How Sensitive is the Geographic Distribution of Poverty to Cost of Living Differences? An Analysis of the Fair Market Rents Index

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Abstract: This paper uses a spatial price index based on the Fair Market Rents (FMRs) data to examine how accounting for cost of living differences across metropolitan and nonmetropolitan areas affects measured rates of poverty. The headcount, poverty gap, and squared poverty gap measures from the Foster-Greer-Thorbecke family of poverty measures provide comparisons of measures that vary in degree of sensitivity to changes in the income distribution of the poor. In every year since the Federal government began tracking poverty, the headcount measure has been higher in nonmetro than metro areas. The metro-nonmetro difference in poverty has been significantly less pronounced when considering the squared poverty gap measure indicating that disproportionately more of the nonmetropolitan poor subsist on incomes near the poverty line. The Fair Market Rents index is approximately 20 percent lower in nonmetro areas than in metro areas and using this index to adjust income for spatial price differences results in a complete reversal of nonmetro-metro poverty rankings over the three measures from 1991 to 2002.

Classification: I32, R1, C81
Key Words: Poverty, Cost of living adjustments, Fair Market Rents data, Urban-Rural Comparison, Sample Design, Current Population Survey

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1. **Introduction**

Estimates of poverty 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. As one example, an 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, and data from the 2003 Current Population Survey indicate that per capita benefits were 39 percent higher in nonmetropolitan (nonmetro) areas than metropolitan (metro) areas of the U.S.[1] As another example, Federal block grants for community development are typically linked to county-level poverty estimates and Reeder (1996, p.1) finds that persistently poor rural counties benefit disproportionately from block grants, receiving more than $1,000 per person in 1994. Finally, Reeder et al. (2001, p.4) show that in 1997, the per capita distribution of Federal funds for social safety net programs was 8 percent higher in nonmetro than metro areas.

It can be cogently argued that this geographic distribution of social welfare assistance is well targeted because 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 (Jolliffe, 2003b). However, this argument is potentially sensitive to the issue that how poverty is defined plays an important role in the geographic distribution of measured poverty, and any changes to the definition of poverty could affect the geographic distribution of poverty and 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). Currently, the official Federal poverty thresholds assume the cost of living is the same over the entire U.S., but the Bureau of Labor Statistics 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 paper is to examine how the use of this index affects the relative distribution of poverty across metro and nonmetro areas of the U.S.

The focus on metro and nonmetro areas is driven largely by the fact that an adjustment for cost of living differences will have the greatest effect on this comparison and also because of the strong historical difference in poverty rates across these areas. Because this paper solely examines how spatial price differences affect poverty rates, it provides information on only one recommendation of the NAS Panel's suggested changes, and it is important to interpret the results with this caveat in mind. Nonetheless, an advantage to this 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 incidence, depth and severity over the entire period considered in this analysis (1991-2002).

[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 Bureaus of Economic Analysis and documents that per capita food stamp benefits were 32 percent greater in nonmetro areas than metro areas during 2001.

This paper adds to the current literature on the reform of the poverty measure in three 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 also 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 incidence of poverty. In this paper, I consider 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. These 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 incidence of poverty. The poverty-gap measure provides a measure of the depth of poverty, and the squared poverty-gap is sensitive to the income distribution of the poor and provides a measure of the severity of poverty.

The final way in which this paper adds to the experimental poverty literature is in terms of methodology. The statistical tests for nonmetro-metro poverty differences are corrected for features of the sample design.[3] Most nationally representative data sets, particularly those from which poverty estimates are formed, are not based on pure random draws from the population, rather they are frequently based on stratified and multi-stage sample designs. As one example, the sample used for the CPS is drawn from a census frame using a stratified, multi-stage design.

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

[3] 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 ½ the median income level). The advantage of the estimates provided in this paper is that they are based on a fixed (or

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 multi-staged, but standard errors are derived from the incorrect assumption of a pure random sample, then the standard errors will significantly under-estimate the true sampling variance. An example from Jolliffe *et al*. (forthcoming) 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 to 212 percent.

The remaining part of this paper proceeds as follows. Section 2 covers poverty measurement issues, which includes a discussion of the Fair Market Rents index, the data, poverty line, poverty measures and the estimates of sampling variance. Section 3 provides a discussion of the results. The primary finding is that without correcting for spatial-price differences, nonmetro poverty is higher than metro poverty. Using the Fair Market Rents index reverses this result during all twelve years examined. Section 4 provides a brief conclusion.

2. Poverty Measurement [4]

2.1 The Fair Market Rents Index

While the data are limited, the evidence suggests that there are significant geographic differences in the cost of living. Up until 1982, the Bureau of Labor Statistics collected data from the Family Budget Program (FPB) 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 there was variation in the cost of purchasing the fixed bundle of goods. For

absolute) poverty line, which is how poverty is measured in the US. Another advantage is that Jolliffe and Semykina (1999) provide a Stata program that estimates the standard errors presented in this paper.

[4] Parts of this section are drawn from Jolliffe (2003b).

example, in urban areas of 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).

Currently, there are some other sources of data on spatial differences in the cost of living, but none of these include both metro and nonmetro regions of the U.S. For example, the Bureau of Labor Statistics has been working on using data from the Consumer Price Index to develop a spatial price index, but these efforts have focused strictly on metropolitan areas (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.[5] The primary shortcoming of this data is that it only provides an estimate of the cost of living in an area if a volunteer has reported data and it is intended to measure differences among urban areas. Further, the ACCRA index is designed to reflect cost of living differences for a professional household and is based on the typically spending patterns of households in the top quintile of income. For the purposes of poverty analysis, this is not a very useful index.

This paper uses the spatial price index currently under consideration in the Bureau of Labor Statistics' experimental poverty measures (Short, 2001a, 2001b) which is based on the Fair Market Rents (FMRs) data collected by the U.S. Department of Housing and Urban Development (HUD).[6] The two primary advantages of these data are that it provides full coverage of the U.S. and reflects spending of lower-income households. HUD produces annual estimates of the Fair Market Rent 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

[5] For an ACCRA example, see Dumond, Hirsch and MacPherson (1999). See Koo, Phillips and Sigalla (2000) for a comparison of a CPI-based and the ACCRA indices.
[6] For a critique of the FMR as a spatial price index, see Short (2001b, Appendix A). For an alternate examination of spatial price differences between metro and nonmetro areas, see Nord (2000).

housing.[7] The purpose of the FMR is to determine the eligibility of rental housing units for the Section 8 Housing Assistance Payments program. Section 8 program participants cannot rent a unit if the rent exceeds the FMR. (FMRs also serve 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 index used in this paper is for 2001 and follows the approach used in Short (2001a, 2001b) of aggregating the county-specific FMRs into 100 different price levels, one for each metro and nonmetro area for all States plus the District of Columbia.[8] The 2001 FMR index is used to adjust poverty estimates over the time period of 1991 to 2002. In future work, I intend to use FMR indices specific to each year; but the 2001 index allows for an initial examination of this issue. Across all years, I've scaled the index to insure that the FMR-adjusted poverty estimates match the national Federal estimates. This scaling simplifies the analysis because any deviation from official estimates will be strictly due to relative price differences across metro and nonmetro areas. Table 1 lists basic descriptive statistics of the FMR index by metro and nonmetro areas. It is striking that this data indicates that FMRs in nonmetro areas are 79 percent of the metro costs. This is the first indication that using this index to adjust for cost-of-living differences is likely to have significant effect in terms of measuring metro-nonmetro poverty differences.

[INSERT TABLE 1 APPROXIMATELY HERE]

[7] From 1995 up to to 2001, the FMR is based solely on the 40th percentile. As of 2001 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.

2.2 The Data: 1992–2003 CPS and the U.S. Poverty Thresholds

The data used in this paper are from the 1992 through 2003 March Supplement to the Current Population Survey (CPS) which is conducted by the Bureau of the Census for the Bureau of Labor Statistics. The CPS data are the basis for the official U.S. poverty estimates and provide information on approximately 50,000 households in each year. 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 to 2003 CPS data provide poverty estimates for 1991 through 2002.

The sample is representative of 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 individuals, so all individuals who are homeless at the time of the interview are excluded from the sample. Estimates of the number of homeless range from a 1990 Bureau of Census estimate of 250,000 to a 1987 Urban Institute estimate of up to 600,000 service-using homeless individuals.[9] The exclusion of homeless persons from the sample frame is noteworthy for poverty analysis as this is a group that has a very high incidence of poverty, and it is noteworthy for a geographic analysis of poverty as homeless persons are disproportionately located in metro areas.[10]

Because the homeless are disproportionately located in metro areas, their exclusion from the sample biases the estimates in the direction of increasing the estimated gap between metro and nonmetro poverty rates. Relative to the population of poor persons (estimated at 33.6 million in

[8] New Jersey and the District of Columbia consist of only metro areas, hence 100 total FMR price levels.
[9] For a discussion of measures of homelessness and potential explanations for the rising incidence, see Quigly *et al.* (2001) and Honig and Filer (1993).
[10] For a discussion of income levels and geographical distribution of homelessness, see Chapters 5 and 13 of Urban Institute (1999).

1990), the homeless population is small and this sample-selection bias will not significantly affect the estimated proportion of persons living in poverty. This statement is tempered though, by noting that the homeless are most likely living in extreme poverty, and their exclusion has a greater impact on the poverty measures that are sensitive to the distribution of income. A primary finding of this paper is that adjusting for cost-of-living differences with the Fair Market Rent index results in a reversal of the nonmetro-metro poverty rankings. If the homeless were included in this analysis, they would further reinforce this finding.

The geographical poverty comparisons considered in this paper are between metro and nonmetro areas. Nonmetro is often referred to as rural, but these terms define different geographic areas.[11] The U.S. Office of Management and Budget, 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; or a county with an urbanized area as defined by Bureau of Census; or a fringe county that is economically tied to a metro area.[12] Nonmetro areas are all areas outside the boundaries of metro areas.

The measure of welfare used in this paper is income as it defined for Federal poverty rates. This definition includes all pre-tax income, but does not include capital gains nor any noncash benefits such as public housing, medicaid, or food stamps. The poverty thresholds used in this paper are the U.S. Federal 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).

[11] Cromartie (2003) shows that 17.4 percent of the population live in nonmetro areas, 21 percent in rural areas. To illustrate the differences in the definitions, 41 percent of all nonmetro residents live in areas that are deemed urban and 13 percent of all metro residents live in areas deemed rural.

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 includes an allowance for nonfood expenditures that was twice the value of the cost of the USDA economy food plan.[13] To account for inflation, the poverty lines set in 1965 are adjusted each year using a price index.[14] The latest poverty line used in this study is from 2002; and it is set at $9,359 for an individual under 65 years of age, $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 listing of 2002 poverty lines for various family sizes, see Proctor and Dalaker (2003, p.4).[15]

2.3 The Foster-Greer-Thorbecke Poverty Measures

The previous section describes the measure of welfare 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, I consider three measures which belong to the FGT family. The first is the headcount measure, (P_0), which is the percentage of the population living in families with family income less than the poverty line. The second measure is the poverty-gap measure, (P_1), defined by 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 counts the nonpoor as having zero poverty gap. The third measure is

[12] For details of the definitions and enacted changes, see U.S. Office of Management and Budget (2000).
[13] For details on the first poverty lines, see Orshansky (1965). For a history of poverty lines prior to Orshansky, see Fisher (1997). For a critical discussion of the official poverty line, see Ruggles (1990).
[14] Prior to 1969, the index used was the changing cost of the USDA economy food plan, and afterwards, the CPI for all goods and services has been used.
[15] The analysis in this paper is based on the full CPS sample, which includes all persons living alone and in families. A family is defined as a group of two or more persons residing together and related by birth, marriage, or adoption. Families also include any related subfamily members, where a subfamily is defined as a married couple with or without children, or a parent with single children under 18 years of age.

the squared poverty-gap measure, (P_2), defined as the mean of the squared proportionate poverty 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 welfare, z is the poverty line, and I is an indicator function which 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 push the poor person over the poverty line. This transfer has no effect on the headcount measure, but the poor person is better off and this welfare improvement is reflected in a reduction of both the poverty-gap and squared poverty-gap measures. 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 measure.[16]

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 frequently stated goal of many programs is the reduction of poverty, but the policies that are appropriate to

[16] 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

attain this goal will vary depending on which poverty measure is considered. If policy makers are focused on the headcount measure, then the most efficient way to reduce poverty is through assistance to the least poor. If, on the other hand, policy makers are concerned about the overall welfare of the poor and not just on reducing the number of persons living in poverty, then the appropriate measure is one that captures the depth and severity of poverty.

2.4 Estimating Standard Errors for FGT Poverty Measures based on CPS Data

In order to answer the question of whether poverty is higher in nonmetro than metro areas, or more generally most any question regarding whether poverty has changed over time or varies over some geographic or demographic characteristic, estimates of the sampling variance for the measures are required. Kakwani (1993) provides two asymptotic estimates for the variance of the FGT poverty measures that are easy to calculate and frequently used. The Kakwani formula for the variance of P_0, the headcount measure, is $P_0(1\text{-}P_0)/(n\text{-}1)$, where n is the sample size. The formula for all other variance estimates of the FGT measures is $(P_{2\alpha} - P_\alpha^2)/(n-1)$. The primary disadvantage of the Kakwani estimates is that they assume the sample was collected using a simple random draw from the population.

As noted in the introduction, using the Kakwani standard errors when the data were collected using a multi-stage sample design, results in a large underestimate of the true sampling variance. The strategy used in this paper 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

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increases in any subgroup, and it does not decrease elsewhere, then aggregate poverty must also increase (Foster and Shorrocks, 1991).

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:

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

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 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:

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

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. Bureau of Census (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 only provided for the headcount measure; there are no corrections provided for any other measures of poverty.[17]

In addition to the issue that Census does not provide sample-design corrections for either the poverty-gap or squared poverty-gap measures, there is the additional problem that the recommended method appears to be significantly less precise for nonmetro-metro comparisons. The proposed correction for all nonmetro statistics provided by U.S. Bureau of Census (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.[18]

Given that the Census-recommended method doesn't 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, I abandon this method. Instead, I follow an approach 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).

[17] Another shortcoming of the Census-recommended method is that corrections are only provided for a limited set of characteristics. For example, U.S. Bureau of Census (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 15 to 24 years of age, the analyst is provided with parameter estimates. If the relevant sub-sample is, say, working-age adults, then Census does not provide the necessary parameters to estimate standard errors.

[18] Personal communication with Census appears to support this 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."

The first step of the synthetic design approach for this analysis of poverty is to sort the data by income.[19] 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. I select the four regions of the U.S. as synthetic strata to capture the geographic aspect of the CPS stratification. Appendix Table 1 provides a summary table from Jolliffe (2003a) illustrating that the synthetic design approach matches the estimates provided by Census for the headcount measure.

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 from above 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:

$$V(P_{\alpha,w}) = \sum_{h=1}^{L} n_h (n_h - 1)^{-1} \sum_{i=1}^{n_h} \left(\sum_{j=1}^{m_{h,i}} w_{h,i,j} \, P_{\alpha,h,i,j} \; - \; \sum_{i=1}^{n_h} \sum_{j=1}^{m_{h,i}} w_{h,i,j} \, P_{\alpha,h,i,j} \right)^2 \qquad (4)$$

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 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_{hi}.[20]

3. Results

3.1 Nonmetro-metro Comparisons of FMR-adjusted Poverty Estimates

[19] The methodology requires sorting the data on the variable most relevant to the analysis.
[20] 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.

Before answering whether nonmetro-metro poverty comparisons are sensitive to spatial price adjustments, it is necessary to establish the baseline for comparison. Appendix Table 2 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 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 people). The metro headcount measure ranges from a high of 0.15 in 1993 (29.5 million people), to a low of 0.11 in 2000, or 24.3 million people living in poverty. The variation in the poverty-gap and squared poverty-gap measures is similar. Across both 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 2 also provides estimates of the design-corrected standard errors, which differentiates this paper from much of the U.S. poverty literature. This table provides 72 poverty estimates (P_0, P_1, and P_2 for each year from 1991 to 2002 by metro and nonmetro areas). For none of the estimates is the design effect 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.[21]

One interpretation of the poverty-gap measure is that it 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. This implies that in 1990 the average shortfall of the poor as a fraction of the poverty line is equal to 40 percent in nonmetro areas and 44 percent in metro areas. In 2002, the average shortfall in nonmetro areas is equal to 44 percent of the poverty line while this shortfall is 47 percent in metro areas. During all twelve 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 there could be differences in the wellbeing of the poor across areas. Figure 1 explores this issue by graphing density estimates of the welfare ratio (sometimes called the income to needs ratio, which is the ratio of income to the poverty threshold).[22] The advantage of welfare ratios over income is that they provide measures of wellbeing that control for demographic differences (and these demographic characteristics may differ across areas).[23] This is because they are a function of the poverty thresholds, which are adjusted to reflect different levels of need for families of various size and age.

Figure 1 provides kernal density estimates of metro and nonmetro welfare ratios for 1992, 1995, 1998, and 2001. For all years, the nonmetro welfare ratio is more peaked near the poverty line indicating that a larger proportion of the nonmetro poor subsist on greater welfare ratios and are therefore 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. One implication of this is that a small change in income, as would be expected from adjusting income for cost-of-living differences is likely to disproportionately affect more nonmetro poor persons than metro persons.

[INSERT FIGURE 1 APPROXIMATELY HERE]

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[21] The largest design effect is 6.1 for the 2001 nonmetro P_1 measure. This means that the corrected standard errors are almost 2½ times greater than what one would estimate if ignoring the sample design.
[22] Blackorby and Donaldson (1987), using this terminology, provide an analysis of welfare ratios as an measure of wellbeing in cost-benefit analysis.
[23] For example, in 1999 the average age of a metro poor person is 28 years, compared to 32 years for the nonmetro poor. In terms of family size, 16 percent of the metro poor live in two-person families compared to 20 percent for the nonmetro poor.

Table 2 synthesizes the poverty estimates from Appendix Tables 2 and 3 for the years 2001 and 2002. The headcount measure for 2001 shows that 14.2 percent of nonmetro residents are poor, compared with 11.1 percent of the metro population. In other words, the nonmetro incidence of poverty is 28 percent greater than the metro rate. This ranking holds for the 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. Table 2 also shows that this pattern continues in 2002. Nonmetro poverty is higher than metro poverty across all three measures, though 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 differences following the Fair Market Rents index. In 2001, the official nonmetro poverty rate of 14.2 percent drops significantly to 10.5 percent when corrected for spatial-price differences. At the same time, the metro poverty rate increases from 11.1 to 12 percent when adjusted following the FMR index. The net effect is that the incidence 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). Table 2 indicates that 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.

[INSERT TABLE 2 APPROXIMATELY HERE]

In order to understand whether this rather striking reversal of the poverty rankings is unique to recent events, I repeat this analysis for all years between 1991 and 2001. Appendix Tables 2

and 3 provide all of the poverty estimates for these years. Panel A of Figure 2 plots the nonmetro-metro percentage differences for the three poverty measures. [24] This panel readily indicates that over all years between 1991 and 2001, all three of the poverty measures indicate that nonmetro poverty is greater than metro poverty.[25] Panel B plots these same differences, but for poverty measures that have been adjusted with the FMR index. This panel reveals that the 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 more than 15 percent less than the price-adjusted metro estimates.

[INSERT FIGURE 2 APPROXIMATELY HERE]

The analysis presented in Panel B of Figure 2 is based on using the 2001 FMR index for all years, which is clearly not the proper strategy. As I revise this report, I aim to obtain or construct a time series of the FMR data so that I can estimate the price-adjusted poverty measures with the matching price index. Nonetheless, a cursory look at the early FMR data files suggests that the results are not likely to be qualitatively much different. To assess this, I examined 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 those reported in Table 1 because they have not been population weighted, but significant temporal variation in the estimates would

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

[25] 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, P0 indicates a much greater nonmetro-metro difference in poverty than does P_1 and P_2.

suggest that the findings in Table 2 could be sensitive. Over the fourteen years examined, the nonmetro mean FMR was between 68 and 77 percent of the metro mean FMR.

3.2 Brief Demographic Examination of 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 disabled and retired while the metro poor are more likely to be going to school. This difference suggests that there are differences in the age structure of the poor in metro and nonmetro areas. Figure 3 provides some support to this 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 above the metro age distribution as age increases (and below for younger ages). There are disproportionately more poor persons over the age of 40 in nonmetro areas than in metro areas (and similarly, disproportionately more of the metro poor are under 40).

While Table 2 indicates that the FMR-adjusted poverty rates produce a stark reversal of the relative rates of nonmetro and metro poverty, table 3 indicates 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. Adjusting for cost of living differences with the FMR reduces the average age of the nonmetro poor by almost 2 years, eliminating the difference in average ages.

[INSERT FIGURE 3APPROXIMATELY HERE]

[INSERT TABLE 3 APPROXIMATELY HERE]

Figures 4a and 4b explore this issue in more detail by plotting the age distribution of the nonmetro poor in 2001 and 2002. In both figures, the nonmetro age distribution is plotted for

those who are poor following the Federal definition and also using the FMR-adjusted rates. In both years, the FMR-adjusted age distribution lies below the age distribution of the poor at ages greater than 60 years and above for ages less than about 25 years. These figures indicate that the FMR adjustments appear to be re-classifying disproportionately more of the nonmetro elderly as not poor.

[INSERT FIGURE 4a APPROXIMATELY HERE]

[INSERT TABLE 4b APPROXIMATELY HERE]

3.3 Extension: Examining a Modified FMR Index

The decision to use the FMR index is primarily based on three considerations. First, these data are available while there are no other data available on spatial price differences. Second, these data reflect prices paid by lower-income households and are therefore appropriate for poverty analysis. Third, expenditure on housing is a significant expenditure of the poor. Bureau of Labor Statistics (2003, Table 1) indicates that expenditure on housing comprises 36 percent of total expenditure for the poorest quintile of the population.

Nonetheless, using FMR data to index total cost of living differences implicitly assumes that the variation in rental prices reflect variation in the prices of other goods and services consumed by the poor. Moulton (1995, p.182) notes that 'interarea variation in cost of shelter tends to be larger than interarea variation in prices of other commodities and services" which would suggest that the FMR index may tend to overstate area differences in the cost of living.

To address this concern, I consider a modification to the FMR index where the only variation in prices is in housing; prices of all other goods and services consumed by the poor are assumed

not to vary across the U.S. Specifically, I weight the FMR index by one third, reflecting the approximate expenditure share on housing of the poor. For example, if the FMR index indicates that the cost of living in a particular area is 9 percent higher than the baseline, then the modified FMR index would indicate that the cost of living in this area is only 3 percent higher than the baseline. The net effect of this modification is to markedly compress the spatial variation in prices with the aim of presenting a lower bound index.[26]

Figure 5 indicates that weighting the FMR index by one third largely negates the complete reversal of poverty rankings. Under the modified FMR index, the prevalence of poverty during the 1990s and early 2000s was greater in nonmetro areas, though the nonmetro-metro difference was not statistically significant in 5 of the last 12 years. The figure also shows that when considering the depth and severity of poverty, metro poverty was greater than nonmetro poverty during the early to mid-1990s; and then the reverse was true in the late-1990s and early 2000s. In terms of statistical significance, once income is adjusted by the modified FMR index, there are no statistically significant differences in the severity of nonmetro and metro poverty (and only two years of statistically significant differences in the depth of poverty).

[INSERT FIGURE 5 APPROXIMATELY HERE]

4. Conclusion

The prevalence of poverty has been greater in nonmetro than 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

[26] The assertion that the modified index is a lower bound excludes the possibility that the prices of other goods and services are inversely related to rental prices. In other words, it assumes that high rent areas are also somewhat higher in the prices of other goods.

is currently examining experimental poverty measures that, among other changes, adjust poverty rates for spatial cost of living differences. Currently 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 paper 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 stark and complete reversal of the nonmetro-metro poverty profile. With no adjustment for cost of living differences, the prevalence of poverty is higher in nonmetro than metro poverty over the last 12 years. (The depth and severity of poverty are also higher in nonmetro areas, but in about 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 than 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.

Holding the national poverty rate fixed, the 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 population, 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 re-identifying many of these 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 these elderly people are receiving Federal funds that are 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 potentially have significant adverse affects on funding for nonmetro social safety nets and developmental block grants.

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Table 1: Scaled Fair Market Rent Index, Nonmetro-metro Comparison (new)

Fair Market Rent Index	Average	Median	(Min, Max)
National	1.00	1.00	(0.74, 1.21)
Nonmetropolitan	0.82	0.81	(0.74, 1.21)
Metropolitan	1.04	1.02	(0.85, 1.19)

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

Table 2: 2001 & 2002 Poverty Measures, Nonmetro-metro Comparison

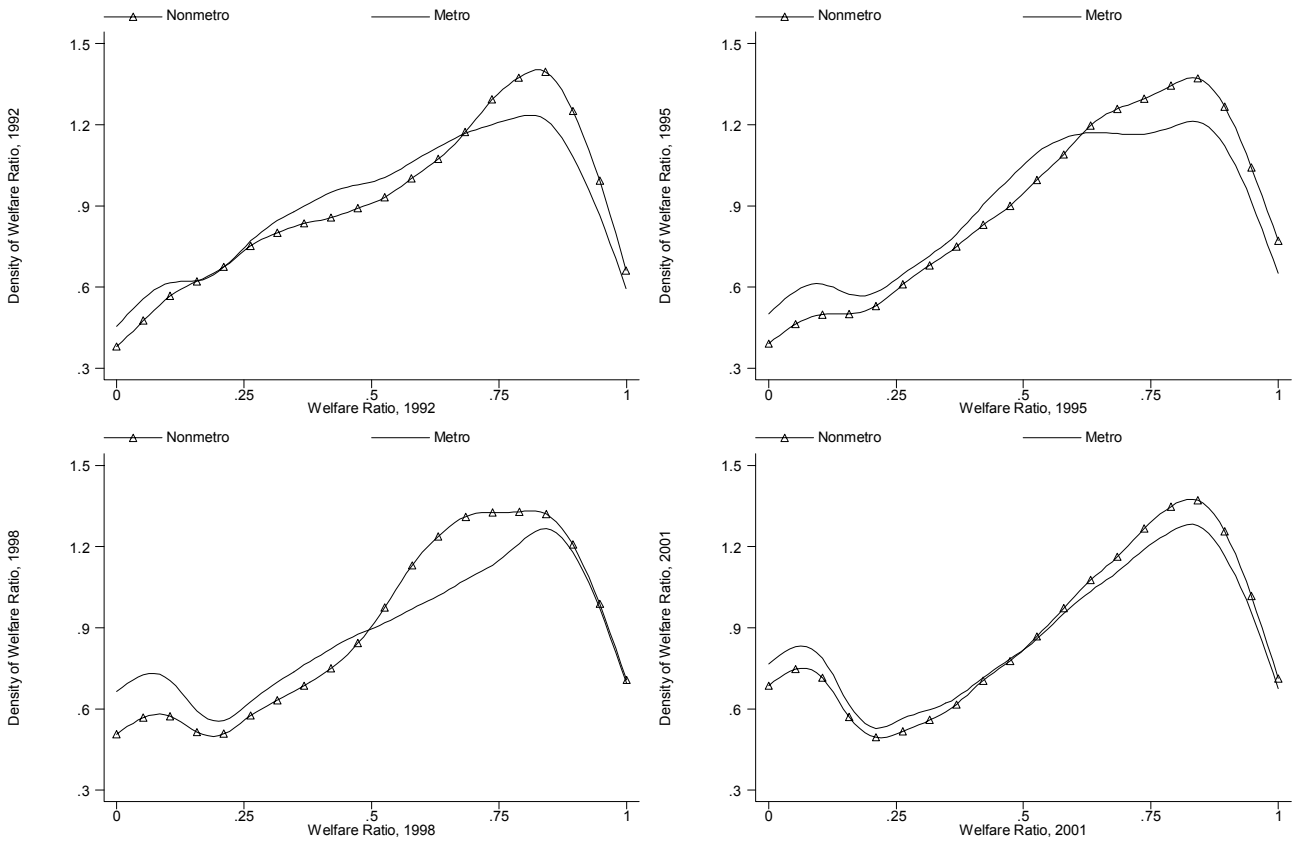
	Headcount, P_0 Measure		Poverty-gap, P_1 Measure		Squared Poverty-gap, P_2 Measure	
	Actual	**FMR adjusted**	**Actual**	**FMR adjusted**	**Actual**	**FMR adjusted**
2001						
Nonmetro	0.142	0.105	0.063	0.050	0.043	0.036
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Metro	0.111	0.120	0.052	0.055	0.036	0.038
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Nonmetro-Metro	28%	-12%	21%	-9%	18%	-5%
Difference	(3.80)	(3.01)	(4.71)	(3.97)	(5.64)	(4.97)
2002						
Nonmetro	0.142	0.105	0.062	0.049	0.041	0.034
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Metro	0.116	0.125	0.055	0.058	0.038	0.040
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Nonmetro-Metro	22%	-15%	13%	-16%	8%	-14%
Difference	(3.55)	(2.76)	(4.06)	(3.33)	(4.73)	(4.11)

Notes: Poverty measures are the Foster-Greer-Thorbecke P_α measures. FMR adjusted 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) using the program described in Jolliffe and Semykina (1999). Standard errors for the differences are second-order approximations by the delta method.

Table 3: Average Age of the Poor by Area

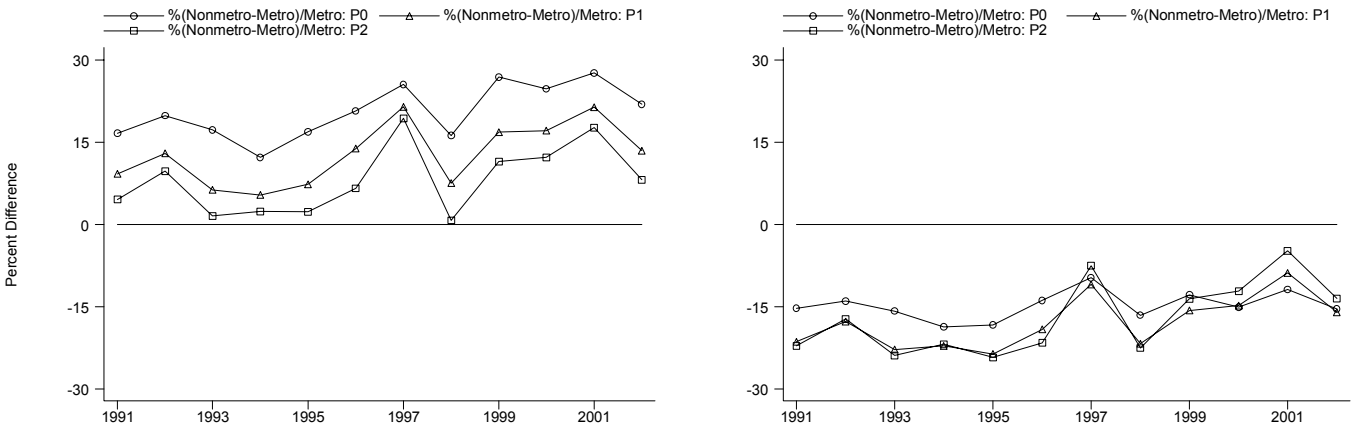
	2001		*2002*	
	Metro	*Nonmetro*	*Metro*	*Nonmetro*
Poor	29.75	32.27	30.20	32.00
	(0.257)	(0.506)	(0.252)	(0.484)
FMR Poor	30.08	30.59	30.40	30.25
	(0.252)	(0.561)	(0.245)	(0.516)

Notes: Age in years of the poor by metro and nonmetro residence. FMR poor are those designated as poor after adjusting income with the Fair Market Rent index. Standard errors corrected for complex design following Jolliffe (2003a).



Notes: Kernal density estimates of metro and nonmetro welfare ratios (income divided by the poverty line) are for 1992 (upper left panel), 1995 (upper right panel), 1998 (lower left panel) and 2001 (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.

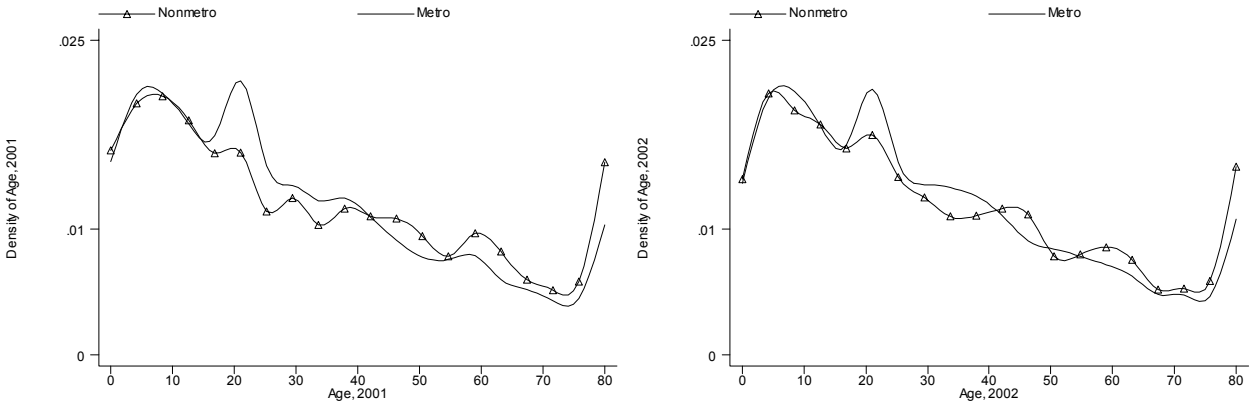
Figure 1: Welfare Ratios of the Poor from 1992 to 2001 by Area



Panel A: P_α Differences (No adjustment) *Panel B: P_α Differences (FMR adjusted)*

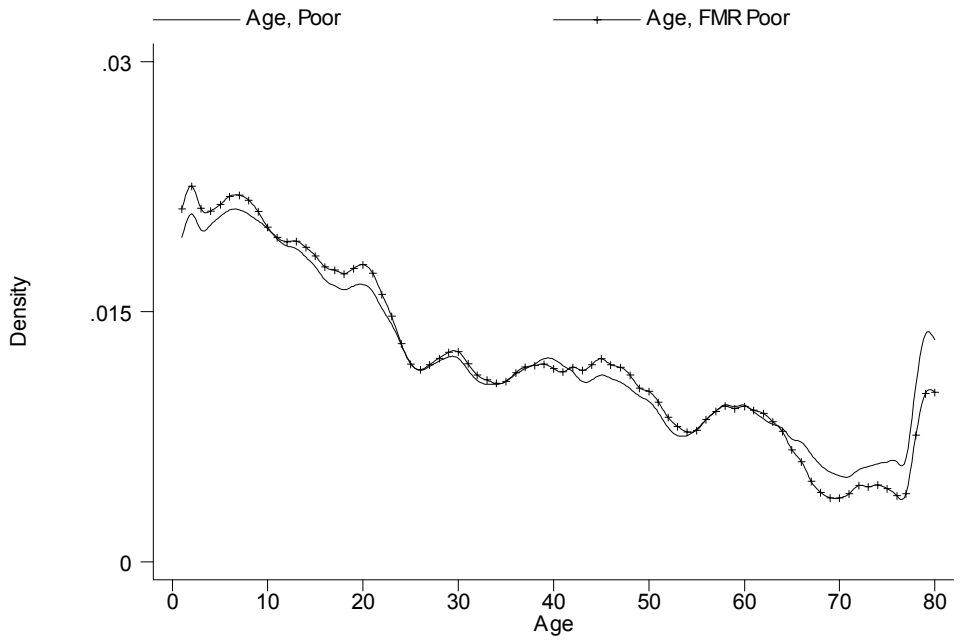
Notes: In the left panel, the 'Pα' lines plot the difference between nonmetro and metro poverty as measured by P_0, P_1 and P_2 using metro poverty as the base, or $[(P\alpha_{nonmetro} - P\alpha_{metro})/ P\alpha_{metro}]$. In the right panel, the 'Pα' lines are adjusted using the Fair Market Rent index to correct for geographic differences in prices.

Figure 2: Nonmetro-Metro Poverty Differences from 1991 to 2002



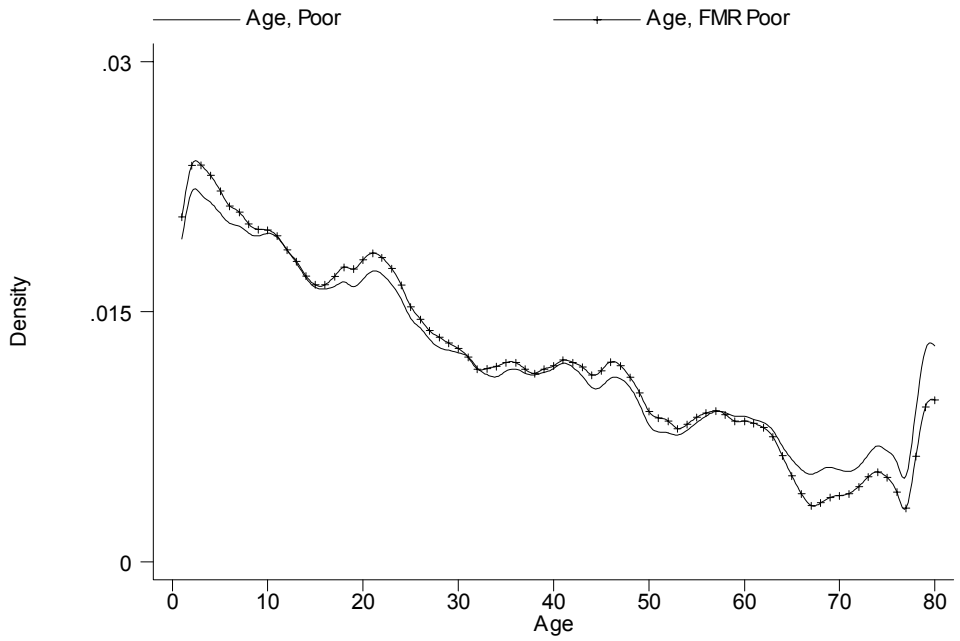
Notes: Kernal density estimates of age in years for metro and nonmetro poor persons. Panel on left-hand side is the age density of the poor in 2001, and the right hand side is age density in 2002. The Epanechnikov kernal is used with a smoothing parameter set to 1.

Figure 3: Age Distribution of the Poor by Area, 2001 and 2002



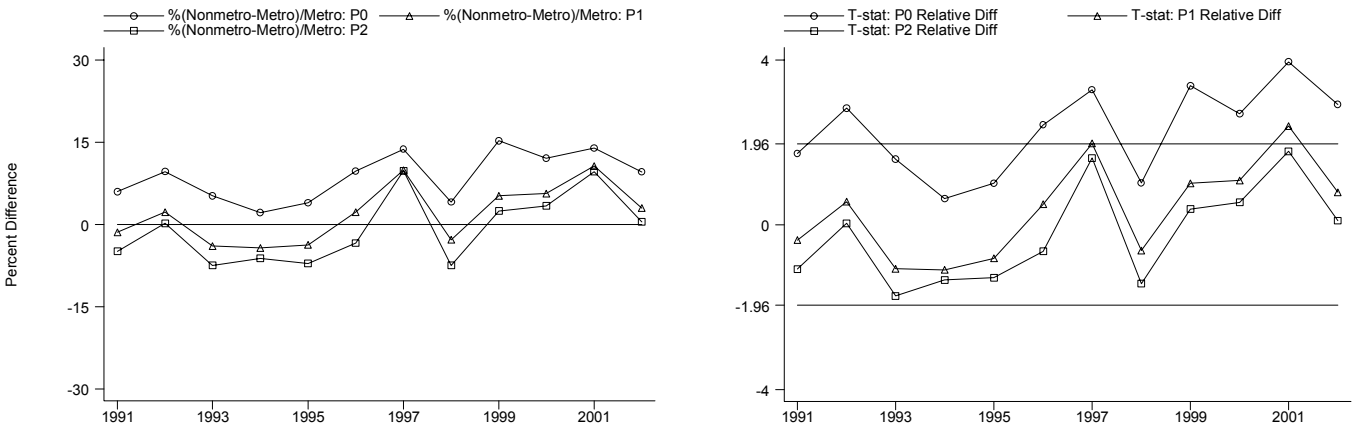
Notes: Kernal density estimates of age in years for nonmetro poor persons. The unmarked line is the age density for those nonmetro residents who were poor in 2001. The marked line is the age density for those nonmetro residents who are identified as poor using the Fair Market Rent index. The Epanechnikov kernal is used for both estimates with a smoothing parameter set to 1.2.

Figure 4a: Age distribution of the Nonmetro Poor in 2001, Comparing Poverty Population with the FMR Poverty Population



Notes: Kernal density estimates of age in years for nonmetro poor persons. The unmarked line is the age density for those nonmetro residents who were poor in 2002. The marked line is the age density for those nonmetro residents who are identified as poor using the Fair Market Rent index. The Epanechnikov kernal is used for both estimates with a smoothing parameter set to 1.2.

Figure 4b: Age distribution of the Nonmetro Poor in 2002, Comparing Poverty Population with the FMR Poverty Population



Panel A: P_α Differences (1/3 FMR adjustment) *Panel B: T-stats of P_α Differences*

Notes: In the left panel, the 'Pα' lines plot the COLA-adjusted difference between nonmetro and metro poverty as measured by P_0, P_1 and P_2 using metro poverty as the base, or $[(P\alpha_{nonmetro} - P\alpha_{metro})/ P\alpha_{metro}]$. The COLA adjustment weights the fair market rent index by 1/3 and assumes that there are no price differences in all other purchases. In the right panel, the lines plot t-statistics of the test for whether the nonmetro-metro difference is statistically significant.

Figure 5: Nonmetro-Metro Poverty Differences, 1/3 FMR adjusted

Appendix Table 1: Comparing 90% Confidence Intervals resulting from Synthetic-Design and Census-Recommended Correction
1999 CPS Headcount Poverty Measures

Characteristics	Ratio Or Percent Poor	Estimated 90% Confidence Intervals						
		Direct and Implied Estimates from the P-60 Report						
		Reported Table A	Implied by Levels	a,b Percentage	a,b Ratio	Match a,b Categories	**Synthetic Design**	Random Sample
Family Status								
Persons	11.8	0.3	0.33	**0.33**	*	yes	0.33	0.16
Persons in Families	10.2	0.3	0.34	0.34	*	no	0.36	0.17
White	9.8	0.3	0.34	**0.33**	*	yes	0.31	0.16
Black	23.6	1.2	1.20	**1.20**	*	yes	1.24	0.66
Under 18	16.9	0.7	0.65	**0.65**	0.66	yes/no	0.64	0.37
18-64 years	10.0	0.3	0.39	**0.39**	*	no	0.30	0.20
65 years +	9.7	0.5	0.53	**0.53**	0.53	yes	0.53	0.43
Families, Total	9.3	0.3	0.33	0.28	**0.34**	yes	0.32	0.29
Total	9.3	0.3	0.33	0.28	**0.34**	yes	0.32	0.29

Source: Jolliffe (2001).
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 bold estimate marks whether Census considers the estimate a percentage or ratio. The next column lists whether there is a direct match in characteristics between the poverty estimates and those characteristics assigned a,b coefficients. The estimates from the synthetic cluster approached are listed next, followed by the confidence intervals from assuming that the data are from a weighted, simple random sample.

Appendix Table 2: Incidence, Depth and Severity of Poverty, Nonmetro-metro Comparison from 1991-2002

	Headcount, P_0 Measure		Poverty-gap, P_1 Measure		Squared Poverty-gap, P_2 Measure	
Year	**Metro**	**Nonmetro**	**Metro**	**Nonmetro**	**Metro**	**Nonmetro**
1991	0.137	0.160	0.061	0.067	0.039	0.041
	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)
1992	0.139	0.167	0.063	0.071	0.040	0.044
	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)
1993	0.146	0.171	0.067	0.072	0.043	0.044
	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)
1994	0.141	0.159	0.065	0.068	0.042	0.043
	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)
1995	0.134	0.156	0.060	0.064	0.039	0.039
	(0.002)	(0.005)	(0.001)	(0.003)	(0.001)	(0.002)
1996	0.132	0.159	0.059	0.067	0.038	0.041
	(0.002)	(0.005)	(0.001)	(0.003)	(0.001)	(0.002)
1997	0.126	0.158	0.058	0.070	0.038	0.046
	(0.002)	(0.005)	(0.001)	(0.003)	(0.001)	(0.002)
1998	0.123	0.143	0.057	0.061	0.039	0.039
	(0.002)	(0.005)	(0.001)	(0.002)	(0.001)	(0.002)
1999	0.112	0.142	0.052	0.060	0.035	0.039
	(0.002)	(0.005)	(0.001)	(0.003)	(0.001)	(0.002)
2000	0.108	0.134	0.049	0.057	0.033	0.037
	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)
2001	0.111	0.142	0.052	0.063	0.036	0.043
	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)
2002	0.116	0.142	0.055	0.062	0.038	0.041
	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)

Notes: Poverty measures are the Foster-Greer-Thorbecke P_α measures. 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).

Appendix Table 3: Spatial-price Adjusted Poverty Measures, Nonmetro-metro Comparison from 1991-2002

	Headcount, P_0 Measure		Poverty-gap, P_1 Measure		Squared Poverty-gap, P_2 Measure	
Year	**Metro**	**Nonmetro**	**Metro**	**Nonmetro**	**Metro**	**Nonmetro**
1991	0.147	0.125	0.066	0.052	0.042	0.032
	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)	(0.001)
1992	0.150	0.129	0.068	0.056	0.043	0.036
	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)
1993	0.157	0.132	0.072	0.056	0.046	0.035
	(0.003)	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)
1994	0.152	0.124	0.069	0.054	0.044	0.035
	(0.003)	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)
1995	0.143	0.117	0.064	0.049	0.041	0.031
	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)
1996	0.141	0.122	0.063	0.051	0.041	0.032
	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)
1997	0.135	0.122	0.062	0.056	0.041	0.038
	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)
1998	0.131	0.110	0.060	0.047	0.041	0.031
	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)
1999	0.121	0.105	0.055	0.046	0.037	0.032
	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)
2000	0.116	0.098	0.052	0.044	0.035	0.030
	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)
2001	0.120	0.105	0.055	0.050	0.038	0.036
	(0.002)	(0.003)	(0.001)	(0.002)	(0.001)	(0.002)
2002	0.125	0.105	0.058	0.049	0.040	0.034
	(0.002)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)

Notes: Poverty measures are the Foster-Greer-Thorbecke P_α measures. 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).