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Why is U.S. Poverty Higher in Nonmetropolitan than Metropolitan Areas? Evidence from the Panel Study of Income Dynamics

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Abstract

In the United States, low-income people are not evenly distributed across the rural-urban landscape. Does this phenomenon *partly* reflect that people who "choose" to live in rural areas have unmeasured attributes related to poverty? To address this question, I use data from nine waves of the Panel Study of Income Dynamics (PSID) to track economic well-being and rural/urban residential choice among a sample of 6,461 householders. A series of multivariate regression models are estimated in which the dependent variable is a householder's income to need and explanatory variables are individual attributes and place-level factors, including whether the county of residence is nonmetropolitan (nonmetro). First I estimate an ordinary least squares (OLS) model which excludes educational attainment variables. I then estimate an OLS model with controls for education. Finally, I estimate an individual fixed-effects regression model that controls for observed education and unobserved income capacity. I find that the effect on income to need of living in a nonmetro area is reduced substantially as more stringent controls for individual heterogeneity are implemented. Specifically, the first regression shows that nonmetro householders have income to need that is 26 percent lower than metro householders. The fixed-effects specification, by contrast, indicates a rural-urban gap in economic well-being of only 7 percent. Taken together, results suggest that one explanation for the higher incidence of poverty in rural than urban areas is that people with personal attributes associated with having low income tend to sort themselves into rural places.

Keywords: rural; poverty; residential mobility; omitted variable bias

Why is U.S. Poverty Higher in Nonmetropolitan than Metropolitan Areas? Evidence from the Panel Study of Income Dynamics

Introduction

In the United States, low-income people are not evenly distributed across the rural-urban landscape. Poverty rates have long been higher in nonmetropolitan (nonmetro) than metropolitan (metro) counties.[1] Detailed data starting in the 1960s, when the United States embarked on a War on Poverty and official measurement of poverty commenced, are shown in Figure 1. Today, one in twenty metro counties and one in five remote nonmetro counties is classified as a high poverty county, having a poverty rate of 20 percent or higher. And persistent poverty counties—those having poverty rates of 20 percent or more in each decennial census between 1960 and 2000—are overwhelmingly rural, less populated, and more remote (see Figure 2). Multivariate statistical analyses further document a rural welfare disadvantage. Extant research shows that the odds of being poor are between 1.2 to 2.3 times higher for people residing in nonmetro compared with metro areas, controlling for individual/family characteristics and, in a few analyses, local context variables (see Weber et al. forthcoming, for a review).

Why is poverty higher in rural than urban areas? One view, the "structural condition hypothesis," ascribes a causal role to place of residence. By this view, otherwise identical individuals will have lower economic well-being in rural compared to urban settings due to the spatial distribution of economic and social opportunities (Tickamyer and Duncan 1990; Tomaskovic-Devey 1987). A second view, the "residential sorting hypothesis," argues that

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[1] The terms "nonmetro" and "rural" are used interchangeably in this paper to refer to counties outside of metropolitan areas.

rural-urban differences in poverty incidence arise because poor people tend to sort themselves into rural communities. From this perspective, individuals with similar levels of human capital will have the same prospects for economic prosperity independent of where they live.

The rural poverty literature has emphasized the structural condition hypothesis. Data indeed confirm that local rural labor markets generally offer fewer job options, and work tends to be concentrated in minimum wage and part-time jobs offering limited security and room for advancement (Gibbs 2001; McKernan et al. 2001). Job access also poses challenges to economic prosperity in rural areas. Recent work in Fresno County, California, for example, documents the challenges faced by remote-rural welfare participants in finding work, due to the spatial mismatch between place of residence and employment center location (Blumenberg and Shiki forthcoming). Moreover, work supports such as job training programs, formal group child care, and public transportation, which are essential for securing and retaining work, tend to be limited or completely absent in rural communities (Colker and Dewees 2000; Fletcher et al. 2002).

Social-context variables, such as community capacity, local social norms and networks, and the power and motivations of local government, also influence the geographic distribution of poverty (Blank 2004; Weber et al. forthcoming). Duncan's (1999) fieldwork in rural communities of Appalachia and the Mississippi Delta, for example, reveals a rigid two-class system in which the relatively well-off have taken advantage of the local social structure to maintain their privileged position and keep the poor marginalized. Rupasingha and Goetz (2003) use principal components analysis to develop a county-based social capital index, combining measures of associational density (e.g. civic associations and religious organizations), political involvement, and response rate to the decennial Census. They find that nonmetro counties with high social capital have lower family poverty rates, all else being equal. In sum, a key explanation for enduring rural poverty is that the local context of many rural areas makes it hard for people to succeed economically.

This article explores the residential sorting hypothesis of rural-urban differences in economic well-being. I ask whether the disproportionate poverty observed in nonmetro communities *partly* reflects that people with personal characteristics that are related to human impoverishment are attracted to rural places, or are otherwise reluctant (or unable) to leave them. The paper does not aim to disprove the structural condition argument. Instead, by investigating a largely overlooked yet plausible explanation for rural poverty, I complement a large literature that documents the role of social and economic context in explaining persistent rural poverty. Certainly a problem as enduring as poverty has numerous causes.

There is some research in support of the residential sorting hypothesis. Nord (1998) uses 1990 Census data to examine the effect on the geographic distribution of poverty of county-to-county migration of the poor and the nonpoor. He finds that more poor people moved into than out of persistent poverty nonmetro counties during the analysis period (1985-1990), a pattern that reinforced the pre-existing spatial concentration of poverty. More recently, Fisher (2004) uses Panel Study of Income Dynamics (PSID) data to examine whether current estimates of the effect of nonmetro residence on poverty are biased because place of residence is a choice variable not an exogenous factor as is commonly assumed. Using instrumental variables estimation to account for possible endogeneity of rural residence, she finds that living in a rural area has no relationship with the risk of being poor. This result provides some evidence that people with characteristics associated with poverty sort themselves into rural localities. Fitchen's (1995) in-depth interviews with low-income families in upstate New York tells a similar story. Her case study community, a rural area facing economic decline, was a migration destination for poor urban families, despite limited employment opportunities.

The findings of existing work beg the following question: Why would people with low income capacity "choose" to live in rural communities? Low out-migration of the poor relative to the non-poor from struggling rural areas is consistent with human capital theories of migration (Sjaastad 1962). But why would people with a higher propensity to be poor choose to move to struggling rural areas? It is conceivable that individuals with low educational attainment and limited work experience are drawn to places that offer opportunities that match their own skills and needs, for example communities that have a high share of entry-level positions and where living costs are relatively low (Nord 1998). Low-skill occupations continue to make up a higher percentage of total jobs in rural areas (42 percent) than in the nation as a whole (35.5 percent) (Gibbs, Kusmin, and Cromartie 2004). Fair Market Rents data show that housing costs in nonmetro counties are 79 percent of those in metro counties (Jolliffe 2004). And evidence suggests that overall living costs are substantially lower in nonmetro than metro areas (Kurre 2003; Nord 2000). Fitchen's (1995) interviews with poor urban migrants, described above, reveals that the main attraction of her case study community was its inexpensive rental housing. Finally, rural places may be attractive to people with low earning-capacity due to possibilities for informal work. Studies document a range of informal employment activities that help the poor weather income shortfalls in rural communities (Fitchen 1981; Jensen, Cornwell, and Findeis 1995); and in some regions, such work features more prominently in the livelihood strategies of rural compared with urban residents (Tickamyer and Wood 1998).

In this article I use data from nine waves of the Panel Study of Income Dynamics (PSID) to track economic well-being and rural/urban residential choice among a sample of householders.

A series of multivariate regression models are estimated to examine the degree to which the sorting into rural areas of people with low income capacity explains rural-urban differences in economic well-being. The present paper complements existing work in several ways. It is the first to employ panel data to examine the effect of residential selection on the spatial distribution of poverty; Fisher (2004) and Nord (1998) relied on static snapshots of the population from cross-sectional and retrospective data. The study also uses Fair Market Rents data to account for cost-of-living differences across metro and nonmetro areas. Analysts agree that adjusting for geographic differences in living costs is critical for obtaining an accurate picture of poverty across regions of the country, but researchers rarely make such adjustment (exceptions are Jolliffe 2004 and Ulimwengu and Kraybill 2004). Finally, the current study contributes to the rural poverty literature by offering another empirical point in a rather scant literature that asks if the higher risk of poverty in rural versus urban areas *partly* reflects a concentration in rural places of people with low income capacity. The answer to this question has important consequences for future research on rural poverty and for anti-poverty policy design.

Modeling Poverty across Place

Empirical studies that examine how place of residence affects poverty can be classified into two types: community studies and contextual studies (Weber et al. forthcoming). Community studies use data at the community level (e.g. census tract, county, labor market area) to examine geographic differences in poverty (e.g. Leichenko 2003; Levernier, Partridge, and Rickman 2000; Lobao, Rulli, and Brown 1999; Rupasingha and Goetz 2003). Contextual studies, such as the present one, examine how individual factors and community social and economic characteristics affect the well-being of individuals and families. In the contextual-effects literature, the standard approach to studying the association between rural/urban residence and economic well-being involves multivariate statistical analysis of an equation of the form

$$y_i = \alpha_0 + \alpha_1 x_i + \alpha_2 n_i + \alpha_3 c_i + \varepsilon_i \,. \qquad (1)$$

In equation 1, i indexes individuals or households and dependent variable y is a measure of well-being such as poverty, income to need, or underemployment. Explanatory variables include a set of individual characteristics $\boldsymbol{x}$ (e.g. age, race, gender, and education of the household head; family structure) and a binary or categorical variable n indicating whether the county of residence is nonmetro. In some studies, analysts also control for additional place-level variables, here denoted $\boldsymbol{c}$, for example region of residence or county unemployment rate (e.g. Brown and Hirschl 1995; Cotter 2002; Haynie and Gorman 1999). Since economic well-being is typically defined in income terms, and the bulk of household income comes from wages, explanatory variables are largely those that determine labor market outcomes. Finally, ε in equation 1 is a random error term assumed uncorrelated with the regressors.

A key interest of rural poverty scholars is to learn through empirical analysis whether individual outcomes are affected by rural living. That is, is there a “rural effect”? A large literature has explored this question, using data from nationally-representative surveys to estimate the relationship between rural residence and well-being for versions of the poverty model in equation 1. Existing work documents a statistically significant negative association between nonmetro residence and economic well-being, controlling for individual and contextual factors. Compared with their urban counterparts, rural people have lower income to need, and have a higher risk of being underemployed and poor (Brown and Hirschl 1995; Brown and Lichter 2004; Cotter 2002; Haynie and Gorman 1999; Jensen et al. 1999; Snyder and McLaughlin 2004; Thompson and McDowell 1994).

The well-documented finding of higher poverty risk in rural localities begs the following question: Is rural living somehow bad for economic well-being, or do poor people tend to sort themselves into rural places, or are both explanations valid? The conventional wisdom is that there is something about rural places that makes it harder for people to succeed economically. People's decisions about where to live should also influence the geographic distribution of poverty, but this contention has received limited attention in the rural poverty literature (Weber et al. forthcoming). The central hypothesis of the present study is that the higher risk of poverty in rural places *partly* reflects a concentration in rural areas of people with characteristics associated with human impoverishment.

To investigate the study hypothesis, I employ an empirical strategy similar to that used by Glaeser and Maré (2001) who examined whether the observed wage premium in large cities reflects that "more-able" workers choose to live in cities. I estimate, for comparative purposes, a series of multivariate regression models that are versions of equation 1 above. The dependent variable in these models is a continuous measure of household income to need, where income is before-tax money income and need is the Census Bureau's family-size conditioned poverty threshold. Explanatory variables are individual-level factors (including the number of household members and presence of a young child in the household, as well as the householder's age, race, gender, marital status, education, and current employment status) and contextual variables (county unemployment rate and binary variables for region and metro/nonmetro residence).

First I estimate an ordinary least squares (OLS) model which excludes some observed measures of human capital, specifically educational attainment variables. I then estimate an OLS model that controls for educational attainment. Finally, I exploit the longitudinal nature of the data, estimating an individual fixed-effects regression model that controls for unobserved income capacity (at least those attributes which are individual specific and time invariant).[2] The logic of the empirical strategy is as follows: If people with a higher propensity to be poor tend to sort themselves into rural areas (either by remaining in a rural area or by moving to one), then imposing controls for personal attributes related to having low income should reduce the absolute value of the (negative) rural effect considerably.

The empirical approach I propose amounts to an examination of the omitted variable bias that occurs when a researcher omits from equation 1 key factors that are associated both with economic well-being and with nonmetro residence. There are two components of bias: (1) the "true" effect on income to need of the omitted variable(s) and (2) the correlation between rural residence and the excluded variable(s) (see Jargowsky 2005 for an excellent mathematical exposition of omitted variable bias). If the bias components are either both positive or both negative in sign, then the estimated negative effect of rural residence on the income-to-need ratio will be understated. If bias components have opposite signs, then the measured negative rural effect on income to need will be overstated.

The first bias component is expected to be positive in sign if human capital characteristics are the omitted variables. Empirical work indicates that the average rate of return to another year of schooling in the United States is around 10 percent (see Psacharopoulos and Patrinos 2004 for a review). Research also suggests that cognitive ability, as measured by IQ-type tests such as the

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[2] Fixed-effects models are commonly used to analyze panel data. In this specification, individual-varying, time-invariant (e.g. gender or "motivation") and time-varying, individual-invariant (e.g. interest rates) omitted variables are assumed to be constant and enter as binary variables in the regression equation (Hsiao 1986).

Armed Forces Qualifying Test or GED examination scores, is a determinant of labor market earnings (Cawley et al. 1997; Tyler, Murnane, and Willett 2000). Furthermore, there is evidence that personality and noncognitive traits such industriousness, motivation, habits, and work attitudes are predictors of wages (see Bowles, Gintis, and Osborne 2001 for a review). For example, Dunifon and Duncan (1998) found that future earnings are higher for young men having an orientation toward challenge and a sense of personal control.

As for the second bias component, the correlation between omitted variables and place of residence, there is only limited evidence. Data from the 2000 Census indicate a metro-nonmetro gap in educational attainment, which is especially pronounced for college completion: 26.6 percent of metro people and 15.5 percent of nonmetro people aged 25 and over have a college degree. To my knowledge, however, there is no evidence that other income capacity traits are unevenly distributed across the rural-urban landscape. It is the correlation between income capability and place of residence that is of primary interest in this study, because it provides an indication of whether people with a higher propensity to be poor tend to sort themselves into rural areas, either by staying in a rural area or by moving to one. The sign of this correlation is indeterminate a priori, but insights are gained through the following experiments.

One experiment is to compare the coefficient on the nonmetro residence binary variable from regressions of income to need on nonmetro residence that, first, exclude and, then, include human capital variables. Hypothesis 1: There is a concentration in rural areas of people with low educational attainment. Support for this hypothesis is a finding that introduction of controls for individual educational attainment causes the estimated rural effect to become smaller in absolute value, because such a finding suggests a negative correlation between educational attainment and rural residence. This is the first testable hypothesis.

A second experiment is to introduce controls for unmeasured income capacity and see what happens to the nonmetro binary coefficient. If controls for unobserved, time-invariant income capability are introduced via a fixed-effects specification, the estimated rural effect may remain unchanged, increase in absolute value, or decrease in absolute value. This suggests a second testable hypothesis. Hypothesis 2: There is a concentration in rural areas of people with unobserved individual attributes associated with having low income. Evidence in support of this hypothesis comes from a finding that an individual fixed-effects specification has the effect of reducing the absolute value of the nonmetro binary point estimate. If the estimated rural effect gets smaller in absolute value, this indicates that the two bias components are of opposite sign. Thus unmeasured individual attributes that are positively (negatively) associated with income to need are negatively (positively) correlated with nonmetro residence. Below I test the study's hypotheses after a discussion of the sources of data used for the analyses.

Data Description

The main source of data for this study is the Panel Study of Income Dynamics (PSID), a longitudinal survey that has followed a representative sample of about 5,000 families and their descendents since 1968 (see Brown, Duncan, and Stafford 1996 and Hill 1992 for detailed descriptions of the PSID). The PSID family and individual files contain data on a wide range of topics including family structure and demographics, socio-economic background, geographic mobility, employment, earnings, income, wealth, welfare participation, housework time, health, and food security. Due to the enormous value of nationally-representative longitudinal data on economic and social issues, the PSID is one of the most widely used datasets in the world. The

PSID dataset is particularly useful for the analyses of this paper because it provides, for public use, information on nonmetro/metro residence for certain years.[3]

The study's analyses focus on nine waves of the PSID, covering the period 1985-1993. I select this analysis period because it is the only continuous period for which a variable indicating nonmetro/metro residence is available in the PSID. In the PSID, this information is provided for the years 1985-1993, 1999, 2001, and 2003. The household head is the appropriate unit of analysis for this study for two key reasons. First, economic well-being is measured at the household level in the United States. Ideally, therefore, one should track households over time. However, it is difficult to arrive at a satisfactory definition of a "longitudinal household" since household composition changes considerably even over short periods (see Duncan and Hill 1985 for a detailed discussion). The household head should serve as a good proxy for the household since the bulk of household income is earned by householders. A second reason for choosing the householder as the analysis unit is that the PSID provides the most comprehensive information for these household members.

In order to assemble a sample suitable for empirical analysis, it is necessary to impose several selection criteria. To retain as large a sample as possible and avoid reducing the sample to a highly selective one, I allow the number of householders to vary across years; that is, my panel of householders is an unbalanced one. It is necessary, however, that sample householders

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[3] The main national surveys used for poverty research are the PSID, the Current Population Survey (CPS), the Survey of Income and Program Participation (SIPP), the National Longitudinal Survey of Youth (NLSY), and the National Survey of America's Families (NSAF). The CPS, similar to the PSID, provides public-use access to data on metro/nonmetro residence.

have at least two years of observations so that controls for individual heterogeneity can be imposed. Other important selection criteria are as follows: For each analysis year, individual householders only enter my sample if they resided in the United States, were part of responding households, and have complete data for all analysis variables. The constructed sample consists of 6,461 individuals who were household heads in 1993 and at least one other year during the period 1985 and 1993. The average number of years that sample householders make it into the sample is eight. The total sample size is 49,095 person-years.

An important question is whether imposing the sample selection rules introduces sample selection bias. Table 1, provides descriptive statistics for the analysis variables for all 1993 PSID responding households and for the sub-sample. Note that sampling weights and variables identifying stratum and sampling error computation units are used to take account of the PSID sampling design and differential attrition, and to approximate nationally-representative estimates. The test statistics shown in the last column of the table enable hypothesis testing for differences in means or differences in proportions. At a 0.05 significance level, we can reject the null hypothesis that means/proportions are the same for the full sample and the sub-sample in the case of three of the 28 analysis variables: race, marital status, and age. The sub-sample appears to differ from the full sample, over-representing individuals whose main race is white and those who are married, and the sub-sample householders are slightly older than those in the full sample. This should be kept in mind in the interpretation of results in later sections of the paper.

The dependent variable for this study is income to need adjusted for spatial housing cost differences. Adjustment is made using U.S. Department of Housing and Urban Development Fair Market Rents (FMR) data, as has been recommended by the National Academy of Sciences

Panel on Poverty and Family Assistance (Citro and Michael 1996).[4] Accounting for regional variations in prices is a critical step in obtaining an accurate picture of rural-urban differences in economic well-being. Studies show that living costs are considerably lower in nonmetro than in metro areas, suggesting that current poverty estimates overstate hardship in rural locations and understate it in urban places (Kurre 2003; Nord 2000). While income to need should be adjusted for overall cost-of-living differences across metro and nonmetro areas and across regions or states, data for such purpose are currently unavailable (Citro and Michael 1996).

The FMR data provide estimates of the cost of gross rent (including utilities) for a two-bedroom apartment at the 45th percentile of the county or metro area Census division. Data are available for 354 metro areas and 2,305 nonmetro counties from 1983 to the present. It is necessary to collapse the county-specific FMRs into fewer groups, because the PSID public-use data do not contain county identifiers for respondents due to confidentiality concerns. Following Jolliffe (2004) and Short (2001), I aggregate the county-specific FMRs into 100 different price levels. For each state there is one index for metro counties and one for nonmetro counties (except New Jersey which has only metro counties), and there is a separate index for the District of Columbia. Spatial housing price indices are compiled in this manner for each analysis year.

Figure 3, which shows FMRs for metro and nonmetro aggregates for 1985-1999, makes clear the need to adjust the income-to-need measure for spatial housing cost differences. I use the housing price indices to adjust 25 percent of a household's need threshold, this is the average percentage of total household expenditures that are spent on housing and utilities according to

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[4] For discussion of the rationale for using FMR data, see Citro and Michael (1996). For discussion of some shortcomings of using FMR data for living cost adjustment see Short (2001).

data from the Consumer Expenditure Survey. Thus, I assume that costs for non-housing items like transportation, food, and clothing are, on balance, the same in nonmetro and metro areas. Some analysts studying rural-urban differences in poverty have instead used housing costs as a proxy for overall living costs (e.g. Jolliffe 2004; Ulimwengu and Kraybill 2004). The latter approach is inappropriate if other household expenditure items are more expensive in nonmetro than metro areas, which is possible. For example, a national survey of 376 supermarkets and 2,002 small groceries found that households in rural areas face food prices that are 4 percent higher than the prices faced by urban households (Mantovani and Daft 1996).

Results

Regression results for three specifications are shown in Table 2. The first two models treat the data as a cross section and differ on whether educational attainment variables are excluded or included. The third specification exploits the panel nature of the data; it is an individual fixed-effects model of income to need. In fixed-effects models, time-invariant variables are not included because they are collinear with the person-specific constant terms. Thus, results for gender, race, and educational attainment (for the PSID this information was only collected once during the 1985-1993 period) are not provided for Model 3. The adjusted R-squared values reported at the bottom of Table 2 indicate that the models fit the data quite well, and that adding controls for educational attainment and unobserved individual heterogeneity improves model fit considerably. The calculated F-statistics are significant at the 95% confidence level, providing support for the hypothesis of joint significance of the explanatory variables. At standard test levels, most of the point estimates are individually significant at the

95% confidence level.[5] While the magnitudes of variable coefficients differ across specifications, the signs of the point estimates are the same. In addition, the set of statistically significant variables is roughly the same; the exception is that the number of regional binary variables that are statistically significant is reduced in the regressions with more controls.

The signs of parameter estimates in Table 2 are consistent with prior research. Coefficients for the variables age and age squared in Model 1 indicate that age of the household head is positively correlated with income to need until the householder reaches the age of 57 years, at which point the correlation becomes negative. The turnaround point for Models 2 and 3 is 65 years and 46 years, respectively. Results show that householders who are female and whose main race is not white have lower economic well-being, all else being equal. Consistent with economic theory and empirical evidence, results for Model 2 indicate that education strongly influences economic well-being. For example, evaluated at the sample average for income to need of 3.67, householders with a college degree have an income-to-need ratio that is 70 percent higher than householders who did not complete high school. Employed individuals have higher economic well-being than their counterparts who are unemployed, out of the labor force, retired, or disabled.

Consistent with other research, marriage is found to be positively correlated with economic well-being. Findings also show that households with more members and with a young child present have lower income to need. Turning to the contextual variables, results suggest that householders who live in New England have higher economic well-being than householders

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[5] Standard errors reported in Table 2 and Table 3 use the Huber/White heteroskedasticity-consistent estimator of variance (Huber 1967; White 1980).

residing in other regions of the country. The county unemployment rate, which reflects work opportunities in a given county, has an expected negative correlation with income to need. Three other contextual studies of rural poverty have included a variable for the county unemployment rate (Brown and Hirschl 1995; Cotter 2002; Haynie and Gorman 1999). In all studies the county unemployment rate has a positive correlation with poverty probability, although the point estimate is statistically significant only in the study of Haynie and Gorman (1999).

I turn now to the study's two hypotheses. The first hypothesis is that householders with low educational attainment tend to sort themselves into rural areas. One way to test this hypothesis is through change in the coefficient on nonmetro residence when controls for educational attainment are introduced, that is compare Models 1 and 2 in Table 2. Model 1 shows a point estimate of –0.97 for nonmetro residence. Evaluated at the sample average for income to need which is 3.67, this result indicates that a householder living in a nonmetro area has income to need that is 26 percent lower than a similar household head residing in a metro area. This gap in economic well-being between rural and urban residents is substantial, especially when one considers that the income-to-need measure has been adjusted for spatial housing price differences. Model 2, which adds controls for householder educational attainment, shows that income to need is 18 percent lower for householders in nonmetro compared with metro areas. Thus, controlling for householder education does not eliminate the urban income premium, but it reduces it by about a third. In tandem, results for Models 1 and 2 suggest that one reason economic well-being is lower in rural compared with urban areas is that there is a relative concentration of people with low educational attainment in rural places.

The second study hypothesis is that people with unobserved attributes related to having low income tend to sort themselves into rural localities. Model 3 controls for unobserved income capacity (at least that which is time invariant), by including individual constant terms for each householder. If unobserved income capability is negatively correlated with rural residence, then controlling for individual heterogeneity should reduce the absolute value of the nonmetro coefficient. Referring to results for Model 3, the urban income premium is in fact reduced substantially with the introduction of individual fixed-effects. The nonmetro coefficient suggests that a householder living in a rural area has income to need that is 7 percent lower than a similar householder residing in an urban place. Overall, the empirical findings suggest a concentration in rural places of people with low educational attainment and with unobserved attributes related to human impoverishment, and this is one reason that the incidence of poverty is higher in nonmetro than metro America.

I turn now to model specifications which exploit more fully the panel nature of the data, allowing different residential changes to have different effects on income to need. This methodology is similar to that of Freeman (1984) who studied the wage premium of union workers. I substitute for the nonmetro binary variable a set of categorical variables indicating types of moves (nonmetro to metro or metro to nonmetro) and types of stays (remained in a nonmetro area or remained in a metro area). During the analysis period, there were 369 metro-to-nonmetro moves and 367 nonmetro-to-metro moves. Using the parameter estimates from the categorical residential mobility variables, one can answer two separate questions: (1) What happens to the economic well-being of an urban householder who moves to a rural place compared with the well-being of a similar urban householder who stays in an urban place? (2) What happens to rural householders who move to an urban area compared to those who remain in a rural area?

Results for three specifications are presented in Table 3. Again the models successively introduce controls for individual heterogeneity. Model 1 shows that urban-to-rural migrants see their income-to-need ratio fall by 24 percent (the coefficient divided by average income to need) immediately after such a move. This effect changes considerably with controls for householder educational attainment and unobservables. Model 3 shows that urban-to-rural migrants have income to need that is 11 percent lower than comparable individuals who remain in urban places.

What happens to the economic well-being of nonmetro householders who move to a metro county compared with those who remain in a nonmetro county? Referring to Table 3, coefficients for the move/stay variables change substantially as more stringent controls for individual heterogeneity are added. In Model 1, all else being equal, a householder who stays in a nonmetro area has income to need that is 8 percent lower than a migrant to a metro county. This figure is the difference between the "stayed in a nonmetro area" and the "nonmetro to metro move" coefficients, divided by the sample average income to need. The urban income premium essentially disappears when individual fixed-effects are considered. The "stayed in a nonmetro" and "nonmetro to metro move" point estimates are statistically significant at the 0.10 probability level in Model 3, and together suggest that, compared with a householder who remains in a rural place, a migrant to an urban area sees only a small rise in income to need (0.3 percent).

In summary, regression results show that introducing controls for educational attainment and individual, time-invariant heterogeneity has the effect of reducing the rural-urban gap in economic well-being considerably, although the disparity is not eliminated. Thus, the sorting of the poor into rural areas is only a partial explanation for the higher risk of poverty in rural areas, but an apparently important one. One question that emerges from the study findings is why urban householders with low income capacity have a tendency to move to rural places, given that such a move is expected to reduce income to need. Table 4, which shows reasons for moves for sample householders who made metro-nonmetro or nonmetro-metro moves during the analysis period, provides possible clues. For the analysis period, householders who moved from an urban to a rural area were more likely than householders making moves in the reverse direction to report consumption-side reasons for the move; this difference is statistically significant at the 90 percent confidence level. These consumption-related reasons for moving include to be able to purchase a home, to live in a better neighborhood, and to pay lower rent. In short, rural living may be associated with somewhat lower economic well-being, as measured by income to need, but it may offer an overall better quality of life for some.

Conclusion and Policy Implications

In this article I used data from nine waves of the Panel Study of Income Dynamics (PSID) to test the hypothesis that the higher incidence of poverty in rural compared with urban America is *partly* explained by a sorting into rural areas of people with personal characteristics that are associated with human impoverishment. Empirical support for the study's hypothesis comes from a series of multivariate regression models in which the dependent variable is a householder's income to need and explanatory variables are individual characteristics and place-level factors, including whether the county of residence is nonmetropolitan. Results show that introducing controls for personal attributes related to having low income has the effect of reducing the absolute value of the rural effect considerably. Specifically, a base regression model that excludes controls for householder educational attainment and for unobserved individual heterogeneity shows that nonmetro householders have income to need that is 26 percent lower than metro householders. By contrast, a regression model that controls for householder education and for unmeasured income capacity via an individual fixed-effects specification shows a rural-urban gap in economic well-being of only 7 percent.

The study's findings appear to suggest that there is a higher concentration in rural areas of people with characteristics related to having low income, and this phenomenon *partly* explains the higher incidence of poverty in rural than urban America. Fisher (2004) reached a similar conclusion using an instrumental variables estimation approach and PSID data. And Nord (2000), using 1990 Census data, showed that between 1985-1990 more poor people moved into than out of persistent nonmetro poverty counties, a pattern that reinforced the geographic distribution of poverty. Finally, Fitchen's (1995) in-depth interviews with low-income families in upstate New York found that a rural area facing economic decline was a migration destination for poor urban families. In short, the evidence is accumulating that people's decisions about where to live have implications for the geographic distribution of poverty.

Extant research stimulates a number questions that warrant investigation. First, why do people with low income capacity choose rural living? Are the poor drawn to rural places because of lower living costs, possibilities for self-employment, quality-of-life factors, or availability of entry-level work? A second question is whether the finding that people with low income capability choose rural residence is robust across regions of the country and for rural areas with varying characteristics (e.g. high versus low amenity counties and remote-rural places versus rural areas adjacent to metro areas). A key drawback of my analysis is the implicit assumption that rural places are homogenous. As articulated by Miller, Farmer, and Clarke (1994, page 3), "If you've seen one rural community, you've seen one rural community.... Thus, to speak of a singular rural America is folly."

Finally, place-level factors not accounted for in this paper, such as a community's level of social capital, the mix of jobs, and availability of work supports, have been shown to play important roles in the geographic distribution of poverty (e.g. Cotter 2002; Rupasingha and Goetz 2003). To assess the relative importance of place-level and individual-level factors in a longitudinal framework is an important area for future research on rural poverty; doing so requires access to confidential data with identification codes for respondents' place of residence. Future empirical work can improve the design of anti-poverty policy, providing insights on the combination of human-capital and community-strengthening policies that are most likely to reduce rural poverty and its unfavorable consequences.

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Table 1

Descriptive Statistics of Analysis Variables, Full-Sample and Sub-Sample of PSID Householders in 1993

	Full Sample		Sub-Sample [a]		Test statistic [c]
	Mean or Frequency [b]	Standard Error [b]	Mean or Frequency [b]	Standard Error [b]	
Income-to-need ratio adjusted for spatial cost-of-housing differences	4.244	0.143	4.308	0.147	-0.315
Householder characteristics					
Age (years)	46.596	0.317	47.536	0.328	-2.060
Female	0.324	0.010	0.309	0.010	1.948
Main race is white	0.828	0.014	0.850	0.015	-3.795
Educational attainment (less than high school is reference category)					
High school degree	0.358	0.010	0.365	0.011	-0.902
Some college	0.201	0.007	0.208	0.008	-0.983
College degree	0.240	0.010	0.242	0.011	-0.314
Work status (employed is reference)					
Unemployed	0.050	0.004	0.044	0.004	1.776
Out of labor force	0.052	0.005	0.047	0.004	1.350
Retired	0.182	0.006	0.193	0.007	-1.676
Disabled	0.033	0.003	0.029	0.003	1.138
Family structure					
Head is married	0.492	0.012	0.514	0.013	-2.772
Household size	2.449	0.026	2.436	0.030	0.341
Young child in family	0.162	0.007	0.152	0.007	1.746
Place characteristics					
Region (New England is reference)					
Pacific	0.141	0.016	0.132	0.018	1.568
Mountain	0.049	0.008	0.047	0.008	0.774
West North Central	0.100	0.027	0.102	0.027	-0.595

West South Central	0.089	0.012	0.086	0.013	0.667
East North Central	0.174	0.021	0.180	0.020	-0.839
East South Central	0.069	0.015	0.072	0.016	-0.680
South Atlantic	0.171	0.021	0.174	0.023	-0.555
Middle Atlantic	0.158	0.020	0.157	0.020	0.131
County unemployment rate (%)	6.261	0.101	6.210	0.105	0.353
Nonmetropolitan county	0.227	0.014	0.236	0.015	-1.312
Number of observations [d]		9,915		6,461	

a. The sub-sample consists of 1993 householders who were household heads in at least one other year between 1985 and 1992. Other selection criteria are as follows: For each analysis year, individual householders only enter the sub-sample if they resided in the United States, were part of responding households, and have complete data for all analysis variables.
b. Means and standard errors are obtained using Stata's "svymean" command. The means are weighted by the PSID combined sample individual weight. To account for the stratified and clustered design of the PSID sampling procedure, standard errors are calculated using PSID stratum and sampling error computation units.
c. The critical value (α = 0.05) for the z-statistic (differences in proportions) and t-statistic (differences in means) is 1.96. The critical value (α = 0.10) for the z-statistic (differences in proportions) and t-statistic (differences in means) is 1.65.
d. For the full sample, the number of observations used to calculate summary statistics is less than 9,915 for certain explanatory variables (race, educational attainment, work status, region, county unemployment rate, and nonmetropolitan county) due to missing values.

Table 2

Regression Results for Householder Income to Need

	Model 1: OLS without controls		Model 2: OLS with education controls		Model 3: Fixed-effects specification	
	Coefficient [a]	Stand. Error [b]	Coefficient [a]	Stand. Error [b]	Coefficient [a]	Stand. Error [b]
Constant	1.063*	0.183	0.092	0.179	2.534*	1.068
Householder characteristics						
Age (years)	0.173*	0.006	0.136*	0.005	0.111*	0.030
Age squared	-0.002*	0.0001	-0.001*	0.0001	-0.001*	0.0002
Female [c]	-0.916*	0.048	-0.869*	0.046		
Main race is white [c]	1.212*	0.031	0.789*	0.029		
Education (less than high school) [c]						
High school degree			0.616*	0.027		
Some college			1.285*	0.037		
College degree			3.024*	0.060		
Work status (employed)						
Unemployed	-1.670*	0.040	-1.333*	0.040	-0.652*	0.034
Out of labor force	-1.469*	0.040	-1.130*	0.039	-0.870*	0.045
Retired	-2.017*	0.070	-1.796*	0.066	-1.099*	0.082
Disabled	-2.555*	0.049	-1.971*	0.045	-0.890*	0.056
Family structure						
Head is married	1.123*	0.055	0.967*	0.053	0.145*	0.061
Household size	-0.390*	0.012	-0.323*	0.012	-0.232*	0.017
Young child in family	-0.355*	0.037	-0.423*	0.036	-0.255*	0.033
Place characteristics						
Region (New England)						
Pacific	-0.335*	0.139	-0.046	0.136	-0.247	0.254
Mountain	-0.689*	0.163	-0.380*	0.158	-0.296	0.266
West North Central	-0.838*	0.138	-0.484*	0.134	-0.090	0.275
West South Central	-0.850*	0.131	-0.454*	0.126	-0.270	0.266

East North Central	-0.382*	0.132	0.078	0.128	-0.231	0.253
East South Central	-0.839*	0.133	-0.359*	0.129	-0.222	0.261
South Atlantic	-0.673*	0.132	-0.132	0.128	-0.124	0.242
Middle Atlantic	-0.401*	0.138	-0.012	0.134	0.026	0.245
County unemployment rate	-0.077*	0.007	-0.051*	0.007	-0.044*	0.013
Nonmetropolitan county	-0.974*	0.033	-0.663*	0.032	-0.248*	0.062
Number of observations		49,095		49,095		49,095
Adjusted R-squared		0.22		0.28		0.68
F-statistic [d]		554.43		589.01		51.40

a. * indicates statistical significance at the 0.05 probability level or better. Not shown in the table are parameter estimates for binary variables indicating the analysis year.
b. Standard errors reported in the table are Huber/White robust standard errors.
c. Variables that are time-invariant are automatically dropped in the fixed-effects specification due to collinearity. PSID householders were asked about educational attainment only once from 1985-1993.
d. For all models the F-statistic has a critical value of 1.46 at the 0.05 probability level.

Table 3

Regression Results for Changes in Householder Income to Need with Moves across Rural and Urban Places

	Model 1: OLS without controls		Model 2: OLS with education controls		Model 3: Fixed-effects specification	
	Coefficient [a]	Stand. Error [b]	Coefficient [a]	Stand. Error [b]	Coefficient [a]	Stand. Error [b]
Constant	1.131*	0.192	0.192	0.187	2.617*	1.131
Householder characteristics						
Age (years)	0.173*	0.006	0.134*	0.005	0.111*	0.033
Age squared	-0.002*	0.0001	-0.001*	0.0001	-0.001*	0.0002
Female [c]	-0.917*	0.051	-0.875*	0.050		
Main race is white [c]	1.223*	0.033	0.792*	0.031		
Education (less than high school) [c]						
High school degree			0.608*	0.029		
Some college			1.296*	0.040		
College degree			3.083*	0.064		
Work status (employed)						
Unemployed	-1.671*	0.043	-1.328*	0.042	-0.624*	0.036
Out of labor force	-1.495*	0.043	-1.139*	0.042	-0.840*	0.049
Retired	-2.050*	0.074	-1.820*	0.070	-1.040*	0.090
Disabled	-2.575*	0.052	-1.984*	0.047	-0.848*	0.061
Family structure						
Head is married	1.122*	0.058	0.960*	0.057	0.096	0.065
Household size	-0.390*	0.013	-0.323*	0.012	-0.209*	0.019
Young child in family	-0.339*	0.040	-0.405*	0.039	-0.256*	0.036
Place characteristics						
Region (New England)						
Pacific	-0.334*	0.142	-0.033	0.139	-0.360	0.290
Mountain	-0.687*	0.170	-0.367*	0.165	-0.439	0.306
West North Central	-0.817*	0.142	-0.454*	0.137	-0.326	0.309
West South Central	-0.871*	0.133	-0.461*	0.128	-0.524	0.306

East North Central	-0.387*	0.134	0.087	0.130	-0.378	0.285
East South Central	-0.849*	0.136	-0.356*	0.131	-0.349	0.292
South Atlantic	-0.668*	0.134	-0.116	0.130	-0.210	0.276
Middle Atlantic	-0.400*	0.141	0.002	0.137	-0.080	0.280
County unemployment rate	-0.079*	0.007	-0.052*	0.007	-0.041*	0.013
Type of move or stay (stayed in metro area)						
Metro to nonmetro move	-0.883*	0.108	-0.775*	0.100	-0.416*	0.091
Stayed in a nonmetro area	-0.974*	0.036	-0.647*	0.035	-0.145*	0.065
Nonmetro to metro move	-0.670*	0.110	-0.680*	0.106	-0.134	0.078
Number of observations		44,651		44,651		44,651
Adjusted R-squared		0.22		0.28		0.69
F-statistic [d]		483.67		519.14		36.12

a. * indicates statistical significance at the 0.05 probability level or better. Not shown in the table are parameter estimates for binary variables indicating the analysis year.
b. Standard errors reported in the table are Huber/White robust standard errors.
c. Variables that are time-invariant are automatically dropped in the fixed-effects specification due to collinearity. PSID householders were asked about educational attainment only once from 1985-1993.
d. For all models the F-statistic has a critical value of 1.46 at the 0.05 probability level.

Table 4

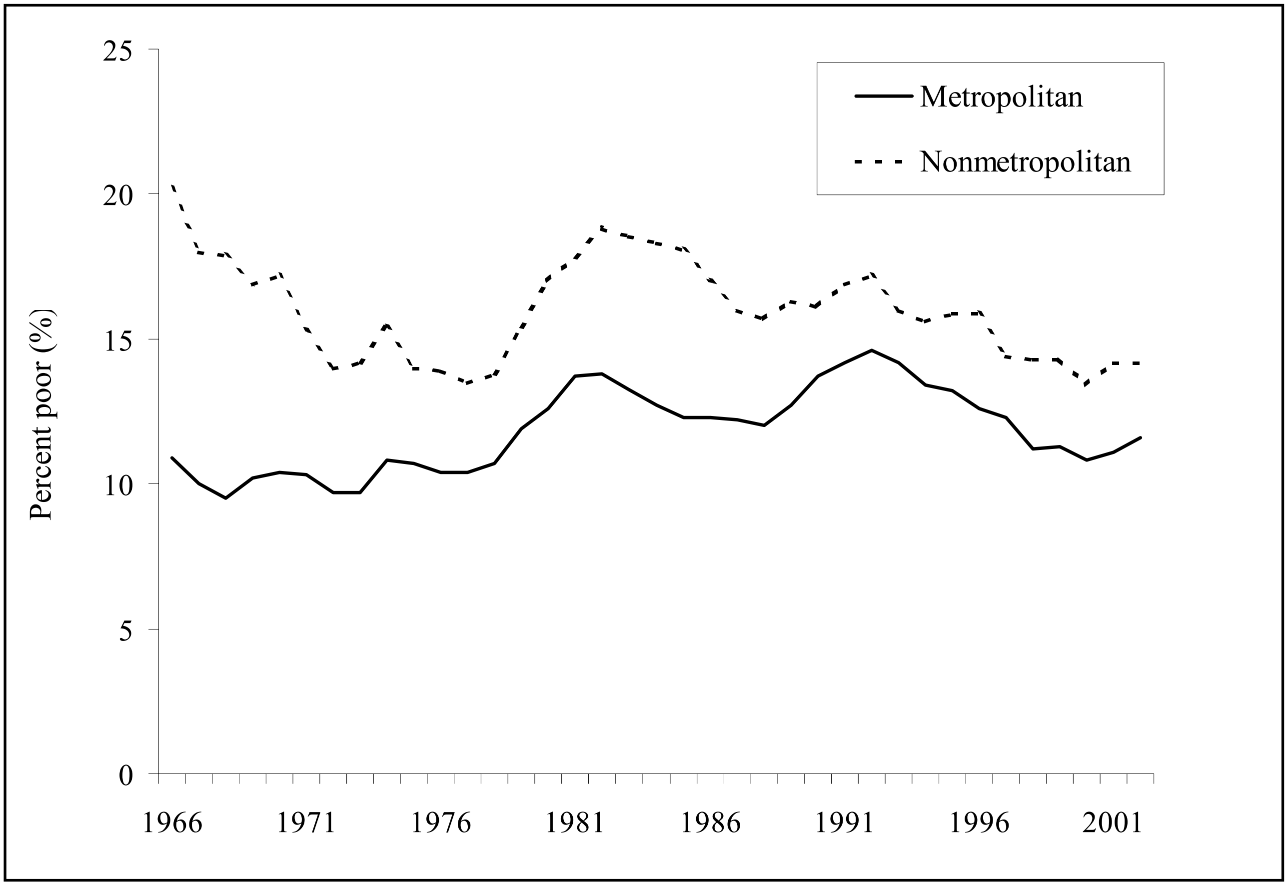
Reported Reasons for Move, by Type: 1985-1993

Reason Moved	Type of Move [a]		Test
	Metro-Nonmetro	Nonmetro-Metro	statistic [b]
Purposive production-related (%) [c]	22.94	27.20	1.3337
Purposive consumption-related (%) [d]	32.29	26.70	-1.6638
Involuntary move (%) [e]	14.96	16.37	0.5263
Other or not available (%)	29.80	29.72	-0.0230
Number of observations	369	367	

a. Percentages are obtained using Stata's "svyprop" command. The percentages are weighted by the PSID combined sample individual weight. To account for the stratified and clustered design of the PSID sampling procedure, standard errors are calculated using PSID stratum and sampling error computation units.
b. Critical values for the z-statistic (differences in proportions) are 1.96 (α = 0.05) and 1.65 (α = 0.10).
c. Reasons for moving include: to take another job, job transfer, to be closer to work, or stopped going to school.
d. Reasons for moving include: expansion or contraction of housing, better neighborhood, lower rent, or want to own house.
e. Response to outside events such as eviction, armed services, health related.

Figure 1

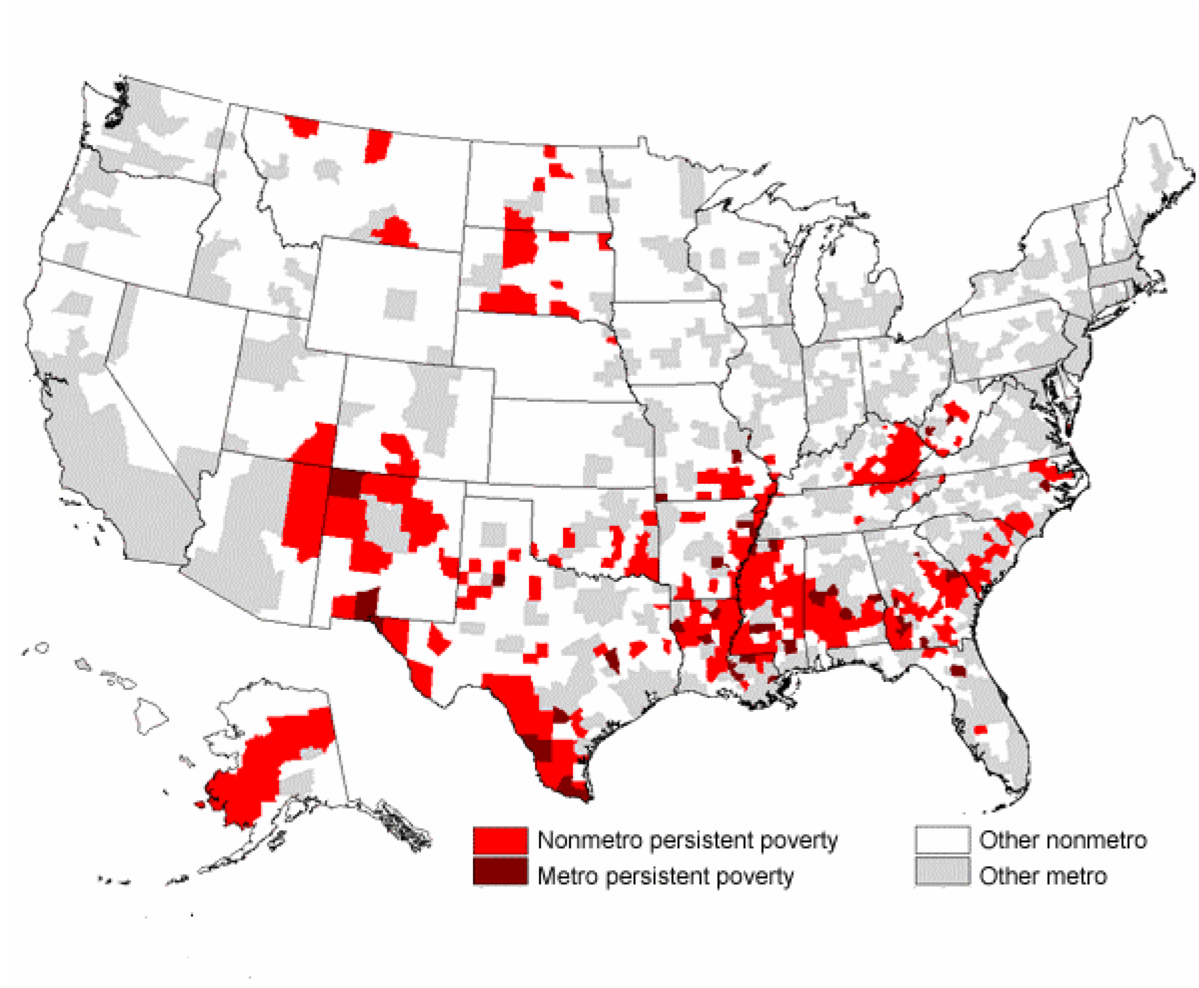
People in Poverty by Residence, 1966-2002



Source: U.S. Bureau of the Census, Current Population Survey, annual March Supplement.

Figure 2

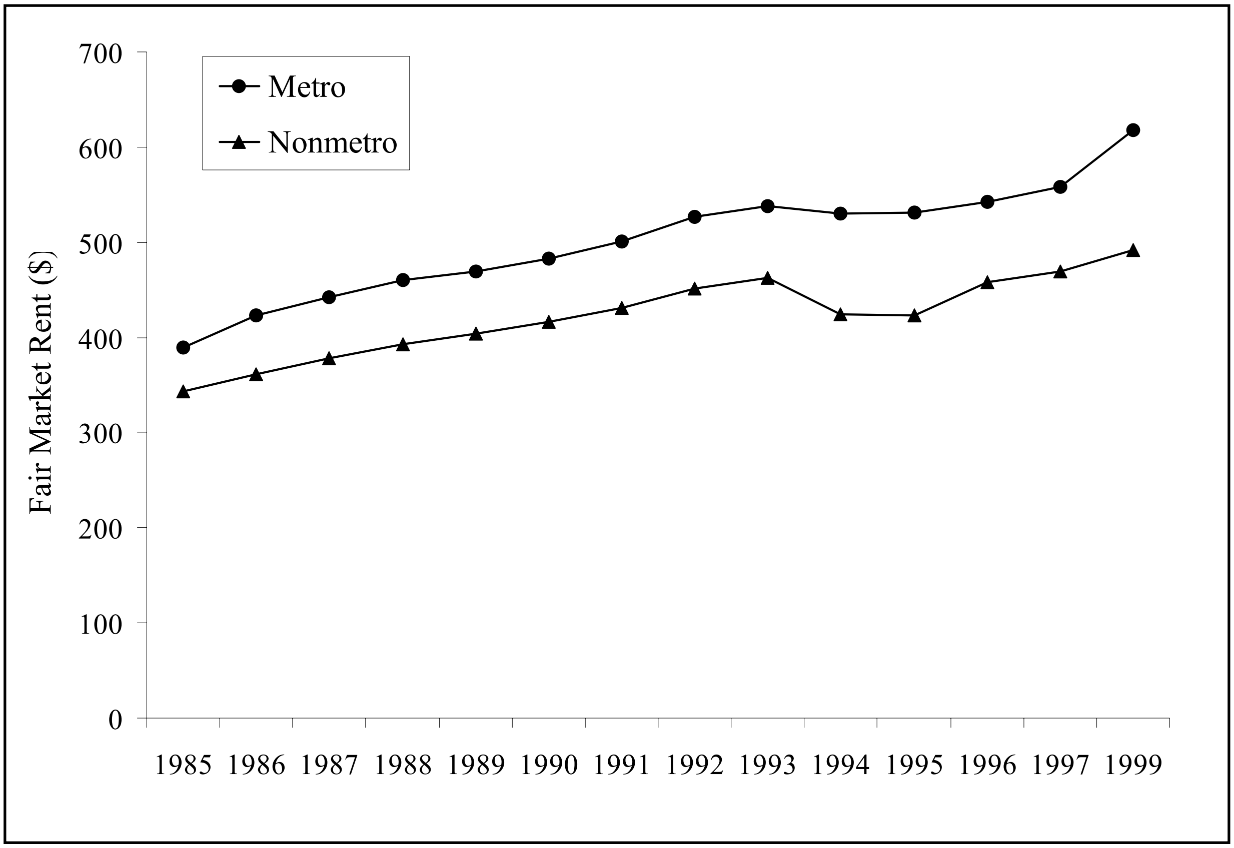
Persistent Poverty Counties, 2000



Source: Economic Research Service, U.S. Department of Agriculture

Figure 3

Fair Market Rents for Nonmetro and Metro Counties, 1985-1999



Source: Author’s calculations based on U.S. Department of Housing and Urban Development Fair Market Rent data