR index increases by 25 percent to 5.5.

For the sake of sensitivity analysis, though, also consider the case of negative correlation between prices of housing and all other goods and services. This study examines the case where the correlation coefficient is -0.2, which would imply a dampening of the variation in prices by 25 percent (relative to the FMR index). If the assumption of negative correlation is justified, then the FMR index would overstate the true spatial variation in prices.

Although the case of negative correlation in prices may seem less plausible, it is useful to consider the extent to which the spatial variation in prices can be dampened and still produce the reversal in rankings. Another assumption of the FMR index is that housing costs comprise 44 percent of the budget of the poor. If we return to the assumption of no variation in the prices of nonhousing goods but reduce the share of the index for housing costs, this too would dampen the price variation. Citro and Michael (1995) note that the CPI basket uses a share of 33 percent for shelter and utilities. If the FMR index were modified such that the weight used for housing expenses dropped from 44 percent to 33 percent, this would dampen price dispersion by 25 percent. Considering the case of -0.2 negative correlation in prices is essentially the same as considering an FMR index with housing assumed to only consume 33 percent of the budget (and no variation in the price of nonhousing goods).

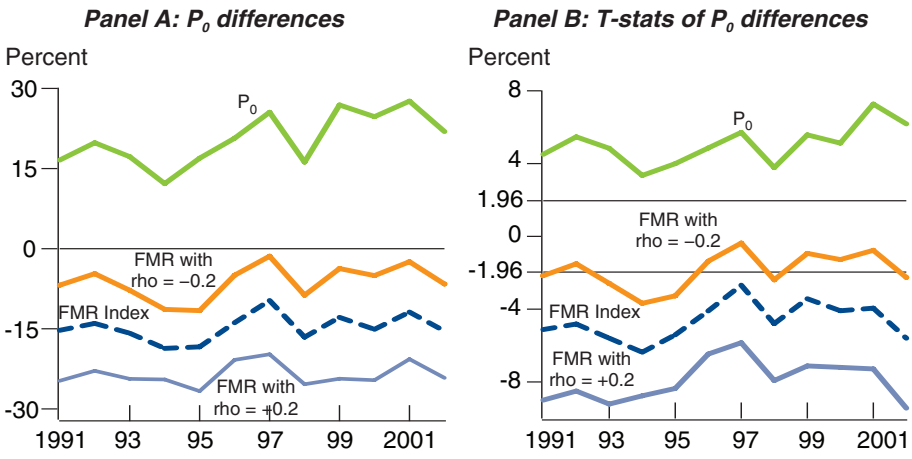
Panel A of figure 5 presents the percentage difference between the nonmetro and metro prevalence of poverty (P_0) under several assumptions. The single line above zero is this difference without any adjustment for spatial price variation. This line reflects the official Federal estimates of poverty in

nonmetro and metro areas, indicating that nonmetro poverty has been uniformly higher than metro poverty. A simple average over the 12 years examined indicates that nonmetro poverty has been 20 percent higher than metro poverty. The three other lines, all falling below zero, have been adjusted using the FMR index and assuming negative, positive, and no correlation between prices of housing and other goods. The middle line of the three is the baseline FMR index. The most negative line assumes positive correlation, and the line closest to zero assumes correlation of -0.2.

As expected, positive correlation magnifies the primary findings. The relative ranking of nonmetro and metro poverty, as before, is completely reversed from the rankings based on the official poverty rates. With the coefficient of correlation at -0.2, the findings are dampened, but the estimated level of nonmetro poverty is still lower than metro poverty over all years examined. Panel B shows the t-statistics for these relative differences. For the FMR index and the FMR index with +0.2 correlation in prices, all differences are statistically significant. With correlation of -0.2, the difference is statistically significant (at the 5-percent confidence level) in 6 of the 12 years considered. If the correlation in prices is negative and greater than 0.2 in magnitude, or if the weight assigned to housing expenses drops below 33 percent, then the primary finding of a reversal in the rankings would no longer hold.

Figure 5

Nonmetro-metro poverty differences, sensitivity analysis, 1991-2001



FMR = Fair Market Rent index.

Notes: In panel A, the P_0 line plots the difference between nonmetro and metro poverty as measured by P_0 using metro poverty as the base, or $[(P_{\alpha_{nonmetro}} - P_{\alpha_{metro}})/P_{\alpha_{metro}}]*100$. The three lines below all reflect the relative difference in P_0 with COLA adjustments. The FMR index line uses the baseline FMR index. The line above the baseline assumes that nonrent prices are negatively correlated (r = -0.2) with FMR, while the bottom line assumes positive correlation (r = +0.2). In panel B, the lines plot t-statistics of the test for whether the nonmetro-metro differences are statistically significant.

Conclusion

The prevalence of poverty has been greater in nonmetro areas than in metro areas in every year since the 1960s when poverty rates were first officially recorded, and accordingly, Federal funds for social safety nets and community development have favored nonmetro areas. The Federal Government is examining experimental poverty measures that, among other changes, adjust poverty rates for spatial cost-of-living differences. The preferred experimental index is one based on the Fair Market Rent data, which reflects spatial differences in the rental cost of low-income housing. The purpose of this study is to examine how the use of this index to adjust for cost-of-living differences affects the distribution of poverty across metro and nonmetro areas.

The primary finding is that adjusting poverty rates with the FMR index results in a complete reversal of the nonmetro-metro poverty profile. With no adjustment for cost-of-living differences, the prevalence of poverty is higher in nonmetro areas than in metro areas over the last 12 years. (The depth and severity of poverty are also higher in nonmetro areas, but in about one-half the cases, the differences are not statistically significant.) When the FMR index is used to adjust for cost-of-living differences, the prevalence, depth, and severity of poverty are higher in metro areas than in nonmetro areas over the last 12 years. In 2001, for example, the prevalence of nonmetro poverty was 28 percent higher than in metro areas. Once adjusted for cost-of-living differences, this is reversed and the prevalence of poverty in nonmetro areas is 12 percent lower than in metro areas.

The analysis also examines how adjusting for cost-of-living differences affects the age composition of the poor. The nonmetro poor consist disproportionately of elderly, many of whom are living on fixed incomes near the poverty line. Using the FMR index to adjust for cost-of-living differences results in reclassifying many of the elderly poor as nonpoor. The average age of the nonmetro poor drops from 32.3 years to 30.6 years when adjusting for cost-of-living differences. To the extent that the reclassified elderly are receiving Federal funds tied to poverty rates, they have the most to lose from the reform. More generally, using the FMR index to adjust poverty rates for cost-of-living differences could have significant adverse affects on funding for nonmetro social safety nets and developmental block grants.

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Appendix: Baseline Measures and Standard Errors

The statistical tests used in this study for nonmetro-metro poverty differences are corrected for features of the sample design.[18] The sample used for the CPS is drawn from a census frame using a stratified, multistage design. Howes and Lanjouw (1998) present evidence that estimated standard errors for poverty measures can have large biases when false assumptions are made on 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 simple random sample, then the standard errors will significantly underestimate the true sampling variance. An example from Jolliffe et al. (2004) shows that, in the case of poverty measures for Egypt, failing to adjust for the characteristics of the sample design would result in an underestimate of the correct standard errors by 187-212 percent.

[18]Zheng (2001) provides design-corrected estimates of sampling variance for poverty estimates based on relative poverty lines (i.e., the poverty line is relative to the distribution of income, such as one-half the median income level). The advantage of the estimates provided here is that they are based on a fixed (or absolute) poverty line, which is how poverty is measured in the United States. Another advantage is that Jolliffe and Semykina (1999) provide a Stata program that estimates the standard errors presented in this report.

The strategy followed in this study to estimate the sampling variance corrected for design effects is to first derive exact (analytical) estimates for the poverty measures, and then to address the issue of sample design. An advantage of the FGT class of poverty measures in this context is that they are additively decomposable, a characteristic that greatly simplifies deriving the analytical estimates of the sampling variance of the poverty measures. To illustrate this, consider any income vector y, broken down into M subgroup income vectors, $y^{(1)}$, ... , $y^{(m)}$. Because P_α is additively decomposable with population share weights, it can be written as:

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

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 is 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:

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

where i subscripts the individual.

The next step is to incorporate the sample design information, which typically requires that the researcher has access to not only unit record data, but also data identifying the characteristics of the sample design. In the case of the CPS data, the sample design information that identifies the strata and primary sampling units (PSUs) has been censored from the public-use files to maintain respondent confidentiality. To compensate for the missing design information, U.S. Census Bureau (2000, Appendix C) provides detailed notes on how to approximate design-corrected standard errors for a limited set of poverty estimates. An important shortcoming of this method is that parameter estimates are provided for only the headcount measure; no corrections are provided for any other poverty measures.[19]

[19]Another shortcoming of the Census-recommended method is that corrections are provided only for a limited set of characteristics. For example, U.S. Census Bureau (2000, Appendix C) provides parameter estimates to adjust the sampling variance for the headcount measure by several age categories. If the analysis is focused on individuals ages 15-24, the analyst is provided with parameter estimates. If the relevant subsample is, say, working-age adults, then Census does not provide the necessary parameters to estimate standard errors.

In addition to the issue of Census not providing sample-design corrections for either the poverty gap or squared poverty gap measures, another problem is that the recommended method appears to be significantly less precise for nonmetro-metro comparisons. The proposed correction for all nonmetro statistics provided by the U.S. Census Bureau (2000, Appendix C) is to multiply the design-correction coefficients by 1.5. The implication of this correction is that, for all statistics, the ratio of the design effects for metro to nonmetro areas is constant. Another factor likely to affect the accuracy of this correction is that it has not been updated in the last 20 years, whereas the design-correction coefficients for all other characteristics are frequently updated.[20]

Given that the Census-recommended method does not provide corrections for the sampling variance of P_1 and P_2, and that the adjustment factor for nonmetro areas appears to be a rough approximation, this method is abandoned. Instead, an approach is followed based on replicating 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 and simulation results suggesting that it provides useful approximations are provided in Jolliffe (2003a).

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 units 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, on average, the actual CPS cluster size. The four U.S. regions are selected as synthetic strata to capture the geographic aspect of the CPS stratification.

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

$$V(P_{\alpha,\omega}) = \sum_{h=1}^{L} n_h(n_h-1)^{-1} \sum_{i=1}^{n_h} \left(\sum_{j=1}^{m_{h,i}} \omega_{h,i,j} P_{\alpha,h,i,j} - \sum_{i=1}^{n_h} \sum_{j=1}^{m_{h,i}} \omega_{h,i,j} P_{\alpha,h,i,j} \right)^2 \quad (4)$$

where the h subscripts each of the L strata, i subscripts the cluster or primary sampling unit (PSU) in each stratum, j subscripts the ultimate sampling unit (USU), so ω_{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_{hi}.[22]

[20]Personal communication with Census appears to support the assertion that the nonmetro adjustment is less precise: "The factor of 1.5 has been used for nonmetro areas as a simple approximation. While the best factor likely varies from characteristic to characteristic, we use 1.5 for all characteristics rather than publishing a different factor for each estimate. Years ago, someone looked at the data for metro/nonmetro areas and decided that 1.5 would be a good, and somewhat conservative, estimate for most characteristics."

[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.

Appendix table 1

Prevalence, depth, and severity of poverty (unadjusted), nonmetro-metro comparison, 1991-2002

Year	Headcount		Poverty gap		Squared poverty gap	
	Metro	Nonmetro	Metro	Nonmetro	Metro	Nonmetro
	----P_0 *measure*----		----P_1 *measure*----		----P_2 *measure*----	
1991	0.137	0.160	0.061	0.067	0.039	0.041
	(.002)	(.004)	(.001)	(.002)	(.001)	(.002)
1992	.139	.167	.063	.071	.040	.044
	(.002)	(.004)	(.001)	(.002)	(.001)	(.002)
1993	.146	.171	.067	.072	.043	.044
	(.002)	(.004)	(.001)	(.002)	(.001)	(.002)
1994	.141	.159	.065	.068	.042	.043
	(.002)	(.004)	(.001)	(.002)	(.001)	(.002)
1995	.134	.156	.060	.064	.039	.039
	(.002)	(.005)	(.001)	(.003)	(.001)	(.002)
1996	.132	.159	.059	.067	.038	.041
	(.002)	(.005)	(.001)	(.003)	(.001)	(.002)
1997	.126	.158	.058	.070	.038	.046
	(.002)	(.005)	(.001)	(.003)	(.001)	(.002)
1998	.123	.143	.057	.061	.039	.039
	(.002)	(.005)	(.001)	(.002)	(.001)	(.002)
1999	.112	.142	.052	.060	.035	.039
	(.002)	(.005)	(.001)	(.003)	(.001)	(.002)
2000	.108	.134	.049	.057	.033	.037
	(.002)	(.004)	(.001)	(.002)	(.001)	(.002)
2001	.111	.142	.052	.063	.036	.043
	(.002)	(.004)	(.001)	(.002)	(.001)	(.002)
2002	.116	.142	.055	.062	.038	.041
	(.002)	(.004)	(.001)	(.002)	(.001)	(.002)

Numbers in parentheses are standard errors.

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

Appendix table 2

Spatial-price-adjusted poverty measures, nonmetro-metro comparison, 1991-2002

Year	Headcount		Poverty gap		Squared poverty gap	
	Metro	Nonmetro	Metro	Nonmetro	Metro	Nonmetro
	----P_0 measure----		----P_1 measure----		----P_2 measure----	
1991	0.147	0.125	0.066	0.052	0.042	0.032
	(.002)	(.004)	(.001)	(.002)	(.001)	(.001)
1992	.150	.129	.068	.056	.043	.036
	(.002)	(.004)	(.001)	(.002)	(.001)	(.002)
1993	.157	.132	.072	.056	.046	.035
	(.003)	(.004)	(.001)	(.002)	(.001)	(.002)
1994	.152	.124	.069	.054	.044	.035
	(.003)	(.004)	(.001)	(.002)	(.001)	(.002)
1995	.143	.117	.064	.049	.041	.031
	(.002)	(.004)	(.001)	(.002)	(.001)	(.002)
1996	.141	.122	.063	.051	.041	.032
	(.002)	(.004)	(.001)	(.002)	(.001)	(.002)
1997	.135	.122	.062	.056	.041	.038
	(.002)	(.004)	(.001)	(.002)	(.001)	(.002)
1998	.131	.110	.060	.047	.041	.031
	(.002)	(.004)	(.001)	(.002)	(.001)	(.002)
1999	.121	.105	.055	.046	.037	.032
	(.002)	(.004)	(.001)	(.002)	(.001)	(.002)
2000	.116	.098	.052	.044	.035	.030
	(.002)	(.004)	(.001)	(.002)	(.001)	(.002)
2001	.120	.105	.055	.050	.038	.036
	(.002)	(.003)	(.001)	(.002)	(.001)	(.002)
2002	.125	.105	.058	.049	.040	.034
	(.002)	(.003)	(.001)	(.002)	(.001)	(.001)

Numbers in parentheses are standard errors.

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